Essays on Microenterprise Growth and Financial Inclusion



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A thesis submitted for the degree of

Doctor of Philosophy in Economics

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This thesis consists of three essays on microenterprise growth and financial inclusion. I focus on two key channels to achieve financial inclusion: (i) encouraging digital technology adoption and (ii) easing frictions in financial markets.

Chapter 1 investigates the extent to which learning barriers limit the adoption of productive digital technologies by firms. I leverage a novel digital technology that overcomes financial management issues that arise due to informality and randomly vary the extent to which learning costs are subsidized. Amongst a sample of microenterprises in India I find that temporarily subsidizing learning costs leads to significant increases in adoption. Firms significantly improve business management (through better financial and marketing practices), and in the process learn about the true profitability of their firm, which dampens adoption. Using a dynamic structural model I highlight the need for a multi-dimensional approach to sustain adoption.

Chapters 2 and 3 focus on easing financial frictions to increase firm productivity. In Chapter 2 my co-authors and I study whether other financial market frictions — in particular, lack of access to a safe place to save — might limit the benefits of credit. Working with Kenyan farmers, we cross-randomize access to a simple savings product with a harvest-time loan. We find increased farm investment and household consumption amongst those who were offered a savings product in addition to a loan offer. In Chapter 3 my co-authors and I study whether a big push microequity contract can generate firm-level and household-level gains while also recovering the initial investment amount for future investments. Working with women-led microenterprises in India we randomize access to performance contingent microequity contracts and document high demand for this novel financial product and sustained improvements in business performance.

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Statement of authorship: The work in this thesis is based exclusively on research carried out by me as a DPhil student in the department of economics at the University of Oxford between October 2018 and July 2023. No part of this thesis has been submitted for a degree at the University of Oxford or any other university. Chapter 1 is single authored. Chapter 2 is joint work with Lauren Falcao Bergquist, Marshall Burke and Edward Miguel. Chapter 3 is joint work with Muhammad Meki and Simon Quinn.

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1 | Introduction

Informal microenterprises form a large share of employment and therefore, play an instrumental role in economic development in low- and middle-income countries (Hsieh and Olken, 2014). These firms are disproportionately poor and are characterized by low levels of productivity. While the importance of increasing productivity for informal microenterprises has been widely acknowledged, open questions remain on how to address various constraints to growth. Limited financial inclusion is at the root of this problem. In recent years innovative digital and financial products have opened new opportunities for financial inclusion. In this thesis I write three essays to study the firm and household level effects of easing constraints to financial inclusion.

Financial inclusion remains a central component of the overall growth strategy. I focus on two key channels to achieve financial inclusion: (i) encouraging digital technology adoption and (ii) easing frictions in financial markets. Chapter 1 focuses on the first channel by studying the role of learning barriers in constraining the adoption of profitable digital technologies. Chapters 2 and 3 focus on the second channel. Chapter 2 documents the extent to which the lack of access to a safe place to save might limit microcredit's benefits. Chapter 3 explores if a novel financial contract, specifically a performance contingent "microequity" contract, can sustain improvements in business performance and household welfare while also recovering the initial investment amount for future investments.

The fast-evolving digital climate allows for innovative tools that are tai-

lored to support the growth of microenterprises. While it is generally accepted that the adoption of improved technology leads to economic development, the process of digital technology adoption is slow, complex and heterogeneous (Alfaro-Serrano et al., 2021). Chapter 1 studies a specific friction that is salient for informal microenterprises — high learning costs at onset. I offer one specific explanation for low adoption of potentially profitable digital technologies: that high learning costs at low levels of experience leads to low adoption of technologies by firms. For informal microenterprises that have low levels of digital sophistication, learning to use a digital technology is analogous to climbing a hill. The initial stretch is hard and difficult to overcome, and in the absence of any intervention adoption remains low. But once these high initial learning costs are overcome firms slide down this hypothetical learning hill and adoption can be sustained. This chapter studies the effect of easing learning costs on dynamic adoption choice, as well as the firm-level effects of adoption.

In this chapter, I examine whether learning costs act as a barrier to digital technology adoption for informal microenterprises in India. Further, I study how digital technology adoption effects firm-level outcomes. I study this in the context of adoption choice around a novel and beneficial financial management app amongst informal women-led microenterprises in Karnataka. Partnering with the NGO Buzz Women and the technology start-up MeraBills, I implement a randomized field experiment where treatment arms vary in the extent to which learning costs are subsidized. I subsidize learning costs by offering firms hand-holding in learning to use the digital technology

in the form of repeated visits from local field officers.

From the randomized experiment I find that a temporary intervention that subsidizes learning costs (by hand-holding them to gain experience in using the technology) leads to significant increases in adoption in the short run. For the digital technology adoption to be beneficial, one would expect firms to use the financial app for two purposes: (i) viewing key statistics and reports about the business (which is otherwise challenging given the informal record-keeping practices) and (ii) to manage trade credit (which is difficult given the large number of informal transactions). I document significant use of the app for both purposes. First, firms in the treatment arms are about 10% more likely to use this digital technology to view key financial reports and about 3% more likely to use the technology to manage trade credit by sending payment reminders and invoices to their customers. Given the significant short-run effects on adoption, I examine firm-level outcomes. I find that firms improve business practices around financial planning and marketing. Adoption also leads to a an interesting but important effect — as firms adopt and improve business practices, they learn about the true profitability of their business. In a setting where firms systematically over-estimate profits at baseline, this leads to a 24% decrease in self-reported firm profits and a 19% decrease in self-reported firm revenues. I argue that this represents a reporting effect rather than a reduction in actual revenues and profits. Learning about the limited profitability of the firm can be beneficial to the micro-firm owner as it allows them to make a more informed choice about running and growing their firm. However, it does dampen firms' future pro-

jection of business profitability and, to some extent, adoption of the digital technology.

While the randomized intervention sheds light on the effects of an intervention that subsidizes learning costs, a comprehensive analysis of the optimal intervention requires a consideration of adoption outcomes under alternative interventions. To do this I write a stylized dynamic model of adoption choice for firms with differential learning costs and structurally estimate it using data from the randomized intervention. I find that the model fits the data well, but only does so under slow learning and high forgetting, highlighting the salience of learning barriers. I explore adoption effects under four alternative interventions; (i) monetary transfers over time to incentivize adoption; (ii) repeated nudges to decrease forgetting; (iii) improving human capital and (iv) updating firm's beliefs about their profitability. Individually these interventions are not sufficient to have a meaningful or sustained impact on adoption. However, my model highlights that bundling any of these counterfactuals (with the exception of the monetary transfer counterfactual) with the hand-holding treatments leads to large and sustained increase in adoption outcomes. This chapter documents the complexity of sustaining adoption even for a profitable digital technology and highlights the need for a multi-dimensional approach.

This chapter provides three key contributions. The first and main contribution of this paper is to evaluate causally the extent to which easing learning barriers leads to increased technology adoption and firm growth. The second contribution lies in the dynamic nature of the experiment and structural

model. Learning costs evolve over time, as do adoption choices. To accurately study learning barriers and adoption choice the research design needs to study the inter-temporal trends. The repeated visits in the randomized experiment and the dynamic nature of the adoption choice model enable me to show how treatment effects evolve over time and correspondingly study dynamic trends in counterfactual interventions. My third key contribution is to use the structural estimation to highlight the need for multi-dimensional interventions to unlock sustained adoption effects.

To comprehensively study the constraints to increasing growth and productivity for informal microenterprises, I move my focus for the remainder of the thesis to studying financial market frictions for microenterprises in low- and middle-income countries. Access to microcredit has had mixed effects on households ability to finance profitable investments and improve key livelihood indicators (Karlan and Zinman, 2011; Angelucci et al., 2015; Attanasio et al., 2015; Augsburg et al., 2015; Banerjee et al., 2015b; Crépon et al., 2015; Tarozzi et al., 2015; Fiala, 2018; Meager, 2018). Even in cases where access to microcredit has had positive immediate effects on revenues, it often fails to translate into sustained consumption gains or business growth for the majority of households (Banerjee et al., 2015b; Meager, 2016). Chapters 2 and 3 highlight the need for academic research and policy to innovate beyond micro-credit and focus on multifaceted financial access programs to unlock opportunities for dynamic firm and household gains.

In Chapter 2, written with Lauren Falcao Bergquist, Marshall Burke and Edward Miguel, we provide evidence for one possible explanation for this lack

of sustained impact of microcredit — that the lack of access to a safe place to save might limit credit's benefits, by preventing recipients from saving investment returns and channeling them into future consumption or productive reinvestment. We study this in the context of African agricultural markets where large seasonal fluctuations in the price of staple commodities are common. This provides substantial opportunities for arbitrage through storage but despite this, smallholder farmers often do not take advantage of this opportunity. It is common for farmers to sell their crops immediately after harvest, when prices are low, and buy back grain for personal consumption in the lean season when prices are higher. Working with smallholder farmers in Kenya, we build on earlier work by Burke et al., 2019 that found that access to a harvest-time loan generated large increases in maize inventories and revenues for farmers, but limited increases in consumption or other productive investments. In a contemporaneous field experiment, we cross-randomize access to a simple savings product with the harvest-time loan. Among farmers who are offered a loan, we document large and significant increases in farm investment (by 11%) and total household consumption (by 7%).

We provide evidence for two mechanisms to substantiate our results. First, the lockbox provides households with a technology to move money intertemporally to times when it is most needed. For example, we see large and significant consumption gains from lockbox usage during the lean season, when the marginal utility of consumption is presumably highest. The welfare effects of consumption gains in the lean season, when consumption of food and non-food consumption typically sees a large drop, is well documented

(Barrett and Dorosh, 1996; Kaminski et al., 2014; Basu and Wong, 2015). Consistent with the idea that lockboxes can shield households against a "kin tax" (Dupas and Robinson, 2013; Jakiela and Ozier, 2016) provide evidence for a second mechanism — that, in addition to enabling the inter-temporal movement of consumption, lockboxes also increase total consumption. We show that households that are most interconnected with friends and family at baseline become less likely to provide money gifts or loans to them when they have access to a lockbox.

To strengthen the central findings of this paper, we provide two additional pieces of evidence. First, we use a second source of variation in the Burke et al., 2019 study on the timing of the loan. They found that returns to loans offered immediately after harvest (in October) yield much higher returns than loans offered three months later (in January). In this paper, we find that the consumption and investment benefits of being offered a lockbox are concentrated among loans that yielded higher returns. This suggests that access to savings is most useful when combined with access to a profitable investment (facilitated here by timely credit). Second, we strengthen our key findings by estimating the effects of a lockbox alone (among households without access to the harvest-time loan), and find null effects on consumption and farm reinvestment. This implies that the results are not the impact of having a lockbox alone. Overall, these results suggest that financial market frictions interact in important ways, and point to the complementarity of financial access programs.

The key contribution of Chapter 2 is to the large literature on the role

of microcredit in enabling productive investments by households. To our knowledge, this paper is among the first to explicitly cross-randomize credit and savings products. By explicitly testing the importance of simultaneous provision of two distinct financial instruments, we show that increasing access to both credit and savings is key to enabling households to undertake productive investments.

In the final chapter of my thesis, I circle back to financial constraints faced by microenterprises and push the frontier on innovations to microcredit financing. Easing financial constraints in informal financial markets is challenging and proposed solutions have a trade-off between impact and financial sustainability. On one hand, provision of large grants to microenterprises has had large and persistent increases in business performance and key livelihood indicators (De Mel et al., 2008; Fafchamps et al., 2014; Banerjee et al., 2015b; Bandiera et al., 2017; Crépon et al., 2020; Balboni et al., 2022; Hussam et al., 2022). However, such interventions have limited sustainability as grants do not allow the money to be redeployed to other firms (Bari et al., 2021). On the other hand, provision of access to microcredit is a more financially viable option. However, microcredit interventions have found mixed evidence on the sustained impact on business profits and key livelihood indicators (Karlan and Zinman, 2011; Angelucci et al., 2015; Attanasio et al., 2015; Augsburg et al., 2015; Banerjee et al., 2015a; Crépon et al., 2015; Tarozzi et al., 2015; Fiala, 2018). Another drawback is the rigid repayment requirements that limit a firm's ability to channel money to lumpy assets (Field et al., 2010).

Chapter 3 is written with Muhammad Meki and Simon Quinn and is part of an ongoing study in Karnataka in India. We address the trade-off discussed above and examine if a “big-push" microequity contract, in the form of performance-contingent financing, can generate sustained improvements in business performance and household welfare, while also recouping the initial investment amount for future investments. Microequity contracts are revenue-sharing repayment contracts with a fixed duration. These contracts provide implicit insurance against risks and are a natural and continuous process of mutual sharing of losses and profits.

Working with Buzz Women, an NGO, and Yunus Social Business (YSB), a financing institution, we run a field experiment that randomizes the offer of microequity contracts in a sample of 28 women-led microenterprises in two sectors of particular relevance for rural and peri-rural areas: (i) animal husbandry and (ii) tailoring. The financing is large relative to typical loans and is channeled toward assets and working capital in the business. Nine months into a three-year intervention, we have three key findings. First, we document high demand for microequity contracts among a sample chosen for their potential interest in the product. Second, using high-frequency daily data, we find sustained improvements in business performance. Firms report a 53% increase in fixed assets and a 275% increase in inventories. And finally, we note that if current repayment trends continue, investors will be able to recoup the initial investment amount. We also observe perfect compliance so far and document no missed repayments. Given the incentive to underreport revenues we verify the accuracy of self-reported data and find accurate

reporting by firms.

Chapter 3 provides the primary contribution of pushing the frontier on innovations to microcredit financing. In the context of informal microenterprises, there is an open question as top such innovative financing can work in practice. To test this, we work intensively with a small sample of firms and collect high-frequency daily data over a long time horizon (Bloom et al., 2013). We document improvements in business and household outcomes, while maintaining low rates of default. Our paper provides insights on what works and what does not work for a potential scale-up. Innovations in the space of digital credit in India (and other LMICs) can drastically reduce the costs of implementing similar contracts. This study is a first step to show that such financing can be implemented and potentially scaled up.

The results of this paper have important implications for policy. First, while the microfinance literature has found limited evidence of business growth for women-led microenterprises (De Mel et al., 2008; Attanasio et al., 2015; Fiala, 2018), this paper contrasts that to find encouraging evidence of a large and sustained growth in women-led microenterprises. Second, in this paper we work with the very “micro" end of microenterprises and, with the results so far, we are able to show positive and financially sustainable effects of an equity-like intervention. In India, microenterprises account for over 97.88% of the population of firms (Hsieh and Olken, 2014) and the results of this paper hold promise of a future scale-up.

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2 | Digital Technology Adoption: Subsidizing Learning Costs for Firms in India

Abstract

In an era of rapid digitalization in low- and middle-income countries, many novel digital technologies are still out of reach for informal micro-firms. Adoption of technology can enable growth and increase productivity for these firms in LMICs. However, across varied settings, adoption remains low for seemingly profitable technologies. In this paper, I offer one specific explanation: that high learning costs at onset leads to low adoption of technologies by firms. First, I offer micro-firms in India access to a novel digital technology that overcomes financial management issues that arise due to informality. I implement a randomized field experiment where treatment arms vary in the extent to which learning costs are subsidized. The subsidy comes in the form of hand-holding in learning to use the new digital technology. I document that a temporary learning subsidy that maximizes initial adoption leads to significant positive effects on adoption, as well as more intensive use of the digital technology. I also offer evidence that as firms use this digital technology, they significantly improve business management (through better financial and marketing practices), and in the process learn about the true profitability of their firm, which dampens adoption. Second, I structurally estimate a dynamic model of adoption choice with differential learning costs and highlight the need for a multi-dimensional approach to sustain adoption of a potentially profitable digital technology.

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2.1 Introduction

Micro-firms represent a large share of the workforce in most low-and middle-income countries (LMICs) and are often characterized by low growth and profitability (Hsieh and Olken, 2014). Innovation through adopting new technologies can be a pathway for growth for micro-firms. [1] In the era of rapid technological change, innovations on the digital front offer promise of a growth potential for microenterprises.(Fernandes et al., 2017; Iacovone et al., 2017; Berrou et al., 2020; Cirera et al., 2021). At the same time, low adoption rates, especially amongst micro-firms, has emerged as a prominent impediment to the realization of this growth potential (Atiyas and Dutz, 2021).

Limited adoption of potentially profitable technologies is by no means a phenomenon that is restricted to digital technologies, but has been documented in a variety of settings (Dercon and Christiaensen, 2011; Duflo et al., 2011a; Suri, 2011). Potential explanations include financial constraints which limit profitable investments (Croppenstedt et al., 2003; Bank, 2005; Mukherjee et al., 2021), large fixed costs (Bassi et al., 2021) and limited availability of inputs and lack of market access (Abrar et al., 2004). More specific to digital technologies are constraints including informational barriers (Foster and Rosenzweig, 1995; Asfaw and Admassie, 2004; Conley and Udry, 2010; Foster and Rosenzweig, 2010; Hanna et al., 2014b; Atkin et al.,

[1] Such technologies include mobile money platforms (Jack and Suri, 2014; Riley, 2022), mini grids for solar and wind energy, pay-as-you-go payment systems (Gertler et al., 2021; Bonan et al., 2023), digital finance apps or hybrid seeds and fertilizers (Suri, 2011).

2017), limited information about true profitability (Dadi et al., 2004; Dercon and Christiaensen, 2011) and the lack of commitment devices (Duflo et al., 2011a). A channel that has received limited attention, but is particularly salient for the adoption of digital technologies, is learning barriers.

Learning costs are the time or cognitive cost of acquiring the human capital needed to use a new technology and can be high at onset. In this paper, I examine whether learning costs act as a barrier to digital technology adoption for informal micro-firms. These costs can evolve over time, that is, as one accumulates experience in using the technology learning costs decrease. I combine a field experiment with a structural model to study the salience of learning costs in adoption choice and examine the downstream effects of adoption on firm-level outcomes. I focus on a specific digital technology: a financial management app that helps firms view key financial statistics and manage cash flow. I partner with an NGO in India that works towards fostering growth for women-led micro-firms in the informal sector. The financial management app is provided by a tech start-up MeraBills who is in the process of scaling the technology in a nationwide program across India. My study considers their main target group — micro-entrepreneurs. I conduct the study in a setting where returns to adoption are potentially high — the study population comprises of entrepreneurs who at baseline often manage their business drawing on mental accounting and diary entries.

It is important to note that digital technology adoption is not a one-time choice. As returns and costs associated with adoption evolve over time, firms tend to drop in and out. Therefore, to understand adoption choice, it is key to

study the problem in a dynamic sense. The theoretical framework describes the dynamic adoption choice made by a firm in the face of high learning costs. It predicts that a front-loaded temporary intervention that maximizes initial adoption (and herein reduces the learning costs), leads to increased adoption in a setting where learning costs decrease as firms accumulate experience.

To test this prediction empirically, I randomize the initial adoption of the technology in the experiment by varying degrees by subsidizing learning costs for varying durations. The subsidy comes in the form of visits to the firm by trained staff who hand-hold them on how to enter transactions and use the digital platform. In line with the theoretical predictions, I find that a temporary front-loaded intervention that subsidizes learning costs (by hand-holding them to gain experience in using the technology) has significant positive effects on adoption. I document two key findings. First, that firms in the treatment arms are about 10% more likely to use this digital technology to view key financial reports, which is otherwise very challenging given informal record-keeping practices. Second, treated firms are about 3% more likely to use the technology to manage trade credit by sending payment reminders and invoices to their customers. This can be particularly beneficial in informal rural/peri-rural markets, since firms tend to make a large proportion of business transactions on credit. The effects of the subsidy on adoption depreciate over time, but are sustainable and remain positive even 7-8 months after the intervention.

Given the significant short-run effects of the learning subsidy on adoption rates, I can leverage the setting to study the causal link between technology

adoption and firm outcomes. I find a striking and surprising result: Supported by the app firms start keeping formal records and this allows them to learn about the true profitability of their firm. I document that firms systematically over-estimate profits at baseline, which prior to adopting the app was estimated based on the entrepreneurs mental records. The formal record keeping results in a 24% decrease in self-reported firm profits and a 19% decrease in self-reported firm revenues. I argue this represents a reporting effect rather than a reduction in actual revenues and profits. I substantiate this with three strands of evidence. First, treated firms show a significant improvement in business practices around financial planning and marketing. This is a key channel through which a firm can learn about their true profitability. Second, I find suggestive evidence that firms report a decrease in new investment (self-reported) by 23% in the short run. I argue this is indicative of more accurate reporting rather than a true worsening of business financials. Third, treated firms have lower expectations about future prospects of the business. Again, I argue this is reflective of having more accurate information about one's firm. The dampening of business sentiment is likely to dampen adoption of the digital technology over time. Using a long run survey (scheduled to be launched in October 2023), I will analyze how firms act on this new and updated information about their business. Learning about the limited profitability of the firm can be beneficial to the micro-firm owner as it allows them to make a more informed choice about running and investing in their firm.

This paper highlights the importance of learning barriers. However, to

comprehensively design policy interventions to sustain adoption, it is key to look at the effects of alternative interventions. I structurally estimate key parameters in my model and use this to study policy counterfactuals. As in the simple theoretical framework and the randomized intervention, learning occurs through accumulating experience on using a technology and learning costs decrease as firms gain experience. The key intuition is as before – if firms are hand-held and moved further enough along the learning curve they can achieve a sustained increase in adoption. I solve the model using value function iteration and compute maximum likelihood estimates for key parameters. I find that the model fits the data well — but only does so under slow learning and high forgetting, highlighting the salience of learning barriers. The parameters computed from structural estimation allow me to study dynamic adoption choice under four alternative interventions; (i) monetary transfers over time to incentivize adoption; (ii) repeated nudges to decrease forgetting; (iii) improving human capital and (iv) updating firm's beliefs about their profitability. Each of these counterfactual interventions alone are not sufficient to have a meaningful or sustained impact on adoption. However, I find that bundling any of these counterfactuals (with the exception of the monetary transfer counterfactual) with the hand-holding treatments leads to large and sustained increase in adoption outcomes. In an economic environment with many constraints to adoption, this highlights the need for a multi-dimensional approach to sustain adoption.

This study is particularly policy relevant because micro-firms form a large share of the workforce in LMICs. In India, more than 80% of the la-

bor force is employed in the informal sector (World Bank, 2022). Within that, micro-firms account for a significant share of the informal sector and have a disproportionately large concentration of vulnerable households. The growth and profitability of these firms therefore have a direct impact on broader economic growth, sustainable development, and poverty alleviation. In addition, given the strong inter-linkages between firms, banks and the government, the informal sector also plays a key role in financial stability. The current period of accelerated digital development has opened new avenues for the use of digital financial services for micro-firms in the informal sector.[2] Policy questions around what drives adoption and the firm-level effects of digital technology adoption have taken prominence in the policy space. In this regard, a low-cost scalable intervention that can enhance adoption of profitable digital technologies can be very beneficial. In this paper, I add to this academic and policy discussion.

The paper adds to the large literature on learning models. To my knowledge, this is one of the first few field experiments specifically designed to test the role of learning-by-doing on technology adoption. Costs associated with learning can drive adoption decisions, and this is especially pertinent for new technologies or technologies that have some level of complexity. Learning models assume that the returns and costs to a technology are not known, but revealed over time. Learning can occur through different channels. A vast literature on social learning uses models that allow users of a new technology to learn from peers (Conley and Udry, 2010; Hardy and McCasland, 2016; Brooks et al., 2018; Cai and Szeidl, 2018; Fafchamps and Quinn, 2018;

[2]Appendix 2.A presents some statistics on the pace of rapid digital growth in LMICs.

Lafortune et al., 2018; Dalton et al., 2021). Another branch of the literature on learning focuses on learning by noticing (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Hanna et al., 2014a; Dalton et al., 2021). Lastly, the seminal work by d'Autume and Michel, 1993 laid the theoretical foundation for learning-by-doing models for firms and a lot of work has been done in this space since (Foster and Rosenzweig, 2010; Thompson, 2010). This paper falls into the learning-by-doing category. By setting up a dynamic model of adoption choice, I provide a framework to understand the temporal dynamics of adoption for informal micro-firms.

The paper also relates to the extensive policy relevant literature on training for firms (McKenzie et al., 2021). It adds to this literature on two fronts. First, instead of the conventional approach of teaching firms to manage their business, this provides firms with the tools to learn. I offer evidence of how temporarily subsiding learning costs can be a cost-effective substitute for an intensive training session. My relatively low-cost temporary intervention, both encourages adoption but also provides firms with a more accurate knowledge of their own profitability. Multiple interventions have tested variants of traditional methods of training (de Mel et al., 2014; Drexler et al., 2014; Berge et al., 2015; Campos et al., 2017; Calderon et al., 2020; McKenzie, 2021). McKenzie et al., 2020 estimates (on average) a 5.6% and 12.1% increase in respectively in sales and profits across studies. McKenzie and Woodruff, 2014 and McKenzie and Woodruff, 2017 argue that the modest effects of training on sales and profits is driven by limited adoption of management practices by firms. The second contribution to this literature lies

in the dynamic nature of the experiment and structural model. It differs from the more “static" approach to training firms. Learning costs evolve over time, as do adoption choices. To accurately study learning costs and adoption choice the research design needs to account for the inter-temporal trends. The repeated visits in the randomized experiment and the dynamic nature of the adoption choice model, enable me to show how treatment effects evolve over time and correspondingly study dynamic trends in counterfactual interventions.

My final contribution is to use structural estimation to highlight the need for multi-dimensional interventions to unlock sustained adoption effects. It links to a vast literature in development economics that highlights the importance of complementary interventions in unlocking gains for firms and households (Kaboski and Townsend, 2005; Duflo et al., 2011b; Suri, 2011; Atkinson et al., 2013; Karlan et al., 2014; Afzal et al., 2018; Mukherjee et al., 2021).

The rest of the paper is structured as follows. Section II presents a model of learning that motivates the empirical analysis. Section III describes the experimental setting. Section IV details the experimental design. Section V presents treatment effects and Section VI details the results from structural estimation, including counterfactual analysis. Finally, Section VII concludes.

2.2 Stylized dynamic model of adoption choice

This section describes a simple model of learning about a new digital technology that is used to guide the empirical work in this paper. Motivated by my interest in studying the role of learning costs as a barrier to technology adoption, I design a stylized dynamic model with differential learning costs and use this to (i) explain adoption choice; (ii) characterize temporal dynamics of adoption; and (iii) in Section 2.6 , I will extend this model to consider plausible outcomes on adoption choice under counterfactual scenarios.

2.2.1 Theoretical framework

The model details the dynamic digital technology adoption choice made by a risk neutral firm that optimizes in an infinite time horizon in discrete time.

A firm produces output q_t in period t. This can be written as, $q_t = n_t \times s$, where n_t is the average number of units sold per transaction and s is the number of transactions that a firm has.[3] The utility per-transaction is given by P. Thus, total utility received by a firm is given by π_t^N, as shown in equation 2.1:

$$\pi_t^N = P \times s. \tag{2.1}$$

In period 0, firms are introduced to a digital technology. They are trained on

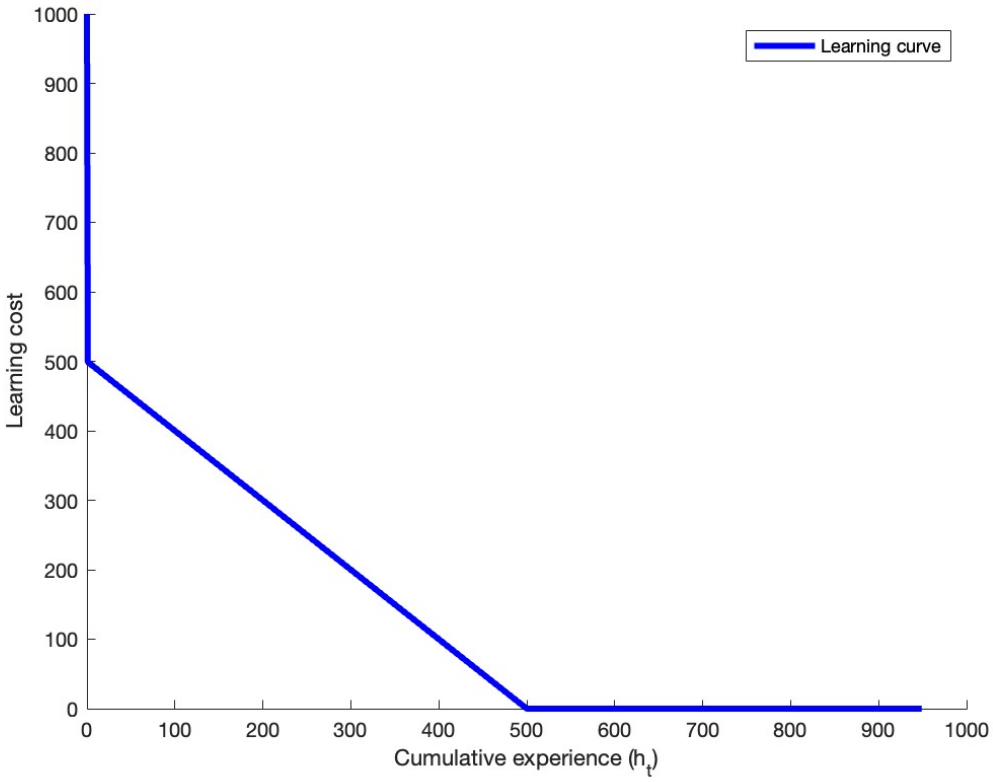
[3]I write q_t in this form as learning costs are associated with experience that is measured by number of transactions. The model assumes that the number of transactions per period for a firm (s) is constant. This is a simplifying assumption and the key intuition for the model will hold even if I allow s to vary over time.

a digital app that helps them manage their business. As they enter transactions on the app, they reap benefits from using it. The returns to adopting this new digital technology is given by ϕ. Firms also face a learning cost which is a per-transaction cost of entering data. One can think of this as the time cost or the cognitive costs of using this new digital technology. This helps capture the productivity growth associated with the accumulation of experience in using the digital technology by a firm. In this setting, the experience of a firm at any given time is measured by the number of transactions they have entered using the digital technology at the start of that period (h_t). In any period t, the learning cost is given by $b_t(h_t)$ if the digital technology is adopted, where h_t is the transaction experience a firm brings into that period. Learning costs decrease as firms accumulate more experience in using the app. When a firm has no experience in using this technology ($h_t = 0$), it faces infinitely high learning costs as I assume that a firm does not naturally start using the app. Beyond a point $\bar{h}$, I assume there is no learning and learning costs are 0. Learning costs also depend on the ability of the entrepreneur which is captured through α_1 and α_2. α_1 is the learning cost incurred by the entrepreneur when they have no experience using the app (that is, $h = 0$). α_2 is the rate at which learning costs decrease as firm's accumulate experience. It is assumed that $\alpha_1 > 0$ and $\alpha_2 > 0$. $\bar{h}$ is given by $\frac{\alpha_1}{\alpha_2}$ and therefore there is no discontinuity in the learning cost function. The plot of learning cost of adoption against the cumulative number of transactions is called the learning curve. Figure 2.1 displays a plot of the learning curve (based on hypothetical parameters). We can write the learning curve

as:

$$b_t(h_t; \bar{h}, \alpha_1, \alpha_2) = \begin{cases} \infty & \text{if } h_t = 0, \\ \alpha_1 - \alpha_2 \cdot h_t & \text{if } 0 < h_t < \bar{h}, \\ 0 & \text{if } h_t \geq \bar{h}. \end{cases} \tag{2.2}$$

Figure 2.1: **Learning curve**



Thus, if a firm adopts the digital technology in period t, it earns a utility

of π_t^D, as shown in equation 2.3:

$$\pi_t^D = \phi \times P \times s - b_t(h_t; \bar{h}, \alpha_1, \alpha_2) \times s. \tag{2.3}$$

A firm enters a period t with experience h_t. Firms then choose whether or not to adopt the technology based on the relative payoff from adopting. The state space comprises of transaction experience h_t. The state variable completely summarizes all information from the past that is required for the forward-looking optimization problem. The control variable comprises of an action $y_t \in \{0, 1\}$. y_t is the choice a firm makes in each period between adopting $y_t = 1$ and not adopting $y_t = 0$ the digital technology.[4]

The transition equation is given by Equation 2.4. This determines how experience evolves over time. When a firm adopts, it gains experience when entering the following period. Thus, if a firm adopts in period t ($y_t = 1$), it enters period $t + 1$ with an additional s transaction experience (and a correspondingly lower learning cost). In addition to learning, the model allows for depreciation of experience (that is, forgetting). That is, if a firm does not adopt in period t ($y_t = 0$), the firm enters period $t + 1$ with d fewer transaction experience as it forgets some of what it had learned. Thus, it faces a correspondingly higher learning cost. Firms know that learning costs are infinitely high when they have not accumulated any experience in using the technology. They also know that these learning costs will reduce to zero after they accumulate a certain amount of transaction experience and they

[4]For simplicity, I assume throughout that, if a firm is indifferent between adopting and not adopting, it will adopt. This changes nothing of the underlying structure of the model.

use this information when making adoption choices. The evolution of h_t can therefore be written as:

$$h_{t+1} = h_t + y_t \times s - (1 - y_t) \times d \tag{2.4}$$

where,

$$h_t = \sum_{i=1}^{t-1} [s \times y_i - (1 - y_i) \times d.] \tag{2.5}$$

The value function given by Equation 2.6 is formed by assuming that the firm makes an adoption decision in each period by comparing the expected discounted future utility from adopting and not adopting. I assume exponential discounting with discount factor δ. The value function can be written as:

$$V(h_t) = E\left[\max_{y_t \in \{0,1\}}\left[y_t \times \underbrace{(\pi_t^D + \delta \times V(h_{t+1}))}_{\text{Maximize if adopt}} + (1 - y_t) \times \underbrace{(\pi_t^N + \delta \times V(h_{t+1}))}_{\text{Maximize if no adopt}}\right]\right]. \tag{2.6}$$

Substituting from equation 2.5, this becomes:

$$V(h_t) = E\left[\max_{y_t \in \{0,1\}}\left[y_t \times \underbrace{(\pi_t^D + \delta \times V(h_t + s))}_{\text{Maximize if adopt}} + (1 - y_t) \times \underbrace{(\pi_t^N + \delta \times V(h_t - d))}_{\text{Maximize if no adopt}}\right]\right]. \tag{2.7}$$

The key intuition behind this deterministic model is that learning is a like a hill. At low levels of experience, the learning costs are high and and the

returns to adoption are not sufficient for firms to adopt. In the absence of any intervention, adoption will be low given the high learning barriers. However, if one were to hand-hold firms and move them sufficiently along the learning curve, there is a point beyond which firms will slide down the learning curve and be more likely to adopt. I call this point the "learning threshold". Using hypothetical parameters to convey the intuition, Figure 2.2 shows the probability of adoption around this learning threshold. As is intuitive, there are two absorbing steady states: (i) no adoption ($h_t = 0$) and (ii) sustained adoption ($h_t \geq \bar{h}$). Figure 2.3 plots this learning threshold on the learning curve.

In Section 2.6, I add more structure to this theoretical framework and estimate parameters of interest using primary data collected from the randomized experiment. I then use these estimated parameters to consider adoption outcomes under various alternative interventions.

Figure 2.2: **Probability of adoption (for a single firm)**

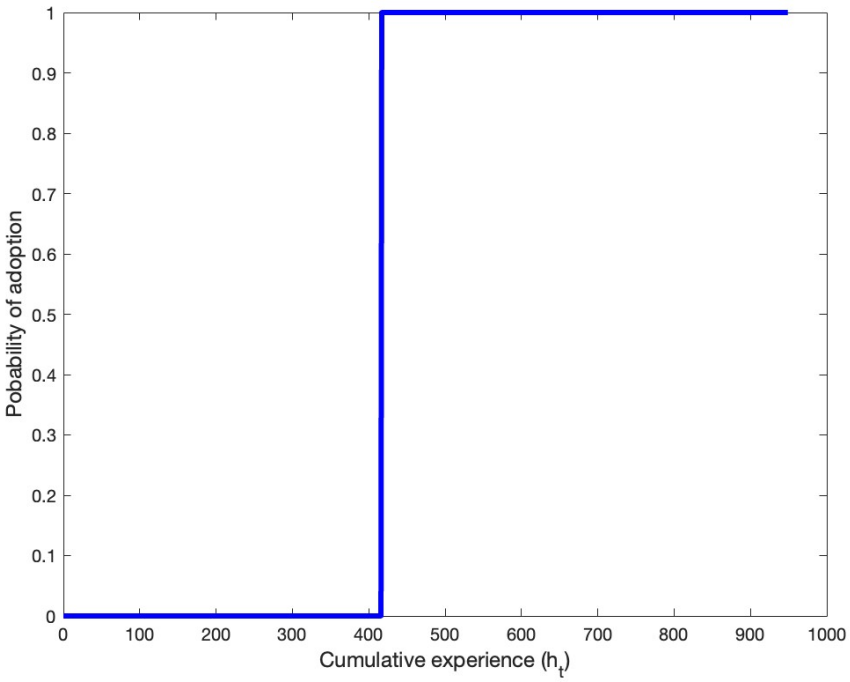
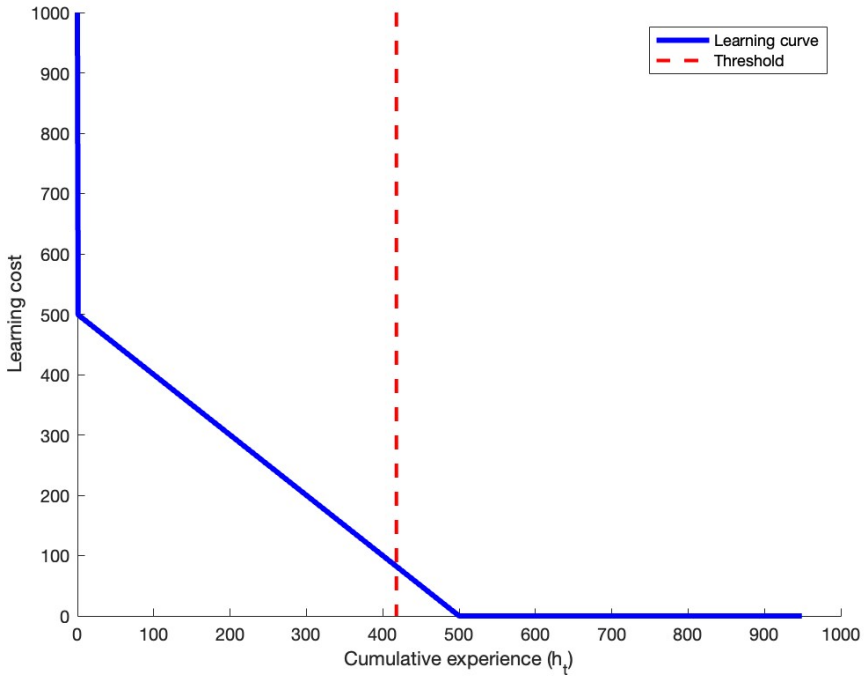


Figure 2.3: **Learning threshold (for a single firm)**



2.3 Setting

2.3.1 Study Context

I conducted this study in Karnataka in India in 2021 and 2022. In recent years, India has seen a rapid rise in the availability of digital technologies. This period of rapid digitalization, has also highlighted the prevalent digital divide based on informality, size of firm, gender and age amongst other variables (Atiyas and Dutz, 2021). In this study, I focus on women-led micro-firms in the informal sector in India, a group that forms a large share of employment but is lagging behind in the adoption of digital technology and productivity.

To study digital technology adoption choice amongst micro-firms, I partnered with Buzz Women, a prominent NGO and Peabody Soft, a tech start-up in India. Buzz Women's mandate is to promote growth for women-led micro-firms. They work with poor women in rural areas to provide training in financial management, entrepreneurship and leadership. They work with about 200,000 women-led firms across five districts in the state of Karnataka. Their mission is "to make low-income women the drivers of prosperity – for their own selves, for their families and for their communities". This study links to their "Buzz Vyapaar" program (which translates to "Buzz Business" in Kannada) that identifies potential or existing micro-firms and helps them run and grow their business. My other partner organization, Peabody Soft, is a tech start-up based in Andhra Pradesh in India and has designed the MeraBills app (a digital financial technology) to help micro-firms run and

manage their business. This novel app is used by over 14,000 firms in 20 states in India and given its success has been promoted by several state governments.

Buzz Women is based in Bangalore, the technology hub of India and the capital city of the state of Karnataka. I sample women micro-firm owners across four districts near Bangalore, including Kolar, Tumkur, Chikkabalapura, and Ramanagar. The sample is comprised of 320 women micro-firm owners who are are actively running a business,[5] are involved in decision making in the business[6] and have regular access to a smartphone[7]. Based on these three criteria, sixteen field officers were selected by Buzz Women and tasked with selecting 20 entrepreneurs each from their respective panchayats. A panchayat is a geographical area within a district. The field officers were asked to choose the women eligible for this study as they have local knowledge. An independent survey team then conducted phone calls to each

[5]In pilot work in September 2021, I observed that during the COVID pandemic a lot of micro-firm owners stopped running their business (temporarily or permanently). To understand the drivers of technology adoption it was important to ensure that I sampled firms that were actively running. Staff from Buzz Women were tasked with conducting in-person visits to ensure this.

[6]In LMIC settings it is quite common for women to be involved in a family business, but not have much agency in the decision making. To study decisions around adoption of a new technology, it was important that the women were closely involved in running the business. Since the sample comprises of women-led micro-firms, Buzz Women tasked field staff to call/ meet with participants and check that they were involved in decision making for the firm.

[7]I ensured that women have a smartphone they regularly use. Driven by the low cost of phone data and widespread use of apps like WhatsApp, Using data from a pilot study conducted in 2021, I find that 25-40% women in the region have a basic smartphone. However, while they "own" a phone, they often do not have the phone with them through the day as it is shared with members of the household. In my pilot study, I find that 70-80% of women who own a smart said that they shared the phone with other members. To be able to adopt this digital technology, it is key that the participants had regular access to the phone. Therefore, instead of asking if participants own a phone, they are asked whether they have a regular access to a phone.

of the 320 participants and double-checked that they met the criteria for this study. I did not limit the sample by the sector the micro-firm works in. I did this in order to obtain a sample representative of the micro-firms in the state and therefore, provide results that have external validity.

2.3.2 Descriptive statistics

Table 4.2.1 presents summary statistics for the sample of 320 micro-firm owners. All are women, with an average age of 35 and 49% have completed above a secondary level of education. 92% can read and write in Kannada (which is the local language). 95% of the sample is married and on average has a household size of 5 members. Only 4% of the women micro-firm owners are the heads of their households. For 86% of the women in our sample, their husband is the household head. Including the micro-firm owner, the average household has 2.3 members who earn any form of income. The average a household has a total monthly income of INR 35,222 or USD 425 (median is INR 25,000 or USD 302).[8] The mean number of businesses run by the household (including the micro-firm in our sample) is 2 and the average total monthly earnings for all businesses in a household is INR 25,844 or USD 312 (median is INR 20,000 or USD 241).

The firms in this sample are mostly family firms. The average micro-firm owner has 10 years of experience in their current business and runs their business for about seven hours each day. 89% of the businesses have no employees and the mean number of employees in my sample of firms is

[8]The USD INR exchange rate is as of December 2022.

0.54 (with a median of 0 employees). The most popular types of business are (i) tailoring (comprising 49% of firms in my sample); (ii) retail stores (comprising 24% of firms in my sample); (iii) cloth business (comprising 7% of firms in my sample); (iv) animal husbandry or the business of selling cow milk (comprising 5% of firms in my sample). The remaining firms are engaged in sectors such as beauty parlors, selling flowers, selling snacks, running stationary shops etc. The average firm in my sample earned monthly profits of INR 6,218 or USD 75 (median is INR 4,000 or USD 48) and reported a mean profit margin of 50%.[9]

The average micro-firm owner in the sample is comfortable using a smartphone, but does not use digital technologies to run and manage their business. For example, 52% of the sample use their phone for more than four hours a day. 89% of the sample reports using a smartphone to watch videos on YouTube; the same proportion reports using a smartphone for WhatsApp. However, only 36% report using mobile money tools (such as PayTM, GPay etc.) in their business. This is a surprisingly small share given the prevalence of mobile money in the country. Further, over 94% of micro-firm owners in my sample report that they need help from their family when using the smartphone.

