Digital Technology Adoption: Subsidizing Learning Costs for Firms in India

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Abstract

In an era of rapid digitalization in low and middle-income countries, many novel digital technologies are still out of the reach of micro-firms, and it is important to study the barriers to adoption of new digital technologies. In this paper, I offer one specific explanation for low adoption: high learning costs for firms. Using a stylized dynamic model of adoption choice with differential learning costs and a field experiment, I show that temporarily subsidizing learning costs leads to a sustained increase in adoption. I also offer evidence on the mechanisms through which technology adoption impacts firm finances and business practices.

1 Introduction

Micro-firms [1] represent a large share of the workforce in most low and middle income countries (LMICs) and are often characterized by low growth and profitability (Nichter and Goldmark, 2009; McKenzie and Seynabou Sakho, 2010; Hsieh and Olken, 2014). Innovation through adopting new technology is a key component of improving productivity in firms. An array of technologies provide profitable opportunities for micro-firms. These include hybrid seeds and fertilizers (Suri et al., 2011), mini grids for solar and wind energy, pay- as-you-go payment systems, mobile money platforms and digital finance apps. The current era of rapid technological change provides opportunities to design and implement policies that promote the growth and productivity of firms (Iacovone et al., 2017; Fernandes et al., 2017; Cirera et al., 2021; Berrou et al., 2020).

Adoption of technology is low, especially in micro-firms in LMICs (Atiyas and Dutz, 2021). Low adoption of potentially profitable technologies has been documented across varied settings (Suri et al., 2011; Duflo et al., 2011; Dercon and Christiaensen, 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), informational barriers (Foster and Rosenzweig, 1995; Asfaw and Admassie, 2004), low levels of human capital, limited availability of inputs, limited profitability (Dadi et al., 2004), lack of market access (Abrar et al., 2004), risk preferences (Dercon and Christiaensen, 2011), lack of commitment devices (Duflo et al., 2011) and misperceptions on the true returns of the technology. In LMICs, many novel technologies are out of the reach of micro-firms and it is important to study the factors that may promote the adoption of new technologies. While several solutions have been put forward, prior academic studies have documented high costs per-firm for encouraging adoption. Policymakers highlight the need to identify low-cost scalable solutions to encourage adoption by micro-firms in informal markets.

The scalability of technology is even more challenging for micro-firms in LMICs where firms typically have low levels of digital literacy and are financially constrained. Unlike many technologies that require large and lumpy investments, digital technologies often require only a mobile phone or similar devices and internet connectivity. One feature of adopting a digital technology that may explain low adoption is that it is costly to use a technology in the initial phase. As one

[1] Micro-firms are firms with fewer than 10 employees.

accumulates experience in using the technology, the "cost" of using it decreases. In this study setting, I think of the "cost" of using the technology as a learning cost. As firms "learn by doing", they are more likely to adopt a technology. Therefore, if temporarily subsidizing the cost of using a digital technology can lead to sustained adoption, this could potentially be a cost-effective option to encourage adoption in a setting that is policy relevant.

In this paper, I examine whether learning costs act as a barrier to technology adoption for informal micro-firms. Motivated by economic theory, I set up a stylized dynamic model of adoption choice with differential learning costs. I then design a field experiment to test the main implications of my model. To study technology adoption choice and the effects on firm growth, I partner with an NGO in India that works towards fostering growth for women led micro-firms in the informal sector. To track the inter-temporal dynamics of technology adoption, I partner with a prominent tech start-up that has developed a novel digital financial technology, the MeraBills app, that helps firms maintain records of business transactions and manage cash flow and trade credit. My intervention increased adoption of the digital technology by a substantial margin and treatment effects persisted even four months after the intervention [2].

In my conceptual framework, learning occurs through accumulating experience on using a technology and learning costs decrease as firms gains experience. I set up a stylized dynamic structural model of adoption with differential learning costs. I solve the model using backward induction from a terminal state and compute maximum likelihood estimates for key parameters. I calibrate the model using simulated data to explain the main implications of my model. Payoffs to adoption are both intrinsic and structural. Intrinsic payoffs are modeled by generating persistence in behavior, where as, structural payoffs are captured by the value function under adoption or no-adoption. The structural model estimates the relative magnitude of these payoffs and provides an economic interpretation for adoption choice. The key implication of the model is that a temporary intervention that subsidizes learning costs at onset can move firms from a low adoption equilibrium to a high adoption one. That is, a front loaded temporary intervention that maximizes initial adoption, leads to a sustained increase in adoption.

For the empirical component of the paper, the design for which stems from my model, I randomize initial adoption of the digital technology to varying degrees by subsidizing learning costs for

[2] I currently have only four months of data, but will update the analysis as additional real-time data comes in.

varying durations. I subsidize learning costs by offering firms visits from trained staff who hand-hold them on how to enter transactions and use the digital platform. In line with the model, 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 sustained adoption. I document two key mechanisms. First, that firms in the treatment arms are $\sim 175\%$ 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 $\sim 238\%$ 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 markets, since firms tend to make a large proportion of business transactions on credit.

Given the large and significant effects on adoption of the digital technology, I examine firm level outcomes to establish a causal link between technology adoption and firm growth. I find a striking and surprising result: treated firms report an 18% reduction in firm revenues and a 27% reduction in firm profits [3] I provide evidence that as firms adopt the digital technology, they keep formal records of their business finances and in the process, learn about inefficiencies in their business. I substantiate this with three strands of evidence. First, treated firms show a significant improvement in business practices around financial planning and inventory management. Second, given treated firms now have more accurate information about firm profitability, they reduce new investment by 38% in the three months after the intervention. Third, firms update downwards their expectations about future prospects of the business. Thus, as firms adopt a new digital technology they learn about the low profitability of their business and act on this information. 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.

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 labor force is employed in the informal sector (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,

[3] these estimates are an average of the decrease in monthly revenues and profits reported in the first three months of the intervention.

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 [4] has opened new avenues for the use of digital financial services for micro-firms in the informal sector. 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.

This paper links to two distinct strands of literature. First, it add to a large literature on learning models. 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 learned 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); 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; 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 in the category of learning by doing. By setting up a dynamic model of adoption choice, I provide a framework to understand the temporal dynamics of adoption for informal micro-firms. To my knowledge, this is one of the first few filed experiments that is designed to test the role of learning by doing on technology adoption.

Second, this paper also relates to the extensive literature on training for firms. In this study, I offer evidence of how temporarily subsiding learning costs can be a cost-effective substitute for an intensive training session. My low cost temporary intervention, both encourages adoption but also provides firms with a more accurate knowledge of their firm profitability. Multiple interventions have tested variants of traditional methods of training ((Drexler et al., 2014; Calderon et al., 2020; de Mel et al., 2014; Berge et al., 2015; Campos et al., 2017). McKenzie et al. (2020) estimates (on average) a 5.6% and 12.1% increase in respectively in sales and profits across studies. McKenzie

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

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 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 my results and Section VI concludes.

2 Stylized dynamic model of adoption choice

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 due course, I will extend this model to allow for counterfactual analysis.

2.1 Model specification

This section describes a simple model of learning about a new digital technology that is used to guide the empirical work in this paper. The basic model describes a digital technology adoption choice made by a firm that optimizes on an infinite horizon in discrete time. In period 0, firms are introduced to a digital technology. They are trained on a digital app that helps them manage their business. As they enter transactions on the app, they reap benefits from using it. They also face a learning cost which is a per-transaction cost of entering data. Similar to "learning by doing", 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 (h_t). Learning costs decrease as firms accumulate more experience in using the app. Beyond a point $\bar{h}$ I assume there is no learning and learning costs are 0. $\bar{h}$ is given by $\frac{\alpha}{\gamma}$ and therefore, there is no discontinuity in the learning cost function. Learning costs also depend on the ability of the entrepreneur which is captured through α and γ. α is the learning cost incurred by the entrepreneur when they have no experience using the app (that is, $h = 0$). γ is the rate at which learning costs decrease as firm's accumulate experience. It is assumed that $\alpha > 0$ and $\gamma > 0$. 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. The plot of learning cost of adoption against the cumulative number of transactions is called the learning curve. Figure 1 displays a plot of learning curve (based on hypothetical parameters).

$$b_t(h_t; \bar{h}, \alpha, \gamma) = \begin{cases} \alpha - \gamma \cdot h_t & \text{if } h_t < \bar{h}, \\ 0 & \text{if } h_t \geq \bar{h} \end{cases} \tag{1}$$

A firm produces output q_t in period t, where $q_t = n_t \times s_t$. s_t is the number of transactions and n_t is the average number of units sold per transaction. 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_t) is constant. This is a simplifying assumption and the key intuition for the model will hold even if I allow s_t to vary over time. Firms use X_t units of input. I normalize the cost of inputs $M \times X_t$ to 0 in equations 2 and 3. Firms take the input price M and per transaction output price P as given.

At the start of each period thereafter, firms choose whether or not to adopt the technology based on payoffs from adopting/ not adopting. If firms adopt, they earn a profit of π_t^D and if they do not adopt they earn π_t^N, as shown in Equation 2 and 3.

$$\pi_t^D = \phi_t \times P \times s_t - b_t(h_t; \bar{h}, \alpha, \gamma) \times s_t - Q \tag{2}$$

$$\pi_t^N = P \times s_t \tag{3}$$

In periods that firms adopt, the net returns to adoption are given by ϕ. I can think of the net returns as the mark-up to revenues minus the hassle cost of adoption. I define ϕ in this manner to capture any time costs or other costs to adoption in the model. It is assumed that $\phi > 1$. Risk aversion is not incorporated in the current model, so there are no probabilities attached to ϕ. Adopting firms also face a fixed cost of adoption C, which is a one time cost incurred in the first period that a firm adopts. In addition, in each period that a firm uses the digital technology, they incur a privacy cost Q. Since mobile phones are shared commodities in this setting, Q incorporates the cost associated with one's spouse seeing all their business transactions.