2.3.3 The digital technology

The digital technology used in this study is a financial management app called "MeraBills".[10] It is an easy to use app that helps entrepreneurs analyze firm

[9]Profit margin is measured as monthly profit divided by monthly revenue at baseline.
[10]This translates to "my bills" in Hindi.

finances, manage cash flow and maintain records of business transactions. It works on all smart-phones and is freely available. The app has a range of functions. First, it allows entrepreneurs to enter business transactions. Second, it provides summary statistics of transactions entered including data on revenue, expenditure, profits, accounts payable and accounts receivable. Third, it allows entrepreneurs to request/make pending payments to buyers/suppliers digitally. Appendix 2.B discusses details on the interface of the digital technology.

Microenterprises in LMICs often use informal methods to maintain records of business transactions. In this study's sample, only 40% of firms at baseline say they maintain ledger books or equivalently organized notes of their business transactions. Maintaining records of business transactions enables firms to manage account payables and receivables optimally. In informal rural markets, this can be particularly beneficial since firms tend to undertake a large proportion of transactions on credit/debit. In this study setting, at baseline, firms owe suppliers (on average) an amount equal to 83% of their monthly revenues and are owed by customers (on average) an amount equal to 61% of their monthly revenue. In addition to managing cash flow, maintaining business records can help microenterprises in several ways. First, maintaining records can help entrepreneurs improve sales, reduce costs and plug leakages. Understanding how different products/ services contribute to revenues and profits, allows entrepreneurs to make informed investment decisions. High-frequency business data also helps manage inventories by providing information on stocking a saleable product mix reducing spoilage.

Given the prevalence of seasonality in these markets, it can help prepare for anticipated shocks to the business (like a seasonal drop in sales). Lastly, it can help draw a distinction between household and firm finances. The micro-firms in our sample are family firms that mostly do not distinguish between household and firm finances. At baseline, fewer than 30% of the sample separates household and firm finances. This is consistent with evidence from rural Thailand where Samphantharak and Townsend, 2012 find that expenses (like, utility bills and rent) and assets are jointly consumed by the firm and the household.

In such a setting, digital tools to manage cash flows and maintain records of business transactions offer firms a potentially profitable opportunity. Relevant digital technologies for these purposes include apps like MeraBills, mobile money platforms, online banking tools etc. Rather than using informal methods like mental accounting or scattered diary entries (as is the case in status quo), firms can use these digital technologies for financial and business management. These digital technologies can also help optimally manage trade credit, and as a result, cash flow. This results in limited cash in the business and challenges growth and profitability. Thus, a digital technology that can help with financial and business management is likely to be profitable.

However, in the absence of any intervention, I find that firms have low rates of adoption for such digital technologies. In qualitative work done for this study in 2021, difficulty in using digital tools were the unprompted explanation given by the majority of firm owners on why they did not adopt

digital technologies that they thought were beneficial. Discussions with field staff at Buzz Women who work closely with the micro-firm owners also highlighted the prominence of high learning costs at onset that could potentially disincentivize adoption. Given low levels of digital literacy (a problem that is common amongst micro-firms in LMICs) the costs of learning to use these technologies remain large. Hand-holding on how to use the digital technology is cheap to provide especially if it can lead to sustained adoption and firm growth.

2.4 Experimental Design and Estimation

2.4.1 Treatment assignment

I randomized micro-firms into one of three groups: (i) control group; (ii) treatment light group; (iii) treatment intense group. All three groups were offered access to the digital technology free of cost. To study whether learning costs drive adoption decisions, I vary the extent to which subsidize learning costs across the three arms.

The control group (C) had 100 firms who were given minimal help in overcoming learning costs. As is common in traditional training sessions, entrepreneurs were provided guidance on why the MeraBills app is helpful and how to use it. Following Drexler et al., 2014, the session provides a rule-of-thumb type training that focused on very simple heuristics or routines for business and financial practices. Participants were also introduced to the MeraBills technology during the training session. Trained field staff helped

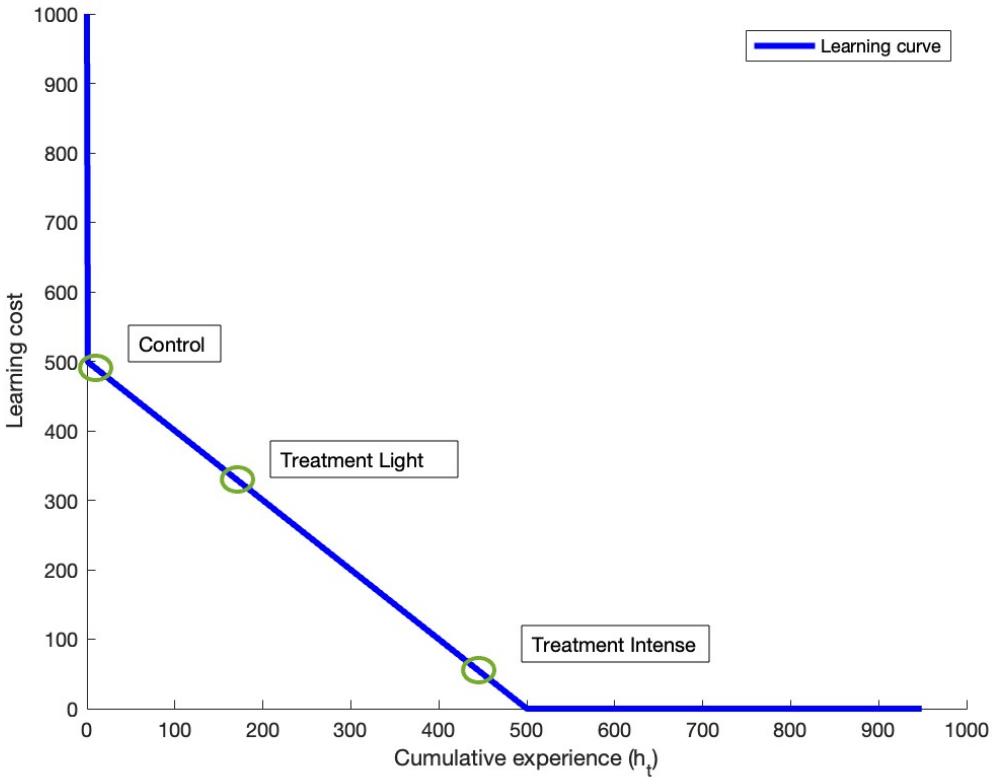
them download the app. The goal of this session was to ensure that the control group had basic knowledge of how to enter business transactions on the app. However, the learning costs were not been subsidized for this group. Entrepreneurs were invited to the induction session in groups of 40, based on their geographic location in the month of June 2022. This was done to ensure maximum attendance in the training session. All firms were provided access to a help-line number they could reach out to if they had any technical issues with the digital technology.

In addition to what was provided to the control group, the treatment light group (with 108 firms) was provided additional hand holding in entering transactions on the app. For this treatment the cost of learning was subsidized by hand holding the entrepreneurs on using the app. This group received three visits in one month by trained staff who handheld them on entering transactions on the MeraBills app and using it to manage their business. As entrepreneurs learn by doing, I hypothesize that this reduces the learning cost that firms bear while using the app after the training sessions. That is, firms will be more likely to adopt the digital technology in the treatment light group as compared to the control group, as treatment light was moved further down the learning curve (as shown in Figure 2.4).

For the treatment intense group (with 112 firms), I intensified the duration for which learning costs were subsidized. For this treatment arm, trained project staff visited the entrepreneurs eight time to hand hold them to enter business transactions on the app. I hypothesize that this group is group is moved further down the learning curve as compared to the treatment light

and control groups (as shown in Figure 2.4).

Figure 2.4: **Learning curve**



I used randomization with stratification to assign participants to the three treatment arms. Preliminary data was collected for all participants who were selected for the study. Using this data, participants were assigned to one of the three groups after stratifying on district, age, and years of experience in running the business. As firms are chosen across four districts, I stratified on this as there was likely to be some regional variation. I also stratified

on age as digital literacy and experience using digital technologies varies by age. Younger entrepreneurs are more likely to have used similar technologies in the past. Lastly, firms in the sample varied in their business experience. For example, firms that have established businesses that have been running for many years are quite different from businesses that may have been newly started. As the likelihood of adoption of a new technology may vary across this dimension, I stratified on this variable. Table 4.2.1 reports normalized differences between my control group and my two treatment groups for a range of baseline characteristics. In Table 4.2.1 I show that the sample is well balanced.

Table 2.4.1: **Summary statistics and balance among baseline covariates**:

Baseline characteristic	Control	Treatment		p-value tested for
		T1	T2	C=T1=T2
Household size	4.64	4.87	4.63	0.52
Number of HH businesses	1.83	1.90	1.93	0.72
Total business HH income	26,044	22,601	28,768	0.48
Total HH income	34,695	32,629	38,158	0.64
Business experience (years)	30.56	36.24	29.24	0.59
Number of competitors (5min walk)	3.17	3.27	2.72	0.64
Number of customers per day	10.82	11.37	15.43	0.04
Number of employees	0.39	0.39	0.82	0.34
Revenue at baseline survey	17,391	15,576	16,484	0.92
Profit at baseline survey	7,710	5,395	5,700	0.26
Fixed assets	36,538	50,256	56,926	0.43
Total current assets	149,697	207,000	130,208	0.08
Loan pending	119,906	101,229	103,900	0.72
Amount borrowed (family/friends)	13,198	17,667	25,273	0.40
Happy	1.55	1.62	1.65	0.53
Family members help use phone	0.97	0.93	0.95	0.50
Family members use phone	0.95	0.93	0.95	0.89
Keep business records	0.65	0.64	0.65	0.97
Seperate HH records	0.23	0.34	0.29	0.21
Hours spent on business	4.10	4.07	4.18	0.97
Hide income from family	0.17	0.30	0.23	0.07

Notes: The first three columns correspond to the mean value of the variable for each treatment arm. The last column presents the p-value on the test of equality between treatment arms.

2.4.2 Data

Data for the study is drawn from two sources. The first is a fairly comprehensive set of individual and business data that was collected through three rounds of surveys — a baseline survey and two follow-up surveys three and six months after the intervention. Baseline surveys were conducted in-person for all participants after randomization. The survey collected data on demographics, household information, household finances, business finances, business practices, time and risk preferences, time use, and household bar-

gaining power. The two follow-up surveys capture the short run and medium run effects. These surveys collected data on experience with using the app, perceived benefits and costs, household finances, business finances, business practices, time and risk preferences, time use, and household bargaining power. I will also conduct a long-run survey one year after the intervention (in September 2023). The surveys collected information on demographics, household information, household finances, business finances, business practices, time and risk preferences, time use, and household bargaining power. Through the surveys I also collected data on how well entrepreneurs have learned how to use the app. Recurring measures of this helps document the process of learning. The second source of data is real-time app usage data from the MeraBills dashboard. This provides detailed information on when and how the app was used by each entrepreneur. Using the high-frequency data on the app, I have constructed weekly measures on outcomes of interest – frequency of using app to enter business transactions, frequency of using the app to manage trade credit, frequency of viewing business statistics and trends on the app.

2.4.3 Estimation

In this section, I present the average treatment effects of the intervention. In doing so, I follow my pre-analysis plan (RCT ID AEARCTR-0008104) registered on September 1, 2021. I explicitly note a few places where I deviate from the pre-analysis plan to explore mechanisms driving key results. Throughout the analysis, I present Intent to Treat effects (ITT). In Appendix 2.F I also

present Local Average Treatment Effects (LATE).[11] Equation 2.4.3 presents the primary econometric specification, which pools data across rounds of data collection:

$$Y_{ir} = \alpha + \beta_1 T_1 + \beta_2 T_2 + \beta_r Y_{i0} + \eta_r + \gamma_s + \varepsilon_{ir}.$$

In equation 2.4.3, the coefficient β estimates the Intent-to-Treat effects, with round fixed effects η_r where $r \in \{1, 2...r\}$, with $r = 1$ indicating the first period (day or week, depending on the variable) after the intervention. The coefficient β can be interpreted as the average effect of being offered the treatment across follow-up rounds. I denote y_{ir} as the outcome of interest for individual i in round r and denote T_{i1} and T_{i2} as an indicator for whether individual i was assigned to treatment 1 or treatment 2 . In terms of additional controls, I follow advice in Bruhn and McKenzie, 2009 and include stratification dummies as controls in my main specification. Following McKenzie, 2012, my main specification pools data across rounds. Standard errors are clustered at the firm level as randomization is at the firm level (Abadie et al., 2017).[12]

[11] The pre-analysis plan did not specify LATE estimates, but it is nonetheless useful to present these results to see the magnitude of treatment effects on compliers. As is expected, LATE estimates are larger than ITT estimates in magnitude, but otherwise tell a similar story.

[12] Abadie et al., 2017 point out that if treatment is assigned at the individual level, one should cluster at the individual level. This is because the unit of randomization is individual, and not individual-time period.

2.5 Treatment effects

2.5.1 Adoption of digital technology

I present the effect of the treatment on the primary outcome variables: (i) a binary variable of adoption measuring whether firms use the app to enter transactions, view reports, send payment invoices and send payment reminders and (ii) the extent of adoption on entering transactions, viewing reports, sending payment invoices and sending payment reminders. Data for the primary outcomes are collected using the MeraBills dashboard which collects real time data on when and how the app is used. For adoption outcomes, the real-time data is pooled across daily and weekly measures. For the adoption outcomes, we do not have a baseline measure of adoption and therefore do not control for it in equation 2.4.3. The results presented in this section uses data for 9 months of adoption data after the intervention. All adoption outcomes are constructed using data after hand-holding was complete for that treatment arm. This is because, during the intervention we would expect to see increased adoption, by design. Appendix 2.C Table 2.C.1 presents details on the adoption outcomes of interest.

Table 2.5.1 presents Intent to Treat effects for a binary adoption dummy, where real time data from the app is aggregated to a weekly level. I estimate equation 2.4.3 using a linear probability model. Column 1 in Table 2.5.1 shows results for the whether firms use the digital technology to enter transactions. This is the first step of accumulating experience and corresponding benefits. I find a 8% and 10% increase in the probability of using the app

for the two treatment arms (significant at the 1% level). This is evidence of higher usage by the treatment arms over a ten month period (after the intervention). Columns 2-4 provide insights into what features of the digital technology firms use. I see a 10% increase in firms viewing financial reports on the app (significant at the 10% level). These reports provide summary statistics on key financial measures: revenue, expenditure, profit, accounts payable, accounts receivable, cash flow etc.. Given the status quo is maintaining lengthy diary entries or mental accounting, the succinct information in the financial reports can draw attention to key business information. Firms also use the digital technology to send invoices to customers when they buy products (albeit, the magnitude if the effect is very small). Lastly, firms use the digital technology to manage trade credit. I see a 3% and 2% increase in sending payment reminders to customers (significant at the 1% level). This can enable firms to better manage cash flow. Overall, I find that subsidizing the cost of learning increases adoption for both treatment arms. Firms in both treatment arms significantly increase the number of days they use the technology, as well as, the number of days they view reports.[13] Notably, I do not find significantly different treatment effects for the two treatment arms. This is not entirely surprising, as it is possible that the small nudge provided to treatment light group was sufficient to sustain adoption in the short and medium run. Appendix 2.E presents the empirical distribution across treatment arms. I find a clear rightward shift of the CDF for adoption outcomes.

[13]Appendix 2.B displays screenshots of reports than can be generated using the digital platform for a dummy profile.

Table 2.5.1: **Treatment effects on adoption**

	(1) Transactions	(2) View Reports	(3) Pay Invoices	(4) Reminders
Treatment Lite	0.08***	0.03*	0.00***	0.03***
	(0.03)	(0.02)	(0.00)	(0.01)
Treatment Intense	0.10***	0.03*	0.00*	0.02***
	(0.03)	(0.02)	(0.00)	(0.01)
Observations	10733	10733	10733	10733
Mean DV	0.09	0.04	0.00	0.00
Std. dev.	0.28	0.20	0.02	0.05
p-value for joint sig.	0.00	0.11	0.01	0.00
p-value test (T1=T2)	0.61	0.92	0.54	0.30

Notes: The dependent variables in this table are adoption outcomes based on real-time data aggregated to the daily level. All adoption outcomes are constructed using data after hand-holding was complete for that treatment arm. The variables presented here are dummy variables which take on a value of 1 if the firm adopts on the day and 0 if not. The variables are measured real time and aggregated to a daily level using the dashboard for the app. Column 1 presents results for the transactions entered on the app. This variable measures the number of times an entrepreneur enters transactions on the app. A "transaction" is a record of a financial transaction (income, expense, payment in or payment out) that is entered on the app. Column 2 presents results for viewing reports on the app. This variable measures the number of times an entrepreneur views reports on the app. The app provides reports on firm finances, income / expense reports, owner withdrawal reports and product reports. Column 3 presents results for the number of payment invoices. This variable measures the number of times an entrepreneur sends invoices for income transactions. Column 4 presents results for the number of payment reminders. This variable measures the number of times an entrepreneur sends payment reminders to their customers to remind them of pending payments. "Treatment Lite" and "Treatment Intense" are indicators for being in these treatment groups. The results are pooled for the study duration. Regressions include day fixed effects and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group.These results will be updated as additional data comes in over the next few months. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Next, I use the adoption data to analyze the extent of engagement with the app. To study the extent of adoption, the real time data is aggregated to a weekly level. I create weekly measures that are then pooled for the study period. In Table 2.5.2, I present results on the extent of adoption. I estimate equation 2.4.3 using a clustered poisson regression. Results based on weekly data reinforce the findings from Table 2.5.1. I find that firms in both treatment arms increase their intensity of adoption. Column 1 shows a 49% and 29% increase in entering transactions (significant at the 1% level). Similar to Table 2.5.1, firms use the digital technology to view reports, send invoices and payment reminders. Again, it is worth noting that the two treatments do not have significantly different effects.

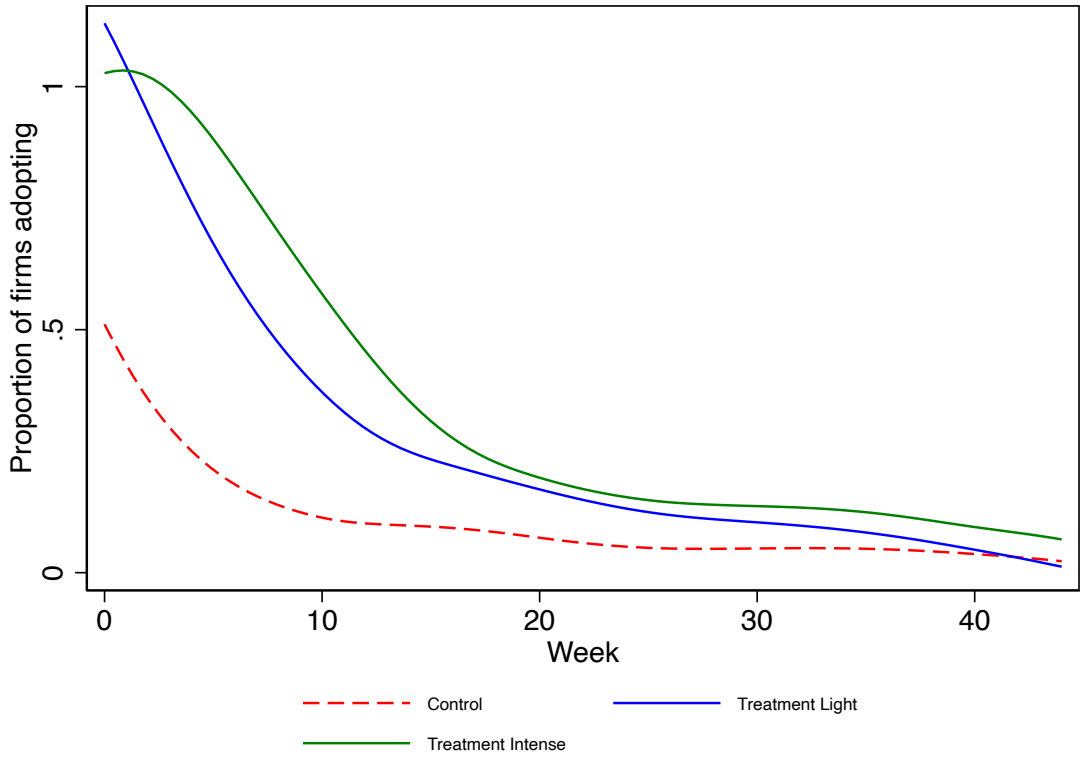
Table 2.5.2: **Treatment effects on extent of adoption** :

	(1) Transactions	(2) View Reports	(3) Invoices	(4) Reminders
main				
Treatment Lite	1.46***	0.85*	2.53***	2.63***
	(0.39)	(0.50)	(0.78)	(0.59)
Treatment Intense	0.85**	0.66	1.87**	1.93***
	(0.34)	(0.47)	(0.81)	(0.60)
Observations	10711	10711	10711	10711
Mean DV	0.59	0.14	0.00	0.01
Std. dev.	2.96	0.94	0.02	0.14
p-value for joint sig.	0.00	0.21	0.00	0.00
p-value test (T1=T2)	0.08	0.68	0.21	0.26

Notes: The dependent variables in this table are outcomes for the extent of adoption. All adoption outcomes are constructed using data after hand-holding was complete for that treatment arm. Column 1 presents results for the number of transactions, aggregated at the weekly level. This variable measures the number of times an entrepreneur enters transactions on the app. A "transaction" is a record of a financial transaction (income, expense, payment in or payment out) that is entered on the app. Column 2 presents results for viewing reports on the app, aggregated at the weekly level. This variable measures the number of times an entrepreneur views reports on the app. The app provides reports on firm finances, income / expense reports, owner withdrawal reports and product reports. Column 3 presents results for the number of payment invoices, aggregated at the weekly level. This variable measures the number of times an entrepreneur sends invoices for income transactions. All the variables presented in this table are measured in real time using the dashboard for the app. Column 4 presents results for the number of payment reminders, aggregated at the weekly level. This variable measures the number of times an entrepreneur sends payment reminders to their customers to remind them of pending payments. "Treatment Lite" and "Treatment Intense" are indicators for being in these treatment groups. The results are pooled for the study duration. Regressions include day fixed effects and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. These results will be updated as additional data comes in over the next few months. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Given the high-frequency nature of the data, I am also able to look at dynamic treatment effects. In Figure 2.5, I present the dynamics of adoption by firms in each treatment arm. In line with the results above, I find that firms in treatment lite and treatment intense groups are more likely to adopt. I find that treatment effects decline over time. I also note that, similar to the adoption results above, there is no significant difference between the treatment lite and treatment intense arm. This is not entirely surprising as it is possible that firms in treatment intense were not moved much further along the learning curve.

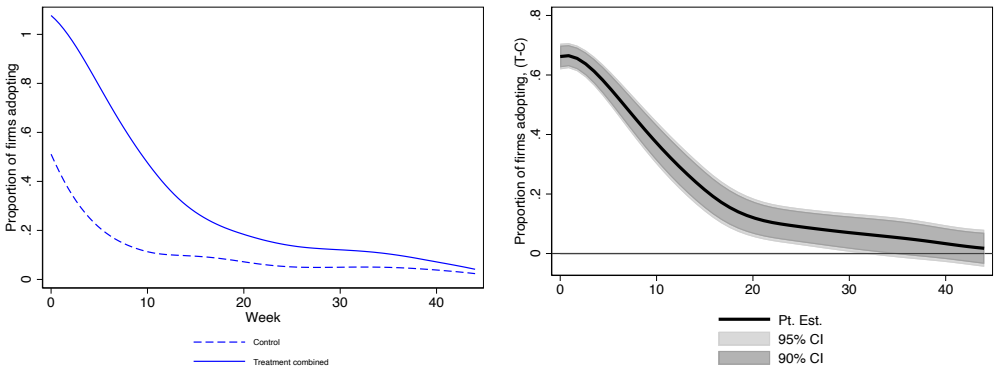
Figure 2.5: **Temporal dynamics of adoption, by treatment group**



In Figure 2.6, I run a non-parametric specification to look at dynamic treatment effects. The left column in Figure 2.6 shows the means for the combined treatment group and the control group over time for the proportion of firms adopting (as estimated using fan regressions). The right column presents a point estimate for the difference in treatment minus control groups over time, with the 95% and 90% confidence interval calculated by bootstrapping the fan regression 1,000 times. Firms respond to the treatment and show higher adoption for about 30 weeks after the intervention (7-8 months). It is possible that the small temporary nudge given to treatment lite group was only sufficient to encourage higher adoption for a 7-8 months. Further nudges may be required to see sustained long term effects.

As the high-frequency adoption data does not show a significant difference in the app usage between the two treatment arms, I do not expect the treatment effects on firm-level outcomes to vary. Thus, I present pooled treatment effects for the two hand holding treatments (Treatment Lite and Treatment Intense) for all outcomes generated using survey data.

Figure 2.6: **Temporal dynamics of adoption, by treatment group**



Data from the in-person field surveys corroborates the increased adoption seen in the real time app usage data. Table 2.5.3 shows that firms in the treatment arms report that they use the digital platform to enter higher transactions (a 47% increase significant at the 1% level), send more payment reminders (a 78% increase significant at the 1% level), manage the amount customers owe them (a 45% increase significant at the 1% level), manage the amount they owe suppliers (a 55% increase significant at the 5% level) and view key graphs and statistics about the business (a 58% increase significant at the 1% level).

Table 2.5.3: **Pooled treatment effects on digital technology usage (self-reported by firms)** :

	Use the app for				
	(1)	(2)	(3)	(4)	(5)
	Transactions	Send Reminder	Owed by customer	Owe supplier	View graphs
Treatment	0.20***	0.18***	0.20***	0.15***	0.20***
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Observations	582	582	582	582	582
Mean DV	0.43	0.23	0.44	0.27	0.34
Std. dev.	0.50	0.42	0.50	0.45	0.47

Notes: The dependent variables in this table are outcomes for dummy variables for app usage, as reported by firms. Each variable takes a value of one if firms report that they use a specific feature of the app and is zero otherwise. Column 1 presents results for whether firms use the app to enter financial transactions. A "transaction" is a record of a financial transaction (income, expense, payment in or payment out) that is entered on the app. Column 2 presents results for whether firms use the app to send payment reminders to their customers. Column 3 presents results for whether firms use the app to keep tabs on how much money customers owe them. Column 4 presents results for whether firms use the app to keep tabs on how much money they owe their suppliers. Column 5 presents results for whether firms use the app to view graphs and key statistics about their business. This includes top level firm financials (such as revenue, expenditure and profit), cash flow details etc. All the variables presented in this table are measured based on self-reported data in the follow-up surveys. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. We do not have a baseline measure for this outcome variable, and hence, are not able to control for it. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

2.5.2 Business practices and firm outcomes

The temporary learning subsidy provided in the intervention clearly resulted in increased and sustained adoption of the new digital technology — but what effect does this increased adoption have on firm-level outcomes? To answer this question, I use two rounds of follow-up survey data. In the tables, I present results for pooled treatment effects (including two round of survey data), as well as results for individual survey rounds — the short-run results

using a 3 month follow-up and medium run results using a 6 month follow-up.

Looking at monthly profit and revenue data, I find a striking result in Table 2.5.4: the treatment caused a large and significantly negative effect on reported firm profit in the three months after the intervention. Columns 1-3 present results on self-reported profits using monthly recall. I find a 14% decrease in firm profits (significant at the 10% level) in the pooled data. The effects are more prominent in the short run where I see a 24% decrease in firm profits. Columns 4-6 present results for self-reported firm revenues using monthly recall. I see a decrease in revenues to a similar magnitude (albeit not significant), suggesting the decrease in profits is driven by a decrease in revenues. Appendix 3.D presents results winsorizing at the 5% level, as well as results for levels (instead of logs). The results are robust to these specifications. I also present results for Local Average Treatment Effects (LATE) in Appendix 2.F. Treatment effects are consistent with the ITT estimates, but as expected, higher in magnitude.

Table 2.5.4: **Treatment effects on Firm Revenue and Profits** :

	Profit			Revenue		
	(1) Pooled	(2) Short run	(3) Medium run	(4) Pooled	(5) Short run	(6) Medium run
Treatment	-0.14*	-0.24**	-0.05	-0.14	-0.20*	-0.10
	(0.08)	(0.11)	(0.10)	(0.09)	(0.11)	(0.11)
Observations	1617	795	822	1626	804	822
Mean DV	8.56	8.36	8.53	9.25	9.03	9.27
Std. dev.	0.90	0.93	0.88	0.97	0.96	0.96

Notes: The dependent variables in this table are outcomes for log profit and log revenue for firms. The profit and revenue data is self-reported by firms during follow-up surveys. All variables presented in this table are winsorized at 1% to control for outliers in the data. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

I explore two possible explanations for the decrease in firm revenue and profit. First, as firms use the digital technology they get more accurate information about their firm finances and learn that their profitability is lower than they had anticipated using informal record-keeping. That is, they may become more aware of potential inefficiencies in their business management. Second, it is also possible that this digital technology is detrimental to the firm.

2.5.3 Learning about low profitability

In this section, I explore the first hypothesis for the negative impact on reported profits: that, as firms use the digital technology to manage their business, they learn that their profitability is lower than anticipated. This is likely to be true if firms systematically over-estimate firm profits. The

challenge with identifying such “over-estimation", is that it is endogenous to adoption. However, in Appendix 2.H, using a complementary dataset I provide evidence of a systematic over-estimation of self-reported profits (using monthly recall) by firms. In a sample of 55 comparable firms, I compare self-reported profits using monthly recall with a measure of “true-profits" and find that firms over-estimate monthly profits by 36%. Appendix 2.H discusses details around measurement.

If it is the case that firms learn about their true profitability, this could lead to changes in outcomes across three broad categories: (i) business practices; (ii) firm investment; (iii) expectations on firm performance. To further investigate this, I study a range of secondary outcomes under these three categories. Under business practices, I create an index for two key types of business practices: Financial planning practices and Marketing practices. For firm investment, I look at assets and investment. For expectations on firm performance, I look at expectations on future business growth, future customers and products.

To study changes in business practices, I present results in Table 2.5.5. In Table 2.5.5 I find that treated firms improve financial planning in the short run. I do not find any significant effects in the medium run (in line with the reduced adoption over time, as seen in Figure 2.5 and Figure 2.6). In column 2, I see a 9% increase (significant at the 10% level). This index comprises of variables such as knowing what the biggest expense in their firm is, maintaining financial statements such as Income and Expense statements, Profit and Loss statement etc. In column 4, I find a 11% increase an index of marketing

practices (significant at the 5% level). This index comprises of variables such as, negotiating prices with their suppliers, obtaining information from their suppliers regarding which products sell best, attracting customers by offering special discounts etc.

Table 2.5.5: **Treatment effects on business practices** :

	Financial planning practices			Marketing practices		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Treatment	0.03	0.09*	-0.03	0.03	0.11**	-0.04
	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)	(0.04)
Observations	574	285	289	574	285	289
Mean DV	0.85	0.76	0.93	0.47	0.51	0.44
Std. dev.	0.33	0.39	0.23	0.37	0.38	0.36

Notes: The dependent variables in this table are indices for financial planning practices and marketing practices for firms. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

If firms were over-estimating firm performance at baseline, this would also result in lower reported investment as firms learn more accurately about firm financials. In Table 2.5.6, column 2, I find that treated firms have a 23% reduction in business investment in the short run (albeit not significant) in the first three months of the study. In column 5, I also see a 40% reduction in fixed assets, again not significant. This is a large reduction in firm investment and fixed assets and provides suggestive evidence of micro-firm owners learning about the low profitability of their business.

In Table 2.5.7, I strengthen evidence on this hypothesis by providing evidence of treated firms having lower expectations about future business performance in the short run. In columns 2 and 5, I find that treated firms reduce their expectations about future firm growth and the number of customers they are likely to have in the future (these estimates have a negative magnitude but are not significant). In column 8, I show that firms in the treatment group expect to sell 45% fewer products in the future.

LATE estimates presented in Appendix 2.F show that the results in the Tables above are concentrated amongst complier firms. As expected, the magnitudes are larger for those who take-up the digital technology. The dampening of business sentiment amongst those using the app could also lead dampen the adoption of the digital technology.

Table 2.5.6: **Treatment effects on investment and firm assets** :

	New Investment			Fixed Assets			Current assets		
	(1) Pooled	(2) Short run	(3) Medium run	(4) Pooled	(5) Short run	(6) Medium run	(7) Pooled	(8) Short run	(9) Medium run
Treatment	-0.05	-0.23	0.08	-0.43	-0.40	-0.45	0.10	0.09	0.08
	(0.15)	(0.22)	(0.18)	(0.31)	(0.38)	(0.51)	(0.12)	(0.18)	(0.17)
Observations	501	242	259	537	263	274	565	281	284
Mean DV	9.39	9.29	9.29	8.68	8.05	8.05	10.28	10.21	10.21
Std. dev.	1.59	1.48	1.48	3.20	3.58	3.58	1.46	1.56	1.56

Notes: The dependent variables in this table are outcomes for log investment and log assets. New investment measures the log of any new investment made by the firm. Total value of fixed assets is defined as a long-term asset that a firm owns and uses in the production of its income and is not expected to be consumed or converted into cash any sooner than at least one year's time. Examples of fixed assets include land, buildings, machinery, manufacturing equipment, office equipment, furniture, vehicles. Fixed assets do not include working capital, inventories, or money used for the running of the business. The total value of current assets is calculated as the sum of inventories, debt and cash in business. All variables presented in this table are in logs and are winsorized at the 1% level to control for outliers. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Table 2.5.7: **Treatment effects on future business outcomes** :

	Future business growth			Future Customers			Future Products		
	(1) Pooled	(2) Short run	(3) Medium run	(4) Pooled	(5) Short run	(6) Medium run	(7) Pooled	(8) Short run	(9) Medium run
Treatment	-0.03	-0.02	-0.04	0.91	-11.55	12.86	-2.37**	-3.39*	-1.37
	(0.03)	(0.04)	(0.03)	(7.08)	(7.54)	(11.20)	(1.06)	(1.99)	(0.96)
Observations	574	285	289	574	285	289	574	285	289
Mean DV	0.91	0.92	0.92	24.47	21.22	21.22	5.74	4.06	4.06
Std. dev.	0.28	0.27	0.27	67.01	64.89	64.89	13.31	9.00	9.00

Notes: The dependent variables in this table measure expectations on future firm outcomes. Future business growth is a dummy variable for whether a micro-firm owner expects their firm to grow in the future. Future customers is a variable that measures the number of new customers a firm expects to sell to in the future. Future products is a variable that measures the number of new products a firm expects to sell in the future. Columns 4-9 are winsorized at the 1% level to control for outliers."Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

2.5.4 Unsuitable technology

In this section, I explore whether the negative effects on revenue and profit is driven by the digital platform being an unsuitable technology — that is, whether the app may actually be reducing revenue and profit. In Table 2.5.8, I find that firms report a positive experience while using the app. These effects persist in the medium run. In column 1, I document that treated firms are 16% (significant at 1%) more likely to recommend the MeraBills digital technology. As reflected in column 4 they are also 15% more likely to teach family and friends how to use the digital technology (significant at 1%). As shown in column 3, treated firms are willing to pay a small positive amount for the digital technology (but the result is not significant). These results reflect a strong positive sentiment regarding the digital technology and are unlikely to be indicative of a bad and unsuitable technology. If it were the case that the technology was detrimental to the business, it is unlikely that use of the digital technology would generate these positive spillovers for family and friends.

Table 2.5.8: **Treatment effects on experience using app** :

	Recommend			Teach			WTP		
	(1) Pooled	(2) Short run	(3) Medium run	(4) Pooled	(5) Short run	(6) Medium run	(7) Pooled	(8) Short run	(9) Medium run
Treatment	0.16***	0.14**	0.17***	0.15***	0.17***	0.13**	3.59	4.46	1.91
	(0.05)	(0.07)	(0.06)	(0.04)	(0.05)	(0.06)	(10.34)	(12.44)	(16.00)
Observations	582	289	293	582	289	293	582	289	293
Mean DV	0.44	0.36	0.36	0.20	0.24	0.24	86.21	124.44	124.44
Std. dev.	0.50	0.48	0.48	0.40	0.43	0.43	113.20	123.90	123.90

Notes: The dependent variables in this table measure a firm's experience using the MeraBills digital technology . Recommend is a dummy variable for whether a micro-firm owner would recommend the digital technology to others. Teach is a dummy variable for whether a micro-firm owner has taught family or friends how to use the digital technology. Column 3 presents results for a dummy variable for whether a micro-firm owner has involved their family in using the digital technology. Column 4 presents results for the amount a firm is willing to pay to use the digital technology. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. We do not have a baseline measure for this outcome variable, and hence, are not able to control for it. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

2.6 Structural estimations and counterfactuals

In this section, I build on the theoretical framework described in Section 2.2. I estimate the model using data from the randomized experiment and present counterfactual analysis.

2.6.1 Model setup

As in Section 2.2, the state space comprises of transaction experience h_t and the control variable comprises of an action $y_t \in \{0, 1\}$ and the transition equation is given by Equation 2.4.

To estimate the model using data from the randomized experiment, I make two key changes to the framework described in Section 2.2. First, learning from the results of the randomized control trial, I add some structure to the parameter describing returns to adoption (ϕ). I allow it to have two components: (i) the perceived returns to digital technology adoption (ϕ_1) and (ii) the change in perceived firm profitability (ϕ_2).[14] That is, as firms adopt I allow them to learn about the profitability of the technology as well as, learn about their own true profitability. I write ϕ as:

$$\phi \equiv \phi_1 \times \phi_2. \tag{2.8}$$

Second, I allow for a stochastic error term to enter the decision making for the firm. The error terms ε_t^D and ε_t^N are identically and independently

[14] ϕ_1 and ϕ_2 reflect percentage changes. I do not constrain the bounds for ϕ_1 and ϕ_2. They are allowed to be negative.

distributed with Gumbel distributions with location parameter $\mu \in R$ and scale parameter $\beta \in R_{>0}$. These are added to the utilities described in equation 2.1 and Equation 2.3 to compute profit under no adoption and adoption in each period:

$$Profit_t^N = \pi_t^N + \varepsilon_t^N \tag{2.9}$$

and

$$Profit_t^D = \pi_t^D + \varepsilon_t^D \tag{2.10}$$

where $\varepsilon_t^N, \varepsilon_t^D \sim Gumbel(\mu, \beta)$.

The value function given by Equation 2.11 is formed by assuming that the firm makes an adoption decision in each period by comparing the expected discounted future utility from adopting and not adopting (while also accounting for the Gumbel noise). I assume exponential discounting with discount factor δ. Substituting from equation 2.5 the value function can now be written as:

$$V(h_t) = E\left[\max_{y_t \in \{0,1\}}\left[y_t \times \underbrace{(\pi_t^D + \delta \times V(h_t + s) + \varepsilon_t^D)}_{\text{Maximize if adopt}} + (1 - y_t) \times \underbrace{(\pi_t^N + \delta \times V(h_t - d) + \varepsilon_t^N)}_{\text{Maximize if no adopt}}\right]\right] \tag{2.11}$$

Figure 2.7 details the timeline for the model within each period. It is important to note that a firm does not observe error terms ε_t^D and ε_t^N at the time it incurs utilities π_t^D and π_t^N or at the time it calculates the value function.

However, it does know that it will observe these error terms prior to making the adoption choice y_t and will maximize rationally at the time. Including the Gumbel noise terms complicates the solution for the value function. However, a property of the Gumbel distribution allows me to simplify the problem. If one adds i.i.d. Gumbel (noise) samples to unnormalized log probabilities, and selects the index with the maximum value, it will follow a Gumbel distribution.[15] Thus, I use the this property to calculate the Bellman equation. I re-write equation 2.11 below:

$$V(h_t) = E\left[\max_{y_t \in \{0,1\}} \left[\log(\theta_{y_t}) + G^{y_t}_{\mu,\beta}\right]\right] \tag{2.12}$$

where,

$$\log(\theta_1) = \left[\pi^D_t + \delta \times V(h_t + s)\right]; \tag{2.13}$$

$$\log(\theta_0) = \left[\pi^N_t + \delta \times V(h_t - d)\right]; \tag{2.14}$$

$$G^1_{\mu,\beta} = \varepsilon^D_t; and \tag{2.15}$$

$$G^0_{\mu,\beta} = \varepsilon^N_t. \tag{2.16}$$

[15] See, for example, Huijben et al., 2022.

A property of the Gumbel distribution that can be used here is,

$$\max_{y_t \in \{0,1\}} \left[\log(\theta_{y_t}) + G^{y_t}_{\mu,\beta}\right] \sim Gumbel(\mu + \beta \log(Z'), \beta) \tag{2.17}$$

where,

$$Z' = \Sigma_{y_t \in \{0,1\}} \left[\exp \frac{\log(\theta_{y_t})}{\beta}\right] \tag{2.18}$$

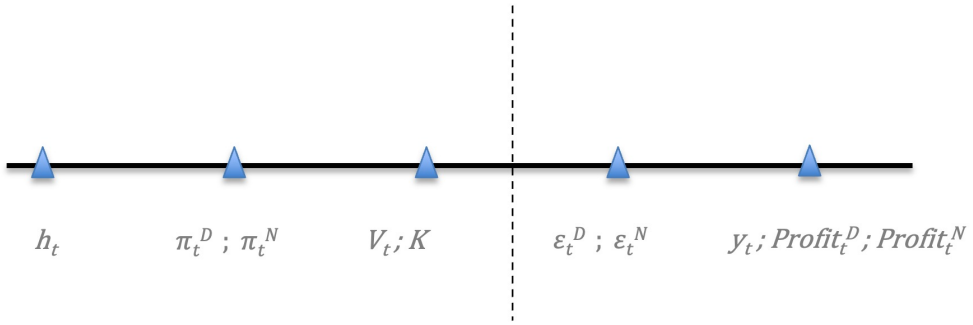
Using equations 2.11 to 2.18, the Bellman equation can we written as the following:[16]

$$V(h_t) = \mu + \beta \times \log \left[\exp \frac{\pi^D_t + \delta \times V(h_t + s)}{\beta} + \exp \frac{\pi^N_t + \delta \times V(h_t - d)}{\beta}\right] + \gamma \times \beta \tag{2.19}$$

where, $\gamma \sim 0.577$ is the Euler-Mascheroni constant.

[16] If X has a Gumbel distribution with location parameter μ and scale parameter β, $E[X(\mu, \beta)] = \mu + \gamma \times \beta$, where, $\gamma \sim 0.577$ is the Euler-Mascheroni constant.

Figure 2.7: **Timeline within a period**



Notes: This figure presents the timeline within on period. The dotted line represents a "veil of ignorance". All decisions made prior to that are made without observing error terms ε_t^D and ε_t^N. When firms calculate utility πt^D and πt^N and estimate the value function they are behind this veil of ignorance. Firms only know that when they do observe the error terms and make adoption decision y_t they will maximize rationally.