To capture that firms move in and out of adoption, I bring in transition probabilities. The transition probabilities help capture the idea that firms can drop in and out of adoption. It also captures stickiness associated with adoption. For example, it is more likely that a firm will adopt today if it adopted last period. The transition probabilities have a functional form Λ, which refers to the *cdf* of the logistic distribution.

$$H_t(h_t) = \Pr(y_t = 1 | y_{t-1} = 1) \tag{4}$$

$$H_t(h_t) = \Lambda(\beta_0 + \beta_1 \times (V_t^D(h_t) - V_t^N(h_t)) + \beta_2 \times y_{t-1}) \tag{5}$$

$$H_t(h_t) = \Lambda(\beta_0 + \beta_1 \times (V_t^D(h_t) - V_t^N(h_t)) + \beta_2) \tag{6}$$

$$G_t(h_t) = \Pr(y_t = 1 | y_{t-1} = 0) \tag{7}$$

$$G_t(h_t) = \Lambda(\beta_0 + \beta_1 \times (V_t^D(h_t) - V_t^N(h_t)) + \beta_2 \times y_{t-1}) \tag{8}$$

$$G_t(h_t) = \Lambda(\beta_0 + \beta_1 \times (V_t^D(h_t) - V_t^N(h_t))) \tag{9}$$

The value function given by Equation 12 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 state space comprises of two variables - transaction experience h_t and the adoption choice in the prior period y_{t-1}. The two state variables completely summarize 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. 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.

$$y_t = \begin{cases} s_t & \text{if } V(h_t; \bar{h}, s_t)^D \geq V(h_t; \bar{h}, s_t)^N, \\ 0 & \text{if } V(h_t; \bar{h}, s_t)^D < V(h_t; \bar{h}, s_t)^N. \end{cases} \tag{10}$$

The transition equation is given by Equation 11. This determines the transaction experience the firm enters each period with. That is, if a firm does not adopt in period t, $y_t = 0$ and the firm enters period $t+1$ with the same transaction experience it entered period t with. That is, it continues to face the learning cost associated with that transaction experience. However, if a firm does adopt in period t, it enters period $t+1$ with an additional s_t transaction experience (and a correspondingly lower learning cost).

$$h_{t+1} = h_t + y_t \times s_t \tag{11}$$

During the period of learning, the value function can be written by Equation 12. V_t^D and V_t^N represent the value function from adoption and no adoption respectively. V_t is the value function from the optimal adoption decision in each period t.

$$V(h_t, y_{t-1}; \bar{h}, s) = \max_{y_t \in \{0,1\}} \begin{cases} \pi_t^D + \delta \times [H(h_{t+1}) \times V^D(h_{t+1}, y_t) + (1 - H(h_{t+1})) \times V^N(h_{t+1}, y_t)], \\ \pi_t^N + \delta \times [G(h_{t+1}) \times V^D(h_{t+1}, y_t) + (1 - G(h_{t+1})) \times V^N(h_{t+1}, y_t)]. \end{cases} \tag{12}$$

This can be simplified by inputting the value of h_{t+1} based on Equation 11.

$$V(h_t, y_{t-1}; \bar{h}, s) = \max_{y_t \in \{0,1\}} \begin{cases} \pi_t^D + \delta \times [H(h_t + s) \times V^D(h_t + s, 1) + (1 - H(h_t + s)) \times V^N(h_t + s, 1)], \\ \pi_t^N + \delta \times [G(h_t) \times V^D(h_t, 0) + (1 - G(h_t)) \times V^N(h_t, 0)] \end{cases} \tag{13}$$

The model parameters I estimate are β_0, β_2 and β_2. Parameters β_0 and β_2 are intrinsic, while β_1 is structural. By solving the model, I assign relative weights to the parameters of interest.

2.2 Solution and calibration

I solve the model in two steps. First, I solve the model from the point where it becomes a stationary problem. That is, once a firm crosses $\bar{h}$, the number of transactions beyond which no learning happens, the problem becomes a stationary one. The model has a fixed end, and all firms know at the beginning when this end will be. Firms know that learning costs will reduce to zero after they accumulate a certain amount of transaction experience and they use this information when making adoption choices. Second, with the solution to the stationary problem in hand, I work backwards assuming that each firm acts to maximize it payoff in each period of the model. I solve the model by backward induction over the fixed number of periods. Once I have the model solution through backward induction, I simulate forward through the model solution and compute maximum likelihood estimates for model parameters.

I now discuss in more detail, the first step in solving the model. The value function for the stationary problem beyond $\bar{h}$ can be written as:

$$\tilde{V}^D = \tilde{\pi}^D + \delta \times [\tilde{H} \times \tilde{V}^D + (1 - \tilde{H}) \times \tilde{V}^D] \tag{14}$$

$$\tilde{V}^N = \tilde{\pi}^N + \delta \times [\tilde{G} \times \tilde{V}^D + (1 - \tilde{G}) \times \tilde{V}^D] \tag{15}$$

The transition probabilities H and G will also be stationary once a firm crosses $\bar{h}$. Therefore, I can write:

$$\tilde{H} = \Lambda(\beta_0 + \beta_1 \times (\tilde{V}^D - \tilde{V}^N) + \beta_2) \tag{16}$$

$$\tilde{G} = \Lambda(\beta_0 + \beta_1 \times (\tilde{V}^D - \tilde{V}^N)) \tag{17}$$

From Equation 14 to Equation 17, I have four equations and four unknowns. While there is no analytical solution for this, I can solve it numerically.

Now, I detail the second step in solving the model. Once I have the solution for the stationary problem beyond $\bar{h}$, I backward induct from $h = \bar{h}$ and solve the problem for all values of h. Using this, I can determine the adoption choice y_t made by a firm for all values of t. To calculate the value function under adoption, this is easy to solve by backward induction. But it is more complicated to calculate the value function in the event of no adoption. Here I have two equations and two unknowns and I can solve.

$$G_t(h_{t+1}) = \Lambda(\beta_0 + \beta_1 \times (V_t^D(h_{t+1}) - V_t^N(h_{t+1})) + \beta_2 \times y_t) \tag{18}$$

$$V^N(h_t, y_{t-1}; \bar{h}, s) = \frac{\pi_t^N + \delta \times G(h_{t+1}) \times V^N(h_t, y_{t-1}; \bar{h}, s))}{(1 - \delta + \delta \times G(h_{t+1}))} \tag{19}$$

This can be simplified to Equation 20 and Equation 21 as $G(h_{t+1}) = G(h_t)$ since $h_{t+1} = h_t + y_t \times s_t$ and $y_t = 0$ in the event of no adoption in period t.

$$G_t(h_t) = \Lambda(\beta_0 + \beta_1 \times (V_t^D(h_t) - V_t^N(h_t))) \tag{20}$$

$$V^N(h_t, y_{t-1}; \bar{h}, s) = \frac{\pi_t^N + \delta \times G(h_t) \times V^N(h_t, y_{t-1}; \bar{h}, s))}{(1 - \delta + \delta \times G(h_t))} \tag{21}$$

In this draft of the paper, I calibrate the model by hand and choose parameters such that the simulated data closely reflects trends in the true data (from the field experiment). I then use this calibration to discuss the key model implications. I am currently working on structurally estimating the model by taking it to the true data and will then use the structural estimates to conduct counterfactual analysis. [5]

2.3 Key implications of the model

The key prediction of the model is that past adoption helps future adoption. In this setting, if a firm can be helped to accumulate experience in using the adopt in a way that lowers learning costs, they will be more likely to adopt in every period thereafter. Figure 3 presents the temporal dynamics of adoption based on the calibrated model. [6]

[5] I use the following parameter values to calibrate the model: $\beta_0 = -0.07$, $\beta_1 = 0.002$, $\beta_2 = 0.07$, $\delta = 0.8$, $\phi = 2$, $P = 50$, $Q = 100$, $\alpha = 500$, $\gamma = 2$, $s = 7$

[6] This looks comparable to the adoption dynamics for the true data, as shown in Figure 5. This will be discussed later in the paper.

To study the role of learning cost as a barrier to adoption, I now bring in differential learning costs. I randomly allocate a simulated sample of 1000 firms to three levels of learning subsidies: (i) A control group that is moved along the learning curve by only a small amount; (ii) treatment lite group that is moved further along the learning curve; (iii) treatment intense group that is moved even further along the learning curve. I display the three groups on the learning curve in Figure 2. I choose magnitudes for the learning subsidy in line with the field data. The key idea here is that if initial adoption can be ensured in a way that reduces learning costs, a firm can be moved along the learning curve. By solving the model, I predict that, this in turn leads to increased likelihood of adoption of the technology in the long run. The results are depicted in Figure 4. The model predicts that the control group will remain in a low adoption equilibrium due to high learning costs. For the treatment groups (treatment lite and treatment intense), subsidizing learning costs resulted in them being in an equilibrium with a higher level of adoption. For the current parameters, I do not see any difference in the adoption outcomes for the treatment lite and treatment intense groups. This, of course, depends on the intensity of the intervention and if a firm is moved far enough along the learning curve, firms in the treatment lite and treatment intense groups can also have different levels of adoption.

3 Setting

3.1 Study Context

I conducted this study in Karnataka in India in 2021 and 2022. In recent years, India (like most other LMICs) 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 (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 it's 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 [7], are involved in decision making in the business [8] and have regular access to a smartphone [9]. 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 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.

[7] 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.

[8] In LMIC settings it is quite 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.

[9] 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.

3.2 Descriptive statistics

Table 1 presents summary statistics for the sample of 320 micro-firm owners. 100% are women with an average age of 35 and 49% have completed above a secondary level of education. 95% and 98% can read and write respectively 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). [10]. 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 average micro-firm owner has 10 years of experience in their current business and runs their business for about 7 hours each day. 89% of the businesses have no employees and the mean number of employees in my sample of firms is 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% [11].

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, 89% 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.

[10] the USD INR exchange rate is as of December 2022

[11] Profit margin is measured as monthly profit divided by monthly revenue at baseline.

3.3 The digital technology

The MeraBills app, which is the digital technology used in this study, is an easy to use app that helps entrepreneurs analyze firm 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 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 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. Rather than using informal methods like mental accounting or scattered diary entries, firms can use digital technologies for financial and business management. Relevant digital technologies for these purposes include apps like MeraBills (which is used in this study), mobile money platforms, online banking tools etc. However, 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. Learning costs decrease as firms gain experience in using a technology.

I study the adoption choice made by micro-firms that operate in predominantly informal rural markets. This setting is ideal to test my hypothesis for three reasons. First, learning costs are salient given low levels of digital literacy and high levels of informality. Second, for the digital technology used in this study adoption choice is made on a daily basis and real-time data on adoption is available from the digital platform. This makes it ideal to study inter-temporal dynamics of adoption choice [12]. Third, there are seemingly profitable returns to using this digital technology in this study setting. The digital technology studied here is well-reputed technology that is currently being used by over 14,000 entrepreneurs across 20 states in India. Further, for micro-firms there is a missing market for an innovative technology to overcome financial management issues that arise due to informality. It is very common for micro and small firms to sell output on credit to their clients or buy inventory on credit from their suppliers. In informal markets, it is particularly difficult to optimally manage trade credit, and as a result, cash flow. This results in limited cash in the business and challenges growth and profitability. This study focuses on women led businesses which on average have no employees besides the owner. In such a setting, a digital technology that can help manage trade credit and cash flows is likely to be profitable. However, 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.

[12]In other settings where technology adoption is commonly studied, like agricultural technologies, adoption choice is typically made once per crop cycle, and therefore, they require a much longer time horizon to have sufficient power to draw similar conclusions.

4 Experimental Design

4.1 Treatment assignment

Micro-firms were randomized into one of three groups: (i) control group (C); (ii) treatment lite group (T1); (iii) treatment intense group (T2). All three groups are 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) was 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. They were provided assistance on how to download it. This was done 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.

In addition to what was provided to the control group, treatment group T1 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 group T1 as compared to group C, as T1 was moved further down the learning curve (as shown in Figure 2).

For treatment group T2, 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 groups T1 and C (as shown in Figure 2).