2.6.2 Structural estimation

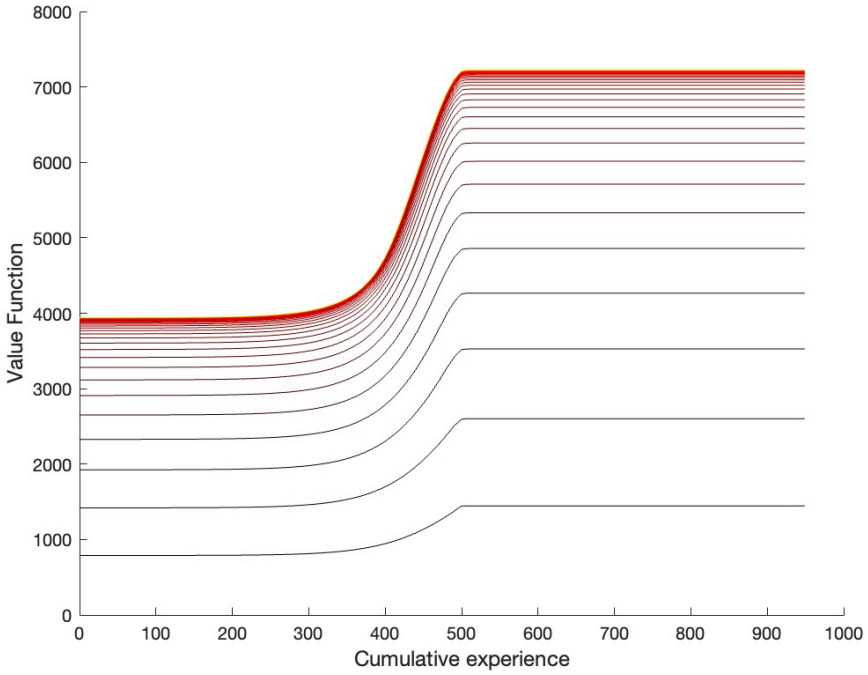
In this section I detail the structural estimation of the dynamic adoption choice model using maximum likelihood. To comprehensively understand optimal policies, I use the estimated parameters to conduct counterfactual analysis. I estimate four key model parameters: (i) scale parameter of stochastic Gumbel error terms, which represents the amount of noise in the data; (ii) returns to adoption given by ϕ_1; (iii) the learning parameter α_1 and (iv) the learning parameter α_2.

For the remaining parameters, I use data collected at baseline for the randomized intervention. These are detailed in Panel A of Table 2.6.1. The number of transactions per period s is the average self-reported number of transactions per week in the baseline survey. The utility per transaction P is calculated as the average weekly self-reported profit divided by the average

number of weekly transactions. The change in perceived firm profitability is taken from Table 2.F.1. I find a 57% decrease in self-reported profits for firms who firms who use the app and this gives $\phi_2 = 1 - 0.57 = 0.43$. The forgetting parameter d is taken from a series of questions on "learning to use the app" during the initial training session and later at follow-up surveys. The forgetting parameter is measured by the proportion of firms who answer a question correctly at the initial training session, but wrong at a later point. Lastly, the Gumbel location parameter is assumed to be 0, as in a standard Gumbel.

I estimate the model in three steps. First, I solve the value function using value function iteration. To solve for the value function using value function iteration, I start with the Bellman equation described in equation 2.19. The dynamic optimization problem is broken into two parts: (i) the current period given by $V(h_t)$ and (ii) all future periods given by $V(h_{t+1})$. I start the iteration with $V(h_{t+1}) = 0$ and use the Bellman equation to update the left-hand side of the equation. I then plug this into the right hand side and continued the process till I find a fixed point where the left and right-hand sides are equal. Once the value function is solved, we have found the optimal dynamic adoption choice for the average firm. Figure 2.8 shows the convergence of the value function to its optimal solution.

Figure 2.8: **Convergence of value function**



Notes: The value function has a reverse S shape which indicates the increase in value from adoption above a certain threshold. This figure shows the convergence of the value function using value function iteration.

Second, the solution to the value function implies transition probabilities. The transition probability K_t is the probability that a firm adopts for a given level of cumulative experience. It captures the idea that firms may move in and out of adoption. The transition probabilities have a functional form Λ, which refers to the *cdf* of the logistic distribution. K follows a logistic distribution as it is the difference of two Gumbel distributed variables:

$$K_t(h_t) = \Pr(y_t = 1|h_t) = \Lambda\left[\frac{\pi_t^D + \delta \times V(h_t + s) - \pi_t^N - \delta \times V(h_t - d)}{\beta}\right]. \tag{2.20}$$

Third, I compute the log-likelihood. To estimate the parameters of interest by maximum likelihood, I choose values of parameters that maximize the likelihood of generating the data from the randomized experiment, given the values of these parameters. The log-likelihood for individual firms is given by:

$$LL_i = y_{it} \times \log\left[K(h_t)\right] + (1 - y_{it}) \times \left[1 - \log(K(h_t))\right]. \tag{2.21}$$

I obtain the the overall log-likelihood by summing the individual likelihoods as shown below:

$$LL = \sum_{i=1}^{N} LL_i. \tag{2.22}$$

Finally, I choose parameter values that maximize the overall log-likelihood. Table 2.6.1 presents the maximum likelihood parameters from structural estimation.

Table 2.6.1: **Parameters in the model**

Variable name	**Notation**	**Value**
Panel A : Parameters estimated from data		
Number of transactions per period	s	7
Utility per-transaction	P	150
Change in perceived firm profitability	ϕ_2	0.43
Depreciation of experience (forgetting)	d	5
Gumbel scale parameter	μ	0
Panel B : Parameters estimated from model		
Learning parameter (intercept)	α_1	386
Learning parameter (slope)	α_2	0.85
Perceived returns to digital technology adoption	ϕ_1	1.4
Gumbel scale parameter	β	850

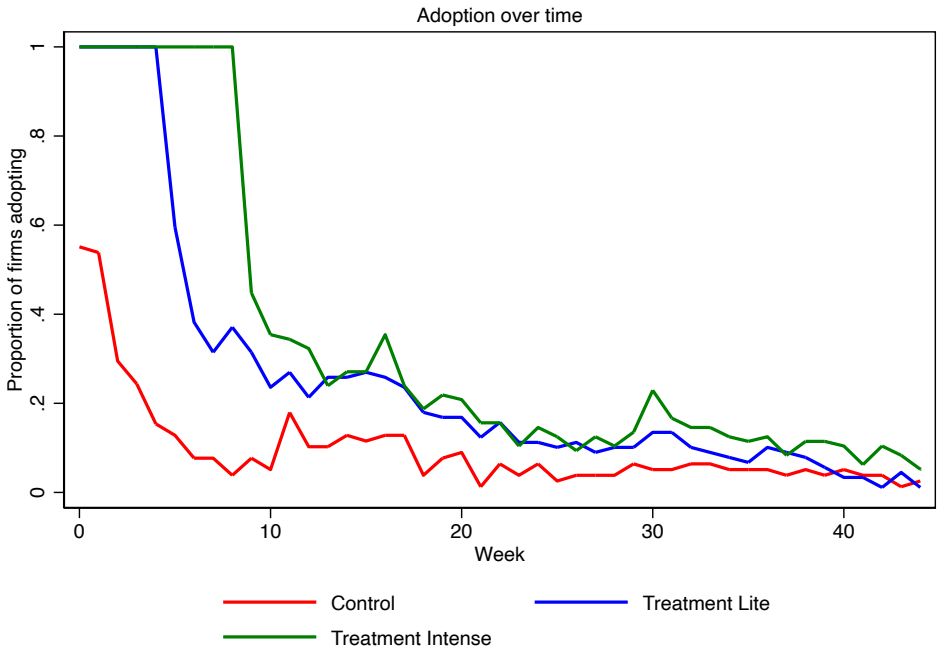
Notes: Panel A details the model parameters that are taken from the data and Panel B presents parameter values as calculated from structural estimation.

To compute treatment effects using model predictions, I follow four steps. The first two steps are the same as for estimating the model (as described in Section 2.6.2). That is, I first use the estimated parameters to solve the value function using value function iteration. Second, I compute transition probability (or probability of adoption) K_t from equation 2.20. Third, I use this probability of adoption to simulate adoption choice over time for a sample of 10,000 firms. Four, I randomize the 10,000 firms into three treatment arms,

like in the randomized intervention (Control, Treatment Light and Treatment Intense). I do this by moving firms to different points on the learning curve (that is, different levels of cumulative experience) in period 1.

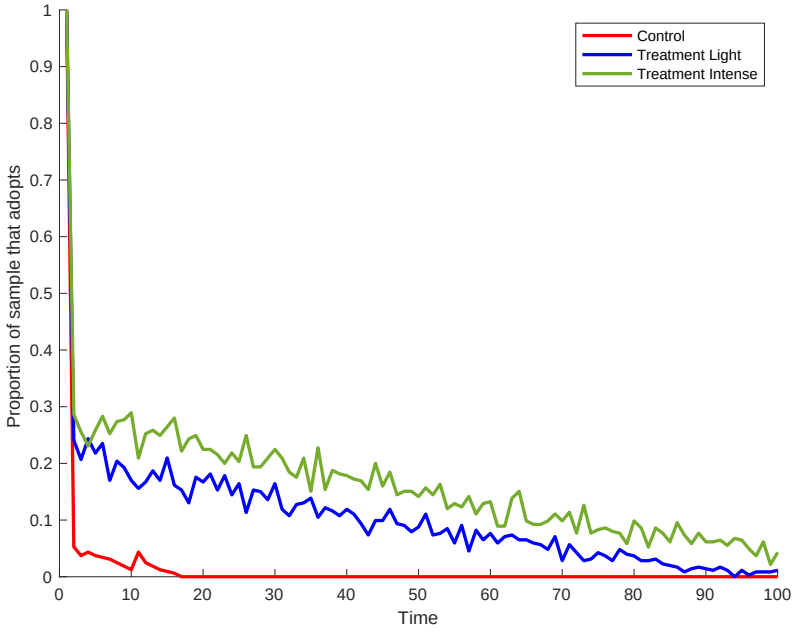
Figure 2.9 and Figure 2.10 present a comparison of the model predictions based on estimated parameters to the data from the randomized control trial. The model fits the data well under low “perceived" returns to technology adoption, low rates of learning and high forgetting. The model predicts a 8.8% and 14% increase for treatment light and treatment intense, which is close to the 8% and 10% increase documented in the empirical data. I do not put much focus on the magnitudes of these effects as it is difficult to compare the model vs. data too closely. However, I check to see that the model captures a few key features of the data. First, the adoption level is highest for the treatment Intense, followed by Treatment Light and the Control group. Second, the treatment arms have higher adoption than the control group for a sustained period. Third, in both the model and data, the adoption trends for all treatment arms move to a steady state of no adoption. This potentially implies that the treatment was not strong enough to entail long run effects. Figure 2.11 shows adoption trends for five hypothetical treatments and Figure 2.12 shows where they fall on the transition probability graph. Treatment 1 and Treatment 2 correspond to treatment light and treatment intense and show that the push for these interventions was too little to sustain adoption, given high barriers to learning, high levels of forgetting and misperceptions about true profitability. Treatment 4 and and Treatment 5 are strong enough to sustain adoption effects.

Figure 2.9: **Data trends**



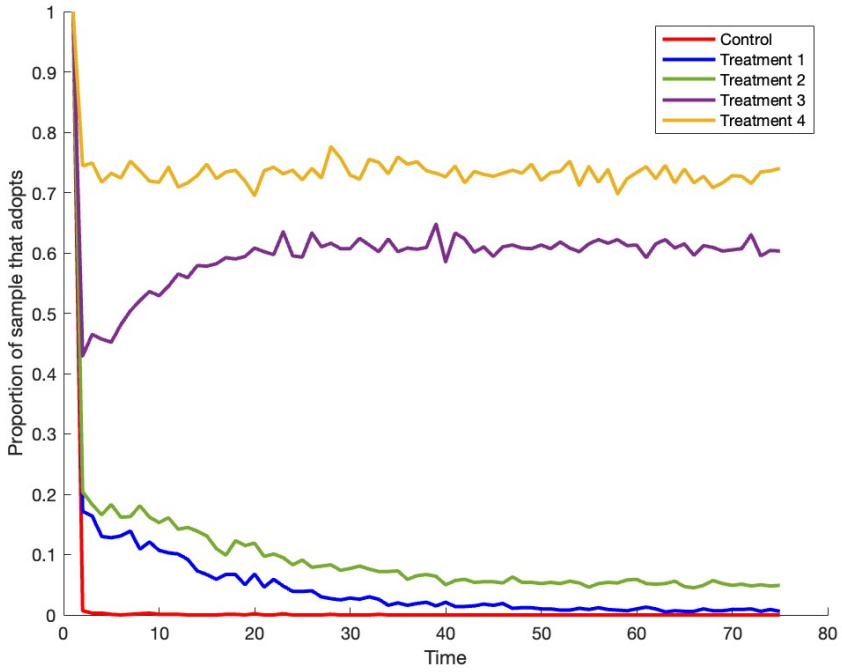
Notes: This figure presents the dynamic adoption trends as per the data from the randomized experiment. The red line is the adoption trend for the control group after the training session. As can be seen in the figure, about 60% of firms try using the app after the session and then adoption tapers off sharply. The blue and green lines show adoption trends for treatment light and treatment intense. These groups get hand-holding for 4 and 8 weeks respectively. After that firms in these arms also show a sharp decline in adoption, but have significantly higher adoption rates that the control group 7-8 months after the intervention.

Figure 2.10: **Model prediction**



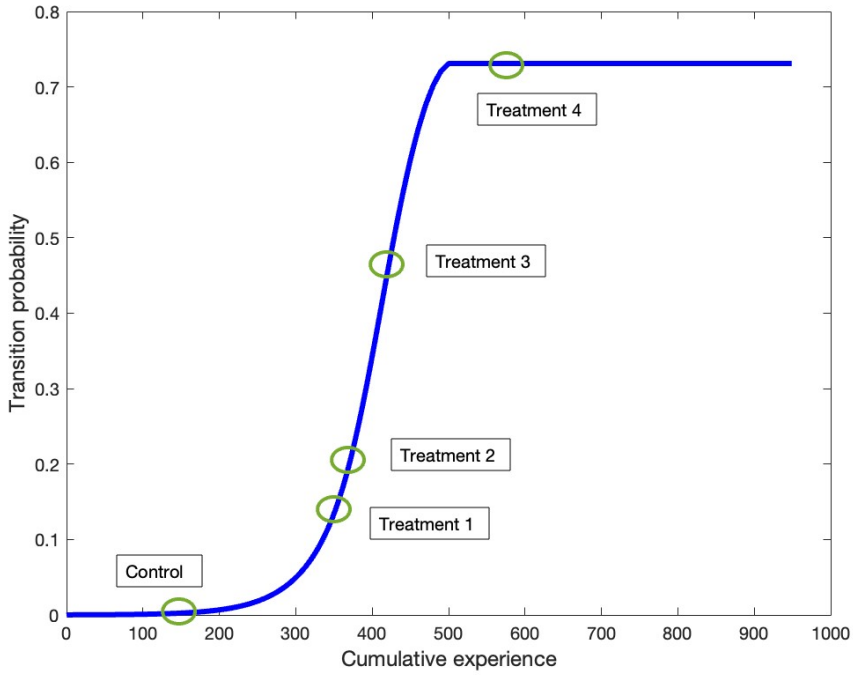
Notes: This figure presents adoption trends based on model simulations using estimated parameters. The red line is the adoption trend for the control group and the blue and green lines show adoption trends for treatment light and treatment intense. Simulated trends look similar to the actual data both in magnitude and rate of decrease.

Figure 2.11: **Is the treatment strong enough to sustain adoption?**



Notes: To see if the hand-holding in the intervention is strong enough to sustain adoption, I compare it to stronger interventions by increasing the amount of hand-holding in the model simulations. The purple and yellow lines show trends for higher levels of adoption. As can be seen, at the higher levels of hand-holding, adoption moves to a higher steady-state equilibrium.

Figure 2.12: **Is the treatment strong enough to sustain adoption?**



Notes: Corresponding to the higher hand-holding in Figure 2.11, I show these stronger interventions on the transition probability graph.

2.6.3 Counterfactual analysis

Using the parameters estimated by the structural model, I estimate counterfactuals from four alternative interventions: (i) monetary transfers over time to incentivize adoption; (ii) repeated nudges to decrease forgetting; (iii) improving human capital and (iv) updating firm's beliefs about their profitability.

For each of these counterfactuals, I start by simulating adoption choice over time for a sample of 10,000 firms (as in Section 2.6.2). I then randomly allocate these 10,000 firms into two treatment arms: (i) a control group and

(ii) a treatment group as per the counterfactual intervention. Table 2.6.2 presents the treatment effect under each scenario. Figure 2.13 shows the change in the transition probability due to the treatment 2.14 shows the inter-temporal treatment effect as per model predictions. In these graphs the blue line represents the treatment group and the red line the control group under each of the four counterfactual interventions discussed below.

1. *Counterfactual 1: Monetary transfers over time to incentivize adoption:* In this counterfactual scenario, firms in the treatment arm receive a monetary compensation contingent on adoption. I allow for a fairly large (and unsustainable) transfer of Rs. 150 per transaction entered, which is equal to the utility per-transaction. Despite this large transfer I find no sustained increase in adoption. Table 2.6.2 shows a very small increase in adoption of 0.07%. I find that a consistent monetary transfer does indeed increase the probability of adoption as shown by the blue line in Panel A in Figure 2.13. However, this amount is not enough to overcome the large learning costs at lows levels of cumulative experience as seen in Panel A of Figure 2.14. Hence, under this intervention firms move to a steady state of no adoption.

2. *Counterfactual 2: Repeated nudges to decrease forgetting:* In this counterfactual scenario, firms in the treatment arm are provided repeated nudges with information on how to use the digital technology. The goal of this intervention is to reduce the amount of forgetting. To compute treatment effects I reduce forgetting by about 50% but see a very small increase in adoption. Table 2.6.2 documents a small and insignificant

increase in adoption of 0.19%. This is because forgetting is a second order problem. If we do not subsidize learning costs in any way, firms do not accumulate any experience at all. Panel B in Figure 2.13 shows that there is no significant change in the probability of adoption. This is expected, as forgetting does not shift the probability of adoption cure. It only makes it easier to move along it. Panel B in Figure 2.14 shows that under this intervention firms move to a steady state of no adoption.

3. *Counterfactual 3: Improving human capital:* In this counterfactual scenario, I improve human capital outcomes for firms in the treatment arm. I do this by reducing the learning cost when firms have no experience (a 35% decrease in α_1) and increasing the rate at which firms learn (a 75% increase in α_2). Again, this intervention alone is not enough 2.6.2 documents a very small increase in adoption of 0.9%. The blue line in Panel C in Figure 2.13 shows a large shift of the probability of adoption to the left; that is, a small amount of hand-holding is now enough to sustain adoption. However, the in the absence of any holding firms move to a steady state of no adoption as show by Panel C of Figure 2.14.

4. *Counterfactual 4: Updating firm's beliefs about their profitability:* In the randomized control trial, as firms adopt they learn two things: (i) technology adoption improves profitability and (ii) their business is less profitable than they thought. The second effect dampens adoption. In this counterfactual scenario, I correct beliefs about true profitability of

the business prior to the intervention. Again, this intervention alone is not enough 2.6.2 documents a very small increase in adoption of 0.7%. In Panel D of Figure 2.13, I see a large upward shift of the transition probability for the treated group (the blue line). This implies, for the same level of experience, firms are more likely to adopt. However, in the absence of any hand-holding or overcoming learning barriers, firms move to a steady state of no adoption as shown in Panel D of Figure 2.14.

Table 2.6.2: **Counterfactual interventions**

Intervention	**Treatment effect**
Panel A : Model prediction for actual intervention	
Treatment Light or T1	0.088^{***}
treatment Intense or T2	0.14^{***}
Panel B : Counterfactual interventions	
Counterfactual 1	0.0007^{*}
Counterfactual 2	0.019^{***}
Counterfactual 3	0.009^{***}
Counterfactual 4	0.007^{***}

Notes: This table compares the intervention implemented in this study to counterfactual interventions. Panel A presents treatment effects for the intervention that was implemented (treatment light and treatment intense), as per the model simulations. Panel B presents treatment effects for four counterfactual interventions, as per the model simulations.

Figure 2.13: **Transition probability for counterfactual interventions**

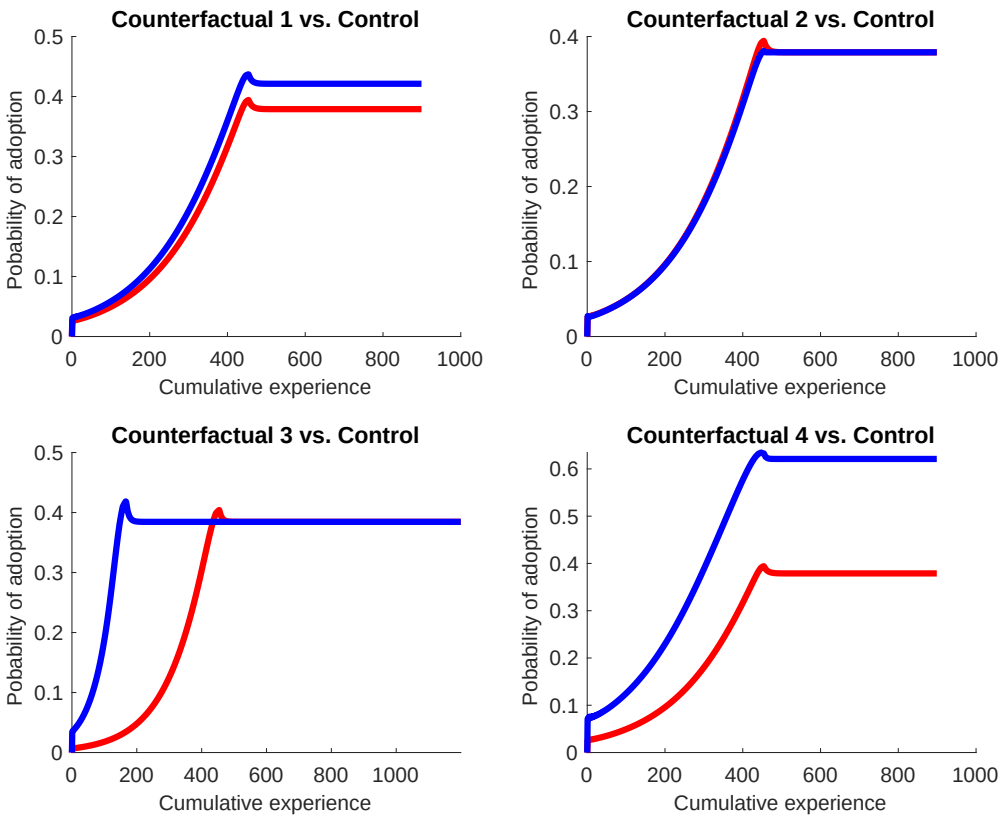
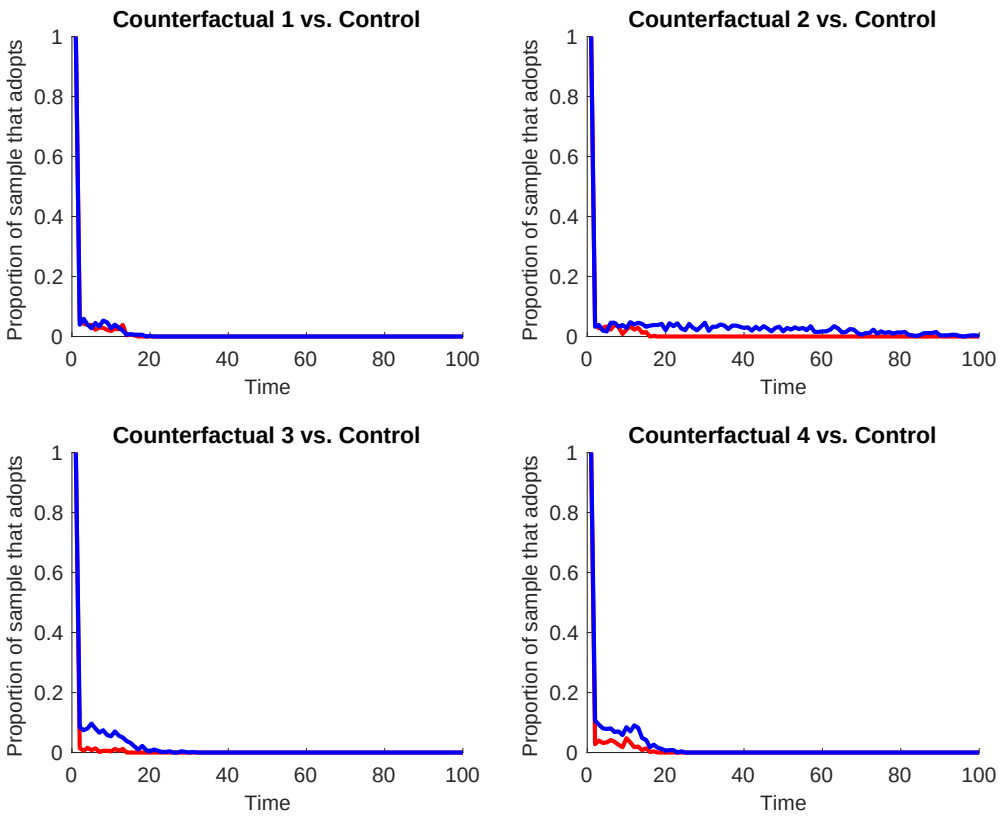


Figure 2.14: **Adoption trends for counterfactual interventions**



2.6.4 Optimal intervention

In this section I discuss the optimal interventions suggested by my empirical and theoretical findings.

High learning costs for informal micro-firms leads to them being trapped in a steady state of no adoption. In this paper, I show that while hand-holding firms to reduce learning costs leads to a significant increase in adoption, but these effects are not sustained. To induce a sustained increase in adoption, firms would need a more intensive hand-holding. The current intervention already provided 4 weeks and 8 weeks of hand-holding respectively to the treatment light and treatment intense groups. Providing a more intensive intervention, can be logistically challenging.

Similarly, I show that various counterfactual interventions, have small effects on adoption that are not sustained. The key to achieving a sustained increase in adoption is to have a bundled intervention that relaxes multiple constraints. That is, easing cognitive constraints, human capital constraints and misperceptions about profitability in addition to reducing learning barriers, can be a more cost-effective way of encouraging adoption of productive technologies.

In Table 2.6.3, I present results by interacting treatment light and treatment intense with each of the above counterfactual scenarios. I document a large increase in the magnitude of adoption. In Figures 2.15 and 2.16 I present the inter-temporal trends in adoption, and find that bundling counterfactuals 2, 3 and 4 (repeated nudges to decrease forgetting, improving

human capital and updating firm's beliefs about their profitability) with the hand-holding treatments leads to a sustained increased in adoption. In these graphs the blue line represents the treatment group and the red line the control group under each of the four counterfactual interventions discussed below.

I document four key results on bundling interventions. First, I find that providing monetary incentives for adoption (counterfactual 1) over a prolonged duration is not successful in sustaining adoption even when bundled with the hand-holding treatment. Second, nudging firms through repeated nudges to decrease forgetting (counterfactual 2) leads to a 26.2% increase in adoption when bundled with treatment light and a 34.1% increase in adoption when bundled with treatment intense (as shown in Table 2.6.3). This is because the two interventions are very complementary. Nudges to reduce forgetting increases adoption when coupled with reducing learning barriers and allows firms to slide down the learning curve faster. Figures 2.15 and 2.16 show that these effects are sustained over time. Third, improving human capital outcomes (counterfactual 3) leads to a 37.6% increase in adoption when bundled with treatment light and a 38.3% increase in adoption when bundled with treatment intense (as shown in Table 2.6.3). Again, reducing learning barriers is complementary to hand-holding firms along the learning curve. Thus, both together lead to a large and sustained increase in adoption (as seen in Figures 2.15 and 2.16). That said, improving human capital remains challenging and expensive in LMICs. Fourth, updating firm's beliefs about their profitability can unleash the true returns to adoption (counterfactual

4) . Table 2.6.3 shows that correcting beliefs leads to a 46.5% increase in adoption when bundled with treatment light and a 58.1% increase in adoption when bundled with treatment intense. These are the largest effects of the counterfactual interventions explored. Figures 2.15 and 2.16 show that these effects are sustained over time. More research is needed to look into how these beliefs can be corrected.

Table 2.6.3: **Optimal counterfactual interventions**

Intervention	**Treatment effect**
Panel A : Counterfactual interventions interacted with Treatment Light	
Counterfactual 1 * T1	0.107^{***}
Counterfactual 2 * T1	0.262^{***}
Counterfactual 3 * T1	0.376^{***}
Counterfactual 4 * T1	0.465^{***}
Panel B : Counterfactual interventions interacted with Treatment Intense	
Counterfactual 1 * T2	0.197^{***}
Counterfactual 2 * T2	0.341^{***}
Counterfactual 3 * T2	0.383^{***}
Counterfactual 4 * T2	0.581^{***}

Notes: This table presents the interaction of treatment light and treatment intense with the four counterfactual interventions.

Figure 2.15: **Adoption trends for counterfactuals interacted with treatment light**

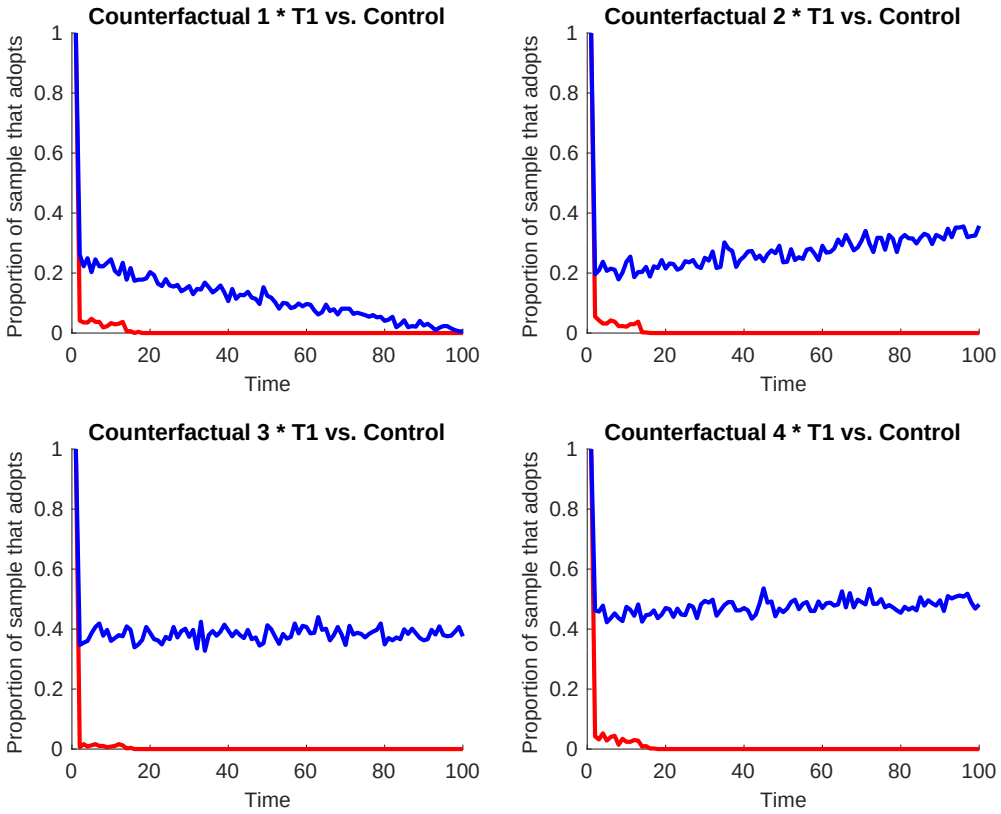
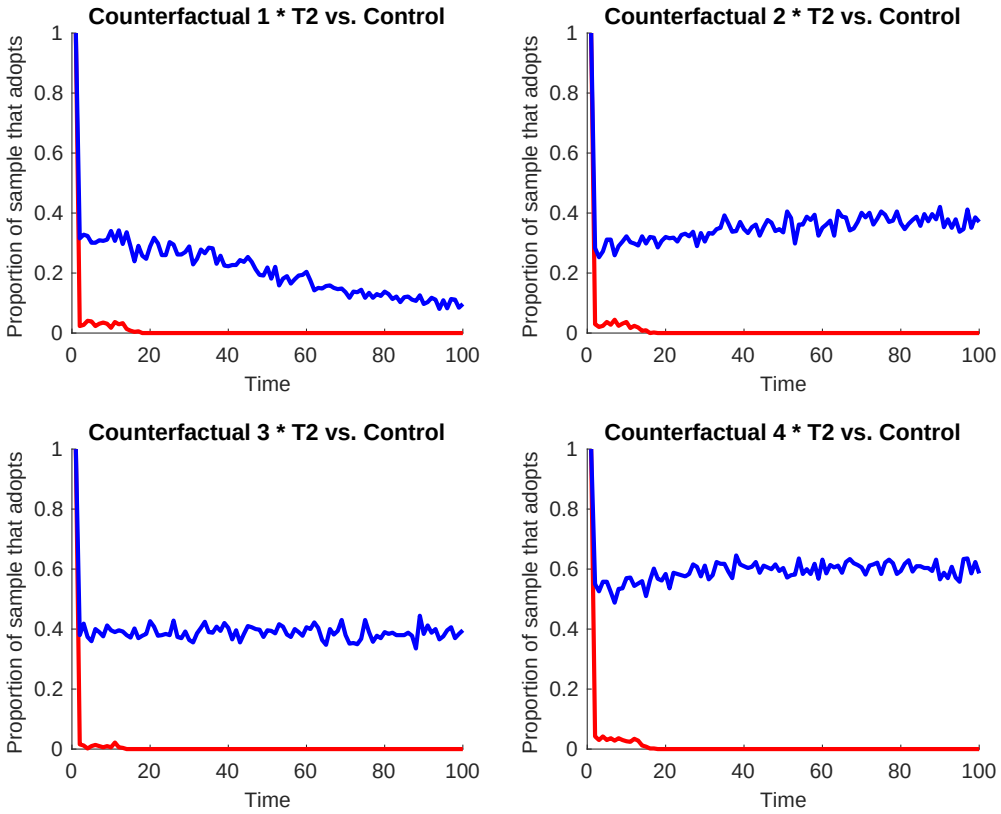


Figure 2.16: **Adoption trends for counterfactuals interacted with treatment intense**



2.7 Conclusion

The rapid digitalization has made the digital divide very stark. New digital technologies can be a tool to increase firm productivity but adoption rates are often low. The role of high learning costs has received limited attention, but is particularly salient for the adoption of digital technologies. This paper offers evidence to support the hypothesis that high learning costs lead to low adoption of technologies by firms. Working with micro-firms in the informal sector in India, I study adoption choice for a novel digital technology that overcomes financial management issues. I use a stylized dynamic model of adoption choice and a corresponding field experiment to show that temporarily subsidizing the cost of learning how to use a digital technology, leads to increased adoption as well as, more intensive use of a digital technology in the short run. I document that firms primarily use the technology to view key financial reports and manage cash flow in their business (by sending payment reminders and invoices).

As firms adopt the digital technology, they surprisingly report (significantly) lower profits and revenues in the short run. I argue that this is driven by firms getting more accurate information about low firm profitability. This decrease in self-reported finances is reasonable if firms systematically overestimate profits at baseline. Using data from a comparable sample of firms, I document a systematic over-estimation. I also offer three strands of evidence to substantiate this finding that firms learn about their true profitability. First, treated firms improve business practices in the short run – a key chan-

nel to learning about profitability. Second, I offer suggestive evidence that firms report lower investment which is reasonable if firms were to learn that they are less profitable than they previously thought. Third, I see lower expectations of future firm growth. It can indeed be beneficial for a firm owner to have better information about firm finances as it enables them to make a more informed choice about running and growing their firm. The limited medium run effects, raises questions about the need for a more sustained intervention, or the use repeated nudges to sustain effects. Further, using long run follow-up data I will look at how firms act on the updated and more accurate information about their firm.

Finally, this paper highlights the need for a multi-dimensional approach to increase adoption amongst informal micro-firms. I generalize the results of the randomized trial with a structural model to study dynamic adoption choice. I use model estimates to explore various alternative interventions such as: (i) monetary transfers over time to incentivize adoption; (ii) repeated nudges to decrease forgetting; (iii) improving human capital and (iv) updating firm's beliefs about their profitability. I find that each of these counterfactuals alone is not sufficient to sustain adoption, but when bundled with the hand-holding treatment can sustain large and meaningful increases in adoption (with the exception of the monetary transfers intervention). The survival, growth and profitability of informal micro-firms has a direct impact on broader economic growth, sustainable development, and poverty alleviation. In an era of rapid digital development, it is key for academics and policymakers to explore new avenues to use digital financial services to sup-

port micro-firms in the informal sector. In this study, I address key policy questions on the drivers of technology adoption and the mechanisms through which technology adoption impacts firm outcomes.

Appendix

2.A Digital penetration in LMICs

Figure 2.A.1 and Figure 2.A.2 shows the sharp rise in mobile subscriptions and smartphones across LMICs. This presents opportunities for digital technologies to be used by informal firms.

Figure 2.A.1: **Growth of mobile phone subscriptions in LMICs**

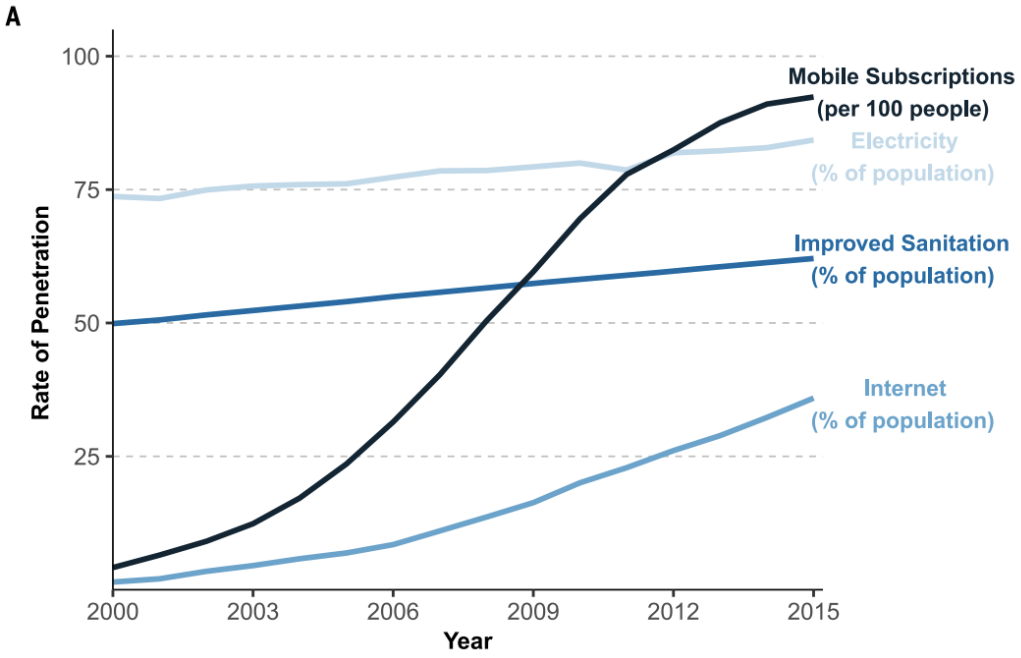
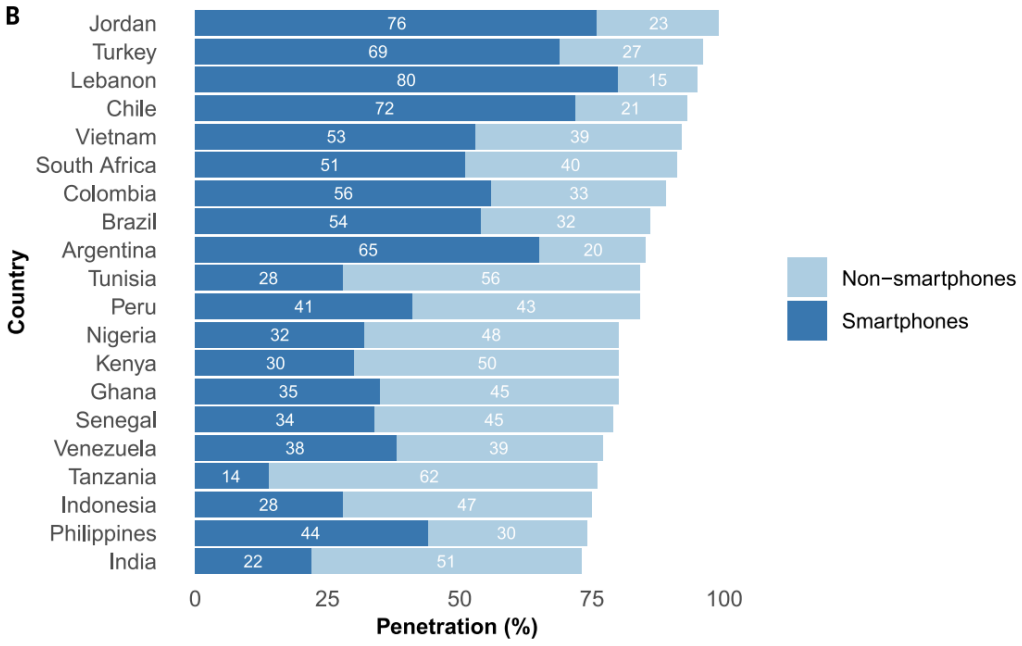


Figure 2.A.2: **Mobile phone penetration in LMICs**



2.B MeraBills digital technology

Under status quo, it is common for micro-firm owners to keep records of business transactions using mental accounting or using diary entries. Given these firms do make a range of fairly complex decisions around financial planning, managing inventories, managing trade credit etc., this leads to inefficiencies in running the firm. Figure 2.B.1 displays an example of informal diary entries that are used in the absence of this digital technology.

Figure 2.B.1: **Books of accounts**

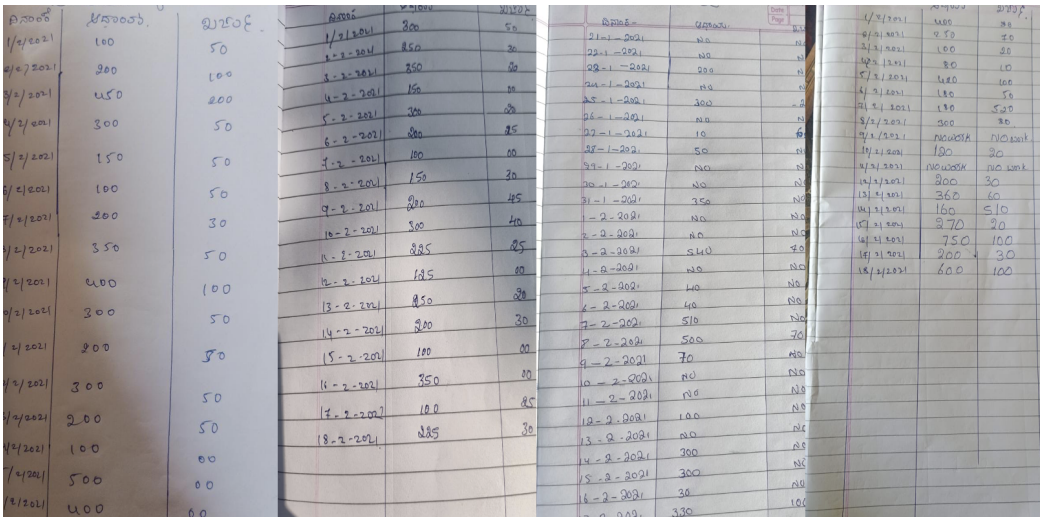


Figure 2.B.2 presents a screenshot of the interface of the easy to use MeraBills digital technology platform. Figure 2.B.3 to Figure 2.B.5 show the various financial reports that can be generated using MeraBills. Figure 2.B.3 shows the monthly firm revenue and profit, as well as, the break-up

of expenditure categories. Figure 2.B.4 shows a category wise break-up of monthly revenue and expenditure. Figure 2.B.5 provides details on liquid assets, amount owed and working capital. Note, I do have access to the financial data on the digital platform, due to data privacy regulations. All the financial data used in this paper is collected via field surveys. However, the micro-firm owners can view these financial reports and use the information while running their business.