Randomization with stratification was used 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 1 reports normalized differences between my control group and my two treatment groups for a range of baseline characteristics. As is expected from randomization, I observe that the sample was well balanced.

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 bargaining power. After baseline surveys were conducted, participants were invited for an induction session where they were informed about the study and the various treatment arms. Following Drexler et al. (2014), the induction 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 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.

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 [13]. 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

[13] the second follow-up survey is currently underway

used by each entrepreneur. Using the high frequency data on the app, I have constructed daily and 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.

5 Treatment effects

In this section, I present the average treatment effects of the intervention. In doing so, I follow the pre analysis plan (available at https://www.socialscienceregistry.org/trials/8104). 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 E I also present Local Average Treatment Effects (LATE) [14]. 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. Equation 22 presents the primary econometric specification, which pools data across rounds of data collection.

$$Y_{ir} = \alpha + \beta_1 T_1 + \beta_2 T_2 + \beta_r Y_{i0} + \eta_r + \gamma_s + \varepsilon_{ir} \tag{22}$$

In Equation 22, 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 will be clustered at the firm level as randomization is at the firm level (Abadie et al., 2017)[15]

[14] As is expected, LATE estimates are larger than ITT estimates in magnitude, but otherwise tell a similar story.

[15] 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.

5.1 Adoption of digital technology

I present the effect of the treatment on the primary outcome variables - a binary measure of adoption and the extent of adoption. Appendix C Table 11 details the adoption outcomes of interest. 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 22. The results presented in this section use three to four months of adoption data after the intervention.

Table 2 presents Intent to Treat effects for a binary adoption dummy, where real time data from the app is aggregated to a daily level. I estimate Equation 22 using a linear probability model. 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[16]. However, 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 lite group was sufficient to sustain adoption.

In addition to analyzing data on degree of engagement with the app, I also use the MeraBills dashboard to see which features of the app are used and how frequently. 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 3 I present results on the extent of adoption. I estimate Equation 22 using a clustered poisson regression. Results based on weekly data reinforce the findings from Table 2. In this cut of the data, I am able to look at a larger set of adoption outcomes. I find that firms in both treatment arms increase their intensity of adoption. The first two column present results based on what entrepreneurs view on the app. I find that they view their home screens more often, which suggests higher engagement with the app. More importantly, they view reports significantly more which indicates that they are viewing reports on firm finances, income / expense reports, owner withdrawal reports and product reports with a higher frequency. I will use follow-up data (that is currently being collected) to study the mechanisms through which this may impact business

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

practices and firm productivity. The last three columns present results on which features of the app are used. I find that firms in both treatment arms enter more transactions on the digital platform. They also send payment reminders and payment invoices with a higher frequency. This suggests that managing trade credit and therefore, cash flow in the business may be the mechanism through which this digital platform is beneficial to firms.

In Figure 6 I present the temporal dynamic 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. Similar to the model, treated firms tend to converge to a higher adoption equilibrium. 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. It is possible, that the small temporary nudge given to treatment lite group was sufficient to encourage higher adoption.

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. I present analysis for individual treatment arms in Appendix F. Overall, while I have less statistical power in this specification, the results tell a similar story.

Data from the in-person field surveys corroborates the increased adoption seen in the real time app usage data. Table 4 shows that firms in the treatment arms report that they use the digital platform to enter higher transactions, send more reminders, manage the amount customers owe them, manage the amount they owe suppliers and view key graphs and statistics about the business.

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

[17] to study the effect of the treatment on firm revenue and profit.

Looking at monthly revenue and profit data for three months after the intervention, I find a striking result in Table 5: the treatment caused a large and significantly negative effect on revenue and profit for three months of the study. Columns 1,2 and 3 present results for monthly revenue. I find a 14%, 5% and 34% decrease in firm revenue in months 1, 2 and 3 of the study. Columns 4,5 and 6 present results for monthly profit. I show that there is a 28%, 18% and 35% decrease in firm profit in months 1, 2 and 3 of the study.

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.

5.3 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. 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 hypothesis, I study a range of secondary outcomes under these three categories. Under business practices, I look at outcomes such as, managing trade credit, managing inventories, managing customers etc. For firm investment, I look at assets, investment, **probability of shutting down, probability of starting new business, number of employees and time use**. 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 Tables 6 and 7. In Table 6 I find that treated firms improve financial planning. In Column 1, I find a large and significant increase in a micro-firm owner's knowledge about key firm expenditure categories. I document that firms' in the treatment groups are 19% more likely to know what the biggest expense in their firm is. In Columns 2 and 3 , I also find a large increase in treated firms' likelihood of maintaining financial

[17]Currently, the results only include one round of follow-up survey data. The second survey round is currently underway in the field.

statements. Column 2 shows that treated firms are 17% more likely to maintain an Income and Expense statement (significant at 10%). Column 3 shows that firms in the treatment group are 7% more likely to maintain a Profit and Loss statement (this is a positive but not significant effect).

In Table 7, I document treatment effects on business practices pertaining to inventory management. In Column 1, I find that treated firms are 27% more likely to negotiate prices with their suppliers. This is in line with the improvements in financial planning practices highlighted in Table 6. In Column 2, I show that treated firms are 27% more likely to obtain information from from their suppliers regarding which products sell best. Again, this is evidence of firms improving business practices in order to manage their business better. In Column 3, I find that firms who received the treatment were 27% more likely to attract customers by offering special discounts. This provides evidence of attempts by the firm to manage customers and increase revenue.

If firms were to learn that their profitability is lower than they had anticipated using more informal record-keeping practices, this could also potentially lead to changes in investment. In Table 8 , column 1, I find that treated firms have a 38% reduction in business investment (significant at 5%) in the first three months of the study. This is a large reduction in firm investment and provides suggestive evidence of micro-firm owners learning about the low profitability of their business. In Column 1, I also see a 16% reduction in fixed assets, albeit not significant.

In Table 9, I strengthen evidence on this hypothesis by providing evidence of a reduction in expectations about future business performance. In Columns 1 and 2 , 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 3, I show that firms in the treatment group expect to sell 45% fewer products in the future.

LATE estimates presented in Appendix E 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.

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. In Table 10, I find that firms report a positive experience while using the app. In Column 1, I document that treated firms are 27% (significant at 5%) more likely to recommend the MeraBills digital technology. As reflected in Column 2 they are also 113% more likely to teach family and friends how to use the digital technology (significant at 1%). As shown in Column 3, treated firms are also 32% more likely ((significant at 10%) to involve their family in using the digital technology. Lastly, Column 4 shows that treated firms are willing to pay 10% more for use of 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 positive spillovers for family and friends.

6 Conclusion

The rapid digitalization has made the digital divide very stark. In LMICs, many novel digital technologies are out of the reach of micro-firms and it is important to study the factors that may promote the adoption of new 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).

Given the large and significant effects on adoption of a digital technology that helps firms maintain business records and manage cash-flow, it is intuitive that firms improve business practices. However, it is surprising that firms report a significantly negative effect on firm revenues and profits in the three months after the intervention. I provide suggestive evidence that this may be driven by firms getting more accurate information about low firm profitability. Firms act on this information by reducing investment and revising downward their expectation of future firm growth. I argue that 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 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 support 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.

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Tables and Figures

Table 1: **Summary statistics and balance among baseline covariates**:

Baseline characteristic	Control	Treatment		p-value tested for			
		T1	*T2*	*C=T1=T2*	*C=T1*	*C=T2*	*T1=T2*
Household size	4.63	4.88	4.64	0.52	0.32	0.95	0.33
Number of HH businesses	1.84	1.91	1.92	0.76	0.56	0.50	0.93
Total business HH income	26,151	22,529	29,448	0.42	0.50	0.54	0.19
Total HH income	34,808	32,530	39,065	0.55	0.71	0.49	0.28
Business experience (years)	31.06	36.53	30.01	0.64	0.47	0.89	0.37
Number of competitors (5min walk)	3.20	3.25	2.75	0.68	0.94	0.48	0.42
Number of customers per day	10.81	11.43	15.82	0.03	0.76	0.01	0.03
Number of employees	0	0	0.83	0.35	1.00	0.22	0.21
Revenue at baseline survey	17,495	15,678	16,955	0.92	0.69	0.90	0.77
Profit at baseline survey	7,768	5,427	5,811	0.28	0.13	0.21	0.80
Fixed assets	36,252	49,297	58,617	0.39	0.43	0.17	0.56
Total current assets	147,031	205,702	129,273	0.09	0.11	0.63	0.03
Loan pending	120,862	101,817	106,123	0.73	0.45	0.56	0.86
Amount borrowed (family/friends)	13,479	17,837	26,227	0.37	0.64	0.17	0.35
Happy	1.55	1.62	1.66	0.46	0.47	0.22	0.59
Family members help use phone	0.97	0.93	0.95	0.52	0.25	0.62	0.50
Family members use phone	0.95	0.93	0.95	0.81	0.67	0.85	0.53
Keep business records	0.66	0.64	0.65	0.97	0.82	0.90	0.92
Seperate HH records	0.23	0.35	0.30	0.22	0.09	0.30	0.48
Hours spent on business	4.10	4.07	4.16	0.98	0.96	0.88	0.84
Hide income from family	0.16	0.30	0.23	0.07	0.02	0.26	0.22

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

Table 2: **Treatment effects on adoption - LPM daily**

	(1) View reports	(2) Transactions
Treatment Lite	0.03***	0.09***
	(0.01)	(0.02)
Treatment Intense	0.04***	0.10***
	(0.01)	(0.02)
Observations	30821	30821
Mean DV	0.02	0.04
Std. dev.	0.13	0.20
p-value for joint sig.	0.00	0.00
p-value test (T1=T2)	0.21	0.59

Notes: The dependent variables in this table are adoption outcomes based on real-time data aggregated to the daily level. 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. "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. We do not have real-time data tags for "viewing home screen", therefore, do not present it here. For other features, including "view payment reminder" and "send invoices" we do not have sufficient data points for this specification. These results will be updated as additional data comes in over the next few months.

Table 3: **Treatment effects on extent of adoption - Poisson (aggregated from daily data)**
:

	(1) View Reports	(2) Transactions	(3) Invite	(4) Pay Inv.	(5) Receipt	(6) Pay. Rem.
main						
Treatment Lite	1.29***	1.71***	16.32***	16.65***	14.06***	3.05***
	(0.39)	(0.33)	(0.71)	(0.29)	(0.76)	(0.66)
Treatment Intense	1.43***	1.54***	16.07***	17.39***	15.77***	3.14***
	(0.30)	(0.26)	(0.69)	(0.37)	(0.50)	(0.61)
Observations	4403	4403	4403	4403	4403	4403
Mean DV	0.25	1.21	0.00	0.00	0.00	0.01
Std. dev.	1.27	4.34	0.00	0.00	0.00	0.21
p-value for joint sig.	0.00	0.00	0.00	0.00	0.00	0.00
p-value test (T1=T2)	0.63	0.54	0.79	0.05	0.05	0.87

Notes: The dependent variables in this table are outcomes for the extent of adoption. Column 1 presents results for the number of times the firm views the home screen, aggregated at the weekly level. This variable measures the number of times an entrepreneur views the home screen. The home screen provides top-level financial numbers for the business. 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 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 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. Column 5 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. "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.These results will be updated as additional data comes in over the next few months.