Figure 2.B.2: **MeraBills app interface**

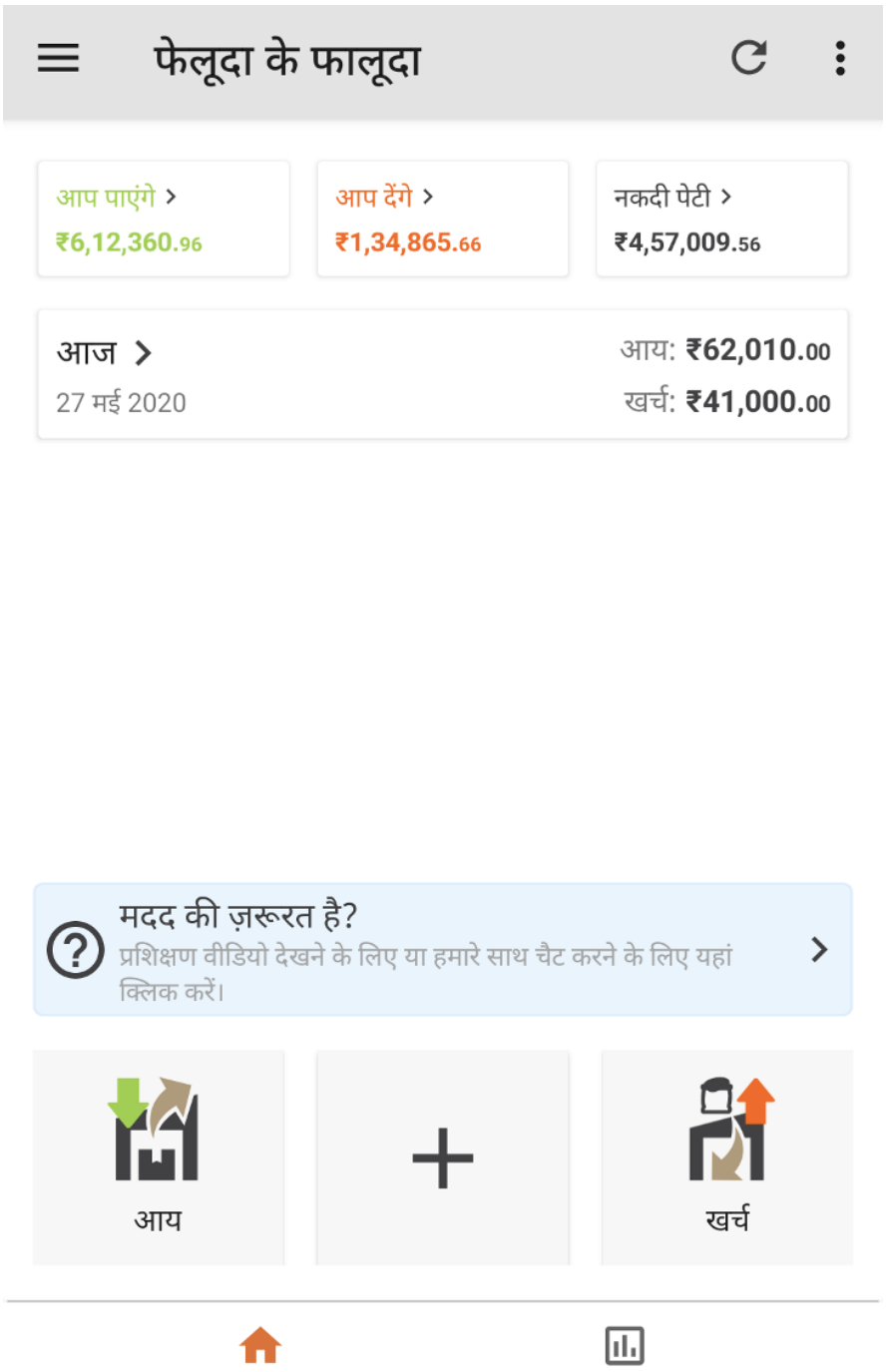


Figure 2.B.3: **MeraBills app interface**

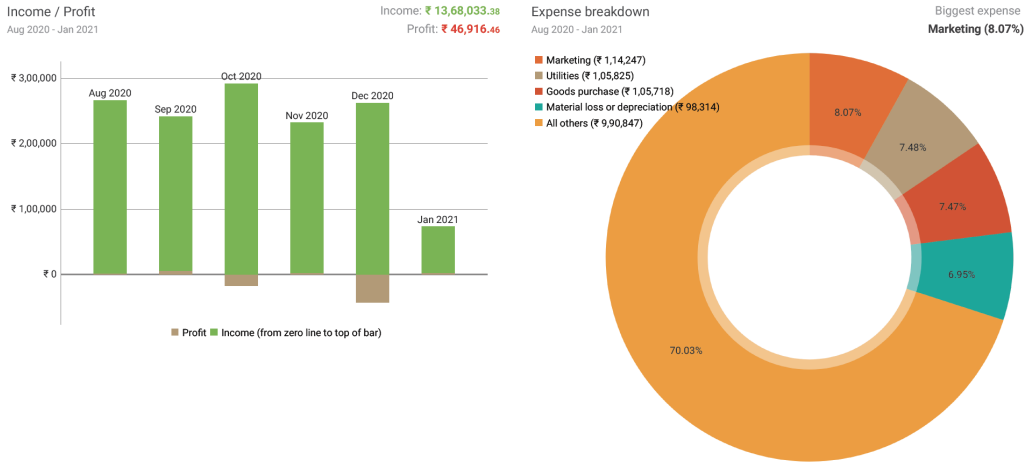
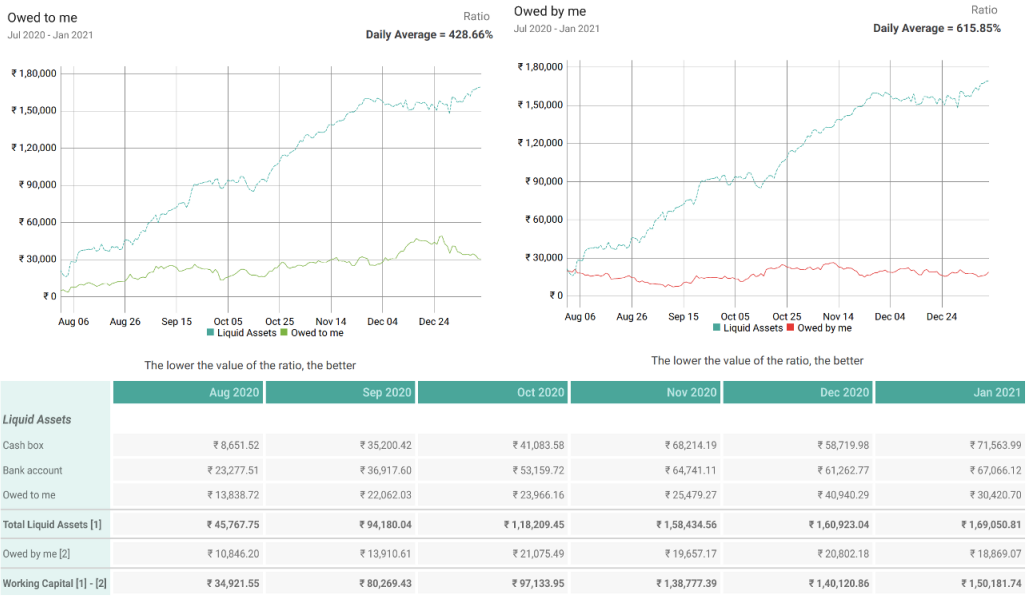


Figure 2.B.4: **MeraBills app interface**

	Aug 2020	Sep 2020	Oct 2020	Nov 2020	Dec 2020	Jan 2021	*Total*
Income type							
Goods or services sale	₹ 68,698.80	₹ 62,072.58	₹ 70,521.49	₹ 59,565.52	₹ 78,175.99	₹ 21,036.45	*₹ 3,60,070.83*
Rent	₹ 63,128.39	₹ 66,853.77	₹ 76,152.00	₹ 57,288.99	₹ 63,947.52	₹ 20,692.15	*₹ 3,48,062.82*
Other income	₹ 71,037.44	₹ 62,107.84	₹ 76,157.92	₹ 59,494.26	₹ 63,372.12	₹ 13,143.44	*₹ 3,45,313.02*
Interest	₹ 63,526.27	₹ 50,776.44	₹ 69,050.37	₹ 55,854.86	₹ 56,852.06	₹ 18,526.71	*₹ 3,14,586.71*
Total Income [1]	**₹ 2,66,390.90**	**₹ 2,41,810.63**	**₹ 2,91,881.78**	**₹ 2,32,203.63**	**₹ 2,62,347.69**	**₹ 73,398.75**	*₹ 13,68,033.38*
Expense type							
Marketing	₹ 19,092.11	₹ 19,494.26	₹ 25,771.66	₹ 12,334.26	₹ 32,032.46	₹ 5,521.79	*₹ 1,14,246.54*
Utilities	₹ 20,458.45	₹ 13,313.29	₹ 28,455.32	₹ 17,542.18	₹ 23,070.73	₹ 2,984.71	*₹ 1,05,824.68*
Goods purchase	₹ 15,439.62	₹ 17,117.61	₹ 23,616.77	₹ 18,732.86	₹ 22,348.35	₹ 8,462.90	*₹ 1,05,718.11*
Material loss or depreciation	₹ 19,194.57	₹ 23,039.62	₹ 21,035.95	₹ 15,689.52	₹ 16,362.58	₹ 2,991.28	*₹ 98,313.52*
All others	₹ 1,90,659.17	₹ 1,62,631.10	₹ 2,10,228.59	₹ 1,65,124.60	₹ 2,11,258.00	₹ 50,945.53	*₹ 9,90,846.99*
Total Expenses [2]	**₹ 2,64,843.92**	**₹ 2,35,595.88**	**₹ 3,09,108.29**	**₹ 2,29,423.42**	**₹ 3,05,072.12**	**₹ 70,906.21**	*₹ 14,14,949.84*
Total Profit [1] - [2]	**₹ 1,546.98**	**₹ 6,214.75**	**-₹ 17,226.51**	**₹ 2,780.21**	**-₹ 42,724.43**	**₹ 2,492.54**	*-₹ 46,916.46*

Figure 2.B.5: **MeraBills app interface**



	Aug 2020	Sep 2020	Oct 2020	Nov 2020	Dec 2020	Jan 2021
Liquid Assets						
Cash box	₹ 8,651.52	₹ 35,200.42	₹ 41,083.58	₹ 68,214.19	₹ 58,719.98	₹ 71,563.99
Bank account	₹ 23,277.51	₹ 36,917.60	₹ 53,159.72	₹ 64,741.11	₹ 61,262.77	₹ 67,066.12
Owed to me	₹ 13,838.72	₹ 22,062.03	₹ 23,966.16	₹ 25,479.27	₹ 40,940.29	₹ 30,420.70
Total Liquid Assets [1]	**₹ 45,767.75**	**₹ 94,180.04**	**₹ 1,18,209.45**	**₹ 1,58,434.56**	**₹ 1,60,923.04**	**₹ 1,69,050.81**
Owed by me [2]	₹ 10,846.20	₹ 13,910.61	₹ 21,075.49	₹ 19,657.17	₹ 20,802.18	₹ 18,869.07
Working Capital [1] - [2]	**₹ 34,921.55**	**₹ 80,269.43**	**₹ 97,133.95**	**₹ 1,38,777.39**	**₹ 1,40,120.86**	**₹ 1,50,181.74**

2.C Details on the outcome variables of interest

In this section, I present tables that discusses how the variables of interest will be constructed and the relevant data source. Appendix 2.C Table 2.C.1 presents details on the primary outcome variables.

Table 2.C.1: **Primary outcome variables**

	Variable description	**Data source**
Panel A : Adoption outcomes		
Adoption dummy	Binary measure of daily adoption	App usage data
Extent of adoption	Weekly measure of number of transactions entered digitally	App usage data

Appendix 2.C Table 2.C.2 presents details on the secondary outcome variables.

Table 2.C.2: **Secondary outcome variables**

	Variable description	**Data source**
Panel A : Firm outcomes		
Revenue	Aggregated from 30-day recall-based questions	Survey data
Profit	Calculated as revenue - expenditure	Survey data
Panel B : Business practices		
Record-keeping	Outcome variables based on type of record keeping number of firm outcomes recorded [17], frequency of recording, ability to use records [18] and separating HH and business finances	Survey data
Planning business	Outcome variables based on frequency of reviewing financials, setting target sales and budgeting costs	Survey data
Inventory management	Outcome variables based on reviewing prices with customers, reviewing prices with suppliers	Survey data
Managing trade credit	A dummy for maintaining written records of pending payments	Survey data

2.D Attrition

Attrition can be of two types in my analysis. First, attrition from the adoption data and second, attrition from follow-up data.

I start with a discussion of attrition in the adoption data from the MeraBills dashboard. There was attrition of 18% at the stage, due to logistical issues around implementation. Of the sample of 320 firms, 61 are not captured in the adoption data (17% of the sample). The most prevalent reason was that the firms refused to or could not attend the training session (43 firms in total). If entrepreneurs did not attend the training session, they did not receive visits from field officers (if they were in the treatment groups).[19] Other reasons included (affecting 18 firms), entrepreneurs choosing not to share the data or experiencing technological issues with their mobile phone.

I do not see differential attrition for firms across treatment arms in Table 2.D.1 (22% for the control group and 16% for the combined treatment group). In Table 2.D.1, I also present differential attrition for the three treatment arms separately. Given the high levels of attrition, I also show a range of baseline characteristics across the two groups and do not see any significant differences between the groups. The one exception is, firms that are observable on the MeraBills dashboard are more likely to have separated business and household records at baseline (significant at the 10% level).

The second type of attrition, is for the follow-up survey data that is

[19]Field officers were recruited only to conduct visits to firm locations and help them in learning by doing. They did not the have skill set to provide the more detailed two hour training session (that was given to all firms at the start of the intervention).

used to analysis firm level outcome variables. We have low levels of attrition during our follow-up surveys. We are unable to reach 2.5% of our sample (a total of 8 firms). Since the analysis of follow-up data pools the treatment arms, we first look at whether firms are more likely to return for follow-up surveys if they are assigned to the treatment arm (see row 1 in Table 2.D.2). We do not see evidence of differential attrition.

I also provide details on attrition without pooling the treatment arms (see rows 2,3 and 4 in Table 2.D.2). When we split the treatment arms, we see some differential attrition between the treatment intense group and the control group. Participants in the treatment intense group are 34% more likely to return for follow-up surveys than the control group (significant at the 5% level). We do not see any differential attrition between the other treatment arms. Since the combined treatment arm is used for follow-up data analysis, the sample composition does not alter the internal validity of the results.

Table 2.D.2 compares how the baseline characteristics of the returners differs from non-returners. A significantly higher proportion of returners have family members who have a mobile phone and as well as, help them use their mobile phone. This is consistent with the idea that women micro-entrepreneurs in this sample struggle to use phones for digital transactions and financial apps.

Table 2.D.1: **Summary statistics for those observable on the MeraBills dashboard and those who are not**:

Baseline characteristic	Not in MB	In MB	Obs	Not-MB - MB	
				Std. diff.	p-val
MB Treatment	0.61	0.70	320	-0.18	0.19
T1 - C	0.46	0.53	208	-0.14	0.43
T2 - C	0.42	0.55	212	-0.26	0.15
T2 - T1	0.46	0.52	220	-0.12	0.50
Household size	4.40	4.77	311	-0.28	0.17
Number of HH businesses	1.90	1.89	311	0.01	0.96
Total business HH income	26,692	25,690	311	0.03	0.87
Total HH income	32,099	35,793	311	-0.13	0.59
Business experience (years)	34.44	31.57	311	0.05	0.73
Number of competitors (5min walk)	3.29	3.00	311	0.07	0.68
Number of customers per day	12.46	12.67	311	-0.02	0.93
Number of employees	0.29	0.59	311	-0.20	0.45
Revenue at baseline survey	13,815	16,940	311	-0.14	0.53
Profit at baseline survey	5,109	6,420	311	-0.26	0.44
Fixed assets	36,911	50,474	311	-0.14	0.45
Total current assets	179,950	158,902	311	0.07	0.60
Loan pending	116,146	106,441	311	0.06	0.72
Amount borrowed (family/friends)	14,897	19,722	311	-0.11	0.64
Happy	1.56	1.62	311	-0.10	0.58
Family members help use phone	0.96	0.95	311	0.04	0.82
Family members use phone	0.92	0.95	311	-0.11	0.41
Keep business records	0.54	0.67	311	-0.25	0.10
Seperate HH records	0.19	0.31	311	-0.31	0.09
Hours spent on business	3.73	4.18	152	-0.21	0.36
Hide income from family	0.23	0.24	311	-0.02	0.92

Notes: "Not in MB" is an indicator for not being captured in the MeraBills database. "In MB" is an indicator for being captured in the sample for adoption data analysis. The first two columns correspond to the mean value of the variable for the two groups. The third column provides the number of observations. Columns 4 and 5 present the standardized difference and the p-value on the test of equality between the two groups.

Table 2.D.2: **Summary statistics for returners and non returners**:

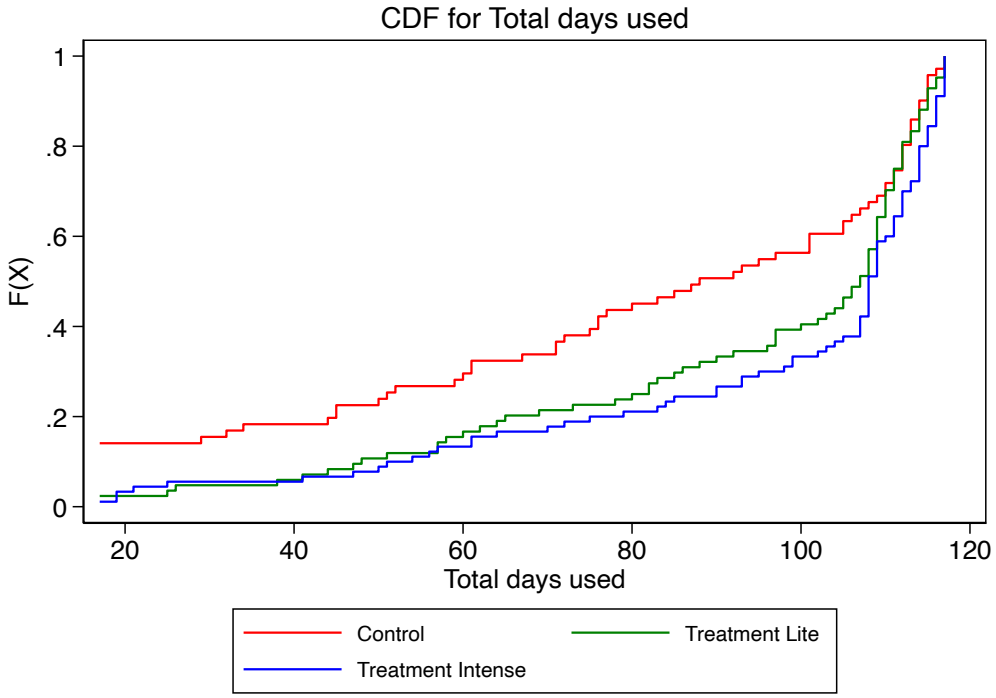
Baseline characteristic	Non-Returner	Returner	Obs	Non-Returner - Returner	
				Std. diff.	p-val
MB Treatment	0.50	0.69	640	-0.37	0.10
T1 - C	0.43	0.52	416	-0.18	0.49
T2 - C	0.20	0.54	424	-0.80	0.04
T2 - T1	0.25	0.51	440	-0.57	0.14
Number of HH businesses	1.75	1.89	622	-0.31	0.64
Total business HH income	13,510.00	26,005.61	622	-0.94	0.35
Total HH income	40,510	35,154	622	0.29	0.73
Business experience (years)	38	32	622	0.16	0.76
Number of competitors (5min walk)	2.75	3.05	622	-0.14	0.85
Number of customers per day	14.50	12.61	622	0.18	0.71
Revenue at baseline survey	9,125.00	16,552.85	622	-1.06	0.51
Profit at baseline survey	5,875.00	6,222.01	622	-0.06	0.93
Fixed assets	5,750	48,936	622	-6.45	0.29
Total current assets	174,250	161,993	622	0.07	0.89
Loan pending	97,500	108,075	622	-0.08	0.87
Amount borrowed (family/friends)	25,000	18,899	622	0.13	0.79
Happy	2	2	622	0.16	0.50
Family members help use phone	1	1	622	-0.44	0.01
Family members use phone	0.25	0.95	622	-1.51	0.00
Keep business records	0.50	0.65	622	-0.28	0.38
Seperate HH records	0.50	0.29	622	0.40	0.19
Hours spent on business	4.00	4.12	304	-0.05	0.91
Hide income from family	0.25	0.23	622	0.03	0.92

Notes: "Non-returner" is an indicator for having exited the sample during the intervention. "Returner" is an indicator for being in the follow-up samples. The first two columns correspond to the mean value of the variable for the two groups. The third column provides the number of observations. Columns 4 and 5 present the standardized difference and the p-value on the test of equality between the two groups. For two variables – household size and number of employees – there is no variation in the value for observations in one of the groups, and therefore, the standardized difference in column 4 cannot be calculated. We drop these two observations from the table. The p-values for these two variables do not show a significant difference between returners and non returners.

2.E Treatment effects on the distribution of adoption outcomes

In Figure 2.E.1 I plot the cumulative distribution function for the total number of days the app has been used. For outcomes such as viewing the home screen and entering transactions, I find that (as expected) all treatment arms have some firms that do not use the app. Amongst those who do, the treatment shifts the distribution to the right.

Figure 2.E.1: **CDF for number of total number days MeraBills was used**



2.F Local Average Treatment Effects

In this section, I present Local Average Treatment Effects (LATE) As is expected, LATE estimates are larger than ITT estimates in magnitude, but otherwise tell a similar story.

2.F.1 Business practices and firm outcomes

Table 2.F.1: **Treatment effects on Firm Revenue and Profits** :

	Profit			Revenue		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Fitted values	-0.57*	-1.04**	-0.36	-0.61	-0.89*	-0.66
	(0.34)	(0.50)	(0.69)	(0.37)	(0.50)	(0.73)
Observations	1617	795	822	1626	804	822
Mean DV	8.56	8.36	8.53	9.25	9.03	9.27
Std. dev.	0.90	0.93	0.88	0.97	0.96	0.96

Notes: The dependent variables in this table are outcomes for log profit and log revenue for firms. The profit and revenue data is self-reported by firms during follow-up surveys. All variables presented in this table are winsorized at 1% to control for outliers in the data. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

2.F.2 Learning about low profitability

In this section, I explore the first hypothesis that as firms use the digital technology to manage their business, they learn that their profitability is

lower than anticipated. Similar to section 4.4, I explore changes in outcomes across three broad categories: (i) business practices; (ii) firm investment; (iii) expectations on firm performance.

Table 2.F.2: **Treatment effects on business practices** :

	Financial planning practices			Marketing practices		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Fitted values	0.11	0.40*	-0.19	0.15	0.51**	-0.28
	(0.12)	(0.21)	(0.19)	(0.14)	(0.23)	(0.28)
Observations	574	285	289	574	285	289
Mean DV	0.85	0.76	0.76	0.47	0.51	0.51
Std. dev.	0.33	0.39	0.39	0.37	0.38	0.38

Notes: The dependent variables in this table are indices for financial planning practices and marketing practices for firms. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Table 2.F.3: **Treatment effects on Firm Assets and Investment** :

	New Investment			Fixed Assets			Current assets		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Treatment on Treated	-0.11	-0.57	0.18	-1.05	-1.02	-1.08	0.24	0.23	0.18
	(0.36)	(0.55)	(0.41)	(0.78)	(0.96)	(1.22)	(0.30)	(0.44)	(0.40)
Observations	501	242	259	537	263	274	565	281	284
Mean DV	9.39	9.50	9.29	8.68	9.35	8.05	10.28	10.36	10.21
Std. dev.	1.59	1.71	1.48	3.20	2.59	3.58	1.46	1.37	1.56

Notes: The dependent variables in this table are outcomes for log investment and log assets. New investment measures the log of any new investment made by the firm. Total value of fixed assets is defined as a long-term asset that a firm owns and uses in the production of its income and is not expected to be consumed or converted into cash any sooner than at least one year's time. Examples of fixed assets include land, buildings, machinery, manufacturing equipment, office equipment, furniture, vehicles. Fixed assets do not include working capital, inventories, or money used for the running of the business. The total value of current assets is calculated as the sum of inventories, debt and cash in business. All variables presented in this table are in logs and are winsorized at the 1% level to control for outliers. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Table 2.F.4: **Treatment effects on future business outcomes** :

	Future business growth			Future Customers			Future Products		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Treatment on Treated	-0.07	-0.06	-0.08	2.21	-28.69	30.24	-5.77**	-8.47*	-3.24
	(0.06)	(0.10)	(0.08)	(17.13)	(18.73)	(26.32)	(2.58)	(4.96)	(2.27)
Observations	574	285	289	574	285	289	574	285	289
Mean DV	0.91	0.90	0.92	24.47	27.94	21.22	5.74	7.54	4.06
Std. dev.	0.28	0.30	0.27	67.01	69.43	64.89	13.31	16.62	9.00

Notes: The dependent variables in this table measure expectations on future firm outcomes. Future business growth is a dummy variable for whether a micro-firm owner expects their firm to grow in the future. Future customers is a variable that measures the number of new customers a firm expects to sell to in the future. Future products is a variable that measures the number of new products a firm expects to sell in the future. Columns 4-9 are winsorized at the 1% level to control for outliers."Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

2.F.3 Unsuitable technology

In this section, I explore the second hypothesis that the technology is detrimental to the firm. Similar to Section 4.4, this is an unlikely explanation.

Table 2.F.5: **Treatment effects on experience using app** :

	Recommend			Teach			WTP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Treatment on Treated	0.38***	0.35**	0.39***	0.35***	0.42***	0.30**	8.68	11.03	4.50
	(0.12)	(0.16)	(0.15)	(0.10)	(0.13)	(0.13)	(24.96)	(30.79)	(37.58)
Observations	582	289	293	582	289	293	582	289	293
Mean DV	0.44	0.52	0.36	0.20	0.15	0.24	86.21	45.24	124.44
Std. dev.	0.50	0.50	0.48	0.40	0.36	0.43	113.20	83.46	123.90

Notes: The dependent variables in this table measure a firm's experience using the MeraBills digital technology . Recommend is a dummy variable for whether a micro-firm owner would recommend the digital technology to others. Teach is a dummy variable for whether a micro-firm owner has taught family or friends how to use the digital technology. Column 3 presents results for a dummy variable for whether a micro-firm owner has involved their family in using the digital technology. Column 4 presents results for the amount a firm is willing to pay to use the digital technology. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. We do not have a baseline measure for this outcome variable, and hence, are not able to control for it. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

2.G Robustness checks

In this section, I provide robustness checks for Table 2.5.4 and 2.F.1. In Table 2.G.1 and Table 2.G.2, I provide evidence of robustness to winsorizing at the 5% level. In Table 2.G.3 and Table 2.G.4, I provide evidence that my results are robust to levels of profits and levels of revenues (instead of logs).

Table 2.G.1: **Treatment effects on Firm Revenue and Profits** :

	Profit			Revenue		
	(1) Pooled	(2) Short run	(3) Medium run	(4) Pooled	(5) Short run	(6) Medium run
Treatment	-0.13*	-0.19*	-0.08	-0.11	-0.14	-0.10
	(0.08)	(0.10)	(0.10)	(0.08)	(0.10)	(0.10)
Observations	1617	795	822	1626	804	822
Mean DV	8.52	8.33	8.50	9.20	8.99	9.24
Std. dev.	0.80	0.86	0.84	0.86	0.89	0.91

Notes: The dependent variables in this table are outcomes for revenue and profit for firms. The Revenue and Profit data is self-reported by firms during follow-up surveys. All variables presented in this table are winsorized at 5% to control for outliers in the data. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Table 2.G.2: **LATE effects on Firm Revenue and Profits** :

	Profit			Revenue		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Fitted values	-0.54*	-0.84*	-0.52	-0.48	-0.61	-0.65
	(0.32)	(0.44)	(0.65)	(0.34)	(0.44)	(0.69)
Observations	1617	795	822	1626	804	822
Mean DV	8.52	8.33	8.50	9.20	8.99	9.24
Std. dev.	0.80	0.86	0.84	0.86	0.89	0.91

Notes: The dependent variables in this table are outcomes for log profit and log revenue for firms. The profit and revenue data is self-reported by firms during follow-up surveys. All variables presented in this table are winsorized at 5% to control for outliers in the data. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Table 2.G.3: **Treatment effects on Firm Revenue and Profits, in levels** :

	Profit			Revenue		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Short run	Medium run	Pooled	Short run	Medium run
Treatment	-1516.58*	-3159.09**	-56.78	-3481.01*	-4982.07*	-2264.83
	(906.54)	(1466.15)	(898.42)	(1772.54)	(2647.42)	(1973.19)
Observations	1722	855	867	1722	855	867
Mean DV	7786.21	6436.71	7067.90	16187.93	12902.27	15335.21
Std. dev.	11758.43	10407.30	8150.13	22156.42	19223.49	16381.42

Notes: The dependent variables in this table are outcomes for profit and revenue for firms. The profit and revenue data is self-reported by firms during follow-up surveys. All variables presented in this table are winsorized at 1% to control for outliers in the data. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Table 2.G.4: **LATE effects on Firm Revenue and Profits, in levels** :

	Profit			Revenue		
	(1) Pooled	(2) Short run	(3) Medium run	(4) Pooled	(5) Short run	(6) Medium run
Treatment on Treated	-6398.96*	-13718.34**	-377.71	-15037.45*	-22245.32*	-15126.59
	(3825.00)	(6366.76)	(5976.65)	(7657.09)	(11820.92)	(13178.71)
Observations	1722	855	867	1722	855	867
Mean DV	7786.21	6436.71	7067.90	16187.93	12902.27	15335.21
Std. dev.	11758.43	10407.30	8150.13	22156.42	19223.49	16381.42

Notes: The dependent variables in this table are outcomes for revenue and profit for firms. The Revenue and Profit data is self-reported by firms during follow-up surveys. All variables presented in this table are winsorized at 1% to control for outliers in the data. "Treatment" is an indicator for a firm being assigned to either treatment 1 or treatment 2. Regressions include a baseline measure for the variable and strata dummies with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The results are pooled for the follow-up survey rounds. The table presents results pooled across survey rounds, as well as for the short-run and medium-run separately. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

2.H Systematic over-estimation of profits

In this section I provide suggestive evidence using novel data collected for another research project in the same study area for a similar sample (prior to this intervention).[20] Working with a group of 55 firms, I am able to get at a measure of "true-profits" (while this is of course, not 'true" in the literal sense, it provides a much more accurate measure of profits). We collected daily self-reported data on revenue and expenditure. At the time this data was collected in 2019, the reports were not linked to any financial access. This was part of the entrepreneurship bootcamp by Buzz Women.

Figure 4.2.1 presents a histogram of the coefficient of variation of firm revenues. While firms have volatile revenues, the coefficient of variation in our data is significantly lower than that documented in the literature (Fafchamps et al., 2012; Banerjee et al., 2015). Revenues and profits are typically measured using monthly recall in survey questionnaires and produce noisy estimates (De Mel et al., 2009; Fafchamps et al., 2012). The daily data on revenues (which minimizes issues around recall) provides tighter estimates for monthly revenues.

Using daily data on revenue and expenditure, I construct a daily measure for profits. This is then aggregated to a monthly level. While this daily data is being collected for a long time horizon (more than 2 years), there is a period of three months where we have survey data that was collected using monthly recall. Comparing the "true-profits" from daily data to the estimated profits

[20]This is joint work with Muhammad Meki and Simon Quinn on "Innovative financing using microequity contracts: Experimental evidence from India".

from survey data, I measure of over-estimation.

Figure 2.H.2 presents a histogram of true minus estimated monthly profits (pooled over three months). A negative number signifies over-estimation. I find a highly left skewed distribution. The average firm over-estimate profits by Rs. 1931, which is 36% of the true monthly profits. It is also interesting to note, that in monthly recall data no firm reports a negative profit, while based on “true-profits" over 10% of firms show negative profits.

Figure 2.H.1: **Coefficient of variation of revenues (pre-intervention)**

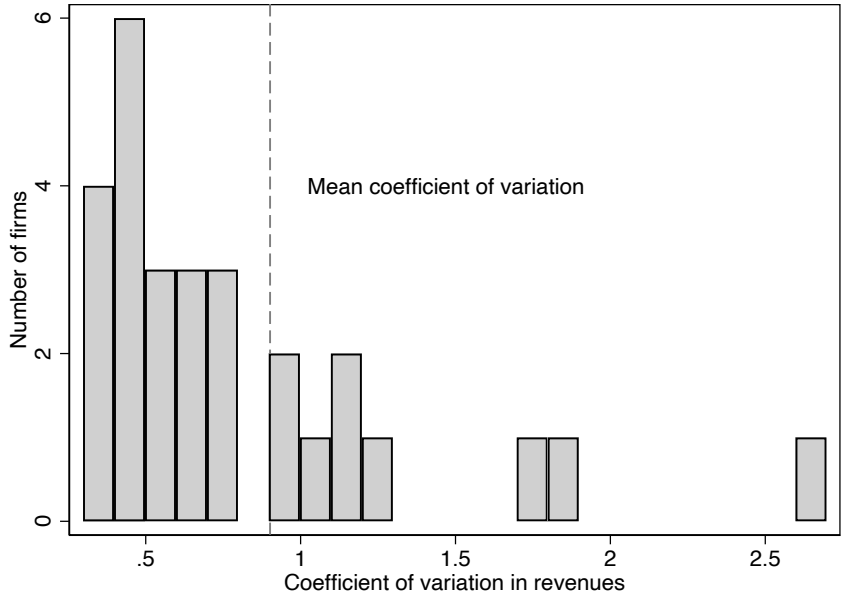
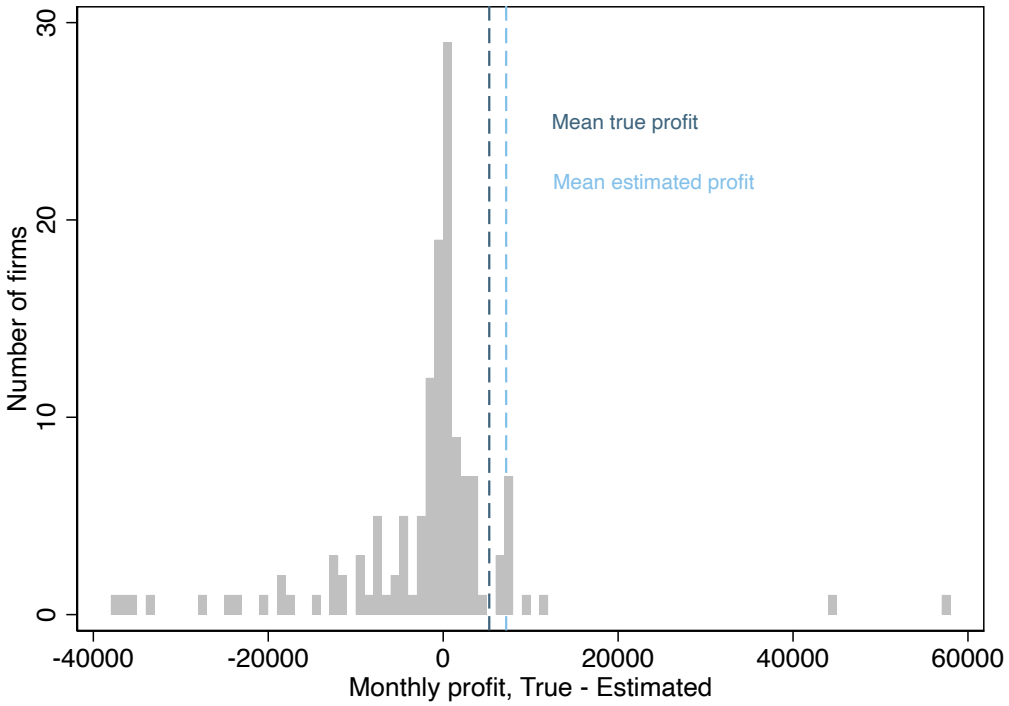


Figure 2.H.2: **Systematic over-estimation of profits** :



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3 | Unlocking the benefits of credit through saving

with **Lauren Falcao Bergquist**, **Marshall Burke** and **Edward Miguel**

Abstract

Access to microcredit has been shown to generate only modest average benefits for recipient households. We study whether other financial market frictions — in particular, lack of access to a safe place to save — might limit credit's benefits, by preventing recipients from saving investment returns and channeling them into future consumption or productive reinvestment. Working with Kenyan farmers, we cross-randomize access to a simple savings product with a harvest-time loan. Among loan offer recipients, the additional offer of a savings lockbox increased farm investment by 11% and household consumption by 7%. Results suggest that financial market frictions can interact in important ways and that multifaceted financial access programs might unlock dynamic household gains.

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3.1 Introduction

A vast literature on microcredit has found mixed evidence on whether credit access allows households to finance profitable investments and improve key livelihood indicators (Karlan and Zinman, 2011; Angelucci et al., 2015; Attanasio et al., 2015; Augsburg et al., 2015; Banerjee et al., 2015; Crépon et al., 2015; Tarozzi et al., 2015; Fiala, 2018; Meager, 2018). Even in settings where microcredit has had positive immediate effects on revenues, it often fails to translate into sustained consumption gains or business growth for the majority of households (Banerjee et al., 2015; Meager, 2016).

One possible explanation for this lack of sustained impact is difficulty in channeling increased revenues into future investments due to limited ability to save. For example, if the timing of when the returns from microcredit-enabled investments are realized does not align with the timing of when those additional revenues are needed for consumption or reinvestment, households lacking a safe way to save may struggle to translate increased revenues into desired investments. Households without access to protected saving vehicles may also face pressure to share any increase in revenue with kin, rather than re-invest.

In this study's Kenyan setting, as in many other low- and middle-income countries (LMICs), households that lack access to credit typically also face barriers to accessing other financial services, including savings products that could help them bridge this gap in timing and protect their returns. Therefore, it may be that – rather than being substitute financial services – credit

and savings products can serve as complements.

We present novel experimental evidence on the complementarities between credit and savings. In the context of African agricultural markets, large seasonal fluctuations in the price of staple commodities provide substantial opportunities for arbitrage through storage. Despite this, smallholder farmers typically sell their crops immediately after harvest, when prices are low; many buy back grain for personal consumption in the lean season when prices are higher. We build on work by Burke et al., 2019, which finds that credit constraints contribute to farmers' inability to take advantage of this arbitrage opportunity. They find that a harvest-time loan allows farmers in Kenya to more effectively time their maize sales and earn higher revenues. However, this productive activity did not on average translate to an increase in consumption or other productive investments.

In this paper, we present the results from a contemporaneous field experiment in Kenya in which we randomly overlay access to the harvest-time loan with access to a simple savings technology, namely, a durable, concealable metal box with a key (or "lockbox").[1] We find that among those who are offered a loan, being offered a savings lockbox enables farmers to move returns

[1]An appendix in Burke et al., 2019 briefly discusses the lockbox, and explores using preliminary and incomplete data the narrow question of whether the lockbox mediated the loan's direct effect on storage behavior. Here, we present the complete analysis of the lockbox experiment, following our pre-analysis plan (registered here: https://www.socialscienceregistry.org/trials/67), to (i) bring in new data from the full trial period and (ii) study the dynamic impacts of access to savings on productive reinvestment, testing whether the "lockbox could help farmers channel the loan to their planned investment, as well as make better use of any profits emanating from the loan" (PAP, pg. 1) by testing whether "access to the savings lockbox increased investment in farm inputs and increased consumption expenditure" (PAP, pg. 11). The analysis in this paper therefore utilizes the complete dataset and explores new (but pre-specified) questions.

(and possibly part of the loan itself) intertemporally, increasing farm investment by 11% and total household consumption by 7% relative to farmers only offered the loan but not the lockbox.

The data suggest that at least two mechanisms are at play. First, the lockbox provides households with a technology to move money intertemporally to times when it is most needed. We see especially large consumption gains from lockbox usage during the lean season, when the marginal utility of consumption is presumably highest. Consumption gains in the lean season can have meaningful positive welfare effects for households, as food and non-food consumption typically sees a large drop in the lean season (Barrett and Dorosh, 1996; Kaminski et al., 2014; Basu and Wong, 2015). Second, consistent with the idea that lockboxes can shield households against a "kin tax" (Dupas and Robinson, 2013b; Jakiela and Ozier, 2016) we find evidence that in addition to enabling the inter-temporal movement of consumption, lockboxes also increase total consumption. Households that are most interconnected with friends and family at baseline become less likely to provide money gifts or loans to them when they have access to a lockbox.

We present two additional pieces of evidence that bolster the central conclusion that access to savings products helps translate credit-enabled returns into long-run reinvestment and consumption gains. First, we exploit a second source of variation in the Burke et al., 2019 study, which found that returns to loans offered immediately after harvest (in October) yield much higher returns than loans offered three months later (in January). In this paper, we find that the consumption and investment benefits of being offered

a lockbox are concentrated among the early loan (October) group, suggesting that access to savings is most useful when combined with access to a profitable investment (facilitated here by timely credit). A second exercise estimates the effects of a lockbox alone (among households without access to the harvest-time loan), and finds null effects on consumption and farm reinvestment, implying that the results are not the impact of having a lockbox alone. These results point to important complementarities between various financial market frictions, and suggest that multifaceted financial access programs that include access to both credit and savings technologies may be well-positioned to unlock opportunities for virtuous cycles of reinvestment and dynamic household gains.

This paper is closely related to a large literature on the role of microcredit in enabling productive investments by households. Summarizing six randomized studies, Banerjee et al., 2015 find that microcredit access increases borrowing, business creation, and investment, but does not lead to a sustained increase in profit, labor supply, and consumption for the average borrower. We also speak to a separate literature on savings in LMICs that highlights the positive impacts that access to savings products — even simple ones like the lockbox studied here — can have on household economic outcomes including income, expenditure, investments and wealth (Dupas and Robinson, 2013a; Dupas and Robinson, 2013b; Karlan et al., 2014b; Prina, 2015; Brune et al., 2016; Chandrasekhar et al., 2018; Schaner, 2018). For example, Dupas and Robinson, 2013b show that a safe place to store cash helps individuals move money inter-temporally and accumulate health sav-

ings, and other studies find that commitment savings products enable higher savings (Ashraf et al., 2006).

In contrast to most of this work, we focus on the interplay between access to a savings product and to credit. To our knowledge, this paper is among the first to explicitly cross-randomize credit and savings products. A handful of recent studies have explored interactions between different types of financial products. For example, Atkinson et al., 2013 find that a commitment savings product allows individuals who are time inconsistent but want to save in the future to transition from a debt-financed to a savings-financed investment path. Kast et al., 2018 test the impact of a peer group savings program on precautionary saving among a sample of microcredit borrowers. Burgess and Pande, 2005 study the impact of access to credit and savings services via large-scale rural bank branch expansion in India and document a significant reduction in poverty. In a framed field experiment, Afzal et al., 2018; Afzal et al., 2022 show that when expenditures are lumpy, individuals tend to demand both credit and savings products.[2] We contribute to this literature by explicitly testing the importance of simultaneous provision of two distinct financial instruments, increasing access to both credit and savings, to enable households to undertake productive investments, in an experimental setting.

[2]Related studies are Kaboski and Townsend, 2005; Duflo et al., 2011; Suri, 2011; Karlan et al., 2014a.

3.2 Setting and experimental design

3.2.1 Arbitrage investment opportunities, reinvestment, and savings access

Agricultural markets in LMICs commonly experience large seasonal price fluctuations. In East African maize markets, prices can rise by over 25% in the months between the harvest and lean seasons. In our study area in rural western Kenya, price fluctuations during the study period of 2013-2014 and 2014-15 were 42% and 45%, respectively (Burke et al., 2019).

These price fluctuations appear to offer farmers a productive opportunity for investment in arbitrage. Rather than sell maize immediately after harvest, when prices are low, farmers can wait to sell until later in the year, when prices are substantially higher. On the other side of the market, farmers who tend to buy maize during the lean season can buy earlier, reducing outlays on the staple commodity. However, we find that most of the smallholders in our sample tend to "sell low and buy high," selling right after harvest when prices are low and buying maize back at high prices later in the year. In particular, in our baseline data we see that over 50% of maize sales occurred when maize prices were low (prior to January).