Table 4: **Treatment effects on App 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	0.23***	0.24***	0.19***	0.14**	0.16**
	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)
Observations	289	289	289	289	289
Mean DV	0.49	0.29	0.45	0.30	0.40
Std. dev.	0.50	0.45	0.50	0.46	0.49

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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

Table 5: **Treatment effects on Firm Revenue and Profits** :

	Revenue			Profit		
	(1) Month 1	(2) Month 2	(3) Month 3	(4) Month 1	(5) Month 2	(6) Month 3
Treatment	-1839.84	-652.00	-5286.95*	-1963.57**	-1301.85	-2916.12**
	(1692.80)	(1486.92)	(2737.14)	(980.57)	(999.73)	(1435.50)
Observations	285	285	285	285	285	285
Mean DV	12405.95	11877.38	15553.57	6982.14	7136.90	8410.71
Std. dev.	14853.33	15132.61	25977.98	8934.02	10658.27	15222.48

Notes: The dependent variables in this table are outcomes for revenue and profit for firms. Columns 1 to 3 present results for firm revenue in months 1, 2 and 3 of the study while columns 4 to 6 present results for firm profit in months 1, 2 and 3 of the study. 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. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

Table 6: **Treatment effects on financial planning practices** :

	(1) Biggest expense	(2) Income Expense Statement	(3) PnL_statement
Treatment	0.13**	0.11*	0.05
	(0.06)	(0.06)	(0.06)
Observations	285	289	285
Mean DV	0.70	0.65	0.73
Std. dev.	0.46	0.48	0.45

Notes: The dependent variables in this table are outcomes for financial planning practices for firms. Columns 1 presents results for a dummy variable that measures whether firms know their biggest expenditure category. Columns 2 and 3 present results for dummy variables for if firms maintain an Income and Expense statement and a Profit and Loss statement respectively. "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 second survey round is currently underway in the field.

Table 7: **Treatment effects on marketing practices** :

	(1) Negotiate with supplier	(2) Info. from supplier	(3) Attract customer
Treatment	0.13*	0.13*	0.12*
	(0.07)	(0.07)	(0.07)
Observations	285	285	285
Mean DV	0.48	0.49	0.45
Std. dev.	0.50	0.50	0.50

Notes: The dependent variables in this table are outcomes for business practices around dealing with suppliers and customers. Columns 1 presents results for a dummy variable that measures whether firms negotiated prices with their suppliers. Columns 2 presents results for a dummy variable for whether firms' obtain information from their suppliers regarding which products sell best. Column 3 presents results for a dummy variable for whether firms attract customers with special discounts. "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 second survey round is currently underway in the field.

Table 8: **Treatment effects on Firm Assets and Investment** :

	(1) Fixed Assets	(2) Current assets	(3) New Investment
Treatment	-13988.38	9082.35	-11627.65**
	(48583.43)	(24724.67)	(5026.81)
Observations	285	285	285
Mean DV	86209.45	91854.77	30794.06
Std. dev.	358728.17	191851.75	47006.04

Notes: The dependent variables in this table are outcomes for investment and assets. Column 1 presents results for the magnitude of new investment made by a firm in the first three months of the study. Column 2 presents results for the total value of fixed assets. I define a fixed asset 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. Column 3 presents results for the total value of current assets. This is calculated as the sum of inventories, debt and cash in business. All variables presented in this table 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

Table 9: **Treatment effects on future business outcomes** :

	(1) Future business growth	(2) Future Customers	(3) Future Products
Treatment	-0.02	-11.57	-3.39*
	(0.04)	(7.53)	(1.99)
Observations	285	285	285
Mean DV	0.90	27.94	7.54
Std. dev.	0.30	69.43	16.62

Notes: The dependent variables in this table measure expectations on future firm outcomes. Column 1 presents results for the a dummy variable for whether a micro-firm owner expects their firm to grow in the future. Column 2 presents results for a variable that measures the number of new customers a firm expects to sell to in the future. Column 3 presents results for a variable that measures the number of new products a firm expects to sell in the future. Columns 2 and 3 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

Table 10: **Treatment effects on experience using app** :

	(1) Recommend DT	(2) Teach DT	(3) Involve HH in using DT	(4) Pay for DT
Treatment	0.14**	0.17***	0.12*	4.46
	(0.07)	(0.05)	(0.06)	(12.44)
Observations	289	289	289	289
Mean DV	0.52	0.15	0.38	45.24
Std. dev.	0.50	0.36	0.49	83.46

Notes: The dependent variables in this table measure a firm's experience using the MeraBills digital technology . Column 1 presents results for a dummy variable for whether a micro-firm owner would recommend the digital technology to others. Column 2 presents results for 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