Why do farmers forgo the seemingly profitable investment of storage? Evidence from Burke et al., 2019 suggests the credit constraints are at least partially to blame. Farmers have large expenses, such as school fees, that come due shortly after harvest. Lacking alternative sources of funds, many

feel compelled to sell their crop for low prices at that time to pay these bills. Burke et al., 2019 find that offering farmers a loan at harvest-time enables them to invest in maize market arbitrage, holding off selling – for some, even buying — immediately after harvest, and selling later in the season at a far higher price. This investment yields increase in revenues of 1,573 Ksh (about US$18) on an average loan size of 5,476 Ksh (US$63) and has a rate of return of 29%. However, Burke et al., 2019 show that this profitable investment fails to translate into meaningful sustained household consumption gains, nor is there significant evidence that these one-time gains are reinvested in future productive capacities, such as farming inputs (see Section 4.4 below).

In this paper, we test one explanation for why farmers have limited ability to convert one-time benefits into sustained dynamic gains, namely that they lack the ability to protect and move profits intertemporally. The intertemporal movement of profits is critical when there is a mismatch in the timing of when an investment yields returns and when those returns are needed for consumption or reinvestment. To see this more clearly, we divide the year into four periods: (i) Harvest (roughly months September to December), (ii) Post-Harvest (months January to March), (iii) Planting (months March to June) and (iv) Lean (months July to August) seasons. The Harvest season is marked by the production of maize, which is the primary source of annual income for most farm households in our setting. They can choose to set aside maize for consumption, sell it immediately for cash, or store it for selling later. In the Post-Harvest season, households have need for large and often lumpy expenditures, including to repay debt that has accumulated

through the year, discretionary expenses and most importantly, school fees, which are usually due in January (a few months after harvest). In our sample, 90% of farmers have school aged children and they report spending 37% of their harvest income on school fees. All together, approximately 43% of total households expenditures are incurred during the Post-Harvest phase. The next period is Planting, when farmers need to invest in farm inputs, which directly affect the following year's harvest. However, given the lag between when income is received and when farm investments are made, farming households often find it challenging to channel funds towards this productive investment. Lastly, the Lean period prior to the next harvest is characterized by a substantial dip in consumption for both food and non-food items.

The pressure to share household resources with family and friends can further limit the reinvestment of profits, by acting like a tax on savings and wealth accumulation (Jakiela and Ozier, 2016; Chandrasekhar et al., 2018). Tight social networks that serve key economic functions are characteristic of rural communities in LMICs (Robinson, 2012), and can provide a system of support and insurance against sudden exogenous shocks. In our data, borrowing from friends is very common, with 20% of the sample having taken a loan from a friend, and over 50% reporting giving a money or maize "gift" to family or friends. However, there may also be a downside to these close social connections in rural communities: returns from profitable investments may be easily accessible by other household members, friends and relatives. This inability to protect individual or household earnings from the demands of relatives, often referred to as a kin tax, could influence the incentives for and

success of attempts to reinvest returns into future profitable opportunities.[3]

If farmers had access to effective, protected, and discreet savings technologies, the mismatch between the timing of returns and timing of when those returns are needed would be less consequential, and demands by kin may be easier to avoid. However, in our setting, access to formal savings remains limited: two-thirds of the sample has no money saved in a formal savings account.[4] The two most prevalent forms of savings in our setting remain the most traditional, namely, cash and bags of maize. However, saving in cash runs the risk of theft and stored maize is less liquid and more prominent to kin. Many farmers therefore lack access to safe and protected vehicles in which to save returns and transfer them from one period to the next.

Given the multiple constraints on household savings noted above, this study examines whether access to an improved savings technology can help convert short-run credit-enabled revenue increases into longer-run investment and consumption growth.

3.2.2 Experimental design

Our sample is comprised of 1589 smallholder farmers in the Webuye and Matete counties of western Kenya (see Burke et al., 2019 for a greater de-

[3]For instance, Anderson and Baland, 2002 find that the probability of a woman participating in a ROSCA has an inverse-U shaped relationship to her income share (or bargaining position) within the household, arguably due to these considerations. Similarly, Squires, 2016 find that kin tax can distort productive decisions, such as investments, in the context of microenterprises in Kenya.

[4]See Dupas and Robinson, 2013a; Karlan et al., 2014b; Prina, 2015; Suri and Jack, 2016; Dupas et al., 2018.

scription of the sample). The design overlaid two treatments: (1) an investment opportunity, in the form of a harvest-time storage loan, and (2) access to a savings product, in the form of a simple lockbox. The storage loan was offered in partnership with the organization One Acre Fund (OAF), a nonprofit social enterprise that supplies financing and training to smallholder farmers. The product was a cash loan provided at harvest.[5] To ensure that farmers took on a loan they were able to repay, the loan size was capped at an amount proportional to the number of maize bags the farmer had in storage at the time of loan disbursal. OAF did not take physical possession of these bags as collateral and there was no formal obligation to store the maize beyond the date of loan disbursal. The cash loans were structured similar to the in-kind loans that OAF had usually offered, with a flat interest rate of 10% and a flexible repayment structure.[6] As noted above, this loan can enable a productive investment, as it allows farmers to potentially earn high rates of return by storing and selling their maize in a timely manner.

The savings product offered to farmers was a lockbox, a simple metal box to which the farmer held the key. Lockboxes can encourage savings through three mechanisms. First, the lockbox is a safe place to store money, with cash less prone to theft compared to other at-home alternatives. Second, since participants are free to keep the box hidden, it can also help shield money from family and friends and thus reduce the magnitude of the kin tax. Third, the product can also facilitate savings through a mental accounting effect, as it provides a soft form of commitment by allocating the savings to a specific

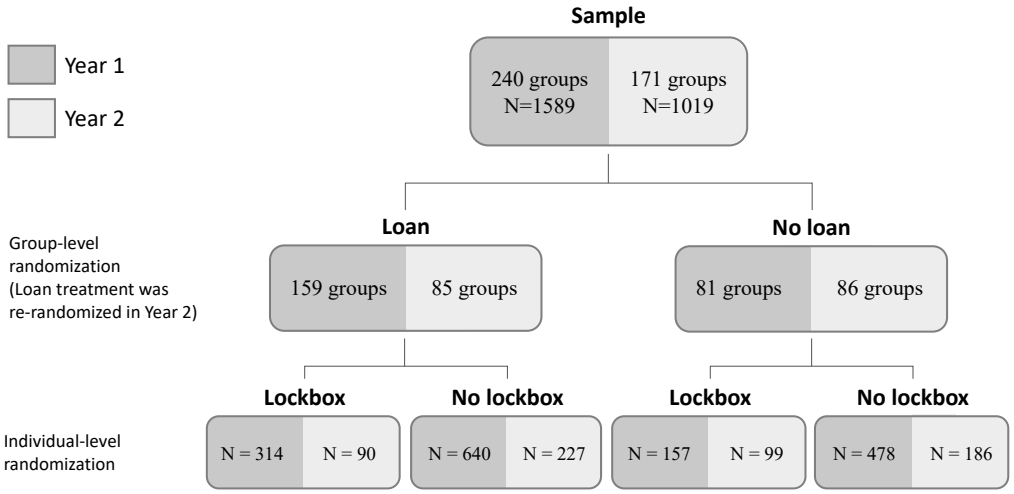
[5]Outside of OAF, access to formal credit was limited in our sample, with only 8% ever having taken out a formal bank loan. See Burke et al., 2019 for details.

[6]The only condition was that full repayment was due at the end of 10 months.

use or labeling (Thaler, 1999; Dupas and Robinson, 2013b). Unlike some commitment accounts, a lockbox allows full flexibility in terms of withdrawal and usage (for the holder of the key), and unlike formal savings accounts can lower transaction or other costs (e.g. time to travel to the bank, or minimum account balances).

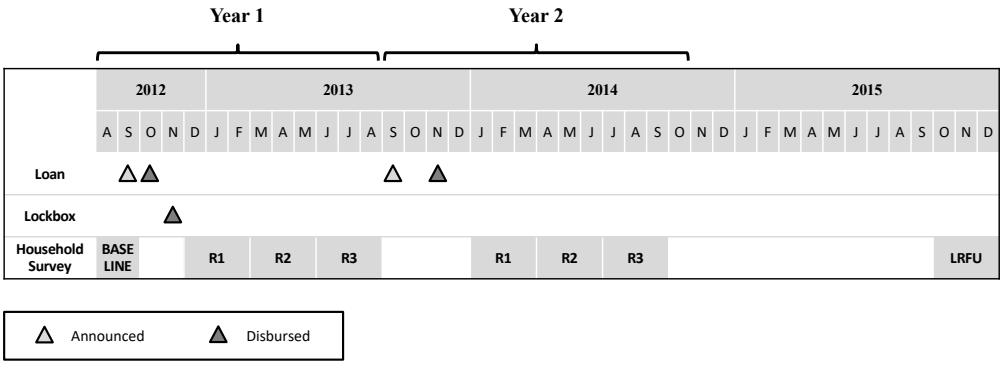
Farmers were first randomized into the loan product. Then, in an additional layer of randomization, farmers in each treatment group were randomized into receiving a lockbox or not. See Figure 3.2.1 and Figure 3.2.2 for details on the experimental design. Because OAF operates in a farmer group model, the loan was introduced to randomly selected groups, which consisted of 8-12 farmers each, all of whom were assigned the same treatment. Randomization was stratified based on geographic sublocation and on whether the group average OAF loan size in the previous year was above or below the median. In Year 1, two-thirds of groups were offered a loan and one-third were not. In addition, in order to test the importance of loan timing, a random half of loan offers in Year 1 were made in October, immediately post-harvest, and the remainder were made in January, when school fees are typically due (in both cases, farmers were made aware of the timing of the forthcoming loan beforehand, in September).

Figure 3.2.1: **Experimental design**



*Notes:*There were two levels of randomization in year one- a loan and lockbox treatment. The loan treatment was randomized at the group level. The lockbox treatment was randomized at the individual level. In Year 2, the loan treatment was re-randomized. The lockbox treatment was not re-randomized in year two, but we follow a sub sample of year one individuals who participated in year two. Numbers of randomized units are given in the boxes.

Figure 3.2.2: **Study timeline**



*Notes:*This figure depicts the harvest periods, timing of interventions and the survey waves.

While all farmers in a particular group were assigned the same loan treatment, for research budget reasons only a random set of 6-8 farmers per group were followed up for survey data collection. Then, within these 6-8 farmers in the study sample, the savings lockboxes were randomized across farmers at the individual level, and this treatment was stratified by the group treatment assignment and gender. On average, 30% of farmers were offered the lockbox. Lockboxes were disbursed in November of Year 1.

In Year 2 of the study, the loan groups were re-randomized, with loan offers stratified based on sublocation and treatment status from Year 1. All loans for Year 2 were offered in November, as immediate-post harvest-time loans were seen to be more effective in Year 1 (Burke et al., 2019). Note that additional lockboxes were not provided in Year 2.

Taken together, in Year 1, the study included 240 farmer groups, for a total sample size of 1589 farmers. In Year 2, there was an attempt to follow all of the same groups, but several groups dissolved or merged, leaving 171 intact groups, and some farmers also re-shuffled among groups. As a result, the Year 2 sample contains 1019 farmers, with 602 farmers remaining from the Year 1 sample and 417 new randomly chosen farmers added from within these groups. Because the lockbox was only distributed at the start of Year 1, these 417 farmers new to the sample in Year 2 are not part of the lockbox experiment and are excluded from the analysis in this paper.

3.3 Data and estimation

The study collected a baseline household survey before Year 1, three follow up rounds each year (Years 1 and 2), and a long-run follow-up (LRFU) survey one year after the completion of the last Year 2 survey round (see Figure 3.2.2 for the timeline). Three follow-up rounds were conducted in each year spanning the nine months after harvest, and were spread out across the post-harvest, planting and pre-harvest (lean) period. Surveys collected data on household information, farming practices, maize harvest and inventory, expenditures, consumption, household finances and transfers, non-farm income, time and risk preferences. The multiple follow-up rounds provide the high-frequency data necessary to document the role of credit and savings products in allowing inter-temporal movement of cash and investment, as well as measuring living standards via consumption expenditures.[7] The LRFU survey followed all 1019 farmers from the Year 2 sample and a representative subset of 481 farmers from the Year 1 sample.

Sample attrition was low, with over 90% follow-up for both years and no differential attrition across the treatment arms.[8] Appendix 3.C presents balance in the characteristics of farmers in the Year 1 sample and the subset who continue into the Year 2 sample, for both the loan and the lockbox treatment groups. We see balance across both treatments for most variables,

[7]Collecting multiple follow up rounds of survey data also improved statistical power (see McKenzie, 2012).

[8]Farmers who received a loan in Year 1 were more likely to return to the study in Year two. However, since loan treatment status was re-randomized in Year 2 and stratified based on Year 1 treatment status, it should not affect the internal validity of the Year 2 results.

and present robustness checks in Appendix 3.C in which we control for any covariates that are imbalanced at baseline.

3.3.1 Estimation of treatment effects

The study has four main outcome variables: net revenues from maize, total household consumption, farm investments, and school fees paid[9]. Net revenues from maize are calculated by subtracting the amount spent purchasing maize from the revenues earned by selling maize. For farmers who received a loan, we also subtract the loan payments made each month. We refrain from calling this measure "profits from maize" as we do not measure all the costs associated with maize farming. Total (log) household consumption is aggregated from a detailed seven-day recall for food expenditure outside the home and 30-day recall for non-food expenditure. For farm investment, we calculate the amount spent on farm inputs in the planting season, including detailed data on the amount spent on hybrid seeds and chemical inputs such as fertilizers. We measure cash payments made towards school fees using a 30-day recall.

We begin by replicating the results in Burke et al., 2019, documenting the effect of the loan on net revenues, consumption, farm investments, and school fees. Equation 3.3.1 presents the primary econometric specification,

[9]These main outcome variables were all pre-specified in our pre-analysis plan (registered here: https://www.socialscienceregistry.org/trials/67), with the exception of expenditure on school fees. School fees represent the largest forward-looking investment that many households in low-income countries make (in this case, investment in human capital). We therefore deemed it worthy of inclusion when testing whether access to savings enables long-term re-investment of the returns to credit. However, since the school fees variable was not pre-specified, the results for this outcome may be viewed as exploratory.

which pools data across survey rounds where such data is available.[10] Y_{ijrm} is the outcome variable of interest for farmer i in group j in round $r \in \{1, 2, 3\}$ in year $m \in \{1, 2\}$. $Loan_{im}$ is an indicator for whether farmer i was offered a loan in year m. The β coefficients capture the intention to treat (ITT) effects. We include round year fixed effects η_{rm} and control for the survey date d_t. We also control for stratification indicators γ_s as per Bruhn and McKenzie, 2009. Standard errors are clustered at the OAF farmer group level, the level of randomization for the loans. For all outcome variables, we present robustness to inclusion of baseline covariates as well as to winsorizing the dependent variable at 5% (see Appendix 3.D).

$$\mathrm{Y}_{ijrm} = \alpha + \beta_1 Loan_{im} + \eta_{rm} + d_t + \gamma_s + \varepsilon_{ijrm}$$

We then proceed to estimate the added effect of offering a lockbox. The main lockbox specification restricts the sample to those who received a loan, and estimates the additional effect of being offered a lockbox as follows:

$$\mathrm{Y}_{ijrm} = \alpha + \phi_1 Lockbox_{im} + \eta_{rm} + d_t + \gamma_s + \varepsilon_{ijrm}$$

The definition of terms is as in Equation 3.3.1, where $Lockbox_{im}$ is the indicator for individual lockbox treatment assignment. To assess whether the gains from the lockbox were more pronounced when combined with more profitable loans, we estimate Equation 3.3.1 by restricting the sample based on the timing of the loan.

Finally, we present the pooled specification as in Equation 3 showing the interaction between loan and lockbox treatments:

[10] For farm investments, there is only data for the planting season, when such investments are made.

$$Y_{ijrm} = \alpha + \phi_1 Lockbox_{im} + \phi_2 Loan_{im} + \phi_3 Lockbox_{im} * Loan_{im} + \eta_{rm} + d_t + \gamma_s + \varepsilon_{ijrm}$$

3.4 Results

3.4.1 Take-up for loan and lockbox

Take-up of both the loan and lockbox treatments was quite high: loan take-up rates were 64% and 62% for Year 1 and 2, respectively, higher than is typical of many other credit interventions in LMICs (Karlan et al., 2010; Banerjee et al., 2015; Jack et al., 2016). Take-up for the lockbox was 97% and, conditional on take-up, 78%, 63% and 50% of farmers report using the lockbox in Year 1, 2 and the LRFU, respectively (see Appendix 3.B and Table 3.B.1 for further descriptive statistics). This high usage rate is a first piece of evidence of the value households attached to this savings technology.

3.4.2 Treatment effects

As shown in Burke et al., 2019, the loan intervention had significant positive effects on the net revenues earned from maize (Table 3.4.1, Panel A, col. 1).[11] Compared to those who did not receive a loan, farmers who were offered a harvest time loan earned Ksh 533 higher net revenues from maize. As discussed in Burke et al., 2019, this was driven by farmers increasing maize purchases when prices were low (in the post-harvest season), holding more inventories of maize, and selling maize when prices were higher (in the planting

[11] Appendix 3.D provides robustness checks, estimating Equation 3.3.1 and 3.3.1 with baseline covariates and by winsorizing the dependent variable at 5%.

and lean seasons). However, while the loan intervention increased revenues, it did not translate to a statistically significant increase in household consumption (although point estimates are positive), nor in farm investments or school fees (cols. 2-4).[12]

[12]Note that due to a minor coding error, results in Panel A Column 4 differ slightly from what is presented in Appendix Table E.4 in (Burke et al., 2019). This coding error only affected this outcome.

Table 3.4.1: **Treatment effects**

	(1)	(2)	(3)	(4)
	Net Revenues	Total HH Consumption	Farm Investments	School Fees
Panel A: Treatment effect of Loan				
Loan	533.44***	0.04	-69.84	3.85
	(195.49)	(0.02)	(155.90)	(244.86)
Observations	6730	6736	2276	6787
Mean DV	-1616.12	9.55	5332.46	3911.31
SD DV	6359.06	0.64	3596.71	8281.46
R squared	0.12	0.06	0.15	0.06
Panel B: Treatment effect of Lockbox, conditional on Loan				
Lockbox	175.60	0.07**	496.03**	418.45
	(237.98)	(0.03)	(223.13)	(310.71)
Observations	3436	3443	1172	3473
Mean DV	-358.80	9.52	4549.72	3400.94
SD DV	6503.00	0.64	3587.37	7455.92
R squared	0.10	0.07	0.18	0.10

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. Panel A shows the treatment effect of the loan treatment. Panel B shows the treatment effect of the lockbox, conditional on being offered the loan treatment. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

We next examine whether combining credit access with a savings technology enables farmers to gain more, either in terms of consumption or long-run productive investment. While the addition of access to a lockbox does not significantly affect farm revenues (3.4.1, Panel B, col. 1), we find that it does enable farmers to protect and safely move cash across seasons: access to a lockbox, conditional on receiving a loan, significantly increased household consumption (col. 2), leading to a 7% increase in average consumption across follow-up survey rounds. In Appendix 3.E, we show that these consumption gains are driven by a 9% increase (significant at 5%) in consumption in the lean season, farming households' neediest period.

We also see evidence that the lockbox enabled farmers to invest gains from a one-time increase in revenues into future productive investments in their farm: farmers who receive a lockbox in addition to a loan increased on-farm investment by 11% compared to farmers who only received a loan.[13] Access to a lockbox, conditional on a loan, also results in a positive, albeit not significant, increase in school fee payments of 12% (col. 4).

3.4.3 Unpacking the timing of savings and consumption

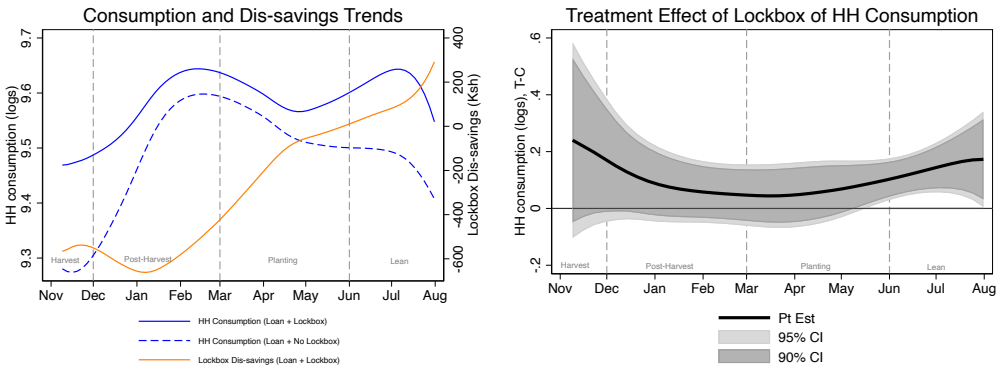
While the above results pool data across survey rounds, we next study the impact of the lockbox on savings and consumption by round in order to unpack exactly how savings access facilitates greater welfare gains when households undertake productive investments. Figure 3.4.1 presents non-parametric estimates for the effects of the lockbox on household savings and consumption

[13]The number of observations for farm investments is about one-third that for all other variables since this data was only collected in the planting season, as noted above.

over time, conditional on being offered a loan. The left panel presents the mean household consumption for those with and without a lockbox, as well as average lockbox dis-savings for those with a lockbox. We see that farmers with access to a lockbox consume more through the entire year (a point to which we return below), and that this gap is particularly pronounced during the lean season, (from June to August), as noted above. The right-hand panel, which shows the difference between treatment and control consumption over time for the lockbox treatment, along with the bootstrap-estimated 90% and 95% confidence interval, confirms that this gap in lean season consumption is significant at 95% confidence. [14] The timing of these consumption gains is important for welfare, as the lean season is a time of particularly high farmer need in which the marginal utility of household consumption is presumably particularly high.

[14]To substantiate the results in Figure 3.4.1, Online Appendix Table 3.E.1 presents treatment effects for consumption by round. We find that the positive and significant effect on consumption in Table 3.4.1 is driven by a 9% increase in lean season (significant at the 5% level).

Figure 3.4.1: **Time trends for HH consumption and Lockbox Dis-savings**



Notes: The left panel shows how average log household consumption and lockbox savings evolve from November to August in Y1 and Y2 (pooled), as estimated with fan regressions. HH consumption (measured in logged Ksh) is aggregated from a detailed 30 day recall consumption module. Lockbox dis-savings is measured as the change in the amount saved in the box at the time of the survey. A positive dis-savings implies a decrease in the amount of savings. The exchange rate during the study period ranged from 80 to 90 Kenyan shillings per USD. The right panels show the difference in treatment minus control over time for the lockbox treatment, with a 90% and 95% confidence interval. This is estimated by bootstrapping a fan regression 1000 times (clustering at the group level), without replacement.

To understand what drives these differences in lean-season consumption, we return to the left-hand panel, on which we have overlaid the dis-savings for those with access to a lockbox. We define dis-savings as negative savings, such that a negative value implies that money was added to the lockbox, whereas a positive value represents money being withdrawn from the lockbox. Note that the positive treatment effect on consumption coincides with the timing of dis-savings from the lockbox. While not dispositive, this does strongly suggest that farmers use the savings accumulated in the lockbox to fund lean-season consumption.

That said, the lockbox appears to work not solely through allowing farm-

ers to move consumption across time. In contrast to a typical "consumption smoothing" mechanism, in which we would expect any increase in lean season consumption to be matched by dips in consumption in other seasons, instead we see that consumption is higher throughout the year. This suggests that a second mechanism may be at play, consistent with results from Jakiela and Ozier, 2016 and Dupas and Robinson, 2013b: specifically, the lockbox may enable households to shield some money from the kin tax imposed by family and friends. As noted above, in the study setting, the pressure to share money with friends and extended family is quite prevalent, and over 50% of the sample reports sharing maize or money with kin at baseline. Consistent with this, we also find that farmers who gave more money to friends and family than they received at baseline are significantly less likely to loan money to people in their social network when they have access to a lockbox (see Appendix 3.F). Of course, the welfare implications of this reduction in kin tax are not obvious as it may have have adverse effects on the kin who relied on farmers in our sample for support and no longer received as much in the way of transfers or loans.

3.4.4 Are the gains from the lockbox most pronounced among the most profitable loans?

In this section, we present additional evidence suggesting that findings we observe are the result of the interplay between access to a profitable investment and a savings technology, by documenting that the gains from the lockbox are most pronounced when combined with the most profitable loans.

In a setting marked by seasonality, the timing of the loan matters. Recall that in Year 1, the timing of the loan was randomized, with half of groups receiving the loan in October, immediately after harvest, and the other half receiving the loan in January. Burke et al., 2019 find that the October loan lead to significantly higher maize inventories, net revenues and household consumption — perhaps because farmers who received the loan in January had already liquidated their maize to meet post-harvest expenditure needs. The October loan thus appeared to open up more productive investments (in this case, greater or longer storage) than the January loan.

Here we analyze whether the lockbox is particularly useful for the October loan group, as one would expect if what the lockbox is doing is enabling better use of the returns from productive investments. We start by replicating the Burke et al., 2019 results in Table 3.4.2, Panel A, in which columns 2, 4, 6 and 8 compare farmers who were offered the loan in October of Year 1 to the control group, while columns 1, 3, 5 and 7 present treatment effects for the January loan treatment groups versus the control group. Being offered the October loan led to a significant increase in net revenue of 588 Ksh, while the average effect of the January loan in Year 1 led to a smaller (and not statistically significant) increase in net revenues. We next examine (Panel B) whether the gains from access to the lockbox savings technology are similarly concentrated among those who received the October loan. We find evidence that this is the case for consumption, farm investment and school fees (effects for for farm investments are not significant, perhaps because this outcome is only observed in one survey round and therefore estimated effects are

less precise)[15]. Taken together, this provides considerable evidence that the savings technology is most impactful when households' have greater returns from a productive investment in hand.

3.4.5 Complementarities between credit and savings

Table 3.4.1 suggests that the lockbox enables both consumption and investment. To identify whether these gains are simply the straightforward benefits of accessing savings technologies — which have been documented in the existing literature — or whether there are truly complementary between savings and credit, we run the interaction specification as described by Equation 3.3.1.

Table 3.4.3 presents results. First, we see no significant positive effect from the lockbox alone on any outcomes, suggesting that the previous results are not simply the effect of accessing savings technologies on its own.[16,17] Rather, we see strong evidence of complementarities, as suggested by the significant interaction term on consumption and school fees (and a positive, albeit not significant effect on farm investment). Point estimates suggest a 14% increase in household consumption, a 445 Ksh increase in farm investment, and a 1251 Ksh increase in school fee investments when farmers

[15]The treatment effect of the lockbox conditional on the October loan is significant with 90% confidence for farm investments when including baseline covariates, as shown in Table 3.D.2

[16]For reasons that are unclear, impacts on school fees paid are surprisingly negative, but are only marginally significant (col. 4).

[17]This is in contrast to Dupas and Robinson, 2013b, who estimate large positive effects for households of being provided with a lockbox alone. While Dupas and Robinson, 2013b also takes place in western Kenya, our population with OAF is focused on farm households. Perhaps it is due to our agricultural household-heavy sample that we do not see positive and significant effects for the lockbox alone.

Table 3.4.2: **Treatment effects by loan timing**

	Net Revenues		Total HH Consumption		Farm Investment		School Fees	
	(1) Oct	(2) Jan	(3) Oct	(4) Jan	(5) Oct	(6) Jan	(7) Oct	(8) Jan
Panel A: Treatment effect of Loan (Oct and Jan)								
Loan	587.81**	-41.21	0.03	0.00	-219.55	-273.09	-310.36	-234.95
	(286.31)	(297.98)	(0.04)	(0.03)	(245.20)	(214.61)	(299.00)	(296.60)
Observations	2534	2536	2535	2534	867	869	2572	2571
Mean DV	-1616.12	-1616.12	9.55	9.55	5332.46	5332.46	3911.31	3911.31
SD DV	6359.06	6359.06	0.64	0.64	3596.71	3596.71	8281.46	8281.46
R squared	0.04	0.04	0.04	0.04	0.08	0.07	0.06	0.06
Panel B: Treatment effect of Lockbox, conditional on Loan (Oct and Jan)								
Lockbox	258.66	33.26	0.10**	0.04	584.08	576.38	1132.37***	-462.69
	(341.56)	(415.86)	(0.05)	(0.05)	(389.94)	(366.27)	(417.79)	(421.42)
Observations	1259	1261	1258	1257	430	432	1272	1271
Mean DV	708.05	284.57	9.45	9.47	3715.63	3823.85	2614.39	3207.12
SD DV	6227.68	6197.31	0.62	0.63	3225.57	3194.25	5947.33	7063.82
R squared	0.05	0.06	0.05	0.05	0.12	0.13	0.10	0.08

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. Panel A shows the treatment effect of the loan treatment. Panel B shows the treatment effect of the lockbox, conditional on being offered the loan treatment. Columns 1,3,5 and 7 shows the treatment effects for October and January loans of the Y1 treatment. Columns 2,4,6, and 8 show the treatment effects for the October loan. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

receive both the loan and the lockbox. Taken together, these patterns suggest that there are meaningful complementarities between the credit and savings products.

Table 3.4.3: **Interaction of the Loan and Lockbox treatment**

	(1)	(2)	(3)	(4)
	Net Revenues	Total HH Consumption	Farm Investment	School Fees
Lockbox	-169.95	-0.06	36.69	-776.20*
	(321.48)	(0.04)	(294.89)	(439.50)
Loan	342.25	-0.02	-175.35	-493.04
	(245.88)	(0.03)	(205.62)	(304.95)
Lockbox*Loan	428.87	0.14***	445.00	1251.03**
	(402.80)	(0.05)	(367.49)	(537.57)
Observations	5534	5546	1885	5595
Mean DV	-1616.12	9.55	5332.46	3911.31
R squared	0.11	0.06	0.15	0.07

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

3.5 Conclusion

This study examines whether access to an improved savings technology can help convert short-run, credit-enabled revenue increases into longer-run investment and consumption growth. We find that providing a savings lockbox, conditional on being offered a loan, helps farmers undertake expenditures that are incurred with a lag after harvest: farmers increase household consumption by 7%, an increase which is driven by improved consumption in the lean season. Farmers are also able to increase productive investments on the farm by 11%. These gains are not observed when farmers are offered a lockbox or loan alone.

How do saving technologies allow farmers to channel returns from short-term productive investments into longer-run consumption gains and reinvestment in future production? We identify two mechanisms: first, savings products allow households to move funds intertemporally, bridging any gap between when the initial investment yields returns and when consumption or reinvestment is needed. Second, savings technologies can enable households to shield returns from kin tax, leaving more funds for personal consumption and reinvestment.

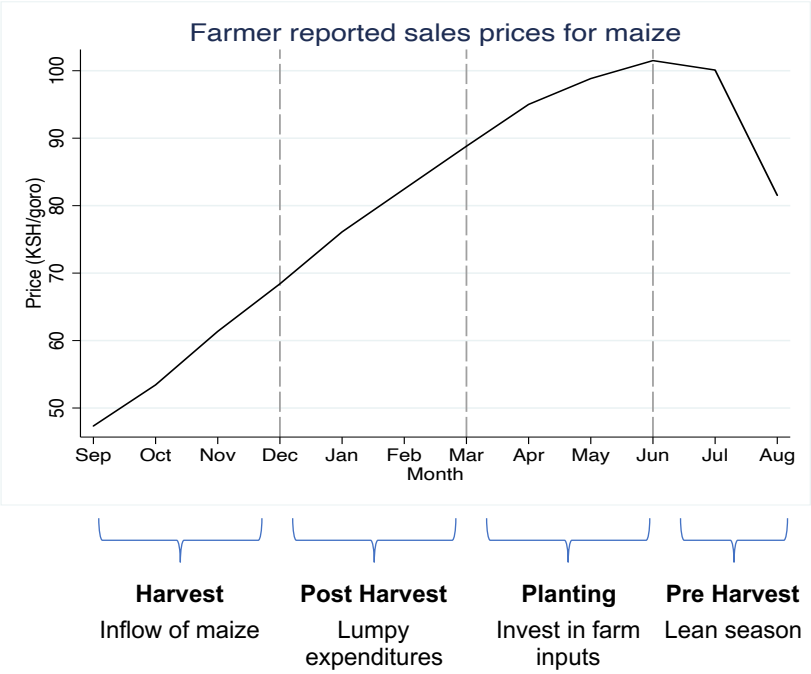
The results highlight the inter-linkages between financial products, and provide one potential explanation for the often disappointing performance of existing microcredit interventions (Banerjee et al., 2015). The findings of this paper also have important policy implications, suggesting that a more integrated microfinance approach that provides households with complementary

credit and savings products could be more effective at meaningfully raising household living standards in low- and middle-income countries.

Appendix

3.A Setting

Figure 3.A.1: **Seasonal price trends in maize markets.**



Notes: Farmer-reported average monthly maize prices for the period 2007-2012, averaged over all farmers in our sample. Prices are in Kenyan shillings per goro (2.2kg). We also show the corresponding periods or seasons in our setting.

3.B Take-up and Use

In year one, 954 farmers were offered a loan, of whom 617 applied and qualified. In year two, of the 522 farmers who were offered a loan, 324 took up the loan. Take up rates of 64% and 62% for year one and two respectively, is quite high relative to similar credit interventions in low income countries (Karlan et al., 2010 find that take up rates range from 2-55% in other settings). The unconditional loan size for the year one loan treatment was 4,817 Ksh (or $57). Conditional on take up the average loan size was 7,533 Ksh ((or $89). Similarly, for year two the unconditional loan size was 6,679 Ksh (or $79) and the conditional loan size was 10,548 Ksh (or $124). The loans were approximately 43% of harvest value, calculated based on harvest time prices. 24% of the farmers opt to take the maximum loan size possible. Default rates were below 2%.

Table 3.B.1: **Descriptive statistics on take-up and use**

	Year 1	**Year 2**	**Long run**
Panel A : Lockbox			
Take up	0.97		
Still has lockbox		0.89	0.51
Uses lockbox	0.78	0.63	0.50
If uses, current balance (in Ksh)			
Mean	683	360	339
Median	400	200	100
SD	798	375	451
Mean number of additions (in a week)	1	1	2
Mean number of withdrawals (in a week)	1	1	1
Panel B : Loan			
Take-up	0.64	0.62	
Average loan size (in Ksh)			
Unconditional	4817	6679	
Conditional on take-up	7533	10,548	

Notes: Uses Lockbox = 1 if there is a non zero amount in the box or money has been added or withdrawn from it in the last week. This metric is conditional on taking up/ still having the box.

Data on balances in the lockbox are self-reported. Enumerators were asked to verify the amount by looking into the lockbox, if the participant was willing. The data on balances and withdrawals were also self reported. They were double checked using the inventory sheet, which the participants were encouraged to maintain. The exchange rate during the study period ranged from 80 to 90 Kenyan shillings per US$.

Take up of the lockboxes was high. 97% took up the lockbox when it was offered in year 1. Conditional on take-up 78% farmers use the lockbox and save an average of 683 Ksh (or $8) in the lockbox. In year two, 89% of farmers reported that they still had the lockbox. Conditional on having the lockbox, 63% used it and saved an average of 360 Ksh (or $4) in the lockbox. On average, in years 1 and 2 of the study, farmers add or withdraw from the lockbox once a week. In the long run follow-up, three years after the lockbox was offered, 51% farmers still had the lockbox. Conditional on having the

box, 50% report using it. The average amount saved in the lockbox was 339 Ksh (or $3). Farmers continued to use the lockbox actively, on average adding to it twice a week and withdrawing from it once a week. Figure 3.B.1 shows the savings amounts in the lockbox over time, pooled for year one and year two. We see that savings are accumulated in the lockbox post harvest, maintained through the planting season and partially used in the lean season. [18]

Figure 3.B.1 shows that farmers consistently save in the lockbox during the study period. We see that farmers who received a loan have higher savings in the lockbox.

Table 3.B.2 presents the treatment effect on total savings, by estimating Equation 3.3.1 and 3.3.1. We find that access to a loan does not have significant effects on household savings. We next examine whether combining credit access with a savings technology enables farmers to save more. Conditional on getting the loan, we see that farmers who were offered a lockbox show a 53% increase in total household savings, which is significant at the 5% level. We see a negative point estimate of the loan on savings *outside* of a lockbox, but this effect is statistically indistinguishable from zero. Thus, though it is possible that farmers who received a lockbox move some of their savings from alternate savings devices to their lockbox, but we do not find any evidence of significant crowding out of savings, and total savings increases.

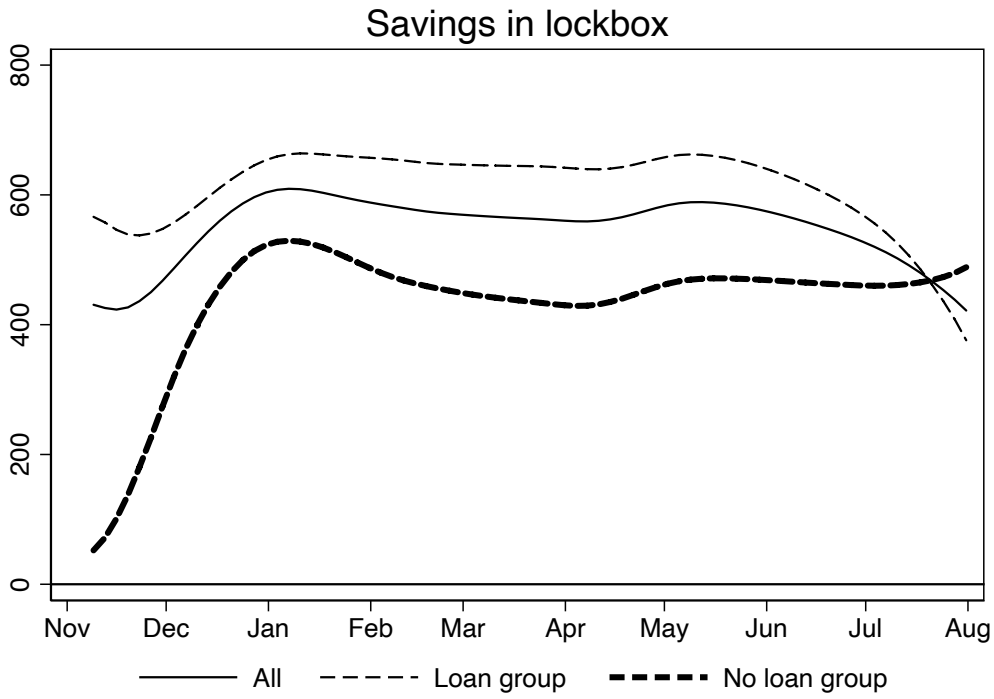
[18]The lockbox in our study is comparable to the safe box in Dupas and Robinson, 2013b paper. In a similar setting in Kenya, Dupas and Robinson, 2013b note that 74% (71%) of participants use the safe box six (twelve months) after it was offered to them. Among those who use the safe box, average balances were 634 Ksh ($8.4) after six months and 311 Ksh ($4.1) after 12 months. Thus, descriptive statistics around take-up and usage are quite similar to our study

Table 3.B.2: **Treatment effect on Savings**

	(1) Total Savings	(2) Savings (excl. Lockbox)
Panel A: Treatment effect of Loan		
Loan	-0.01	-0.10
	(0.21)	(0.22)
Observations	1299	1299
Mean DV	6.88	6.73
SD DV	3.10	3.18
R squared	0.07	0.07
Panel B: Treatment effect of Lockbox, conditional on Loan		
Lockbox	0.53**	-0.20
	(0.26)	(0.27)
Observations	862	862
Mean DV	6.63	6.63
SD DV	3.40	3.40
R squared	0.09	0.09

Notes: Data on savings was only collected in in the Year 1 - round 3 survey. Total Savings is the log of Total HH savings (measured in logged Ksh), at the time of the survey. It includes the amount saved in a bank account, ROSCA, SACCO, mobile money and the lockbox. Savings (excl. Lockbox) measures the log of total savings in all savings devices excluding the lockbox."Lockbox" is an indicator for being in the lockbox treatment group. The first two columns, show results for the Loan group and the last two columns show the results for the No Loan group. Regressions include strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at $90\%(*), 95\%(**), 99\%(***)$ confidence. Standard errors in parentheses.

Figure 3.B.1: **Savings in lockbox over time**



Notes: Amount saved in the lockbox at the time of the survey. The data is pooled across Year 1 and Year 2 of the study.

3.C Summary Statistics and Balance Tables

In this section, we present balance tables for year 1 of the study.[19] Table 4.2.1 present balance checks for the loan and lockbox treatment respectively, conditional on the loan. For the loan treatment, we observe balance. For the lockbox treatment (conditional on loan) we observe balance on most baseline variables at 1% and 5%, but at the 10% level we have more than expected variables that are not balanced.

We present robustness checks in Table 3.C.2, controlling for all baseline covariates that show any imbalance at 10%. We continue to observe positive and significant effects on farm investment. Though effects on pooled consumption decline and are no longer statically significant, we cannot reject equality with the original point estimate.[20] Moreover, we continue to see a significant 8% increase in consumption in the lean season, the period in which the lockbox is particularly critical for smoothing consumption (see Column 3 in Table 3.C.2). This is consistent with Figure 3.4.1, which highlights the increase in lean season consumption.

[19]For the loan treatment, the Year 2 study was designed to follow the sample of farmers we studies in Year 1. Due to administrative issues, farmer group compositions changed in Year 2. As a result, 417 of the 1019 farmers in year two were new to the sample. We did not collect baseline data for these farmers.

[20]We compare the two specifications by taking a bootstrapped sample and computing the difference between the point estimates over a 1000 repetitions. Results available upon request.

Table 3.C.1: **Summary statistics**

Baseline characteristic	Loan				Lockbox, conditional on Loan			
			(T-C)				(T-C)	
	obs	C mean	std diff	p-val	obs	C mean	std diff	p-val
Male	1,589	0.33	-0.08	0.11	954	0.30	-0.02	0.78
Number of adults	1,510	3.20	-0.09	0.06	903	2.96	0.07	0.34
Children in school	1,589	3.07	-0.04	0.46	954	2.96	0.06	0.35
Finished primary school	1,490	0.77	-0.13	0.02	890	0.73	-0.05	0.49
Finished secondary school	1,490	0.27	-0.04	0.46	890	0.25	-0.01	0.86
Total cropland (acres)	1,512	2.40	0.01	0.79	906	2.38	0.07	0.37
Number of rooms in household	1,511	3.25	-0.05	0.17	904	3.06	0.02	0.75
Total school fees	1,589	29,814	-0.06	0.18	954	25,332	0.18	0.02
Avg consumption (Ksh)	1,437	15,371	-0.03	0.55	858	15,080	-0.02	0.72
Avg consumption/capita (log)	1,434	7.96	0.02	0.72	855	7.98	-0.03	0.68
Total cash savings (Ksh)	1,572	8,021	-0.09	0.01	943	4,537	0.15	0.07
Total cash savings (trim)	1,572	5,390	-0.05	0.33	943	4,227	0.15	0.07
Has bank savings acct	1,589	0.43	-0.01	0.82	954	0.39	0.18	0.01
Taken bank loan	1,589	0.08	-0.02	0.73	954	0.07	0.06	0.40
Taken informal loan	1,589	0.25	-0.01	0.84	954	0.24	0.06	0.39
Liquid wealth (Ksh)	1,491	97,281	-0.03	0.55	893	89,704	0.14	0.09
Off-farm wages (Ksh)	1,589	3,797	0.01	0.85	954	3,447	0.15	0.07
Business profit (Ksh)	1,589	1,802	0.08	0.32	954	2,481	-0.04	0.50
Avg %Δ price Sep-Jun	1,504	133	0.00	0.94	900	134	-0.00	0.99
Expect %Δ price Sep12-Jun13	1,510	117	0.14	0.15	905	129	-0.09	0.15
2011 LR harvest (bags)	1,511	9.03	0.02	0.67	905	9.37	-0.00	0.98
Net revenue 2011 (Ksh)	1,428	-4,089	0.03	0.75	857	-1,970	-0.06	0.32
Net seller 2011	1,428	0.30	0.05	0.39	857	0.32	0.02	0.81
Autarkic 2011	1,589	0.06	0.03	0.51	954	0.08	-0.11	0.08
% maize lost 2011	1,428	0.01	0.03	0.57	850	0.02	-0.12	0.06
2012 LR harvest (bags)	1,484	11.03	0.02	0.74	890	11.13	0.02	0.81
Calculated interest correctly	1,580	0.73	-0.03	0.50	950	0.70	0.09	0.21
Digit span recall	1,504	4.58	-0.01	0.89	900	4.56	0.02	0.80
Maize giver	1,589	0.26	-0.00	0.99	954	0.25	0.09	0.21

Notes: Balance table for the Y1 study (restricted to the Y1 sample, for which we have baseline characteristics.) "Total school fees" are the total school fees paid by the household in the past 12 months. "Avg. consumption (Ksh)" and "Avg. consumption/capita (log)" are calculated using monthly consumption numbers. Taken bank loan" is whether anyone in the household taken any loans from a commercial bank or commercial lender in the past 12 months. 'Taken informal loan" is whether anyone in the household taken any loans from a moneylender or someone else outside the household in the past 12 months."Liquid wealth" is the sum of cash savings and assets that could be easily sold (e.g. livestock). "Off-farm wages" is the total amount earned by anyone in the household who worked in a job for cash in the past month. "Business profits" are the total profits earned from all business run by anyone in the household. "Avg %Δ price Sep-Jun" is the percentage difference between the (self-reported) average market price for maize in September and June over the past five years. "Net revenue," "net seller," and "autarkic" refer to the household's maize marketing position. "Maize giver" is whether the household reported giving away more maize in gifts than it received over the previous 3 months. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence.