Figure 1: Learning curve

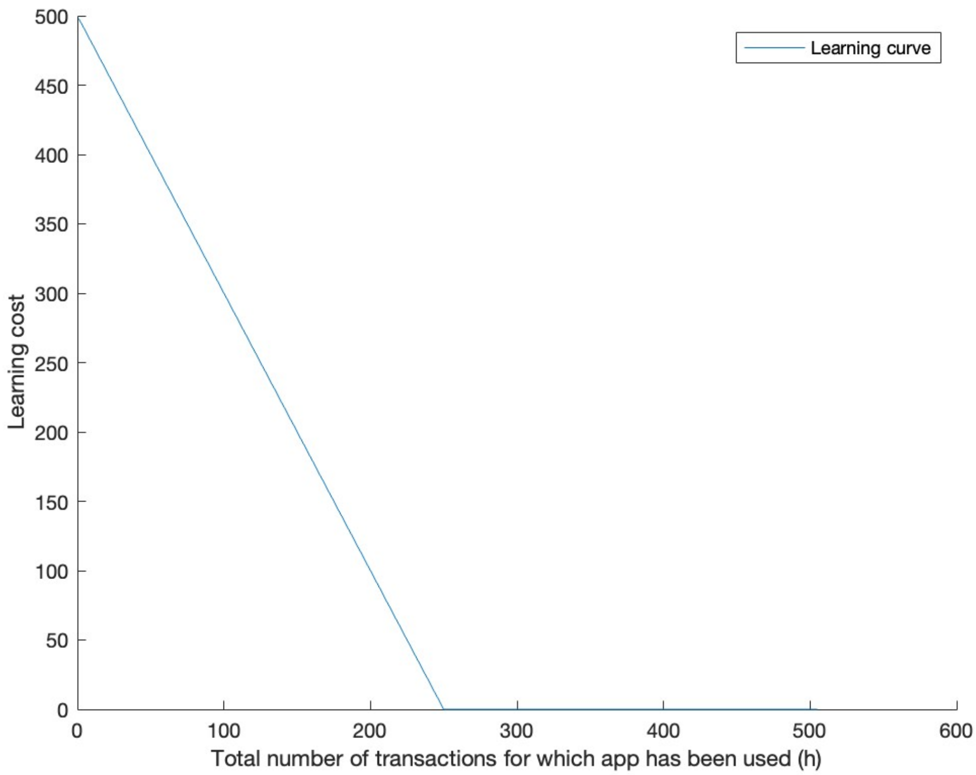


Figure 2: Learning curve

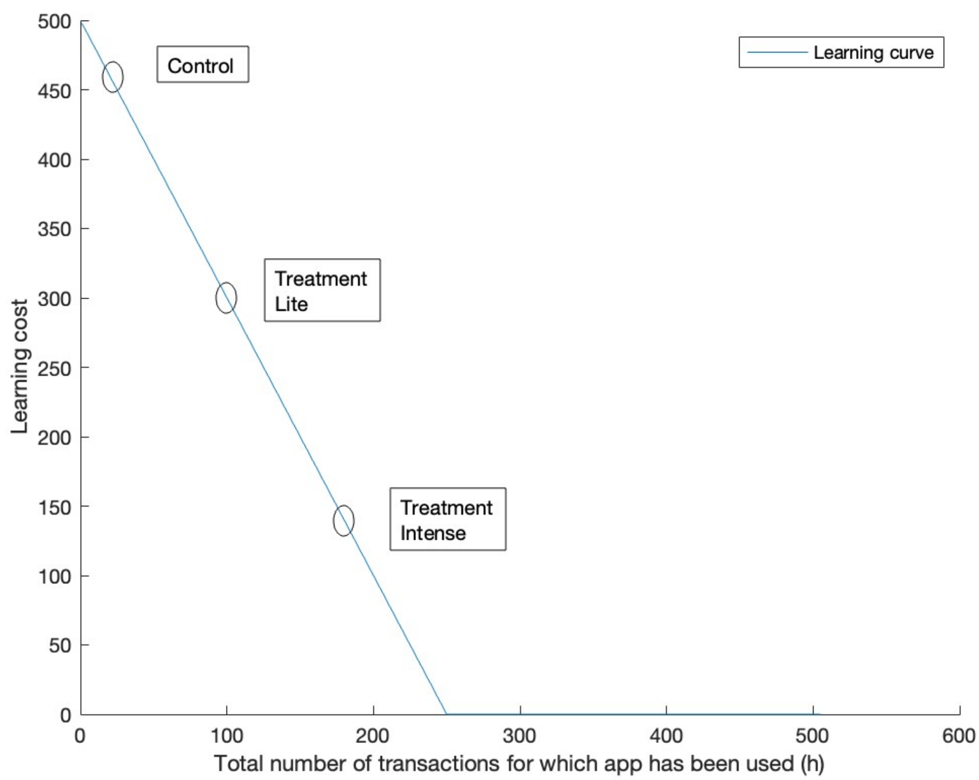


Figure 3: Predicted results based on simulated data

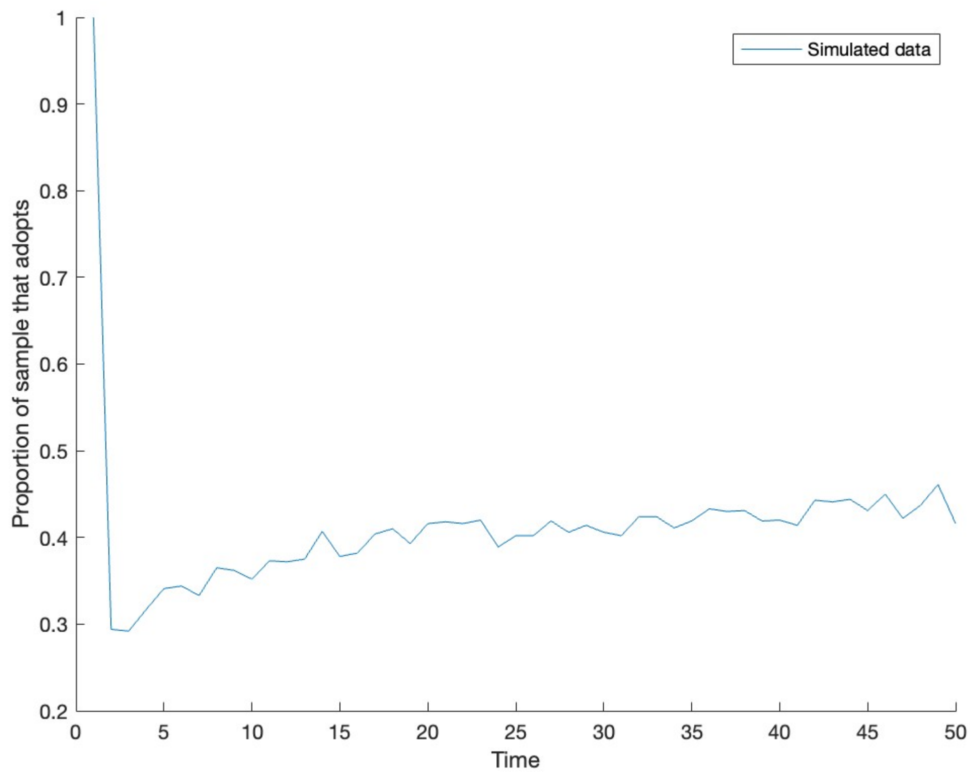


Figure 4: Predicted results based on simulated data - subsidizing learning costs

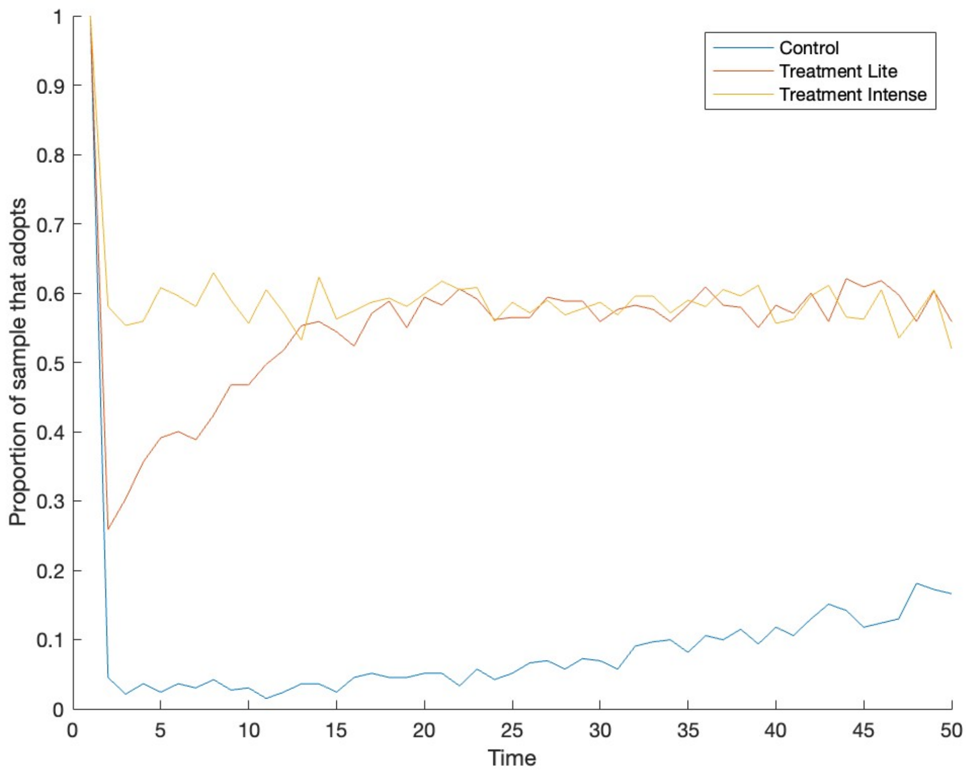


Figure 5: temporal dynamic of adoption - Full sample

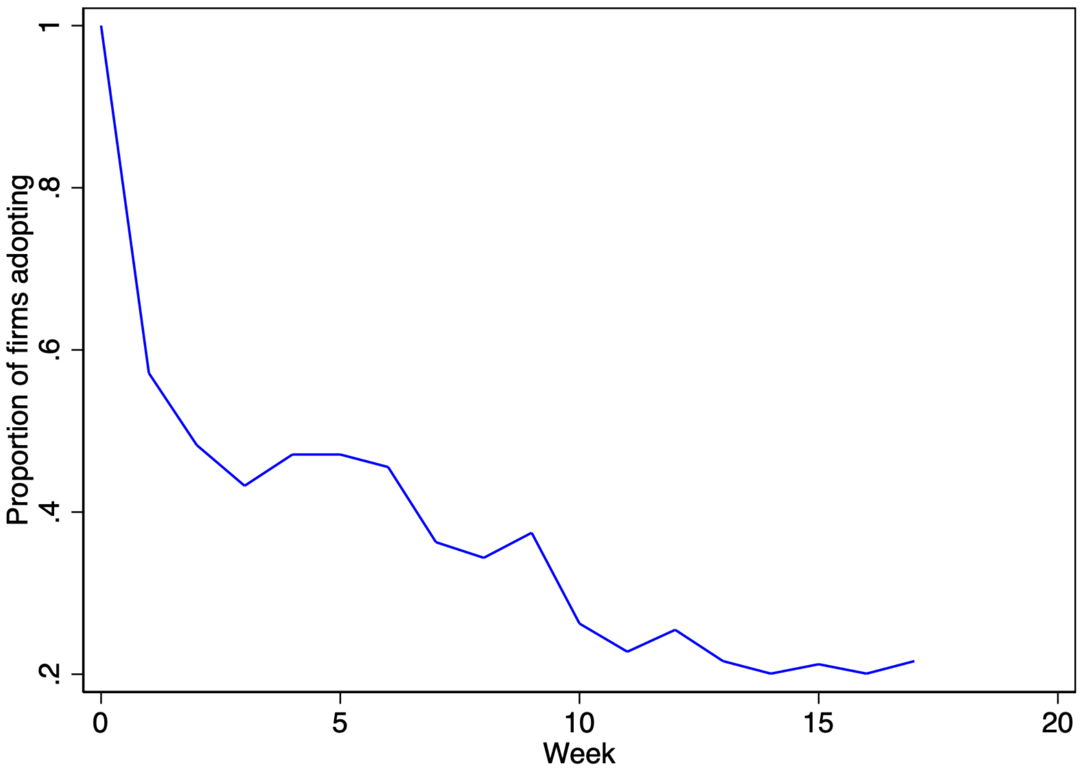


Figure 6: temporal dynamic of adoption, by treatment group

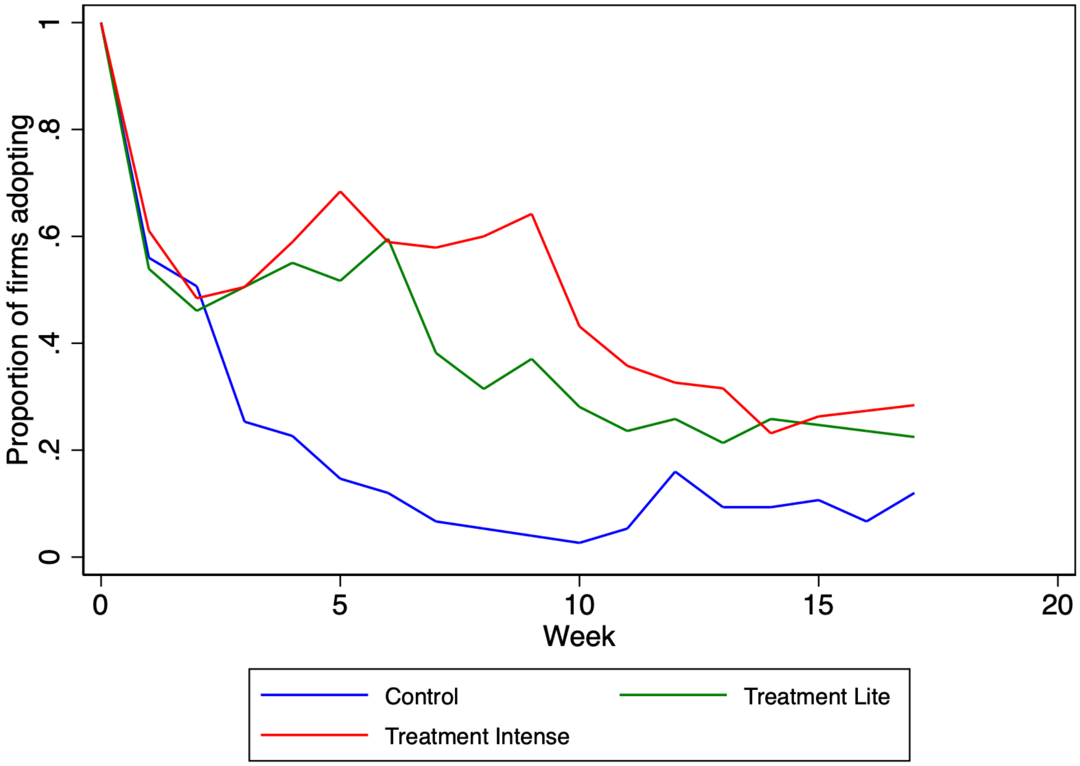


Table of Contents

A Digital penetration in LMICs

Figure 7: Growth of mobile phone subscriptions in LMICs