Table 3.C.2: **Balance - Treatment effect of Lockbox, conditional on Loan**

	Net Revenues	Total HH Consumption		Farm Investments	School Fees
	(1)	(2)	(3)	(4)	(5)
	Overall	Overall	By round	Overall	Overall
Lockbox	111.37	0.02		469.82*	-30.63
	(286.22)	(0.03)		(256.05)	(316.51)
Lockbox - R1			-0.03		
			(0.05)		
Lockbox - R2			0.00		
			(0.04)		
Lockbox - R3			0.08*		
			(0.04)		
Observations	2328	2323	2323	797	2348
Mean DV	-358.80	9.52	9.52	4549.72	3400.94
SD DV	6503.00	0.64	0.64	3587.37	7455.92
R squared	0.06	0.18	0.18	0.19	0.12

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. The results are pooled for year one and two of the study. Columns 1, 2, 4 and 5 present results pooled across all rounds, while Column 3 presents results by round. Regressions include round-year fixed effects, strata dummies, controls for survey date and and all baseline variables that are not balanced at 10%, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (*), 95% (**), 99% (***) confidence. Standard errors in parentheses.

3.D Robustness checks

In this section we check robustness of treatment effects to including baseline controls and winsorizing the dependent variable at 5%.

Table 3.D.1 provides robustness checks for Table 3.4.1. Columns 1 to 2 present the results for Net revenues from maize, Columns 3 to 4 present the results for Total household consumption, Columns 5 to 6 present the results for Farm investments and Columns 7 to 8 present School fees results. Regressions with baseline controls and winsorization of the dependent variable are shown in columns 1, 3, 5 and 7 in both tables and regressions with winsorization of the dependent variable are shown in columns 2,4,6 and 8. The number of observations, the mean and standard deviation of the dependent variable for the control group, as well as the R- squared of the regression is presented in each column of the table. We present short-run results by pooling year one and two of the study. We see from Table 3.D.1 that our results are robust to including baseline controls and winsorizing the dependent variable at 5%.

In Tables 3.D.2 and 3.D.3 we check for robustness of results in Table 3.4.2. We show that the results are robust to including baseline controls and winsorizing the dependent variable (at 5%). Further, with the inclusion of controls, the effect of the lockbox on farm investments is statistically significantly larger for the October loan group. In summary, we see that farmers earn a much higher return (higher net revenues) to the October loan in comparison to the January loan. This provides evidence that the savings

technology is most impactful when household have greater returns from a productive investment in hand.

Lastly, Table 3.D.4 provides robustness checks for Table 3.4.3. Regressions with baseline controls are shown in columns 1, 3, 5 and 7 and with winsorization of the dependent variable (at 5%) in columns 2,4,6 and 8. Results are broadly robust to both, suggesting the loan and lockbox are complementary for consumption, farm investment, and school fees, though results lose some precision with the inclusion of controls (t-stats remain above 1).

Table 3.D.1: **Treatment effects**

	Net Revenues		Total HH Consumption		Farm Investments		School Fees	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Treatment effect of Loan								
Loan	465.82**	473.70***	0.03	0.03	-38.19	-73.23	-24.99	51.76
	(187.02)	(158.52)	(0.02)	(0.02)	(163.90)	(138.83)	(244.26)	(170.53)
Observations	5533	6730	5307	6736	1906	2276	5649	6787
Mean DV	-1616.12	-1616.12	9.55	9.55	5332.46	5332.46	3911.31	3911.31
SD DV	6359.06	6359.06	0.64	0.64	3596.71	3596.71	8281.46	8281.46
R squared	0.17	0.14	0.18	0.05	0.24	0.16	0.13	0.07
Panel B: Treatment effect of Lockbox, conditional on Loan								
Lockbox	91.69	116.15	0.05*	0.06**	456.38**	514.60**	131.42	371.78*
	(216.04)	(191.24)	(0.03)	(0.03)	(213.59)	(204.62)	(305.90)	(217.88)
Observations	3421	3436	3236	3443	1172	1172	3473	3473
Mean DV	-358.80	-358.80	9.52	9.52	4549.72	4549.72	3400.94	3400.94
SD DV	6503.00	6503.00	0.64	0.64	3587.37	3587.37	7455.92	7455.92
R squared	0.17	0.10	0.18	0.07	0.28	0.19	0.15	0.09
Baseline controls included	Yes	No	Yes	No	Yes	No	Yes	No
Dep. var. winsorized (5%)	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. Panel A shows the treatment effect of the loan treatment. Panel B shows the treatment effect of the lockbox, conditional on being offered the loan treatment. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (*), 95% (**), 99% (***) confidence. Standard errors in parentheses.

Table 3.D.2: **Treatment effects by loan timing (with baseline controls)**

	Net Revenues		Total HH Consumption		Farm Investment		School Fees	
	(1) Oct	(2) Jan	(3) Oct	(4) Jan	(5) Oct	(6) Jan	(7) Oct	(8) Jan
Panel A: Treatment effect of Loan (Oct and Jan)								
Loan	555.23**	34.57	0.03	0.00	-204.19	-219.90	-231.91	-101.26
	(250.25)	(245.12)	(0.03)	(0.03)	(228.84)	(217.62)	(286.80)	(287.14)
Observations	2520	2518	2414	2420	867	869	2572	2571
Mean DV	-1616.12	-1616.12	9.55	9.55	5332.46	5332.46	3911.31	3911.31
SD DV	6359.06	6359.06	0.64	0.64	3596.71	3596.71	8281.46	8281.46
R squared	0.10	0.15	0.17	0.17	0.18	0.13	0.12	0.13
Panel B: Treatment effect of Lockbox, conditional on Loan (Oct and Jan)								
Lockbox	-26.72	237.98	0.08**	0.06	621.55*	505.18	762.34*	-463.28
	(312.31)	(345.79)	(0.04)	(0.04)	(352.71)	(373.76)	(415.09)	(407.64)
Observations	1258	1256	1184	1190	430	432	1272	1271
Mean DV	708.05	284.57	9.45	9.47	3715.63	3823.85	2614.39	3207.12
SD DV	6227.68	6197.31	0.62	0.63	3225.57	3194.25	5947.33	7063.82
R squared	0.12	0.23	0.16	0.17	0.26	0.18	0.14	0.14

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. Panel A shows the treatment effect of the loan treatment. Panel B shows the treatment effect of the lockbox, conditional on being offered the loan treatment. Columns 1,3,5 and 7 shows the treatment effects for October and January loans of the Y1 treatment. Columns 2,4,6, and 8 show the treatment effects for the October loan. The results are pooled for year one and two of the study. Regressions include baseline controls, round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (*), 95% (**), 99% (***) confidence. Standard errors in parentheses.

Table 3.D.3: **Treatment effects by loan timing (Dep. var. winsorized (5%))**

	Net Revenues		Total HH Consumption		Farm Investment		School Fees	
	(1) Oct	(2) Jan	(3) Oct	(4) Jan	(5) Oct	(6) Jan	(7) Oct	(8) Jan
Panel A: Treatment effect of Loan (Oct and Jan)								
Loan	530.67**	-53.50	0.02	0.00	-216.70	-271.51	-116.48	-109.68
	(238.89)	(240.65)	(0.03)	(0.03)	(233.27)	(203.90)	(230.94)	(227.99)
Observations	2534	2536	2535	2534	867	869	2572	2571
Mean DV	24.69	24.69	9.48	9.48	5192.91	4245.24	2815.48	2815.48
SD DV	4834.84	4834.84	0.58	0.58	3137.26	3149.13	5173.96	5173.96
R squared	0.05	0.05	0.04	0.04	0.09	0.07	0.06	0.06
Panel B: Treatment effect of Lockbox, conditional on Loan (Oct and Jan)								
Lockbox	167.66	59.07	0.09**	0.03	597.90	530.48	861.59***	-277.70
	(277.59)	(320.10)	(0.04)	(0.04)	(362.46)	(330.36)	(315.88)	(311.41)
Observations	1259	1261	1258	1257	430	432	1272	1271
Mean DV	362.12	-44.95	9.46	9.47	3662.33	3770.61	2349.57	2776.98
SD DV	5073.20	4834.96	0.58	0.57	2994.07	2914.60	4492.93	5011.96
R squared	0.05	0.06	0.05	0.05	0.13	0.13	0.11	0.09

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. Panel A shows the treatment effect of the loan treatment. Panel B shows the treatment effect of the lockbox, conditional on being offered the loan treatment. Columns 1,3,5 and 7 shows the treatment effects for October and January loans of the Y1 treatment. Columns 2,4,6, and 8 show the treatment effects for the October loan. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. The dependent variable is winsorized at 5%. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (*), 95% (**), 99% (***) confidence. Standard errors in parentheses.

Table 3.D.4: **Treatment effects**

	Net Revenues		Total HH Consumption		Farm Investment		School Fees	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockbox	132.92	-141.62	-0.01	-0.06*	1.87	-58.55	-489.54	-694.64**
	(313.41)	(260.77)	(0.04)	(0.04)	(275.42)	(252.83)	(424.22)	(287.89)
Loan	473.31**	353.73*	0.01	-0.02	-191.99	-225.18	-266.21	-347.33
	(219.80)	(206.04)	(0.02)	(0.03)	(197.36)	(187.37)	(288.37)	(212.14)
Lockbox*Loan	24.52	313.12	0.05	0.12***	448.51	558.23*	662.45	1087.12***
	(382.48)	(323.04)	(0.05)	(0.05)	(346.54)	(323.03)	(525.06)	(358.54)
Observations	5482	5534	5244	5546	1885	1885	5595	5595
Mean DV	-1616.12	-1616.12	9.55	9.55	5332.46	5332.46	3911.31	3911.31
R squared	0.17	0.12	0.18	0.06	0.24	0.16	0.13	0.07
Baseline controls included	Yes	No	Yes	No	Yes	No	Yes	No
Dep. var. winsorized (5%)	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (*), 95% (**), 99% (***) confidence. Standard errors in parentheses.

3.E Consumption effects

In this section, we provide further insights and robustness checks on the consumption effects discussed in the Section 4.4.

In Table 3.4.1 we found that combining credit access with a savings technology enables farmers to increase total household consumption. In Table 3.E.1 we show a break-up of the treatment effect by rounds of data collection. The positive and significant treatment effect for round 3 in Table 3.4.1 col.1 shows that the increase in consumption is most marked in the lean season. This is a time of particularly high farmer need in which the marginal utility of household consumption is presumably particularly high. This suggests that farmers use the savings accumulated in the lockbox to fund lean-season consumption. We also observe a positive coefficient for rounds 1 and 2. Contrary to a classic "consumption smoothing" story, in which we would expect any increase in lean season consumption to be matched by dips in consumption in other seasons. Instead we see that consumption is higher throughout the year. This points to a second mechanism that may be at play, where a lockbox helps protect money from the kin tax imposed by family and friends.

Table 3.E.1: **HH consumption - Treatment effect of Lockbox on Loan group**

	(1) Overall	(2) By round
Lockbox	0.07**	
	(0.03)	
Lockbox - R1		0.06
		(0.04)
Lockbox - R2		0.06
		(0.04)
Lockbox - R3		0.09**
		(0.04)
Observations	3443	3443
Mean DV	9.52	9.52
SD DV	0.64	0.64
R squared	0.07	0.07

Notes: The dependent variable is Total HH consumption. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Columnn 1 presents results pooled across all rounds, while Column 2 presents results by round. "Lockbox" is an indicator for being in the lockbox treatment group. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

3.F Sharing with Kin

As discussed in Section 4.4, a lockbox may enable households to shield some money from the kin tax imposed by family and friends. In Table 3.F.1 we look at treatment effects of the loan and lockbox (conditional on loan) on money and maize lent. To study the kin tax mechanism, we look at heterogeneity by a baseline measure of being a giver of money and maize respectively. Columns 1 and 3 show loan amounts (for money and maize respectively) and columns 2 and 4, show a dummy variable for whether a loan was given (for money and maize respectively). In columns 1 and 2, the variable “Giver" refers to farmers who gave more money to friends and family than they received at baseline. In Columns 3 and 4, “Giver" refers to farmers who gave more maize to friends and family than they received at baseline.

We look at whether a lockbox may enable households to shield some money from the kin tax imposed by family and friends, in a setting where there is pressure to share with kin. In Table 3.F.1 Panel A, we see that the interact term “Loan*Giver" term is positive for all columns, albeit not significant, providing some suggestive evidence that farmers who were money or maize “givers" at baseline, are more likely to lend money or maize when they receive a loan. In 3.F.1 Panel B, we see that the interact term“Lockbox*Giver" term is negative across all columns, suggesting that farmers who were money “givers" at baseline are less likely to lend money when they receive a lockbox. In Col, 2, we find that farmers who gave more money to friends and family than they received at baseline are significantly less likely to loan money to

people in their social network when they have access to a lockbox.This is consistent with the kin tax mechanism discussed in section 4.4. However, the welfare implications of this reduction in kin tax are not obvious.

Table 3.F.1: **Treatment effects - Triple Interaction Specification**

	Money transfer		Maize transfer	
	(1)	(2)	(3)	(4)
	Loan Amount	Loan Dummy	Loan Amount	Loan Dummy
Panel A: Treatment effect of Loan				
Loan	-31.27	-0.02*	17.38	0.03*
	(21.47)	(0.01)	(33.55)	(0.02)
Giver	-0.66	0.01	42.80**	0.02**
	(23.59)	(0.01)	(18.93)	(0.01)
Loan*Giver	11.51	0.01	26.34	0.01
	(27.18)	(0.02)	(28.61)	(0.01)
Observations	4484	4518	4388	4460
Mean DV	227.19	0.23	278.98	0.26
SD DV	848.55	0.42	980.53	0.44
R squared	0.13	0.04	0.13	0.10
Panel B: Treatment effect of Lockbox, conditional on Loan				
Lockbox	-7.33	0.01	28.11	0.00
	(21.36)	(0.02)	(49.64)	(0.02)
Giver	20.37	0.03***	74.70***	0.04***
	(15.83)	(0.01)	(27.44)	(0.01)
Lockbox*Giver	-29.66	-0.05**	-14.28	-0.01
	(20.66)	(0.02)	(46.38)	(0.02)
Observations	2727	2746	2672	2716
Mean DV	92.69	0.21	357.59	0.29
SD DV	554.28	0.40	1051.43	0.45
R squared	0.14	0.04	0.13	0.11

Notes: The dependent variables are the value of loans given and the likelihood of giving loans. In columns 1 and 2, we show “Money Transfers" (loan amount and dummy variable respectively) and in columns 3 and 4, we show “Maize Transfers" (loan amount and dummy variable respectively). For Maize Transfers, we calculate value of loans based on baseline expectations of maize prices for that month. In Panel A, the dependent variable is regressed on the “Loan" variable, the standardized baseline heterogeneity variable (“Giver"), and an interaction term (“Loan*Giver"). In Panel B, the dependent variable is regressed on the “Lockbox" variable, the standardized baseline heterogeneity variable (“Giver"), and an interaction term (“Lockbox*Giver"). In columns 1 and 2, the variable “Giver" refers to farmers who gave more money to friends and family than they received at baseline. In Columns 3 and 4, “Giver" refers to farmers who gave more maize to friends and family than they received at baseline. The results are pooled for year one and two of the study.

Table 3.F.2: **Treatment effects**

	(1) Net Revenues	(2) Total HH Consumption	(3) Farm Investments	(4) School Fees
Panel A: Treatment effect of Loan, conditional on money giver				
Loan	861.25	0.08	579.68	-344.45
	(552.10)	(0.07)	(539.67)	(786.43)
Observations	864	860	290	873
Mean DV	-921.96	9.64	5115.09	4921.57
SD DV	6744.97	0.70	3779.10	9890.97
R squared	0.20	0.18	0.17	0.24
Panel B: Treatment effect of Lockbox, conditional on Loan and money giver				
Lockbox	477.50	0.07	939.22	537.09
	(805.17)	(0.10)	(767.86)	(1122.79)
Observations	512	508	171	517
Mean DV	-200.04	9.69	5132.61	4858.28
SD DV	6683.03	0.66	3479.65	9832.94
R squared	0.20	0.21	0.24	0.31

Notes: The dependent variables are Net Revenues, Total HH consumption, Farm Investment and School Fees. Net revenues are measured by the value (in Ksh) of maize sales minus the value of maize purchases that round. The exchange rate during the study period ranged from 80 to 90Kenyan shillings per USD. Total HH consumption is the log of HH consumption (measured in logged Ksh), aggregated from a detailed 30 day recall consumption module. Farm Investment is the value (in Ksh) of hybrid seeds, DAP (fertilizer), and CAN (fertilizer) used on maize plots in the season following the loan disbursal (because the Year 2 survey only measured the quantities used, average prices from Year 1 are used to get values in Year 2). This variable was only measured in round three for each year, as that is when farmers undertake this investment. School Fees are the expenditures on school fees over the past month (in Ksh). "Lockbox" is an indicator for being in the lockbox treatment group. Panel A shows the treatment effect of the loan treatment, conditional on being a "money giver" at baseline. Panel B shows the treatment effect of the lockbox, conditional on being offered the loan treatment and being a "money giver" at baseline. "Giver" refers to farmers who gave more money to friends and family than they received at baseline. The results are pooled for year one and two of the study. Regressions include round-year fixed effects, strata dummies, and controls for survey date, with errors clustered at the group level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

Next, we investigate whether the increase in Total HH Consumption and Farm Investments documented in Section 4.4 is driven by net givers of money. We focus on "money givers" as we hypothesize that the a lockbox can help farmers shield money. To study this we run our primary specification (Equations 3.3.1 and 3.3.1) additionally conditioning on being a money giver and maize giver at baseline. Results are presented in Table 3.F.2. In Table 3.F.2 Panel B, we see that the magnitude of treatment effects are larger than those seen in Table 3.4.1; however, we are under-powered to detect differences in effects.

Taken together, we view this as suggestive — albeit not dispositive evidence, given the imprecision of some of these estimates — that that a lockbox may be particularly beneficial to farmers who are "money givers" at baseline, as it helps shield money from kin.

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4 | Innovative financing using microequity contracts: Experimental evidence from India

with **Muhammad Meki** and **Simon Quinn**

Abstract

Access to large grants for microenterprises has shown sustained improvements in business performance and household welfare. In ongoing work in India, we study whether a big push microequity contract can generate similar outcomes while also recovering the initial investment amount for future investments. Working with women-led microenterprises, we randomize access to microequity contracts that facilitate the purchase of productive assets through a performance-contingent repayment schedule. Among firms that were offered the contract, we document full take-up as well as no missed repayments. We document that firms channel funds into productive assets and working capital — and, in line with this, we present evidence of a 58% and 56% increase in weekly firm revenues and profits respectively. Results suggest that microequity contracts can foster business growth for women-led microenterprises — a group for which it has been difficult to unlock meaningful gains.

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4.1 Introduction

Financing microenterprises in low- and middle-income countries is of immense policy interest but remains challenging. Proposed solutions have a trade-off between impact and financial sustainability. One option is to provide access to large grants to microenterprises that has had large and persistent increases in business performance and key livelihood indicators (De Mel et al., 2008; Fafchamps et al., 2014; Banerjee et al., 2015b; Bandiera et al., 2017; Crépon et al., 2020; Balboni et al., 2022; Hussam et al., 2022). However, a key drawback is the limited sustainability as grants do not allow the money to be redeployed to other firms (Bari et al., 2021). Another option that has been explored is to provide access to microcredit, which has found mixed evidence on the sustained impact on business profits and key livelihood indicators (Karlan and Zinman, 2011; Angelucci et al., 2015; Attanasio et al., 2015; Augsburg et al., 2015; Banerjee et al., 2015a; Crépon et al., 2015; Tarozzi et al., 2015; Fiala, 2018). While microcredit is more financially sustainable, a key drawback is that rigid repayment requirements limits a firm's ability to channel money to lumpy assets (Field et al., 2010). The paper by (Banerjee et al., 2015b) highlights the need for future research to explore variations in financial contracts that may be effective in fostering business growth.

In this paper we directly address this gap by examining if a "big-push" microequity contract (or performance-contingent financing) can generate sustained improvements in business performance and household welfare, while

also recouping the initial investment amount for future investments. We work with Buzz Women, an NGO, and Yunus Social Business (YSB), a financing institution, to run a field experiment in India that randomizes the offer of microequity contracts in a sample of 28 women-led microenterprises in two sectors of particular relevance for rural and peri-rural areas: (i) animal husbandry and (ii) tailoring. For the representative firm in these sectors there are several kinds of assets that have high returns but are beyond the financial reach of many microenterprises.

There are several key reasons that equity-like products might be particularly attractive in this context. First, productive assets are lumpy investments and cost approximately Rs.70,000 (USD 850), which is over 11 times the monthly revenue earned by firms in our sample. Microequity financing facilitates the purchase of these assets (and complementary working capital). Second, in a setting firms have large fluctuations in earnings, microequity contracts offer some much needed flexibility. Standard financial contracts have rigid repayment requirements, which are not ideal to finance large and lumpy investments (Field et al., 2010). In contrast, microequity contracts provide implicit insurance against risks and are a natural and continuous process of mutual sharing of losses and profits.

Nine months into a three year intervention, we have three key findings.[1] First, there is high demand for microequity contracts among a sample chosen for their potential interest in the product. All firms who were assigned to the treatment arm accept the microequity financing. They also demand the

[1]The pre analysis plan was registered at the AEA registry prior to the intervention. The RCT ID is AEARCTR-0009675.

maximum financing amount of Rs. 100,000 (≈ USD 1200). Second, we document sustained improvements in business performance. Using quarterly phone surveys, we find that being offered a microequity contract enables firms to finance large and profitable fixed assets and corresponding working capital. Using two rounds of follow-up survey data we document a large and significant increase in assets. Firms report a 53% increase in fixed assets and a 275% increase in inventories relative to the control group.[2] Weekly aggregates of daily self-reported data shows that this investment leads to a significant increase in weekly revenues and profits by 58% and 56% respectively, and this pattern persists nine months after the intervention. Third, we find that firms repay the amount due at the end of every month and there are no missed repayments so far. If currents trends continue investors will be able to recoup the initial investment amount.

While it is encouraging that we see no missed repayments, it is important to verify the accuracy of self-reported data. Since repayments under the microequity are revenue contingent, firms have a clear incentive to under-report revenues. In the absence of fully functional financial markets in LMICs, relational contracts play a major role (McMillan and Woodruff, 1999; Banerjee and Duflo, 2000; Antras and Foley, 2015; Macchiavello, Morjaria, et al., 2015; Macchiavello and Morjaria, 2015). Monthly repayments under the microequity contract are calculated based on self-reported revenues; these self reports are then verified using several monitoring technologies. Specifically, entrepreneurs were asked to self-report revenues using either (i) a digital app

[2]The average firm in our sample has an inventory to fixed capital ratio of ≈ 2.5%. This is why we see such a large treatment effect in inventories in percentage terms.

(called 'MeraBills'), or (ii) via text messages to their respective field officers. Then — with the prior consent of participants — we set up credible monitoring mechanisms to guard against systematic under-reporting. Several papers highlight the importance of credible threats to deter non-compliers (Slemrod et al., 2001; Kleven et al., 2011; Pomeranz, 2015; Kleven et al., 2016; Perez-Truglia and Troiano, 2018; Brockmeyer et al., 2019). For those in tailoring, we used motion sensors attached to tailoring machines; these monitor the hours of operation each day. For those engaged in animal husbandry, entrepreneurs were required to submit receipts that they receive from the dairy, on a bi-weekly basis. In addition, for both sectors we sent (randomly assigned) 'secret shoppers' to entrepreneurs' workplaces (clients were informed in advance that this was a possibility). The revenue earned from the transaction with the secret shopper should be reflected in that day's revenue report. Using these monitoring methods, we strikingly find no evidence of systemic under-reporting of self-reported revenues. Our finding highlights the importance of relational contracting — and, by implication opportunities this might place in innovations to conventional microcredit contracts.

The key contribution of this paper is to push the frontier on innovations to microcredit financing. A number of recent studies have introduced flexibility in the contract structure and observed positive effects on lumpy investments and profits (Gamba and Triantis, 2008; Field et al., 2010; Bari et al., 2021; Battaglia et al., 2021). Specifically, this paper focuses on the limitations associated with rigid repayment structures of standard microcredit contracts. Traditional debt contracts ease the credit constraint but often

limit entrepreneurs from undertaking bulky and illiquid capital investments. Since the majority of entrepreneurs do not have a smooth flow of income, the rigid payment schedules under conventional microcredit contracts pose a problem. Such contracts provide minimal protection against large income shocks. Thus, despite having access to microcredit contracts, it is commonly observed that entrepreneurs are risk averse and do not undertake high risk high return investments (Fischer, 2013). Microequity financing can overcome these issues by channeling funds into productive assets (and working capital) and allowing for performance contingent repayments. However, microequity financing while feasible in theory is quite hard to implement (De Mel et al., 2019). There is an important and open question question amongst academics, policymakers and funders whether this will work in practice. To test this, we work intensively with a small sample of firms and collect high-frequency daily data over a long time horizon (Bloom et al., 2013). We document improvements in business and household outcomes, while maintaining low rates of default. This is a first step to show that such financing can be implemented and potentially scaled up.

This paper also adds to the literature on microinsurance products. Unlike a conventional insurance product, the downside risk sharing under microequity is less "binary" (either paying out if some event is triggered or not). This more regular and continuous sharing of downside risk also has the potential to be more valued by firms. For example, in contrast to the evidence of extremely low take-up rates for conventional microinsurance even when heavily subsidized (Cole et al., 2013) we find high take-up rates for microe-

quity contracts.

The results of this paper have two key implications for policy. First, this paper presents evidence of a large and sustained growth in women-led microenterprises in contrast to the microfinance literature that has found limited evidence of business growth for women-led microenterprises (De Mel et al., 2008; Attanasio et al., 2015; Fiala, 2018). In comparison to men, women face disproportionately limited access to economic opportunities and have lower bargaining power in the household (Ashraf, 2009; Lechene et al., 2021). Another factor which is less discussed is the pressure women face to make financial transfers to their husband and other family. This lack of independence to make financial or business decisions often leads to inefficient investment decisions.[3] By channeling funds directly into productive assets and not liquid cash, we overcome some of these gender specific constraints. Further, the literature has shown that income in the hands of a woman is more likely to be spent on investments in children's education, nutrition as well as on housing (Thomas, 1990; Duflo, 2003). Given the long duration of our study we are interested in studying such positive externalities from microequity lending.

The second policy implication is around the scaleability of the interven-

[3]Fafchamps et al., 2014 in their work in Ghana highlight the "flypaper effect" which is prominent for women microentrepreneurs. That is, directly injected capital sticks in the business, but cash does not. Jakiela and Ozier, 2016 find that individuals, especially women, are willing to bear a significantly high cost to hide income from their kin in Western Kenya. Baland et al., 2011 cite credit cooperatives in rural Cameroon where more than 20% of loans are fully collateralized by liquid savings. Members prefer to pay interest payments and take a loan rather than use their savings to finance projects. One reason presented in the paper is the desire to avoid external pressure from kin to share liquid savings. Other innovative financial tools that help keep money safe from others have had positive effects on business outcomes (Field et al., 2016).

tion. In India, microenterprises (enterprises with fewer than 10 employees) account for over 97.88% of the population of firms (Hsieh and Olken, 2014) and are often characterized by low growth and profitability. The lack of sustainability of these microenterprises is commonly attributed to the lack of access to functional credit markets (De Mel et al., 2008; Banerjee and Duflo, 2014) as well as being exposed to idiosyncratic income shocks (Samphantharak and Townsend, 2012). Microenterprises in India face major challenges in sustaining and expanding. It is well established that imperfect credit and insurance markets pose severe limitations to how much these enterprises can grow. Rigid debt contracts limit microenterprises from undertaking 'high-risk/high-return' investments. Lack of insurance against exogenous shocks further accentuates this problem. If scaleable, this study has the the potential to simulate growth in microenterprises through a sustainable financial intervention that combines innovative financial contracting with technology.

The rest of the paper is structured as follows. Section II describes the experimental setting and design. Section III details the data and estimation. Section IV presents the results and Section V concludes.

4.2 Setting and experimental design

4.2.1 Study context

We conducted our study in the southern Indian state of Karnataka in India starting in 2021; the study is ongoing. We work with women microentrepreneurs across 16 villages in the Bangalore and Tumkur districts. Our

partner organization, Buzz Women, works towards empowering women entrepreneurs in Karnataka by providing access to training, financial knowledge, credit and support systems. Working with over 400,000 women, Buzz enables its members to start and run enterprises. In our setting, running a business is one of the most common forms of employment for women.

Our sample comprises of 28 women-led microenterprises who were affiliated with Buzz Women in 2021 and had expressed interest in expanding their business. Firms are drawn from two sectors of particular relevance for rural and peri-rural areas: (i) animal husbandry and (ii) tailoring. These are businesses that can be run from the household and hence are prevalent in this context. Table 4.2.1 presents summary statistics for our sample. Our sample is representative of the average women-led business in the region. Based on a survey of 240 firms conducted by Buzz Women they document that 57% of the firms in the region are engaged in animal husbandry or tailoring.

The firms in this sample are mostly family firms. They are established firms that have on average over 10 years of experience in their current business. 86% of the businesses have no employees and the mean number of employees in my sample of firms is 0.43 (with a median of 0 employees). The average firm in my sample earned monthly profits of INR 7,600 or USD 93 (median is INR 6,130 or USD 75) and reported a mean profit margin of 62%.[4]

The women entrepreneurs in our sample contribute significantly to their

[4]Profit is measured as net income after all expenses but before paying one's own wage. Profit margin is defined as monthly profit divided by monthly revenue at baseline. The profit margins we see here are quite high. The true profit margin (after accounting for own wage) would be lower and more in line with conventional levels. Further, it is worth noting that in measuring profit, we do not account for depreciation expenses.

household income. The average household runs two businesses (including the business run by the microentrepreneur in our sample). In our sample, 14% of the women firm owners are the heads of their households. For 75%, their husband is the household head. Including the firm owner, the average household has 2.4 members who earn any form of income. The average household has a total monthly income of INR 27,300 or USD 333 (median is INR 19,150 or USD 234).[5] The mean number of businesses run by the household (including the micro-firm in our sample) is two and the average total monthly earnings for all businesses in a household is INR 16,640 or USD 203 (median is INR 12,660 or USD 154).

As is characteristic of microenterprises, the firms in our sample have volatile revenues. For the three-month period pre-intervention where we have survey data based on monthly recall, we see that revenues and profits have a high standard deviations of Rs. 13,000 and Rs. 8,000 respectively (these numbers are higher than the mean revenue and profit estimates). Figure 4.2.1 presents a histogram of the coefficient of variation of firm revenues using 16 months of pre-intervention daily data (aggregated to the monthly level). While firms have volatile revenues, the coefficient of variation in our data is significantly lower than that documented in the literature (Fafchamps et al., 2012; Banerjee et al., 2015a). Revenues and profits are typically measured using monthly recall in survey questionnaires and produce noisy estimates (De Mel et al., 2009; Fafchamps et al., 2012). In this paper, we collect daily data on revenues (which minimizes issues around recall) and hence have tighter estimates for monthly revenues.

[5]The USD INR exchange rate is as of May 2023.

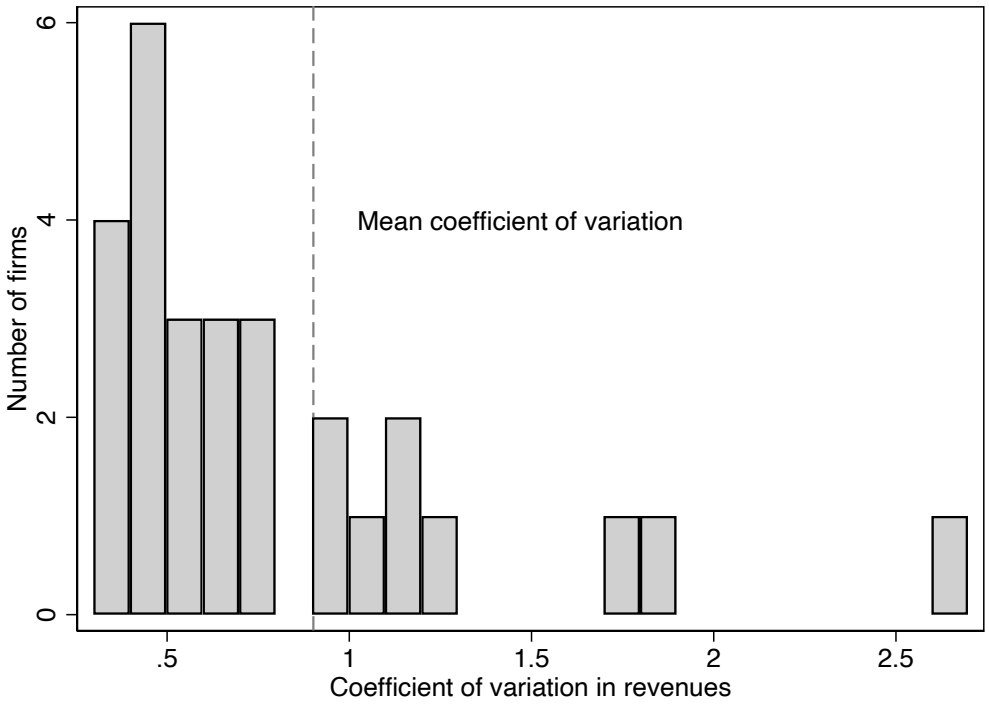
Table 4.2.1: **Summary statistics and balance among baseline covariates**:

Baseline characteristic	Treat	Control	Obs.	T-C		
				Std. diff.	p-value	RI test p-value
Household size	4.87	4.62	28	0.22	0.56	0.62
Business sector	1.73	1.77	28	-0.08	0.83	1.00
Number of businesses run by family	1.87	1.85	28	0.03	0.93	1.00
Total HH income from all businesses	20,012	12,755	28	0.80	0.14	0.17
Total HH income	30,032	24,086	28	0.28	0.49	0.58
Years of experience running business	167	151	28	0.20	0.60	0.57
Number of competitors in 5min walk radius	4.67	4.46	28	0.05	0.88	0.96
Number of customers per day	5.40	5.69	28	-0.03	0.92	0.87
Number of employees	0.40	0.46	28	-0.04	0.91	1.00
Revenue at baseline survey	15,782	12,698	28	0.19	0.61	0.60
Profit at baseline survey	8,024	7,049	28	0.16	0.69	0.69
Fixed assets	126,867	46,262	28	1.13	0.29	0.44
Total current assets	125,853	102,754	28	0.08	0.80	0.84
Loan pending	43,867	91,769	28	-0.40	0.21	0.22
Amount borrowed from family and friends	12,000	16,923	28	-0.09	0.79	0.63
Cash savings	7,800	6,769	28	0.10	0.81	0.88
SHG saving	10,337	13,115	28	-0.22	0.49	0.48
Deposit saving	8,613	172,385	28	-0.33	0.24	0.16
Bank saving	32,400	22,385	28	0.58	0.47	0.65
Latest 3m avg revenue	10,915	6,195	28	0.91	0.17	0.11
Latest 3m avg profit	2,764	3,191	28	-0.07	0.84	0.85
Loan from bank	22,667	40,000	27	-0.25	0.46	0.48
Still owed to bank	10,133	30,833	27	-0.36	0.25	0.27
Pending payment to supplier	681	538	28	0.10	0.80	0.96

Notes: The first two columns correspond to the mean value of the variable for the treatment and control groups. The third column gives the total number of observations. The fourth column gives the differences in means normalized by the standard deviation in the control group. The fifth column provides the corresponding p-value on the test of equality. Finally, the last column provides the p-value on the test of equality using randomization inference.

The project is funded by USAID's Development Innovation Ventures. They fund the cost of implementing the project as well as the equity financing amounts. The microequity financing is disbursed through our financing partner Yunus Social Business (YSB), a prominent non profit financing insti-

Figure 4.2.1: **Coefficient of variation of revenues (pre-intervention)**



tution. They fund over 17 million people in East Africa, Latin America and India. In Karnataka, they fund three million low-income local customers.

4.2.2 Study design

We designed a screening mechanism to select a sample for the study. We asked 20 field officers from the chosen locations to choose 10 entrepreneurs (within the chosen business sectors) based on four selection criteria. First, we identified women-led enterprises. We used the local knowledge of field staff to ensure that the woman was running or actively involved in running the business. Second, we identified businesses that were stable over a period

of time: we selected firms with a monthly revenue above a threshold of Rs. 8000 (110 USD) that were running for at least one and a half years. Third, we identified businesses that were not high-risk. We required that the amount of outstanding debt be less than Rs. 70,000 (approximately USD 900), there was no active court cases against the entrepreneur and the entrepreneur did not have any severe health issues. Lastly, we identified growth-oriented businesses. To ensure that the entrepreneur was keen on growing her business and had a desire to invest in her business, we required participants to have a well-thought-out plan for the investment. 200 firms were screened using these criteria about 75 were found to be eligible.

Given the lack of good preliminary data prior to starting the study, we used the local knowledge of the field officers who work extensively with the entrepreneurs. We then conducted a detailed baseline survey with this selected group. This shortlisted group was then invited to attend a two-day entrepreneurship bootcamp. The bootcamp included role-plays, discussions and quizzes around financial literacy, bookkeeping practices and identifying a market. After the bootcamp, the entrepreneurs in the sample attending training sessions/ meetings every quarter. They were also required to maintain and report daily business records to their field officer. This helped the women better understand their business and also helped us draw projections of their revenue and profit streams. We had intended the pre-intervention data collection phase to be three-four months long. However, due to the pandemic COVID this period lasted for over a year. We see the sustained involvement of the sample in the project despite the longer than expected time

gap between when we selected entrepreneurs and when we offered contracts as a sign of commitment towards the project. The extensive pre-intervention data is helpful to shortlist the final sample.

Through the many steps detailed above, we arrived at a motivated and able group of 55 women. This group was invited to a contract explanation session to ensure that firms understood the nature of this financial contract. In this session Buzz Women explained the details of a microequity contract and how it differed from a standard debt contract. Appendix 4.G details the script used for the contract explanation session. Entrepreneurs were also provided a one page written description they could take home for reference. This is discussed in Appendix 4.H. Of these 55 entrepreneurs, 43 applied for a loan. The loan application required identification documents, the filling out of a loan application form and a detailed business plan on how they would spend the microequity loan. Most firms used 70% to buy a productive fixed asset and the rest to purchase working capital. Specifically, for firms working in animal husbandry, most of them purchased cows (with accompanying cow feed); for firms working in tailoring, they purchased sewing and embroidery machines (with accompanying textile inventories). Appendix 4.C lists each of the financed assets.

The maximum amount they could submit an application for was Rs. 100,000 ($\approx$ USD 1200).[6] All firms submitted an application for the maximum amount. Of the firms that did not apply for a loan, we did qualitative interviews with them and found that they refrained from applying due to

[6]We decided not to ask for a financial deposit.

personal reasons. There was a a gap of about six months from when they were selected to be in the final sample to when they were asked if they wanted to submit a loan application. For a subset of firms, circumstances changed in this period an they were not looking to invest in the business at the time the microequity loan application was opened.Of the 43 firms that applied for a loan, 28 were approved for the loan by YSB. This was done as per the usual process of credit checks that YSB conducts. For the 28 firms that were selected by YSB, all were were offered the maximum amount of Rs. 100,000. After the offer was made, entrepreneurs had about 2 weeks to decide if they wanted the loan. All firms decided to accept and signed the contract.

We chose the sample carefully to be the policy-relevant for this kind of intervention — in a context where it is not clear whether this kind of financial product is even viable at all. Post the selection process, we have a sample of firms that look similar on observables to the larger sample — but these firms are carefully selected to be representative of the subset of firms that might be interested in a potential scale-up. In Appendix Table 4.A.1 we compare our study sample to larger sample of 310 microenterprises in the region, using data that was collected prior to starting this study in 2019. We see that the two samples look very similar. While microequity financing has the potential to be beneficial and scaleable, it has not been implemented successfully for informal microenterprises. As we (the researchers, partner organizations and funders) did not know if such an intervention was feasible to implement, we decided to work with a small sample. Working within the constraints of a very small sample, we designed the study to collect high-frequency data

Bloom et al., 2013.

4.2.3 Treatment assignment and contract design

The 28 participants were randomized into two treatment arms: (i) the control group who continued to receive business-as-usual support from Buzz Women; and (ii) the treatment group who was offered a take-it-or-leave-it opportunity receive a microequity loan that facilitated the purchase of productive assets and working capital through a performance-contingent repayment schedule. The business-as-usual support from Buzz Women includes quarterly meetings or training sessions with Buzz staff that focuses on fostering entrepreneurship. The randomization was stratified based on the firm's sector of operation. Of the 28 firms in our sample, 21 are in the animal husbandry sector and seven are in tailoring sector. For the animal husbandry sector, we further stratify on above and below median of monthly business revenue earned by the firm. To get a more accurate measure of business revenue, we take the three month average. For the tailoring sector, we do not further stratify on above and below median revenue, as the sample size is too small. Table 4.2.1 presents summary statistics for a range of variables as measured at baseline. We observe balance on most of these variables across the treatment and control group.

The microequity loan offered a total sum of Rs. 100,000.[7] Firms were required to spend 70% of the financing amount on fixed assets and the re-

[7]This is a large financing amount in the setting that we work in. It is ≈ 11 times their monthly revenue, ≈ 1.6 times their total loan amount pending at baseline across all loans they have taken and ≈ 1.4 times their total fixed assets.

maining 30% on working capital. Repayments had two components: (i) a fixed payment of Rs. 1000; and (ii) a flexible payment of 15% of the monthly revenue (where that revenue is calculated using self-reported data and verified using a variety of monitoring mechanisms). Given the focus on fostering business growth we chose a longer duration of of 36 months (or three years) with a grace period of three months. All loans were individual liability loans.

The terms of the microequity loan contract were calculated by comparing it to the terms of a standard debt contract in the region. The standard contract we considered is a three-year contract with a 15% interest rate (compounded annually). YSB wanted to recover 30% of the principal in fixed payments; we therefore set the fixed payments to Rs. 1000 per month for a period of 33 months. To compute the revenue sharing ratio for the flexible payments, we projected revenues for firms in our sample and computed the sharing ratio required for our contract to closely resemble the total payments made in a standard debt contract.

4.2.4 Monitoring mechanisms

Costly state verification is a key theoretical challenge that can limit the implementation of microequity contracts (Townsend, 1978). Monthly repayments under the microequity contract is calculated based on self-reported revenues. In this section we discuss the monitoring mechanisms that we use to ensure revenue is verifiable. In the setting we work in we cannot observe perfectly our clients' revenues. This creates an incentive for firms to under-report since repayments are revenue-contingent. We take a range of steps to mon-

itor the accuracy of self-reports, and then test if the self-reported revenues are credible.