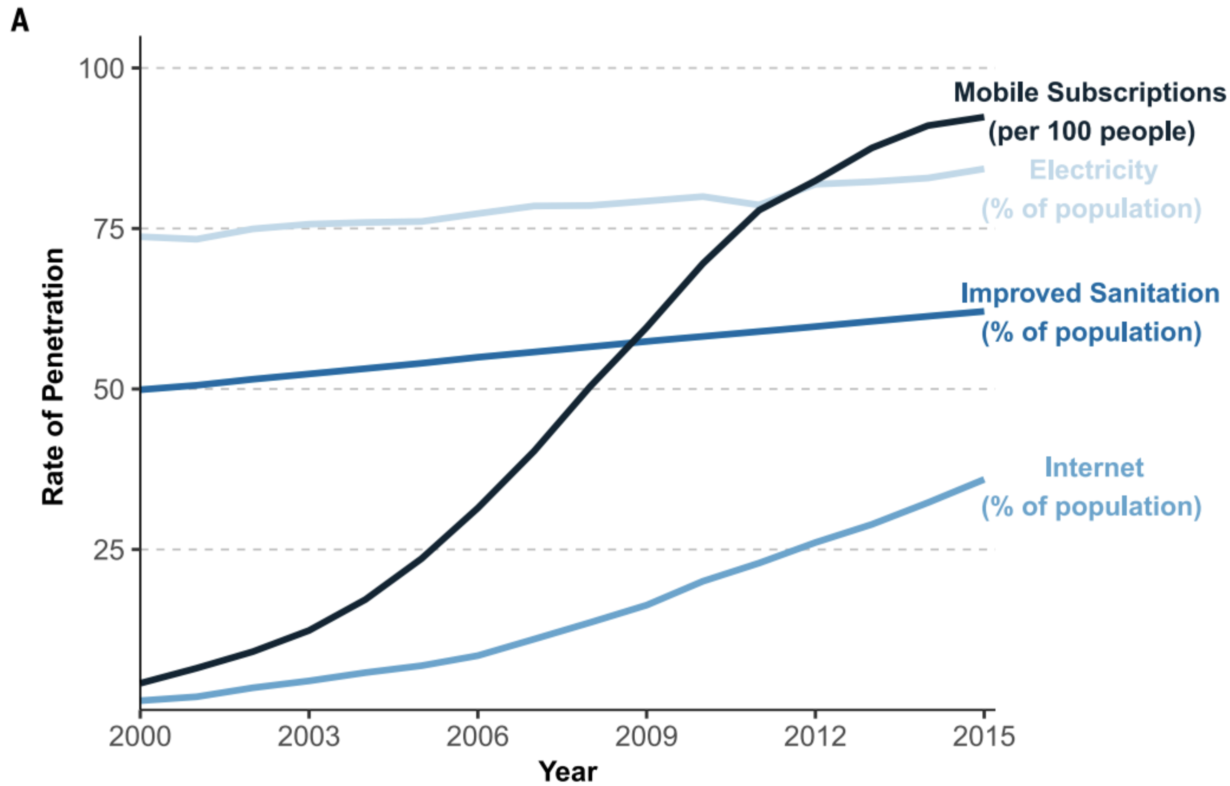
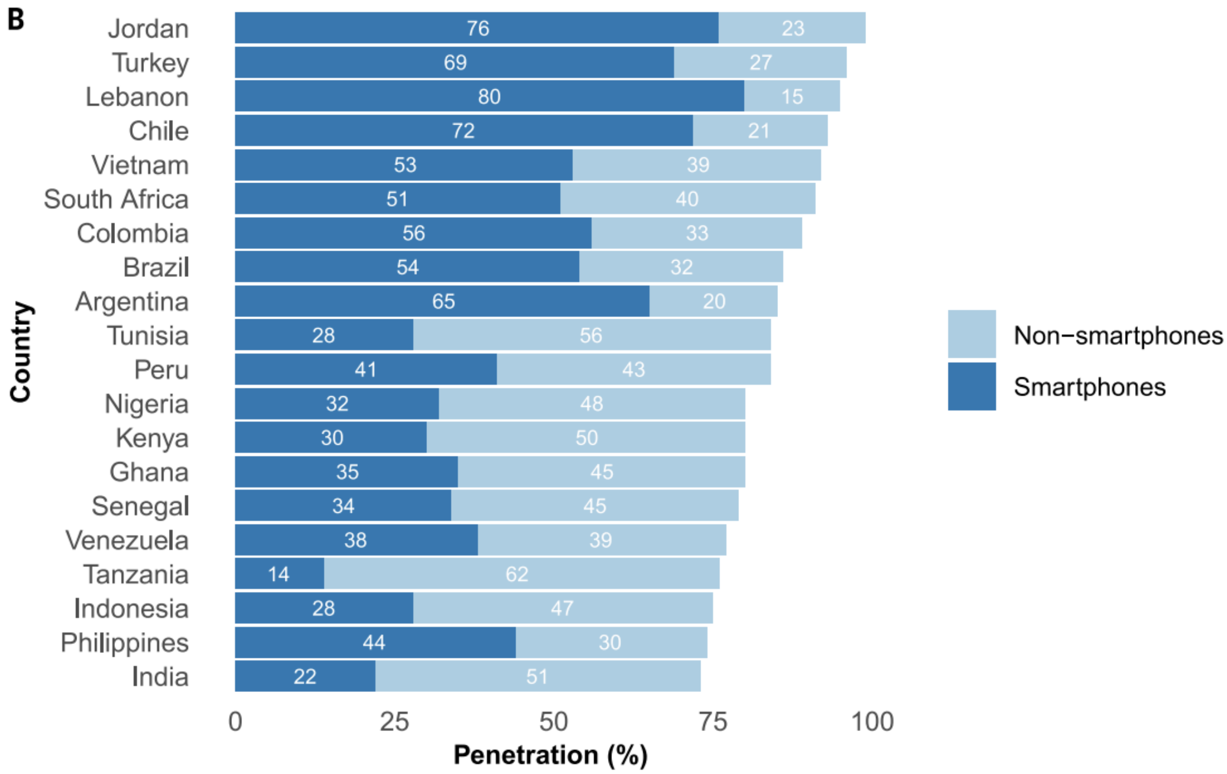


Figure 7 and Figure 8 shows the sharp rise in mobile subscriptions and smartphones across LMICs. This presents opportunities for digital technologies to be used by informal firms.

Figure 8: Mobile phone penetration in LMICs



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 9 displays an example of informal diary entries that are used in the absence of this digital technology.

Figure 9: Books of accounts

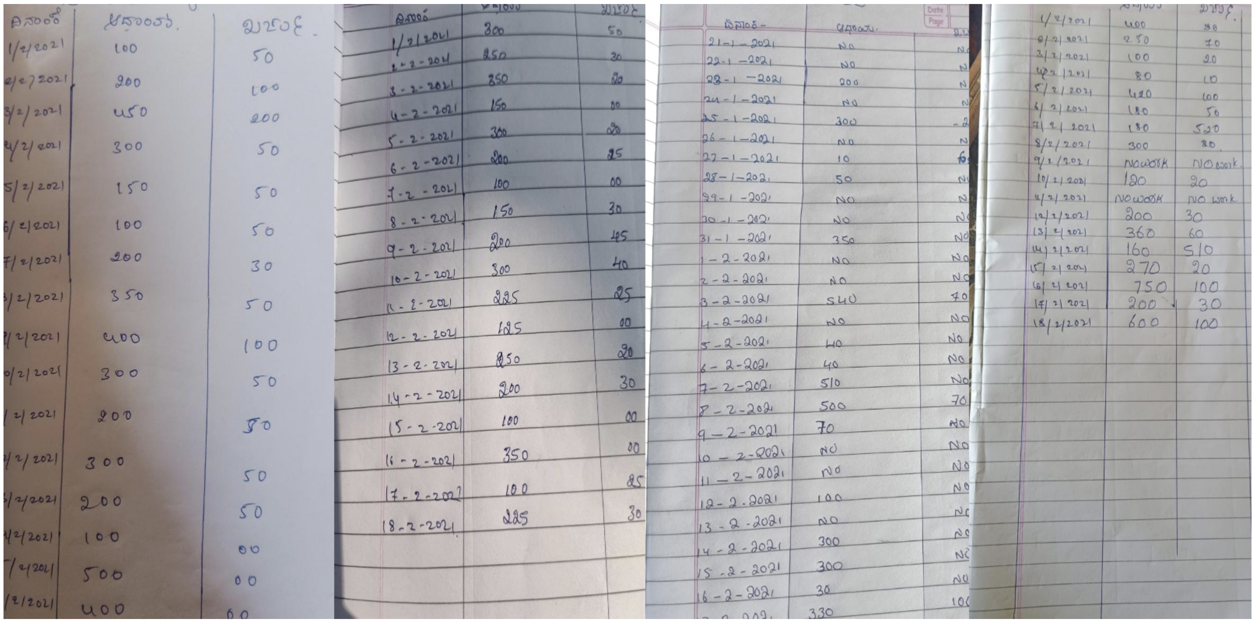
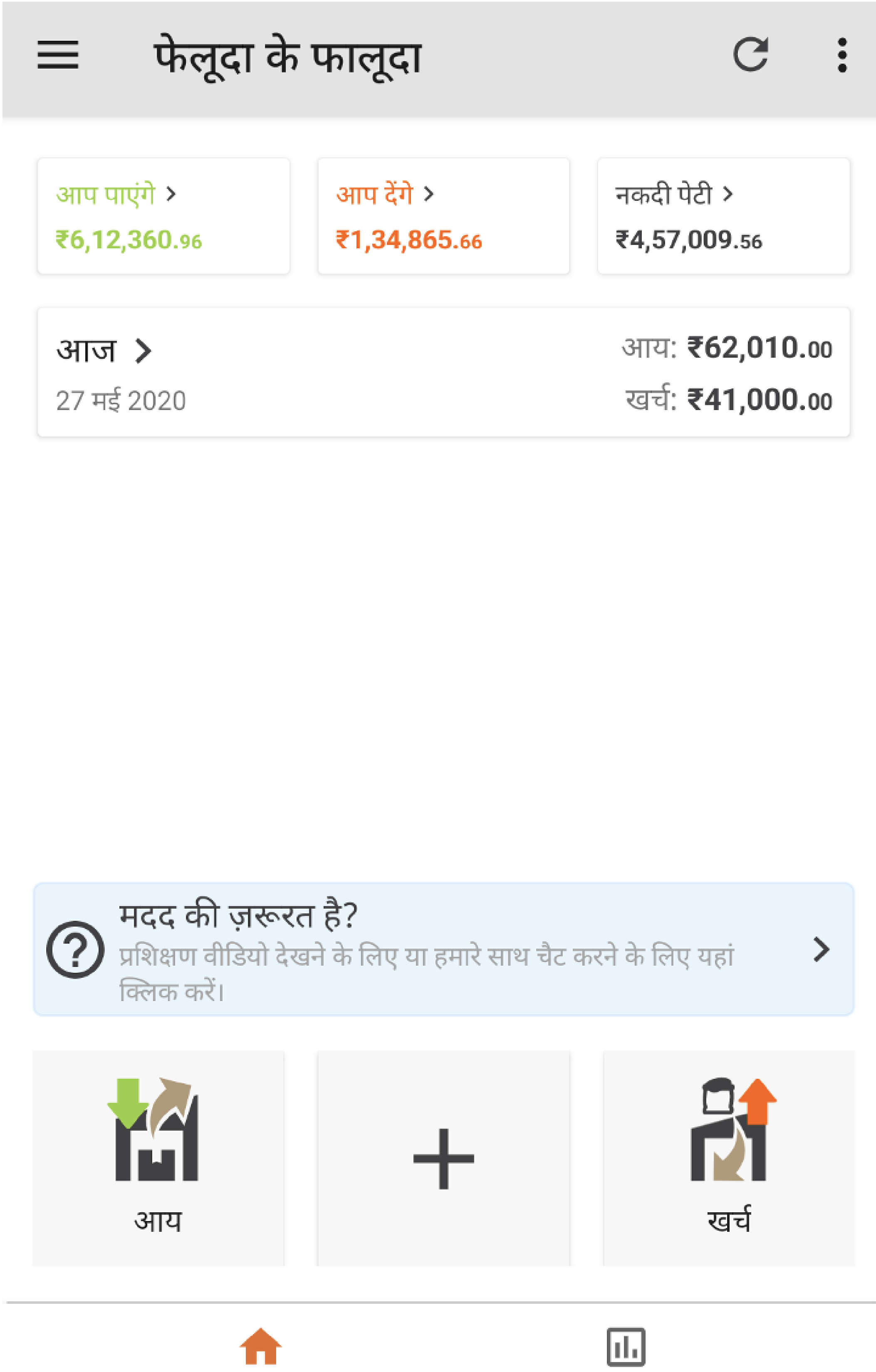
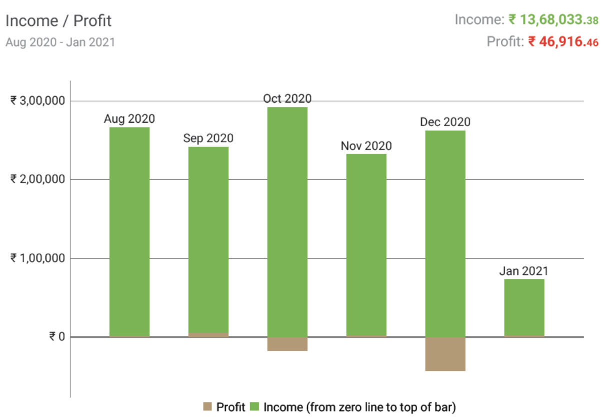


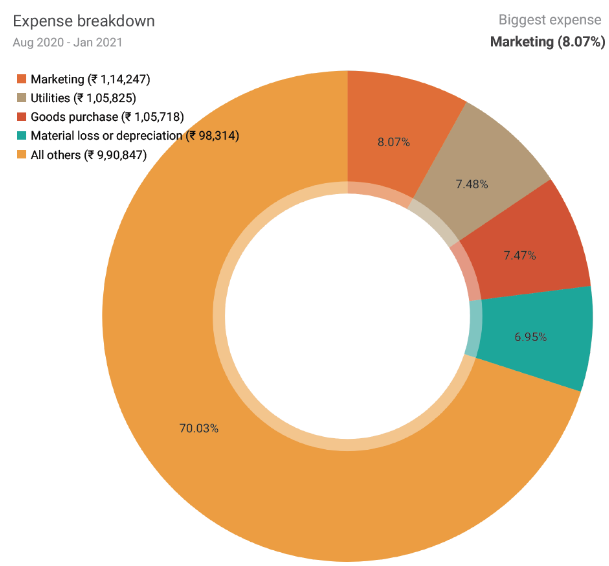
Figure 10 presents a screenshot of the interface of the easy to use MeraBills digital technology platform. Figure 11 to Figure 13 show the various financial reports that can be generated using MeraBills. Figure 11 shows the monthly firm revenue and profit, as well as, the break-up of expenditure categories. Figure 12 shows a category wise break-up of monthly revenue and expenditure. Figure 13 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 10: MeraBills app interface



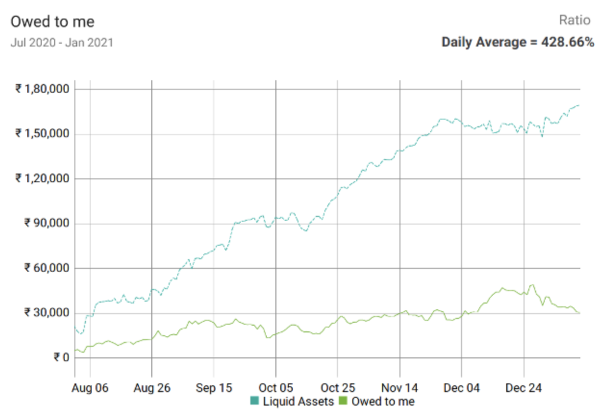


Income / Profit
Aug 2020 - Jan 2021
Income: ₹ 13,68,033.38
Profit: ₹ 46,916.46
₹ 3,00,000
₹ 2,00,000
₹ 1,00,000
₹ 0
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Profit
Income (from zero line to top of bar)

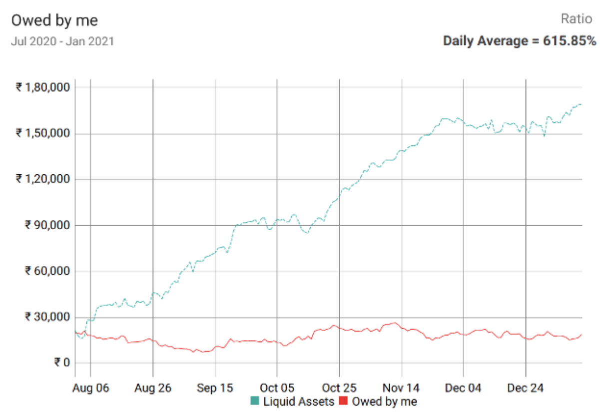


Expense breakdown
Aug 2020 - Jan 2021
Biggest expense
Marketing (8.07%)
Marketing (₹ 1,14,247)
Utilities (₹ 1,05,825)
Goods purchase (₹ 1,05,718)
Material loss or depreciation (₹ 98,314)
All others (₹ 9,90,847)
8.07%
7.48%
7.47%
6.95%
70.03%

	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***



The lower the value of the ratio, the better



The lower the value of the ratio, the better

	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**

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 C Table 11 presents details on the primary outcome variables.

Table 11: **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 C Table 12 presents details on the secondary outcome variables.

Table 12: **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 [18], frequency of recording, ability to use records [19] 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

D Treatment effects on the distribution of adoption outcomes

In Figures 14 - 16, I plot the cumulative distribution functions for key outcomes that indicate the extent of adoption. This is The real time data aggregated at the weekly level is use for this

[18]This includes revenue, expenditure, pending payments to supplier, pending payments from customers, and inventories

[19]This is based on whether firms use records to manage cash and manage products

graph. In addition to the primary adoption outcomes, I also add an outcome that measures 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 14: CDF for number of total number days MeraBills was used