To start with entrepreneurs are required to self-report daily revenues. They could choose to do this using either (i) a digital app (called "MeraBills"[8]), or (ii) via text messages to their respective field officers. With the participants' consent, we use these reports to provide credible monitoring mechanisms to guard against systematic under-reporting. To verify these self-reported revenue numbers, we set up some sector-specific monitoring mechanisms.

i For those engaged in animal husbandry, entrepreneurs are required to submit weekly receipts that they receive from the dairy.

ii For those in the tailoring sector, we attach motion sensors to tailoring machines to record the the daily hours of operation.

iii As another check, we send "secret shoppers" to visit the entrepreneur in their workplace (and entrepreneurs will know in advance that this is a possibility) and check if the revenue earned from the transaction with the secret shopper is reflected in that day's revenue report.

To catch under-reporting, we flag issues that we see based on our monitoring systems. We then regularly monitor these flags to catch persistent under-reporting. Buzz is also leveraging its social capital to ensure women that women do not persistently under-report. In line with the monitoring mechanisms, the flags to catch under-reporting are also sector-specific.

[8]MeraBills is a digital app that helps entrepreneurs keep track of their business transactions and manage cash flow. Over 4000 users across India are using the MeraBills app.

i For entrepreneurs engaged in animal husbandry, self reported revenue should be equal to or greater than the dairy receipts (as dairy receipts do not capture non-dairy sales). We allow some room for recall bias and measurement error, but flag it if we see significant and persistent under-reporting.

ii For entrepreneurs engaged in tailoring, we reconcile self-reported data with sensor data. It is difficult to predict revenues from hours of machine usage. Orders for tailors sometimes take a few days to complete. For example, a machine may run for several days, but the revenue is reported only later when the customer pays for it. Further, different tasks require different intensity of machine usage (for e.g., repairs vs. embroidery). Therefore, we only use data from sensors to catch large and systematic under-reporting. For example, if a firm were to report zero revenues for an entire month but we saw that the tailoring machine was in use during that period, it would raise a flag.

iii For secret shoppers, we expect the daily report to be greater than the amount of the secret shopper purchase. If we see repeated omission by a particular firm, we raise a flag.

4.3 Data and Estimation

4.3.1 Data collection

We collect data from five sources. First, we conduct a baseline survey and two follow-up surveys. The surveys collect data on demographics, socioeconomic

variables, business outcomes like profit, revenue, investment and access to financial services, etc. The follow-up surveys are collected 18 months and 36 months after the intervention. The second source of data collection is phone surveys that collect data on key variables of interest on a quarterly basis. Thus, for these variables we have 12 rounds of data over the study period. Third, we collect daily data on revenue, expenditure, and profit. We have over 16 months of pre-intervention data for these variables and are continuing to collect these for the study duration (we have nine months of post intervention data so far). Fourth, we collect repayment data on a monthly basis. Lastly, we collect data on under-reporting based on the monitoring mechanisms discussed above. Data collection is still ongoing for this project.

4.3.2 Estimation Strategy

In this section we outline our strategy for testing the effect of the treatment on our outcome variables. Equation 4.1 presents the primary econometric specification, which pools data across across weekly measures (for daily self-reported data) or pools data across monthly/ quarterly rounds for the other variables:

$$Y_{ir} = \beta_0 + \beta_1 \cdot T_i + \beta_2 \cdot Y_{i0} + \gamma_r + \omega_s + \varepsilon_{ir}, \tag{4.1}$$

where γ_r represents time dummies and ω_s is a strata dummy.

In equation 4.1, the coefficient β estimates the Intent-to-Treat effects and can be interpreted as the average effect of being offered the treatment across follow-up rounds (denoted by week r). We denote T_i as an indicator for whether individual i was assigned to treatment, and y_{ir} as the outcome of interest for individual i in week r. In terms of additional controls, we follow advice in Bruhn and McKenzie, 2009 and include stratification dummies as controls in our main specification. Standard errors are clustered at the firm level. We adjust standard errors for clustering using the parametric Moulton correction factor.[9]

We estimate equation 4.1 for the direct measures of business performance and the secondary outcome variables using ANCOVA and conduct randomization inference. We cluster at the firm level, and resample according to the underlying stratification scheme. For direct measures of business performance, we also exploit the large time series of around 52 rounds of weekly pre-intervention data and 156 rounds of weekly post-intervention data.[10]

4.4 Results

4.4.1 Business performance

For microequity financing to improve business performance, it needs to be invested in the business. As per the study design, the financing amount was meant to be channeled towards fixed assets ($\approx$ 70% of the financing

[9]We did not pre-specify this, but include this adjustment given the small sample size. The standard errors do not change in a meaningful way with this adjustment.

[10]The daily self-reported data is aggregated to a weekly measure.

amount) and working capital ($\approx$ 30% of the financing amount). In Table 4.4.1 we study the effect on the accumulation of fixed and current assets. We use data from the quarterly phone surveys and estimate equation 4.1 using ANCOVA and randomization inference. We cluster at the firm level, and resample according to the underlying stratification scheme.

In column 1, we document a 53% increase in fixed assets (significant at the 10% level). The treatment effect on fixed assets is slightly lower than the amount an average firm invested in fixed assets using microequity assets.[11] This is because the control group has also borrowed and invested in their business, in this duration. An average firm in our sample has an inventory to fixed capital ratio of $\approx$ 2.5%. This is why we see such a large treatment effect in inventories in percentage terms. Columns 2 presents the results for the total current assets, which is positive but not significant. Columns 3 -5 show treatment effects for the various components of current assets. As expected, we see a positive effect on inventories (significant at 5%). The effect reflects a 275% increase. The large magnitude in percentage terms is due to a low inventory to fixed asset ratio.[12]

[11] Firms invested 70% of Rs. 100,000 in fixed assets.

[12] The average firm in our sample has an inventory to fixed capital ratio of $\approx$ 2.5%.

Table 4.4.1: **Treatment effects on assets**

	Fixed assets	Current assets			
	(1)	(2)	(3)	(4)	(5)
	Total	Total	Cash	Accounts receivable	Inventories
treat_ME	53.7*	1.3	4.9	-12.1	7.0*
	(28.9)	(16.4)	(3.6)	(8.6)	(3.7)
Observations	56	56	56	56	56
Number of firms	28	28	28	28	28
Mean Dependent Variable	101.8	35.6	8.1	19.3	2.6
SD Dependent Variable	81.4	56.4	11.4	34.8	2.3
RI test p-value	0.11	0.93	0.19	0.25	0.15
KS test p-value	0.21	0.38	0.21	1.00	0.10

Notes: The dependent variables are fixed assets, current assets. Fixed assets (in 1000 INR) are measured as the total value on all non-land fixed assets. Current assets (in 1000 INR) are short term assets that a firm expects to be converted into cash within one year. It includes all the cash / money that you use for the running of your business, inventories that you will sell, and any other short-term assets that you can convert into cash easily. Columns 3 presents the total current assets. Columns 3 to 5 present a break-up of current assets by category - Cash, Debt and Inventories. Cash is the estimated total value of cash in the business and household. Accounts receivable is the estimated value of debt a firm is expecting to receive from debtors. This includes money that a firm has lent and expects repayment for. Inventory is the raw materials, work-in-process goods and completely finished goods that are considered to be the portion of a firm's assets that are ready or will be ready for sale. The data for firm assets is collected on a quarterly basis. The exchange rate during the study period ranged from 72 to 85 INR per USD. "Treatment" is an indicator for being in the microequity treatment group. The results are pooled across survey rounds. Regressions include baseline controls, strata dummies, survey round dummies, with errors clustered at the firm level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table also presents p-values for randomization inference and the KS test. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

We next examine whether the microequity intervention had a direct impact on business performance. We use the daily financial data collected for firms to estimate equation 4.1. In Table 4.4.2, we aggregate the daily data at the weekly level and present results for the Revenue, Expenditure and Profit variables. The data is pooled across weeks and we include baseline controls,[13] strata dummies, and controls for report date, with errors clustered at the firm level.

In Column 1 of Table 4.4.2, we find a 58% increase in weekly revenues (significant at the 1% level). This is also significant using p-values by randomization inference and the KS test. The magnitudes are in line with the percentage increase we see for fixed assets. We also see a 68% increase in expenditure (significant at the 10% level). Expenditure reports do not include loan repayments. This is because firms report expenditure on a daily basis and do not know the daily loan repayment amounts.[14] Finally, we see a 56% increase in profits in Column 3.[15]

[13]We use the pre-treatment mean for each variable, which is measured using the long time series of pre-intervention data.

[14]We are collecting data on loan repayments to provide estimates of the effect on expenditure, including loan repayments.

[15]Profits are inferred in this data from revenue and expenditure reports.

Table 4.4.2: **Treatment effects on firm financials**

	(1) Revenue	(2) Expenditure	(3) Profit
Treatment	0.9***	0.4*	0.5**
	(0.3)	(0.2)	(0.2)
Observations	1344	1344	1344
Number of firms	50	50	50
Mean Dependent Variable	1.4	0.6	0.9
SD Dependent Variable	2.2	1.0	1.6
RI test p-value	0.03	0.06	0.08
KS test p-value	0.00	0.00	0.02

Notes: The dependent variables are Revenue, Expenditure and Profit. Revenue (in 1000 INR) is measured as the total amount earned from the sale of goods and services. Expenditure (in 1000 INR) is the aggregate of all expenses incurred by the firm. It includes wages of employees but does not include any wages or income paid to oneself. It also does not include loan repayments. Profit (in 1000 INR) is inferred as revenue less expenditure. The data for revenue and expenditure is collected on a daily basis and aggregated at the weekly level. The exchange rate during this period ranged from 72 to 85 INR per USD. "Treatment" is an indicator for being in the microequity treatment group. The results are pooled across weeks. Regressions include baseline controls, strata dummies, and controls for report date, with errors clustered at the firm level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table also presents p-values for randomization inference and the KS test. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

In Figures 4.4.1, 4.4.2 and 4.4.3, we present three empirical CDFs for revenue, expenditure and profit. We document a clear shift of the distributions to the right. In Appendix 4.F, Figure 4.F.1 - Figure 4.F.3, we also present the empirical CDFs for revenue, expenditure and profit prior to the intervention, using the 16 months of daily data. We see that the distributions looks very similar for all three variables.

Figure 4.4.1: **Empirical CDF for revenue**

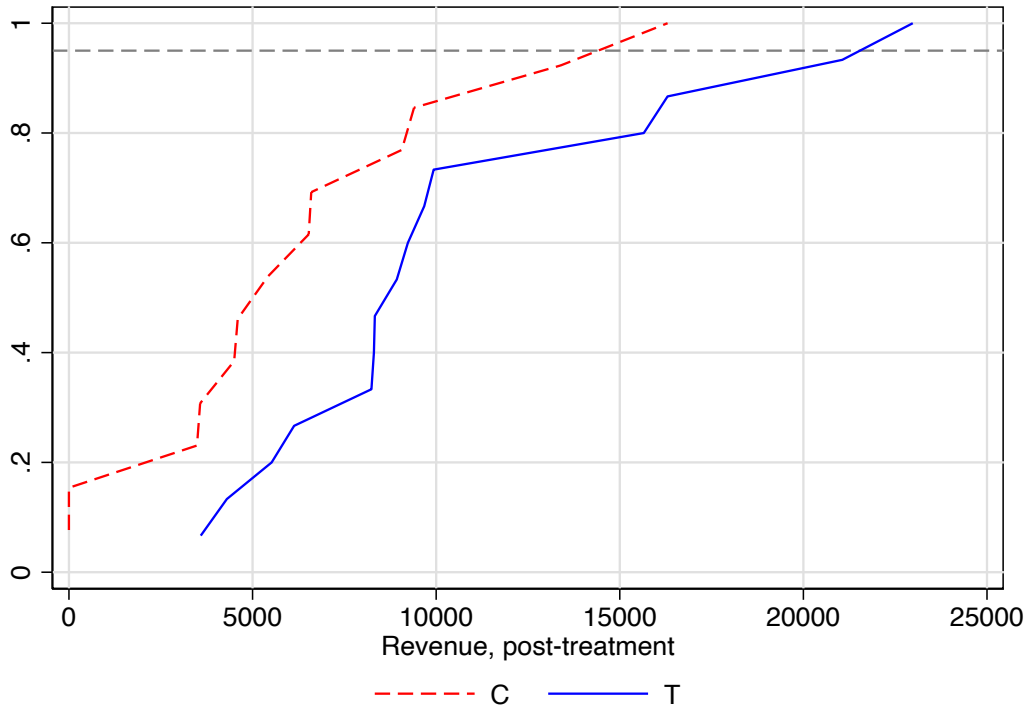


Figure 4.4.2: **Empirical CDF for expenditure**

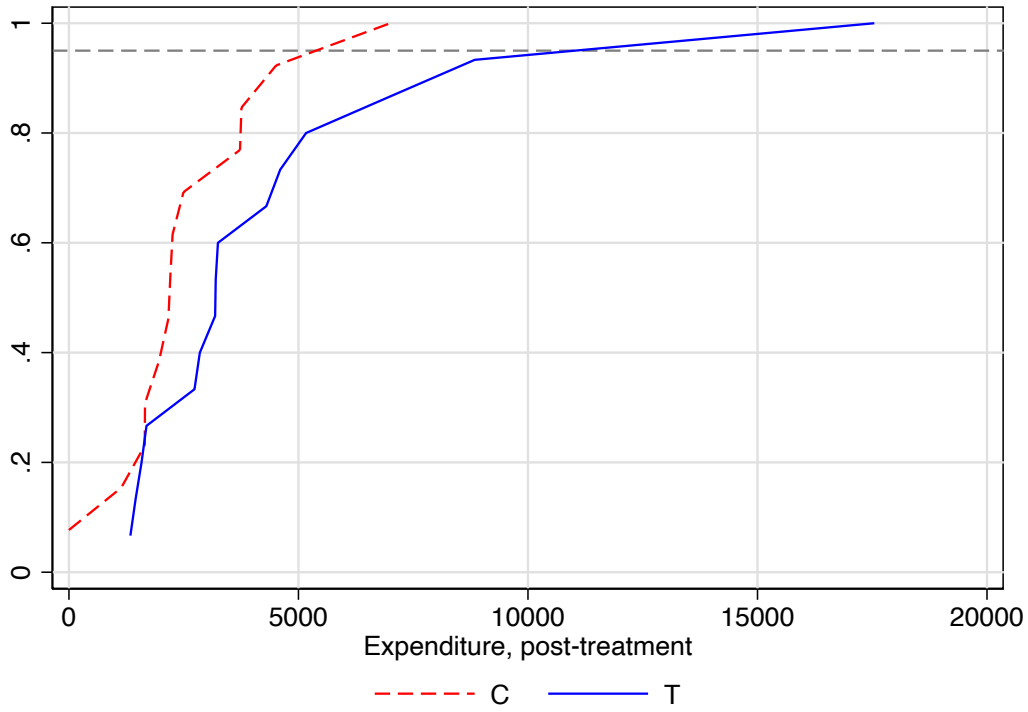
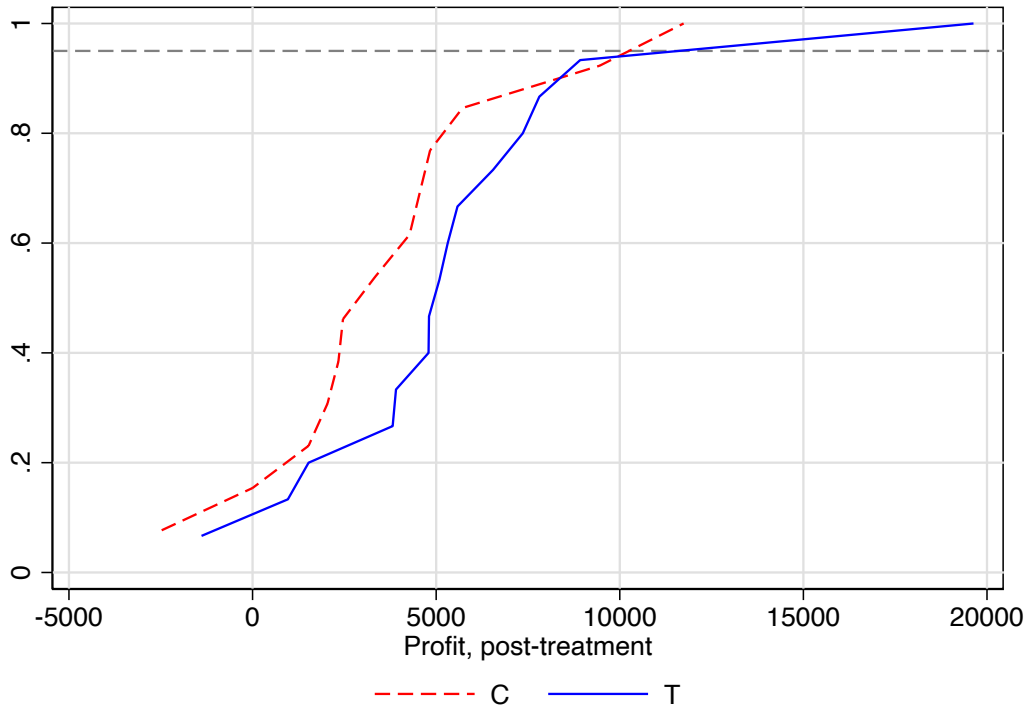


Figure 4.4.3: **Empirical CDF for profit**



Finally, we present non-parametric results on how treatment effects on revenue, expenditure and profit evolve over time. The rich daily data enables us to highlight how treatment effects evolve over time. In Figures 4.4.4, 4.4.5 and 4.4.6, we run kernel regressions using the daily financial data. The blue and red lines show trends in the pre-intervention period for the control and treatment group and as expected, track each other closely for all variables. The green and orange line present time trends for the control and treatment group in the post-intervention period. In Figure 4.4.4, we see a clear increase in the revenues for the treatment group and these effects are stable over time. We see these effects immediately after assets are provided. This is intuitive,

as firms mostly expand the number of assets they own. That is, firms in the animal husbandry sector buy more cows and firms in the tailoring sector, buy more sewing machines. Therefore, there is no period of “learning" how to use these assets. In Figure 4.4.5, we see an increase in expenditure in the post intervention period, but these effects take a few months to show. This is because firms in our sample stock inventory fairly infrequently and therefore, we do not expect to see large increases at the time assets are bought. In line with the treatment effects over time for revenue and expenditure, we see profits increase over time in Figure 4.4.6.

Figure 4.4.4: **Treatment effects on revenue over time**

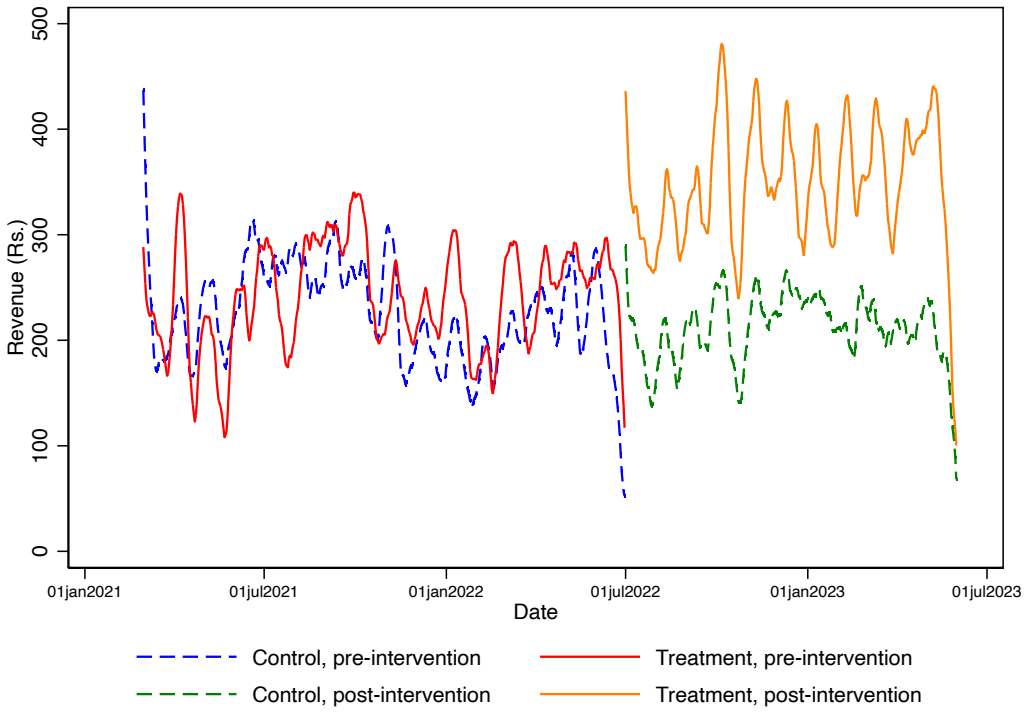


Figure 4.4.5: **Treatment effects on expenditure over time**

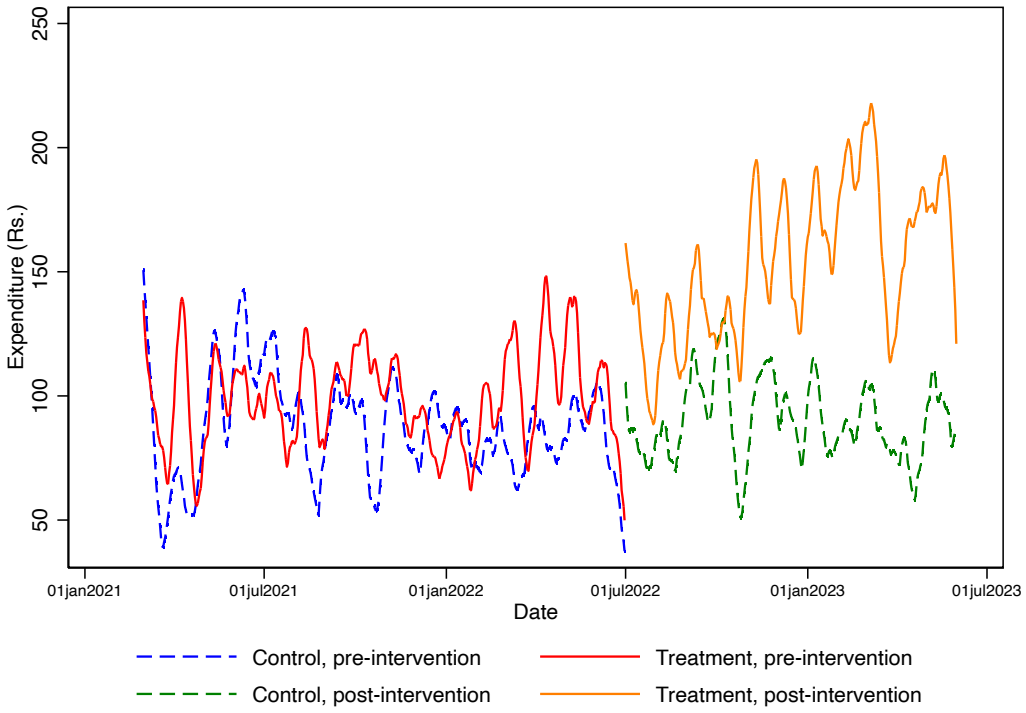
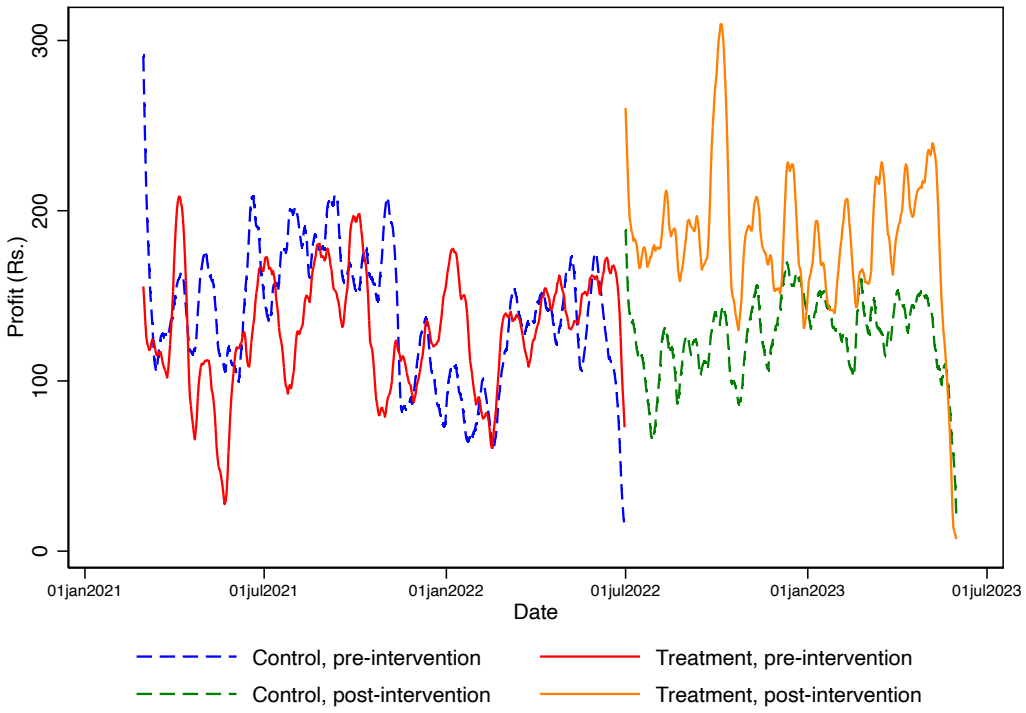


Figure 4.4.6: **Treatment effects on profit over time**



4.4.2 Microequity loan repayments

We begin by looking at the monthly repayments made by the entrepreneurs. In Figure 4.4.7, we illustrate repayment trends for the microequity contract. The thick solid brown line represents the average monthly repayment made by all firms in each month. The blue dots represent the average monthly repayment due in each month. If the dot lies below the thick brown line it would signify that firms are repaying less than the amount they are due to pay. The dotted lines illustrate (i) repayments made by each firm in the tailoring sector (dark blue), and (ii) repayments made by each firm in the

animal husbandry sector (light blue). To compare these repayments to a conventional debt contract we add two solid lines: (i) the repayment due each month if a firm was to hypothetically repay the amount invested over 33 months (dark green) and, (ii) the repayment due each month if a firm was hypothetically to repay the amount invested with a 15% interest compounded annually over 33 months (navy).

Nine months into the intervention, we see 100% compliance on repayment, that is, all firms repaid the amount due as per the contract. The blue dots in Figure 4.4.7 lie on the solid brown line indicating that all firms have made the full repayment each month. The solid brown line almost overlaps with the constant repayment (with no interest) line. If this trend persists over the 33 month period, this would imply that the lender recovers the money invested (in nominal terms). However, the solid brown line is below the constant repayment (with 15% interest) line.

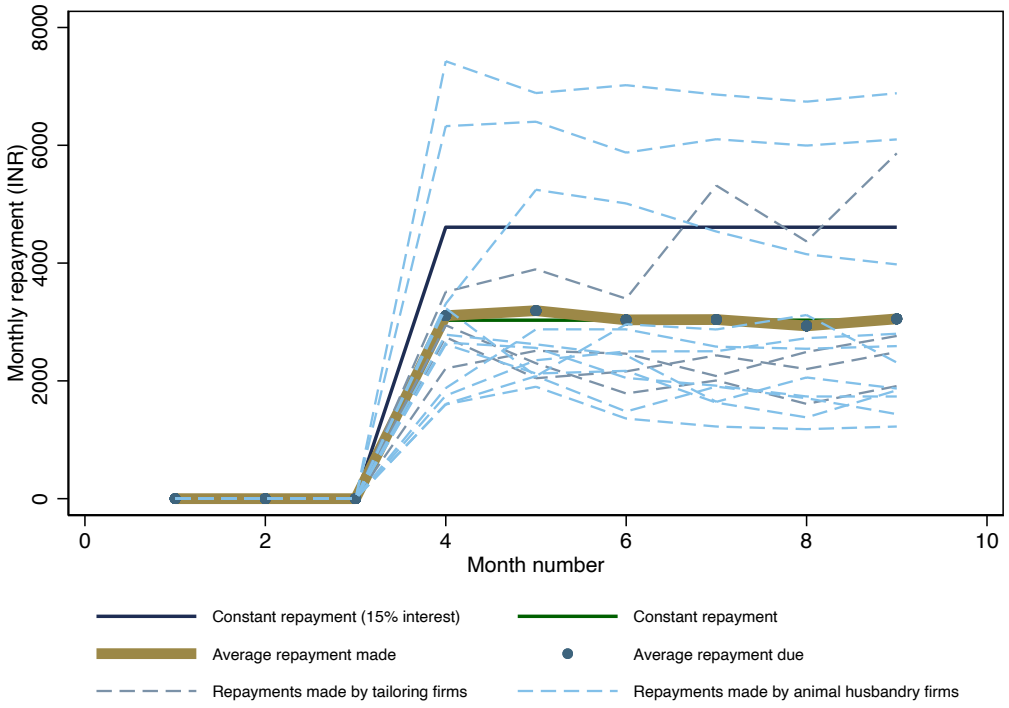
We also see a lot of heterogeneity in the repayment made by individual firms. Some firms repay significantly less than the constant repayment (with no interest) amount and some pay significantly higher than the constant repayment (with 15% interest) amount. We also see substantial variation in the monthly repayment due for each firm. This highlights the large fluctuations in monthly revenues, a common feature for microenterprises. Repayments being revenue contingent provides a cushion in months that firms have lower revenues. This relieves the pressure on firms to take on additional loans to repay the current amounts due (as is common in conventional microcredit contracts). In Appendix 4.D, we present supplementary graphs for cumula-

tive repayment trends.

Microequity contracts by design create an incentive to under-report revenues. While we see full compliance in repayments, we carefully look at whether firms are reporting accurately. In an informal economy, we cannot perfectly observe revenues and state verification is costly. Monthly repayments under the microequity contract is calculated based on self-reported revenues. But we verify these reports using three monitoring checks. First, all firms receive random secret shopper visits (with permission obtained from all participants in advance). In 18 out of 19 secret shopper visits, we verify that firms include the secret shopper's purchase in their daily report (in full).[16] Second, for firms in the tailoring sector, we use motion sensors (again, with the permission from participants in advance) for a subset of automatic sewing machines. This helps us catch gross under-reporting. For example, if firms report zero revenue but are using the sewing machine, this would raise a flag. We have not observed any flags in the data so far. Third, for firms in the animal husbandry sector, we collect dairy receipts from the firms are verify their self-reports. There has during the study been a change in the frequency of receiving receipts from the dairy (for bi-weekly to daily), which has made it harder to collect these receipts. We are looking at how best to collect these from entrepreneurs to verify reports. Overall, we do not observe any under-reporting of revenues.

[16]For the one case where the firm did not report the amount that was spent by the secret shopper we are uncertain if this was deliberate or a mistake. We continue to monitor this closely to see if there is a consistent pattern.

Figure 4.4.7: **Repayment over time (INR)**



4.5 Household accounts

Next, we provide suggestive evidence on household welfare. In Table 4.5.1 we present results for key household outcomes. In column 1, we see an increase in household income for treated firms (with a p-value of 0.10; albeit not significant). From Columns 2 and 3, we see that this does not translate to an increase in household consumption or household saving. It is possible this money is being channeled towards other household businesses. We will continue to monitor these outcomes as they have immense relevance for welfare.

Finally, we look at effects on household debt. Given high interest rates, rigid repayments and short maturity of average debt based contracts, high levels of debt are very prevalent. There is limited work on the debt undertaken by informal microenterprises to repay microcredit and other loans. Microenterprises have large fluctuations in income and often cannot repay loans with business profits. Default is not an option for most firms, given this limits the ability to borrow in the future. Thus, firms often take new loans to repay older loans. By allowing for performance contingent repayments, microequity contracts can limit this kind of debt loop. In Column 4, we see a 30% decrease in the loans taken (albeit not significant) for the treatment group. Given high interest rates, rigid repayments and short maturity of average debt based contracts, we believe this has positive effects on household welfare.

Table 4.5.1: **Treatment effects on household outcomes**

	(1)	(2)	(3)	(4)
	Total HH income	Total HH consumption	Savings	Loans
Treatment	7.5	0.1	0.3	-16.9
	(4.7)	(3.0)	(7.5)	(18.3)
Observations	56	56	56	56
Number of firms	28	28	28	28
Mean Dependent Variable	5.4	11.0	29.8	50.5
SD Dependent Variable	10.5	10.9	30.8	69.0
RI test p-value	0.10	0.96	0.98	0.40
KS test p-value	0.00	0.34	0.53	0.39

Notes: The dependent variables are total HH Income, total HH consumption, savings and loans. Total HH income (in 1000 INR) is the total income for the household excluding the income earned by the entrepreneur. This includes income from household businesses, casual labor, fixed wage work, salary, transfers from family/ friends or other sources. Total HH consumption (in 1000 INR) is aggregated from a detailed 30 day recall consumption module. Savings (in 1000 INR) includes total saving in the household from bank accounts, Self Help Groups (SHGs), government schemes, formal institutions, informal institutions, post office, cash, loans that the firm has given to others and other sources. Loans (in 1000 INR) includes the total outstanding household borrowing from family, friends, banks, microfinance institutions, other financial institutions, moneylenders etc. For the treatment group, this includes the microequity loan. The data for household outcome variables is collected on a quarterly basis. The exchange rate during the study period ranged from 72 to 85 INR per USD. "Treatment" is an indicator for being in the microequity treatment group. The results are pooled across survey rounds. Regressions include baseline controls, strata dummies, survey round dummies, with errors clustered at the firm level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table also presents p-values for randomization inference and the KS test. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

4.6 Conclusion

The results of this paper have lessons for both policy and research. In India, micro-firms represent over 97.88% of the population of firms (Hsieh and Olken, 2014) and face major challenges in sustaining and expanding. The lack of sustainability of these microenterprises is commonly attributed to the lack of access to functional credit markets (De Mel et al., 2008; Banerjee and Duflo, 2014) as well as being exposed to idiosyncratic income shocks

(Samphantharak and Townsend, 2012). Rigid debt contracts limit microenterprises from undertaking 'high-risk/high-return' investments. Lack of insurance against exogenous shocks further accentuates this problem. Fostering growth and profitability for these firms in a financially sustainable manner has remained an open question.

Based on current results, our interpretation is that a big-push microequity financing can improve business performance and key livelihood indicators, while also recovering the initial investment amount for future investments. Working with a sample of 28 firms that are representative of firms in the region we find a high demand for microequity financing among the selected sample. We document sustained improvements in business performance and accurate reporting of revenues. If current repayment patters were to continue, we expect investors are able to recoup the initial investment amount (but not earn any additional interest).

Depending on how these results change as we collect further data, we are exploring options to scale up this intervention. This merits careful consideration of a suitable sample and setting. YSB is in discussions with some state governments in India that may be interested in piloting this at a larger scale. We are also looking to explore innovations in the digital credit space in India. For example, digital footprints through mobile money platforms could be leveraged to monitor revenues which would largely improve the east and cost of implementation. Overall, the lessons from this paper can inform a scale-up of microequity financing in various settings.

Appendix

4.A Setting

In this section, we compare our group of Buzz entrepreneurs to the larger Buzz sample. From a survey in 2019 (two years prior to the intervention), we have details on a larger sample of about over 300 firms affiliated to Buzz. Of these, five are currently in our sample. In Table 4.A.1, we compare the broader group of 300 to the smaller group of 5 from our current Buzz sample. As can be seen from the sample means in Columns 2 and 4, the samples look very similar. Thus, while we chose our sample of 28 firms very carefully to be suited for a scale-up, in effect they look quite close to the average Buzz entrepreneur.

Table 4.A.1: **Comparing the microequity sample to a more general sample (INR)**:

Baseline characteristic	Comparison Sample		Microequity Sample	
	Obs	Mean	Obs	Mean
Age	310	37.22	5	36.40
Has children	306	0.94	5	1.00
Number of children	288	1.97	5	1.80
Lives in joint family	308	0.20	5	0.60
Family helps in HH chores	308	0.44	5	0.20
Has smartphone	310	0.46	5	0.60
Employed in animal husbandry	315	0.09	5	0.20
Employed in Tailoring	315	0.41	5	0.80
Monthly business revenue	310	12,097	5	10,400
Monthly business revenue, good	284	14,785	5	13,200
Monthly business revenue, bad	284	7,415	5	7,600
Monthly business profit	310	5,923	5	7,000
Months running business	310	41.70	5	45.60
Number of employees	310	0.39	5	0.00
Keeps business records	310	10.71	5	0.40
Loan amount	99	57,551	3	40,000
Amount desired for expansion	284	87,993	5	130,000

Notes: The first two columns correspond to the mean value of the variable for the treatment and control groups. The third column gives the total number of observations. The fourth column gives the differences in means normalized by the standard deviation in the control group. Finally, the last column provides the corresponding p-value on the test of equality.

4.B Data collection

In this section, we detail the various types of data collected. Figure 4.B.1, lays out the timeline and frequency of data collection.

The first two sources of data are used to study the effects on business performance, we collect daily financial data starting March 2021. We have 16 months of pre-intervention data and as of now, ten months of post intervention data. Firms report daily revenues and expenditures to field officers. They have the option of reporting via WhatsApp, text message, a phone call or a digital app. Almost all have chosen to report by WhatsApp. All firms in our sample have attended Buzz's entrepreneurship bootcamp. This was done to ensure that firms were aware what components to include in revenue and expenditure estimates. Daily reports also minimize the amount of recall-bias in these numbers. As seen in Figure 4.2.1 the coefficient of variation in our revenue estimates is significantly lower than that documented in the literature (Fafchamps et al., 2012; Banerjee et al., 2015a). The second source of data is the quarterly phone survey that collects data on key variables to study business performance. This includes, assets, investments, loans, household income, employment etc. We track these on a quarterly basis to be ab;e to study the time trends for these variables.

The third and fourth sources of data correspond to repayments. In the post intervention period, we collect monthly data on the repayments made by firms. The fourth source relates to verifying the self-reported daily data to ensure that the repayments due are accurate. As discussed in Section 4.2,

we have multiple sources of general and sector-specific monitoring.

The last source of data is the field survey at a baseline and two follow-ups through the intervention period. This collects extensive data on firm and household outcomes.

To summarize the various data collected, Table 4.B.1 details our key outcome variables and the corresponding dataset.

Figure 4.B.1: **Timeline for data collection**

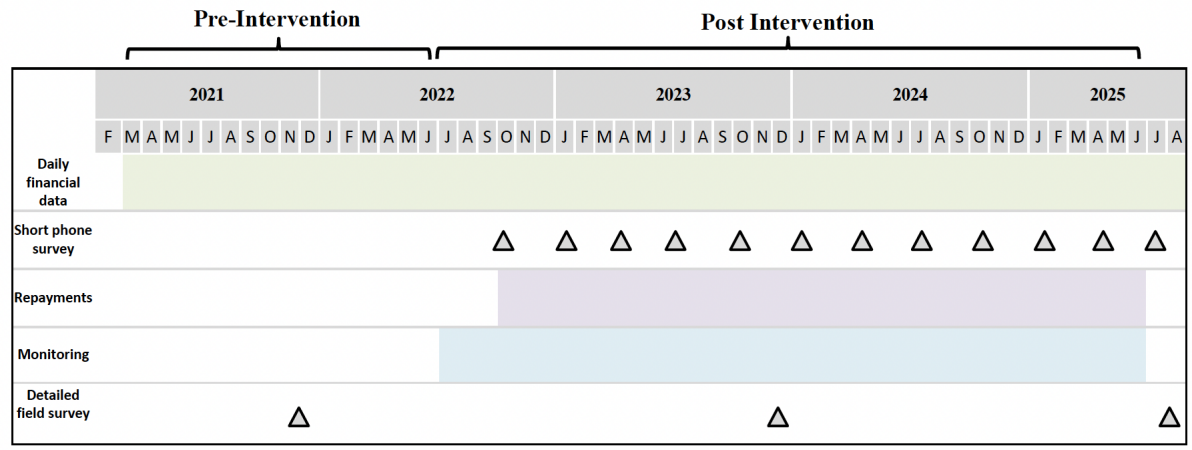


Table 4.B.1: **Outcome variables**

	Variable description	**Data source**
Panel A : Direct measures of business performance		
Revenue	Weekly measure of revenue	Daily self-reported data
Expenses	Weekly measure of expenses	Daily self-reported data
Profit	Weekly measure of profit	Daily self-reported data
Repayment	Total amount repaid per month	Monthly repayment data
Net profit	Total monthly profit net of microequity loan repayment	Daily self-reported data Monthly repayment data
Panel B : Secondary outcomes		
Compliance	Weekly measure of compliance on daily reports	Daily self-reported data
Work days	Number of days worked per week	Daily self-reported data
Total HH consumption	Calculated using 30 day recall	Quarterly phone surveys
Employment	Number of workers employed	Quarterly phone surveys
Fixed capital investment	For HH or business	Quarterly phone surveys
Missed payment	Difference between payment due and payment made	Daily self-reported data Monthly repayment data
Misreporting	Difference between self-reported revenue and monitoring revenue	Daily self-reported data Monitoring data

4.C List of financed assets

In this section we provide details on loan utilization for the treatment group. Firms spent $\approx 70\%$ on fixed assets and the remaining $\approx 30\%$ on working capital. Details are listed below:

1. 2 cows and cow-feed
2. 2 cows and cow-feed
3. 2 cows and cow-feed
4. 2 cows and cow-feed
5. 2 cows and cow-feed
6. 1 cow, shed repair and cow-feed
7. 1 cow, shed repair and cow-feed
8. 1 cow, shed repair and cow-feed
9. 1 cow, shed repair and cow-feed
10. 1 cow, shed repair and cow-feed
11. 1 cow, shed repair and cow-feed
12. 1 tailoring power machine and shop repair
13. 1 tailoring machine and materials purchase
14. 1 tailoring machine and materials purchase
15. 1 Zig-zag machine and materials purchase

4.D Repayment

In this section, we provide some additional graphs on cumulative repayment trends to supplement the results on repayments in Section 4.4. In Figure 4.D.1, we plot the cumulative repayment trends for the average firm in the sample. The solid brown line presents the repayments made by the firm over time. The blue dots show the repayment due over time. As can be seen, we have full compliance in repayment. The blue green lines show the constant repayment lines with 15% and 0% interest. The 0% interest line almost overlaps with the repayment paid line. The dotted gray and blue lines show repayments made by each firm in the animal husbandry and tailoring sector.

Figure 4.D.2 shows the cumulative repayment made by the average firm. The dotted orange and red lines show the 75th and 25th percentile values for the repayments made. Figure 4.D.3 and Figure 4.D.4 show the repayment trends broken down by business type and by individual firms.

Figure 4.D.1: **Cumulative repayments over time (INR)**

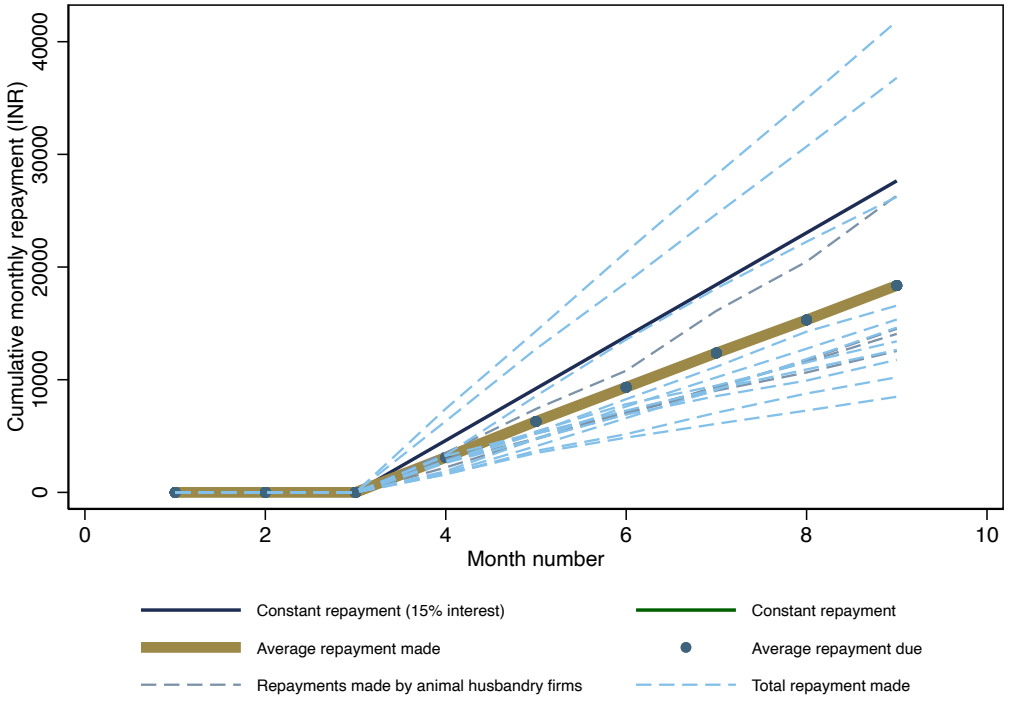


Figure 4.D.2: **Repayment by the average firm (INR)**

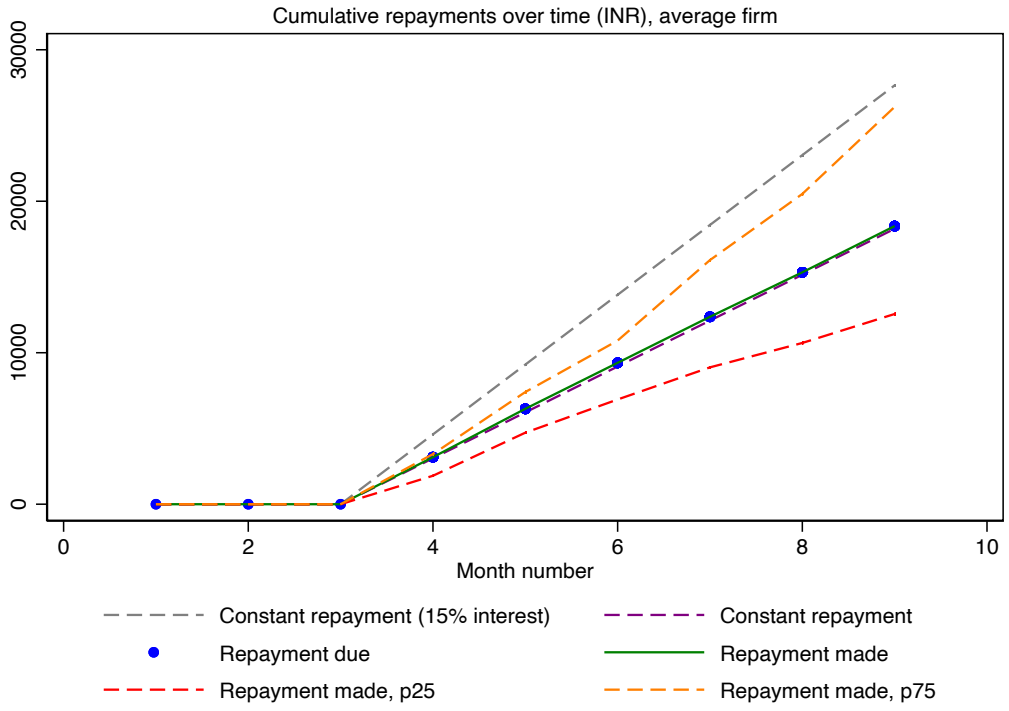


Figure 4.D.3: **Repayment by the average firm by business type (INR)**

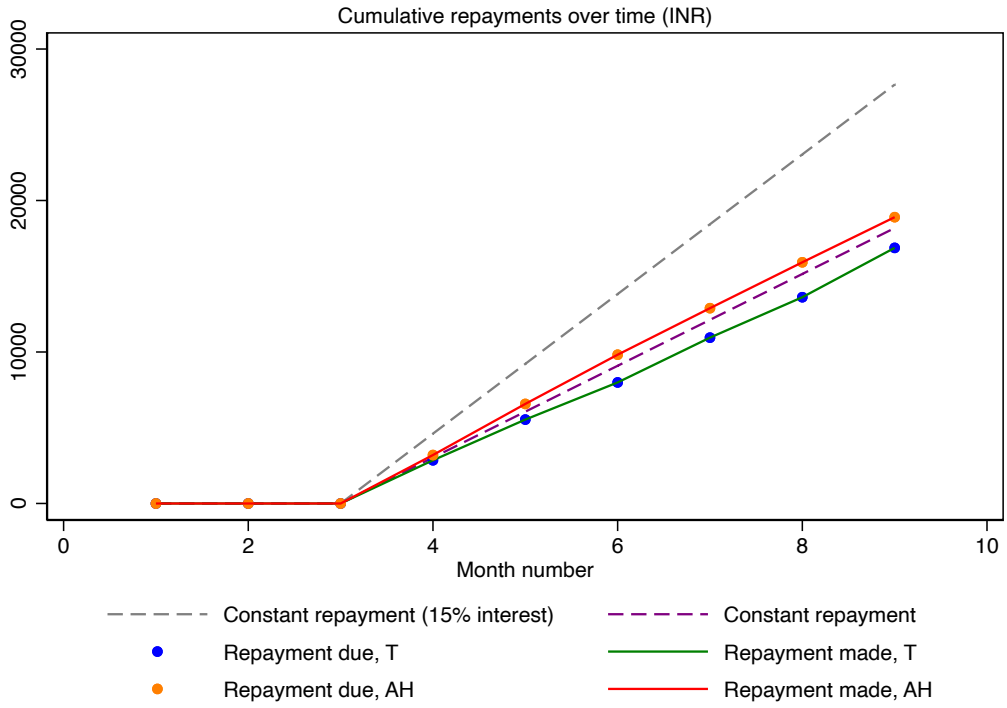
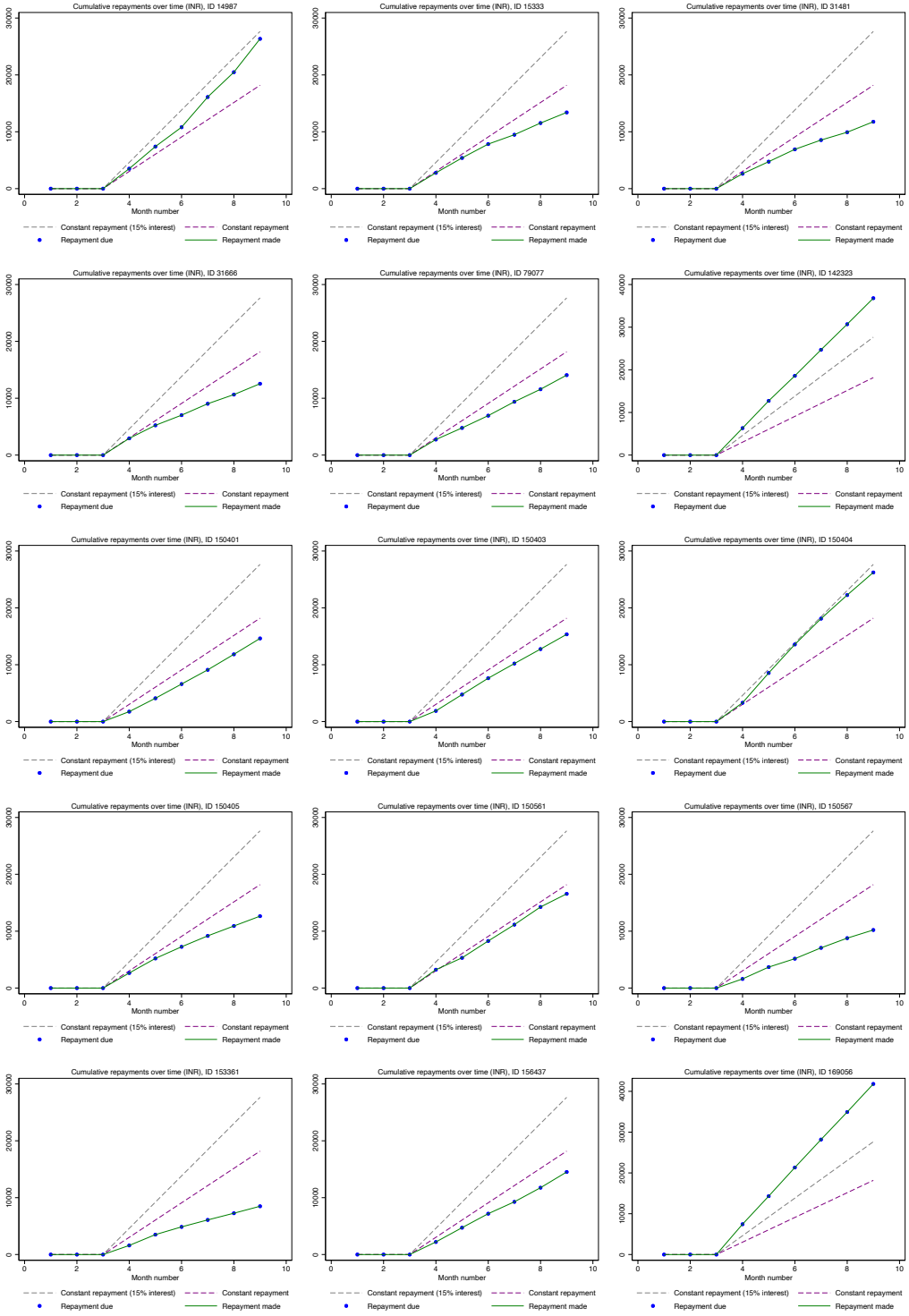


Figure 4.D.4: **Repayment by individual firms (INR)**



4.E Other outcome variables

In this section we present results on other outcome variables of interest. Table 4.E.1 presents results on employment outcomes. We do not see any significant increase in employment, despite the large improvements in business performance. As is common in informal settings, we see a larger increase in unpaid employees or family help (Column 2) than paid employees (Column 1). A quick back of the envelope calculation, reveals that this makes economic sense as the average monthly profit (excluding loan repayments nd any payment to self) is not sufficient to pay the wage for an additional employee.

Table 4.E.1: **Estimation using ANCOVA (INR)**

	(1) Paid employees	(2) Unpaid employees
Treatment	0.03	0.23
	(0.04)	(0.28)
Observations	56	56
Number of firms	28	28
Mean Dependent Variable	0.00	1.50
SD Dependent Variable	0.00	1.14
RI test p-value	1.00	0.42
KS test p-value	0.97	0.77

Notes: The dependent variables the number of employees. Columns 1 and 2 present results for paid and unpaid employees. This includes both part time and full time workers. “Paid" only includes people wjo are paid to work in the firm. It does not include family members.“Unpaid" includes people who are involved in the business but are not paid to do so. This includes family members who help in the business. The data is collected on a quarterly basis. “Treatment” is an indicator for being in the microequity treatment group. The results are pooled across survey rounds. Regressions include controls for strata dummies, survey round dummies, with errors clustered at the firm level. Regressions do not include baseline controls for employment variables as this data was not collected at baseline. “Mean DV” and “SD DV” are the mean and standard deviation of the dependent variable among the control group. The table also presents p-values for randomization inference and the KS test. Significant at 90% ($*$), 95% ($**$), 99% ($***$) confidence. Standard errors in parentheses.

4.F Pre-treatment trends

We also plot CDFs for revenue, expenditure and profit by treatment status in the pre and post treatment periods. As expected, we do not see any significant differences in the distributions in the pre-treatment period.

Figure 4.F.1: **CDF - Revenue in pre-treatment period (INR)**

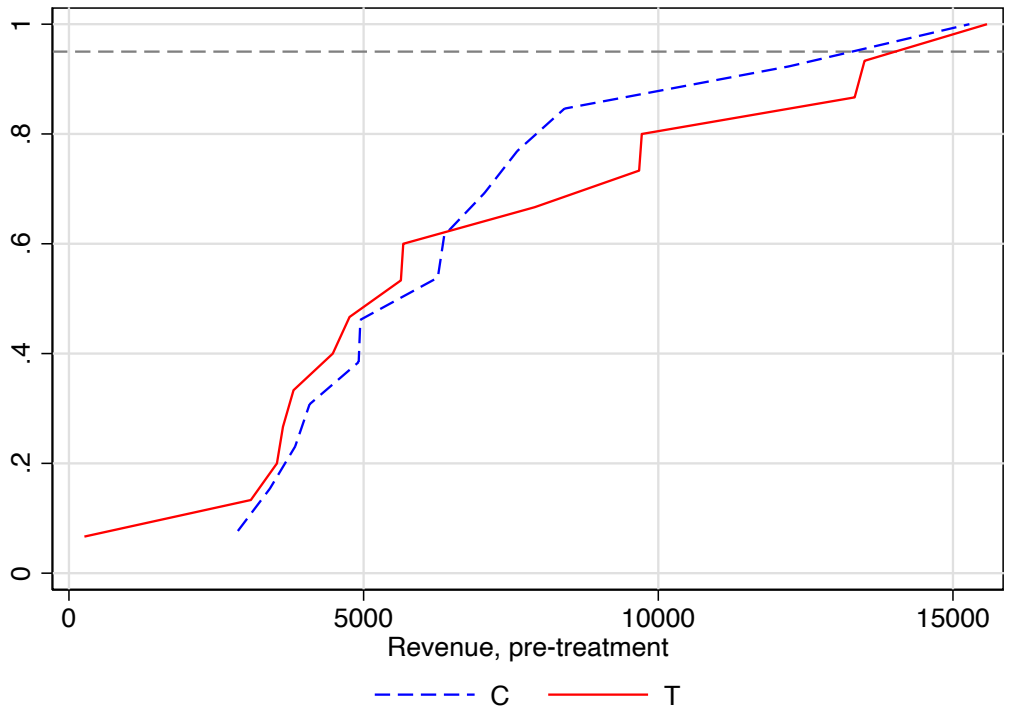


Figure 4.F.2: **CDF - Expenditure in pre-treatment period (INR)**

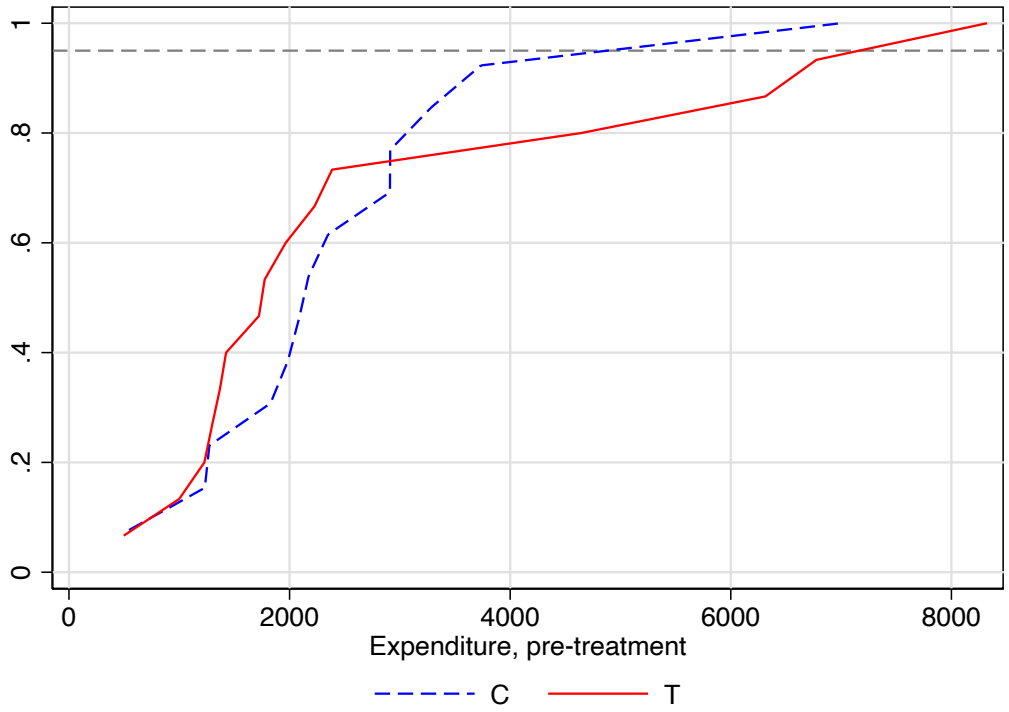
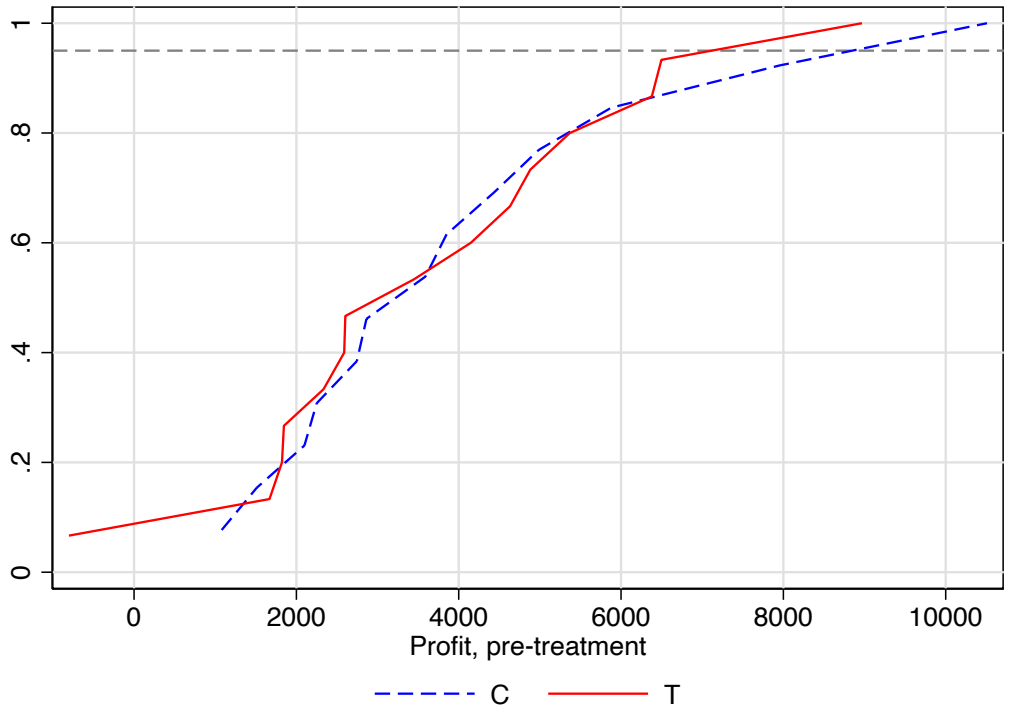


Figure 4.F.3: **CDF - Profit in pre-treatment period (INR)**



4.G Microequity contract explanation session script

This section provides the script for the contract explanation session. Since this is a novel contract that firms in the region are not familiar with, we put in a lot of effort to ensure that firms understood the contract they were signing.

4.G.1 Understanding a Micro Equity Contract

The facilitator Introduces the team and others, they lay the objective for the meeting. (15min) Good morning/afternoon everyone. We have gathered here today since you have been selected to receive a unique kind of finance. I am here to explain the details of it and answer any questions that you may have. As you all know we have been partnering with Oxford university for a research programme and you have been attending bootcamps on business programs. As part of the research, we have selected you to receive this unique funding. For this program, YSB will be the lending partner and the Buzz Women will be the implementing partner. As you are the first group of entrepreneurs ever to receive this, there is also a responsibility on your part to be honest with us about the data so that it will help Oxford to build a similar lending product for others in future.

Through this meeting we can understand how microequity loans work and what are the potential benefits of micro equity. Topics that will be covered in the session are as follows:

1. Why we want to invest in your business
2. How we will invest in your business
3. What is microequity
4. Understanding microequity contracts
5. Your responsibilities
6. Research on microequity

4.G.2 Why we want to invest in your business

(note to facilitator - Be positive, inspiring and motivating) We have been working with you for some time now to help you develop your business. We chose you because you are strong and impressive women who want to grow your business. You have been running a stable business for a long time and have a clear and sound business plan. To grow a business you need training, finance and support. We have already invested in training and support, now we would like to invest in your business by providing you finance. We believe in your business potential and want to see you become an even more successful entrepreneur.

4.G.3 How will we invest in your business?

We would like to provide you funding up to Rs. 1 lakh to invest in your business. We would like you to use this money to invest in asset and buy inventories for your business.

Invest in asset:

We will work with you to buy an asset that will help you grow your business. For the tailors in this group, this can be a sewing machine or an embroidery machine, while for animal husbandry entrepreneurs, this can be a cow or building a shed for the cows. You can also choose any other asset that will help your business grow. You know your business best!

Buy inventories:

In addition, we would like you to invest in inventories for your business. For tailors, this can be cloth, thread etc. For animal husbandry entrepreneurs, this can be cow feed etc. The goal is to channel this money in the most productive manner into your business. This funding will be provided via "microequity contracts". So let us now understand what we mean by "microequity".

4.G.4 What is Microequity?

The microequity contract structure is more flexible than traditional microcredit loans. The payments are contingent upon your business income and will be repaid over a three-year term.

Performance contingent repayments:

Every month you will repay a fixed amount of Rs. 1000 and a flexible amount that equals 15% of your monthly income. We understand that your business income fluctuates a lot. In some months you do well and earn high incomes. However, in some months you may not do as well and earn low

incomes. We have designed a repayment structure that allows your business to grow.

You may be familiar with microcredit contracts, or standard loan agreements. These are contracts where the investor provides the entrepreneur money that is to be repaid using a fixed (and rigid) repayment schedule. Having to pay a fixed amount every month can be a big burden, especially in months that you earn low incomes. Having to pay a fixed amount every month also makes it difficult for you to invest in large high-risk and high-return investments.

To overcome these problems, we offer a microequity contract that is more flexible. In months that you do well, you repay more. In months you don't do well, you can repay less. As you can see, in the microequity model, your repayments depend on how well you do. If you do well, the investor (YSB) gets back more money. If you don't do well, the investor gets back less money. Thus, we also have a stake in your business. Buzz will work with you to help you grow your business. We provide you training, money and support. This is why we call it equity!

Three-year repayment period:

We understand that it takes time for your business to grow. Very often, microcredit contracts or standard loan agreements have short repayment periods. This forces you to focus on making repayments rather than focussing on growing your business. In the microequity model we spread the repayments over a three-year period. This ensures that you are not compelled to

repay large amounts immediately.

So let us revise what we just learnt! What are the advantages of microequity over a standard loan?

1. Use the money to invest in your business: The money will be invested directly in your business, as per your business plan/
2. Flexible repayment: We have designed the contract to ensure the repayment is not a burden on you. The repayment amount depends on your monthly income.
3. Long duration contract: The duration given for the repayment is long. This ensures that you can spread the repayment over a longer period and focus on growing on your business.

The facilitator will pause and encourage the group to ask if they have any doubts and clarify. the facilitator will should give 5 mins on this topic.

The facilitator: Now we will understand how the payment is done, how to calculate the interest to be paid, what will be considered as security and how will we monitor the data.

Before we look at microequity contracts in detail, let us spend five minutes discussing what we mean by income.

Income is the money received from the sale of goods and or services. This includes payment in the form of cash GPay, PhonePe and PayTM. The payment received will be included in the monthly income only when you actually receive the money. For example, if a customer buys a product from

you today, but pays you for it next month, the payment will be counted in next month's income.

Now, let us consider some examples.

Scenario 1:

A customer wanted a saree blouse to be stitched which costs around Rs., 400rs. The entrepreneurs promised the customer that they would give the finished product in two days. Two days later the customer collects the saree blouse and pays via was ready to pay the amount through GPay. How will this be, how should we consider this? Answer: It should be considered as a cash transaction; on the day the entrepreneur receives the payment.

Scenario 2:

Customer X gave a piece of cloth to be stitched into a dress for the festival in the coming month. She agreed to make the payment after the festival. One month later customer X makes the payment, as promised. When should the entrepreneur include the payment in her monthly revenue?

Ans: The entrepreneur should consider the payment on the day she receives the amount and not the day when she received the order from the customer or delivered the order to the customer.

Scenario 3:

A customer wanted to buy 1ltr of milk worth 30rs, as the customer is a petty shop owner, he offered to give a credit for 30rs in his shop. how will you consider this?

Ans: This will not be considered as cash payment, as this becomes a barter or exchange system.

4.G.5 Understanding microequity contracts

In this section, we will discuss all the features of a microequity contract., It is particularly important you understand what microequity contracts are. Please stop us and ask questions at any time.

Loan amount

You can take a loan for any amount up to Rs. 1,00,000 (one lakh rupees).

Duration of contract

The loan duration is three years or 36 months.

Deposit

When you sign the contract, you must pay a deposit of Rs. 1000. This will count towards your loan repayment.

Grace period

You do not need to make any repayments for the first three months. We want to give you some time to grow your business before you have the pressure of making repayments. You will start making the payment only after the 3rd month, this acts as a buffer for you to settle down in the business and have a steady growth. From the 4th month you will have to make repayments.

Repayment schedule

As per the contract, your monthly repayment will have two components. A fixed payment of Rs. 1000 every month and a flexible payment which is 15% of your monthly income.

Now, let us take some examples to understand how repayments work in microequity contracts.

Example 1) If you monthly income for June is Rs. 4000, you are expected to pay Rs. 1000 (fixed amount) + Rs. 400 (10% of 4000) = Rs. 1400 for the month.

Example 2) For those months when you make no revenue, you are expected to pay only the fixed amount: Rs. 1000 (fixed amount) + Rs. 0 (10% of 0) = Rs. 1000 for the month.

We have designed this repayment structure to reflect the repayment capacity of the borrowers. We do not want to burden you to pay back large amounts when your business is not doing well. This is a very flexible method of repayment.

Ownership of asset: Ownership of asset:

You own your business, and you own your new asset/ new inventories. You are responsible for maintaining your asset in good condition.

Collateral/ Security

The asset you purchase will belong to you. However, in the event of a default the lender (YSB) has the right to repossess the asset.

Calculating repayment amounts

The repayment amount will be determined based on the daily reports you provide. You must record your daily income and expenditure every day. You can enter this information in the MeraBills app, or you can report it to your GF via WhatsApp, a text message, or a phone call. We will use the daily data you provide to calculate your monthly repayment amount.

You must remember that we are placing a lot of trust in you by offering these flexible microequity contracts. Buzz in working with you over a period of three years to help your business grow. The only way this project will succeed, is if you honestly report your income and expenditure.

We will have some mechanisms to check the reports you provide. These checks will depend on your business sector: For tailoring: The sewing machines will be attached with a sensor, this will help us in understanding how long the machine was in use. Based on this we can estimate how many clothes have been stitched and how much income has been earned. We will also have secret shoppers who may visit your store and buy something from you. We will then check that you have reported the income earned in your daily reports. For Animal Husbandry entrepreneurs: You will have to present the receipts received from the dairies for the milk sold to them. You will also have secret shoppers who visit you from time to time and buy milk from you. We will then check that you have reported the income earned in your daily reports.

Repayment dates

Repayments will be due on the 15th day of the next month. On the 5th

day of the month, we will inform you of the amount you need to pay for the last month. We will send you a reminder on the 10th day of the month. You can make the payment via cash, bank transfer, or PayTM.

For example, the payment for the month of June will be due on 15th July. On 5th July we will inform you how much you need to pay. On 10th July, we will send you a reminder.

The facilitator will pause and encourage the group to ask if they have any doubts and clarify (10mins)

The facilitator: Now we will have a look at the different situations that could occur during the 36 months of the contract period. Cases of theft and loss (15mins)

You must inform the GF (Gelathi Facilitator) and YSB team within 24hrs of the loss/ theft. All relevant contact details are in the one pager provided to you. You should provide all the necessary information and details to your point of contact. The YSB team will visit the place and conduct an inspection.

Case of Default

If you are unable to make payments, you must immediately inform the GF and YSB representative. All relevant contact details are in the one pager provided to you. We will provide you advice and guidance to ensure you do not default on the microequity contract. In the event, we cannot avoid default, Buzz and YSB will work with you to handle default proceedings. YSB will have the right to repossess the asset you have bought with the

microequity loan. They will work with you to recover (what is possible) from the outstanding loan amount. YSB may also charge you a default interest of 1%.

Making major business decisions

You must inform us of any changes you make to your business. We have invested time and money in your business and therefore during the repayment period, you must inform us before you make any major business decisions. Major decisions include, expanding your business, changing the nature of your business, shutting your business down or changing ownership of business.

Examples:

1. Within your main line of business, you can sell more goods or services from your shop/ business location. For example, as a tailor you can stitch skirts in addition to blouses. As an animal husbandry entrepreneur, you can sell milk to general customers in addition to the dairy. You do not need to inform us of this.

2. You are not allowed to hand over the business to friends and relatives ex: my daughter will take care; my aunt will look after the business. If you choose to do this, you must consult us.

3. You are not allowed to shift your primary business to a different business. like; a tailor becoming a vegetable vendor. If you choose to do this, you must consult us.

4. You are allowed to take a loan but you will have to inform the GF and

the YSB team about the type and value of loan you are taking.

5. You must consult and inform The GF and YSB before you shut down your business.

(the facilitator will encourage the group to ask any questions and clarify them. the facilitator will conclude the programme with a quiz game and if any wrong answer is given, they will explain to the entrepreneurs why were they wrong) Quiz time - 30min

4.G.6 Your responsibilities

1. You must attend all the bootcamps for the microequity project.
2. You must attend all the training sessions organised by Buzz for the microequity project. In these training sessions we will discuss your business progress and help each other solve business related problems. In case of emergency, you are exempted from any of the training and bootcamps.
3. You must record and report your daily income and expenditure numbers. Your monthly repayments depend on these reports.
4. It is your responsibility to be honest with us and report these numbers correctly.
5. Maintain (and if needed, repair) your asset.
6. Inform us about loss/ theft of asset
7. Inform us about major business decisions

4.G.7 Value of Microequity research

As you are the first group of entrepreneurs ever to receive this, there is also a responsibility on your part to take part in this program in good faith. Buzz, YSB and the University of Oxford want to learn from your experience and build a similar lending product for others in future. We want to identify and help many more successful businesswomen like you. we value your feedback through the project and are excited to work with you.

Hypothetical Calculation questions 1) Lakshmi has a tailoring business, she took a loan of 50,000.00rs to buy a zig zag machine, this has helped her boost her revenue. She logged in 7000 of revenue that month. How much should she pay back?

Ans: revenue earned for the month 7,000.rs Interest on the revenue (10Fixed amount for the month 1,000.rs Total amount to be paid for the month is 1,700.rs

2) Shabina has 2 cows and 1 buffalo; she took a loan of 70,000.00 and bought 2 calves (cow and buffalo). Due to unknown reasons, she loses her milking cows and her revenue for the month is 0. How much is she liable to pay.

Ans: Revenue for the month 0rs Interest on the revenue (10Fixed amount for the month 1000.rs Total amount to be paid for the month is 1000.rs

4.G.8 Quiz

True or False

Create pluck cards stating true or false on either side of the card, they can be seated in the same place. When each question is asked the individual can show their answer. After every question the facilitator will look around and explain why they have got the answer wrong. This exercise will help the group give individual answers rather than group answering, this will intern help us in understanding how much the group has understood, if more explanation is required.

1. You are given upto 1lakh to invest into your business- True
2. You will use this money to buy asset that will help you improve your business- True
3. The asset purchased will be considered as security – True
4. Repayment period starts from the 1st month - False
5. For months that you do well, you repay more. In months you don't do well, you can repay less. - True
6. We don't need to keep track of everyday earnings and expenditure data – False
7. You need to attend the bootcamp and trainings when necessary – True
8. You are allowed to expand within your main line of your business- True
9. In case of theft/ accident,you should inform your respective GF and YSB team - True

The women are given a set of multiple-choice questions and basic calculations on repayment, they should mark the correct answer. Once the

questionnaires are answered they need to swap the sheets and correct each other's paper. The facilitator will go through the entire questionnaire along with the group to mark the right answer. In the end the facilitator will explain each answer and its reason. Multiple choice questions (tick the correct answer for the following questions) 1) What is the duration of the contract? a) 0 months of grace period + 33 months repayment period b) 3 months of grace period + 36 months of repayment period c) 3 months of grace period + 33 months of repayment period 2) What are the components of the repayment you will make every month? a) Fixed payment only b) Fixed payment + flexible payment c) Flexible payment only 3)Which day of the month will you have to make repayments? a) Receive a reminder on the 10th day of every month and make the payment on the 15th day of the month b) Receive a reminder on the 15th day of the month and make the payment on the same day c) Receive a reminder on the 12th day of the month and make the payment on the 20th day of the month

4) Tick your roles and responsibilities a) Need to attend boot camps and trainings without fail b) Record and report your daily income and expenditure c) Maintain your assets d) Report the numbers correctly e) Inform GF and YSB before taking additional loan f) Inform GF and YSB before making a major change in the business g) Make sure your sensors are working properly

5) In case of theft what should you do. a) Inform the GF and YSB team within 24 hours b) No need to take any action

4.G.9 Common questions

1) What is the interest rate? As you all know that this is a research program and the payment method is not conventional here, there is no fixed interest for every month/year. We will know the actual interest rate only at the end of 3 years, but when we do a rough calculation, it calculates to 15

2) Do we still need to update our monthly income on the MeraBills app or report it directly to the GF? Yes, we encourage you to update your revenue via the MeraBills app. The app has many useful features that will help you as an entrepreneur. This will help us tell you how much you need to pay for the month. In addition, this data will help the research team to develop similar models and help more women.

If you are not able to use the app, you can report your daily data by Whatsapp, a call or a text message.

3) I might not be unable to attend one of the boot camps during the 36 months. We understand that there might be situations where you might not be able to attend a bootcamp due to emergencies. Please inform us in advance, if you know you will not be able to attend. These boot camps are designed to help you in understanding your business better. Our request with all of you is to attend every training and bootcamp session.

4) If I need to repay the loan early, how can I do that? This contract does not allow early repayment.

5) How can I expand my business? With the help of the loan amount, you

are buying an asset which will help you improve your business. You can also buy complimentary inventories that will help you with your business. Over time, you can also start selling products related to your primary business. For example, A tailor can sell cloth materials, beads, lace etc. Animal husbandry can sell cattle feed, cattle care like ropes etc.

4.H Microequity one pager

This section provides details of the short document that was shared after the contract explanation session. This was circulated to all entrepreneurs. They has one month to take this home and discuss with their family before they made a decision on whether to apply for the microequity loan.

What is micro equity and what are its advantages

- The micro equity contract structure is more flexible than traditional microcredit loans. The payments are contingent upon your business income and will be repaid over a three-year term.
- In months that you do well, you repay more. In months you do not do well, you can repay less.
- It provides funds up to 1lakh rupees to invest in your business in the form of an asset.
- In the microequity model, we spread the repayments over a three-year period. This ensures that you are not compelled to repay large amounts immediately.

What is considered as income?

- Income is the money received from the sale of goods and or services. This includes payment in the form of cash, GPay, PhonePe and PayTM.
- The payment received will be included in the monthly income only when you receive the money.

Contract understanding

- You can take a loan for any amount up to Rs. 1,00,000 (one lakh rupees).
- The loan duration is three years or 36 months. Three months of grace period. Payment starts from the 4th month. Loan repayment tenure is effectively 33 months.
- Payment structure has two parts: Fixed payment + Flexible payment Fixed payment: A fixed amount of Rs. 1000 to be paid every month Flexible payment: 15% of your monthly income.

Security

- The asset purchased from the loan amount will be considered as security

Monitoring the revenue of the entrepreneurs

- It is your responsibility to share your daily income and expenditure to the Gelathi facilitator daily through WhatsApp/ message/ phone call or MeraBills app.
- Your monthly income will be calculated based on your daily reports.
- We will check you are reporting accurately using the below mechanisms.
- Animal Husbandry: the receipt received from the dairies against the milk sold for the day will be considered.
- Tailor: A sensor attached to the machine will give us an estimate on how long the machine was in use, we can calculate the average stitching

for the day.

- We will also send secret shoppers to your store from time to time.

Repayment dates

- On the 5th day of every month, we will inform you of the amount you need to pay for the last month.
- A reminder on the 10th day of the month.
- Payment to be done on the 15th day of the month.
- Payment to be done via cash, bank transfer or PayTM.

Case of loss/ theft

- You should notify the GF and the YSB team within 24 hours of the incident occurring.
- The YSB team will visit the place and conduct an inspection.

Cases of Default

- Buzz and YSB will work with you to handle default proceedings.
- YSB will have the right to repossess the asset you have bought with the micro equity loan. They will work with you to recover (what is possible) from the outstanding loan amount.
- YSB may also charge you a default interest of 1%. Major business decision
- Within your main line of business, you can sell more goods or services

from your shop/ business location.

- You must inform us of any changes you make to your business.
- You are not allowed to hand over the business to friends and relatives.
- You must consult and inform the GF and YSB before you shut down your business.

Other Loans

- You are allowed to take a loan but you will have to inform the GF and the YSB team about the type and value of loan you are taking.

Your roles and responsibilities

- You must attend all the bootcamps for the micro equity project.
- You must record and report your daily income and expenditure numbers. Your monthly repayments depend on these reports.
- It is your responsibility to be honest with us and report these numbers correctly.
- Maintain (and if needed, repair) your asset.
- Inform us about loss/ theft of asset
- Inform us about major business decisions

4.I Power Calculations

To check for statistical power prior to the intervention, we ran our key specifications based on simulated data. These results including the code used are pre-registered in our analysis plan registered in the AEA registry (RCT ID is AEARCTR-0009675). We do this to check for statistical power given the small sample size. As discussed in Section 4.3.1, we have collected 16 months of pre-intervention daily data (on revenue, expenditure and profit) for all participants in the study. We use this pre-intervention data to simulate a 50% increase in revenue due to the intervention over a period of three years. Based on simulated post intervention data, we check for power by estimating Equation 4.1 using ANCOVA and conducting randomization inference. We cluster at the firm level, and re sample according to the underlying stratification scheme. Table 4.I.1, presents the results for simulated data. Despite the small sample size, we believe we are powered to detect treatment effects equivalent to a 50% increase in revenue (which is a reasonable effect size given the large capital injection).

Table 4.I.1: **Estimation using ANCOVA with simulated data (INR)**

	(1) Revenue	(2) Profit
Treatment	0.9***	0.9***
	(0.1)	(0.1)
Observations	4340	4340
Number of firms	28	28
Mean Dependent Variable	1.8	0.9
SD Dependent Variable	3.2	2.6
RI test p-value	0.00	0.00
KS test p-value	0.00	0.00

Notes: The dependent variables are Revenue and Profit. Revenue (in 1000 INR) is measured as the total amount earned from the sale of goods and services. Expenditure (in 1000 INR) is the aggregate of all expenses incurred by the firm. It includes wages of employees but does not include any wages or income paid to oneself. It also does not include loan repayments. Profit (in 1000 INR) is inferred as revenue less expenditure. We simulate a 50% increase in the pre-intervention revenue data. We do not simulate any changes in expenditure. The data for pre-intervention revenue and expenditure is collected on a daily basis and aggregated at the weekly level. The exchange rate during this period ranged from 72 to 85 INR per USD. "Treatment" is an indicator for being in the microequity treatment group. The results are pooled across weeks. Regressions include baseline controls, strata dummies, and controls for report date, with standard errors clustered at the firm level. "Mean DV" and "SD DV" are the mean and standard deviation of the dependent variable among the control group. The table also presents p-values for randomization inference and the KS test. Significant at 90% (∗), 95% (∗∗), 99% (∗ ∗ ∗) confidence. Standard errors in parentheses.

For variables collected using the quarterly phone surveys, preliminary power calculations suggest that with full take-up, a sample size of 30 is powered (at 77%) to detect effect sizes of greater than 0.45sd.[17]

[17]For repayment data, we are unable to compare the treatment and control groups as the control group is not offered a loan.

4.I.1 Graphical representation of Treatment effects based on simulated data

Based on simulated data, we also present graphical results to document how the treatment evolves over time. We show this for variables where we will have high-frequency daily data (revenue, expenditure and profit) using a kernel regression. For all the figures below, we assume a 50% increase in revenue due to the intervention over a period of three years. We also present results assuming a 100% increase in revenue due to the intervention over a period of three years.

Figure 4.I.1: **Kernel regression - Simulating a 50% increase in revenues (INR)**

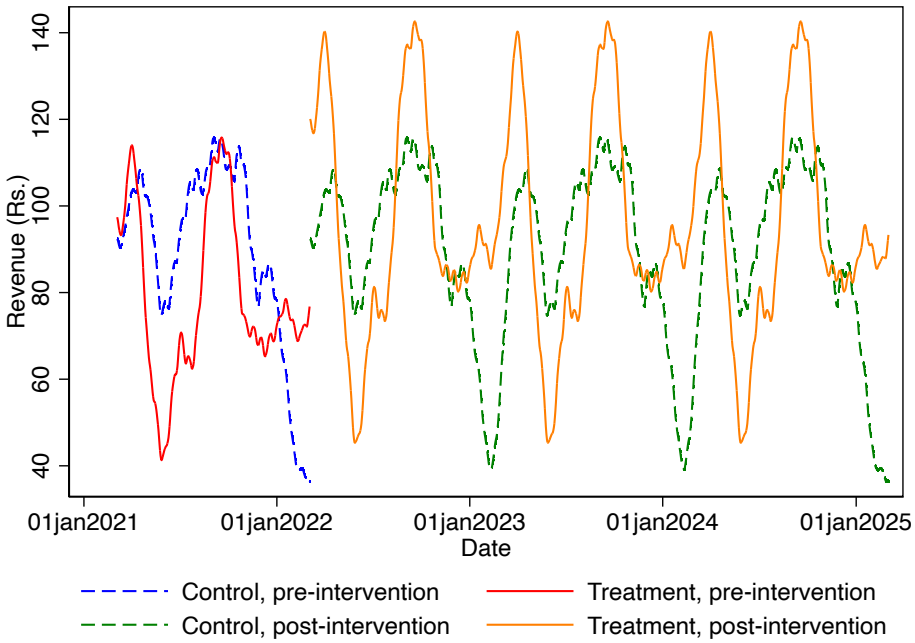
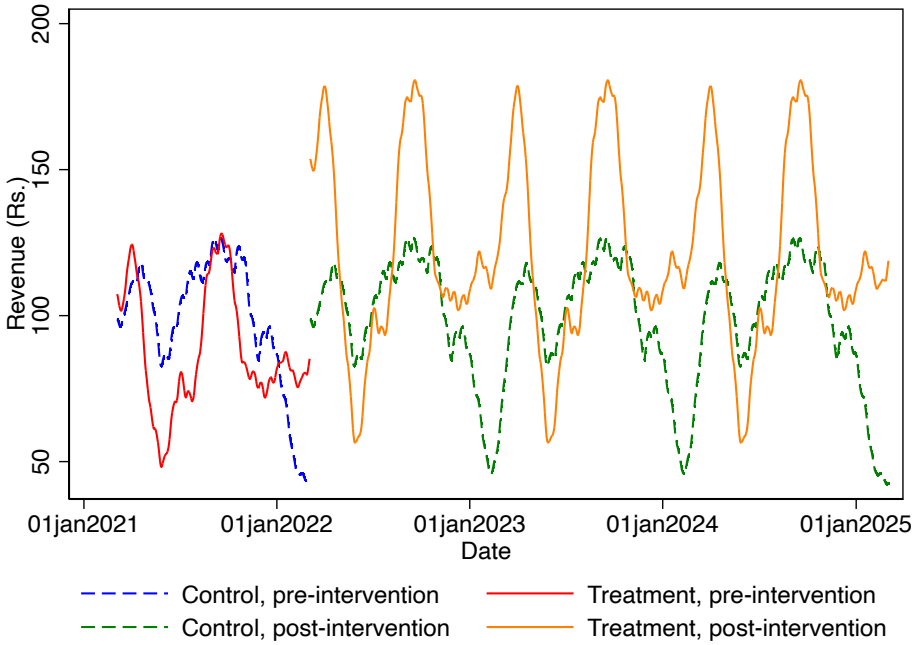


Figure 4.I.2: **Kernel regression - Simulating a 100% increase in revenues (INR)**



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