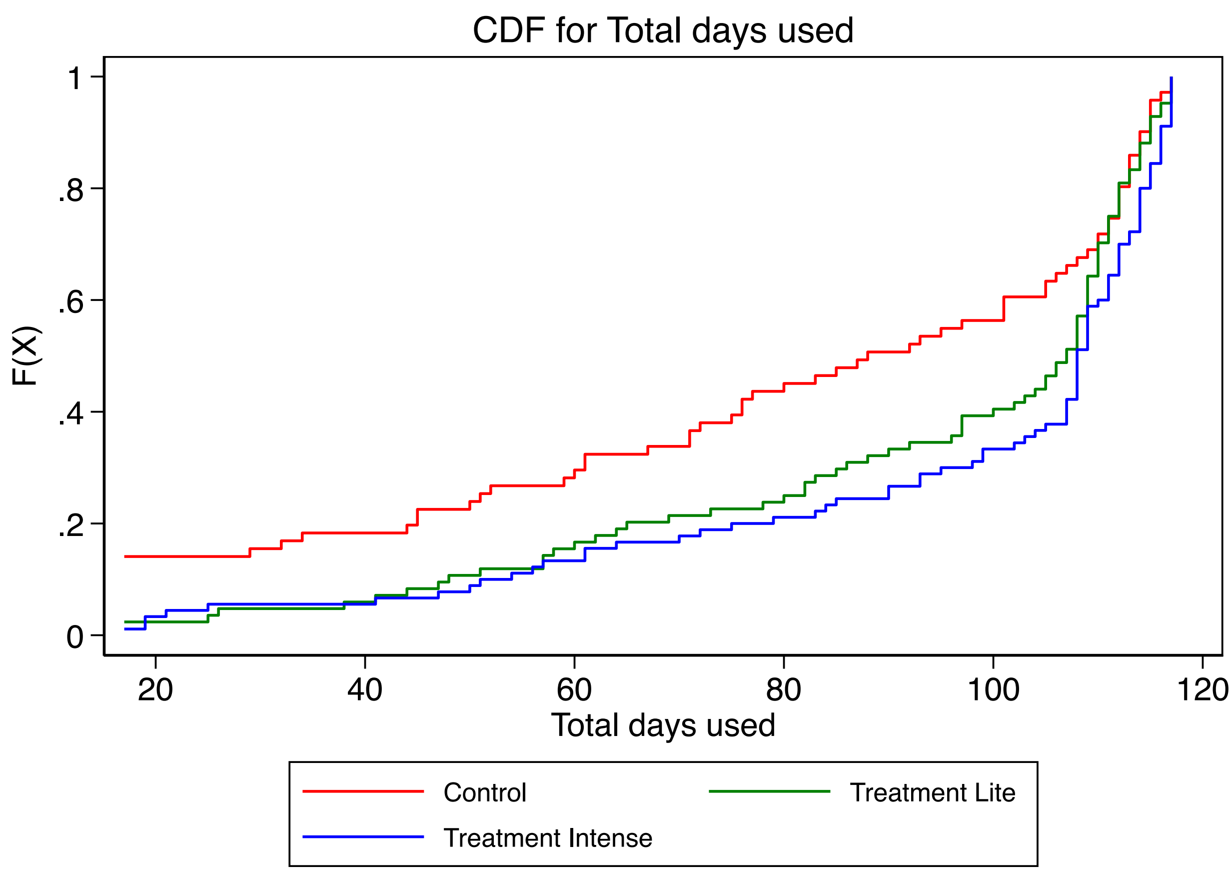


Figure 15: CDF for Number of time MeraBills was opened per week

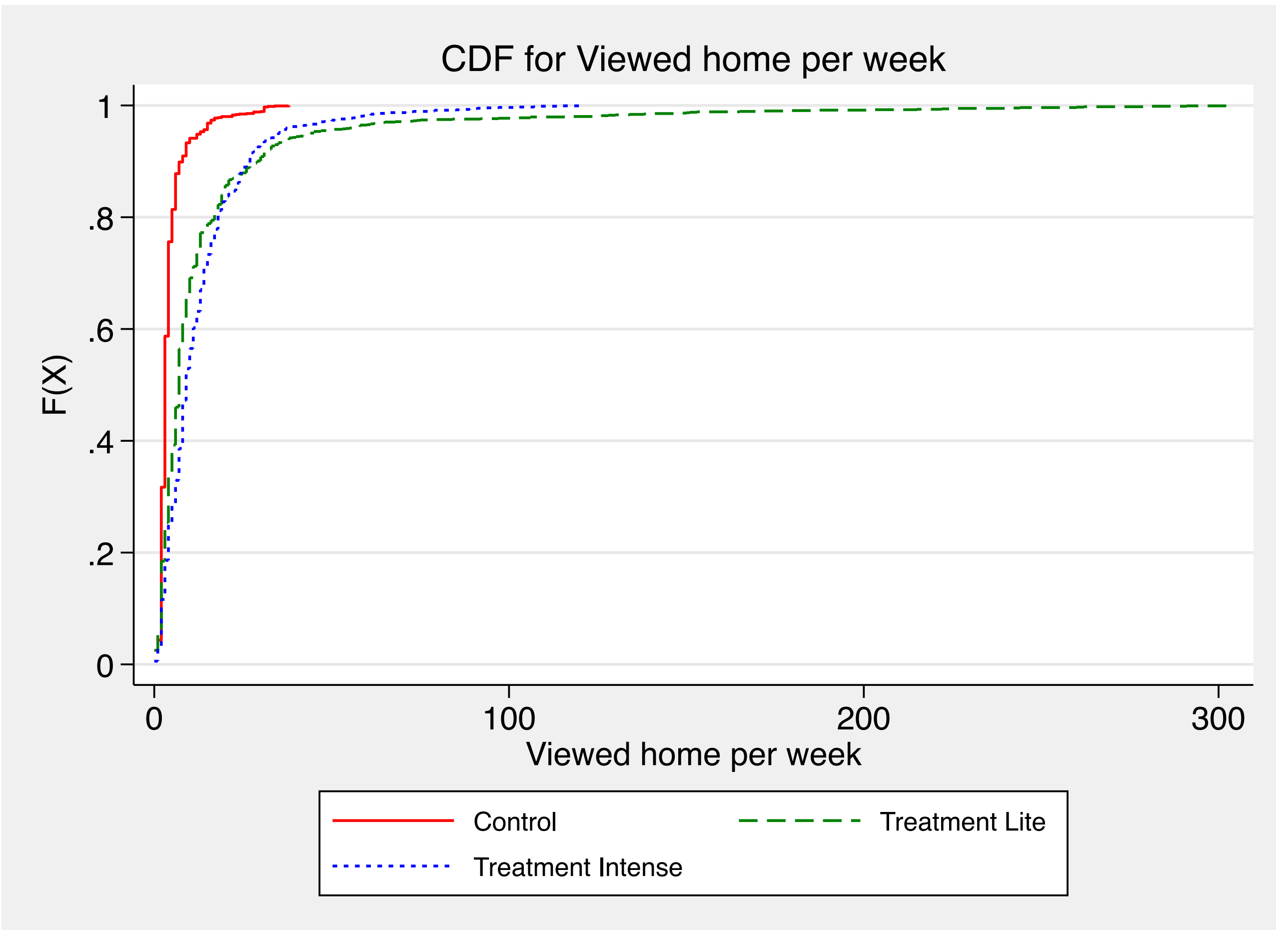
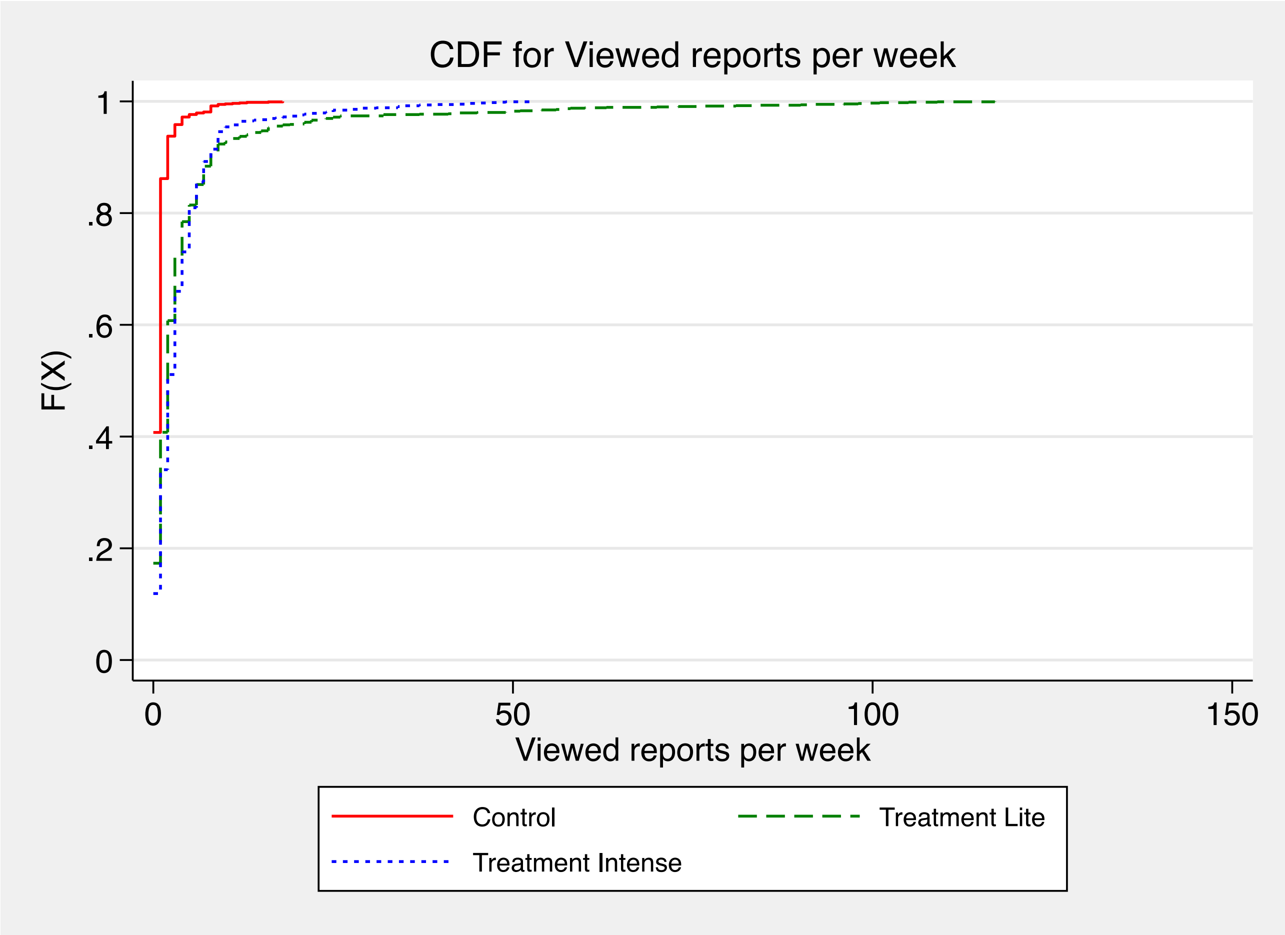


Figure 16: CDF for Transactions entered on MeraBills per week



E Latent 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.

E.1 Business practices and firm outcomes

I start by looking at the effect of increased adoption on firm level outcomes? The direction of effects are similar to the ITT estimates, but the magnitudes are larger as treatment effects are concentrated on firms that adopt the digital technology.

Looking at monthly revenue and profit data for three months after the intervention, I find a striking result in Table 13: the treatment caused a large and significantly negative effect on revenue and profit for three months of the study. Columns 1,2 and 3 present results for monthly revenue. I find a 36%, 14% and 85% decrease in firm revenue in months 1, 2 and 3 of the study. Columns 4,5 and 6 present results for monthly profit. I show that there is a 70%, 45% and 85% decrease in firm profit in months 1, 2 and 3 of the study. As in section 5, I explore the two possible explanations for the decrease in firm revenue and profit.

Table 13: **Treatment effects on Firm Revenue and Profits** :

	Revenue			Profit		
	(1) Month 1	(2) Month 2	(3) Month 3	(4) Month 1	(5) Month 2	(6) Month 3
Treatment on Treated	-4555.27	-1611.44	-13104.72*	-4861.28**	-3191.77	-7110.49**
	(4191.21)	(3674.97)	(6784.53)	(2427.63)	(2451.04)	(3500.22)
Observations	285	285	285	285	285	285
Mean DV	12405.95	11877.38	15553.57	6982.14	7136.90	8410.71
Std. dev.	14853.33	15132.61	25977.98	8934.02	10658.27	15222.48

Notes: The dependent variables in this table are outcomes for revenue and profit for firms. Columns 1 to 3 present results for firm revenue in months 1, 2 and 3 of the study while columns 4 to 6 present results for firm profit in months 1, 2 and 3 of the study. 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. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

E.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 5, I explore changes in outcomes across three broad categories - (i) business practices; (ii) firm investment; (iii) expectations on firm performance.

To study changes in business practices, I present results in Tables 14 and 15. In Table 14, I find that treated firms improve financial planning. In Column 1, I find a large and significant increase in a micro-firm owner's knowledge about key firm expenditure categories. I document that firms' in the treatment groups are 44% more likely to know what the biggest expense in their firm is (significant at 5%). In Columns 2 and 3 , I also find a large increase in treated firms' likelihood of maintaining financial statements. Column 2 shows that treated firms are 42% more likely to maintain an Income and Expense statement (significant at 10%). Column 3 shows that firms in the treatment group are 25% more likely to maintain a Profit and Loss statement (this is a positive but not significant effect).

In Table 15 I document treatment effects on business practices pertaining to inventory management. In Column 1, I find that treated firms are 67% more likely to negotiate prices with their suppliers (significant at 10%). In Column 2, I show that treated firms are 65% more likely to obtain information from from their suppliers regarding which products sell best (significant at 10%). Again, this is evidence of firms improving business practices in order to manage their business better. In Column 3, I find that firms who received the treatment were 67% more likely to attract customers by offering special discounts (significant at 10%). This provides evidence of attempts by the firm to manage customers and increase revenue.

If firms were to learn that their profitability is lower than they had anticipated using more informal record-keeping practices, this could also potentially lead to changes in investment. In Table 16 , column 1, I find that treated firms have a 93% reduction in business investment (significant at 5%) in the first three months of the study. This is a large reduction in firm investment and provides suggestive evidence of micro-firm owners learning about the low profitability of their business.

In Table 17, provide evidence of a reduction in expectations about future business performance. In Columns 1 and 2 , 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 3, I show that firms in the treatment group expect to sell 112% fewer products in the future (significant at 10%).

Table 14: **Treatment effects on financial planning practices** :

	(1) Biggest expense	(2) Income Expense Statement	(3) PnL_statement
Treatment on Treated	0.31**	0.27*	0.11
	(0.14)	(0.15)	(0.15)
Observations	285	289	285
Mean DV	0.70	0.65	0.73
Std. dev.	0.46	0.48	0.45

Notes: The dependent variables in this table are outcomes for financial planning practices for firms. Columns 1 presents results for a dummy variable that measures whether firms know their biggest expenditure category. Columns 2 and 3 present results for dummy variables for if firms maintain an Income and Expense statement and a Profit and Loss statement respectively. "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 second survey round is currently underway in the field.

Table 15: **Treatment effects on inventory management practices** :

	(1) Negotiate with supplier	(2) Info. from supplier	(3) Attract customer
Treatment on Treated	0.32*	0.32*	0.30*
	(0.16)	(0.17)	(0.16)
Observations	285	285	285
Mean DV	0.48	0.49	0.45
Std. dev.	0.50	0.50	0.50

Notes: The dependent variables in this table are outcomes for business practices around dealing with suppliers and customers. Columns 1 presents results for a dummy variable that measures whether firms negotiated prices with their suppliers. Columns 2 presents results for a dummy variable for whether firms' obtain information from their suppliers regarding which products sell best. Column 3 presents results for a dummy variable for whether firms attract customers with special discounts. "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 second survey round is currently underway in the field.

Table 16: **Treatment effects on Firm Assets and Investment** :

	(1) New Investment	(2) Fixed Assets	(3) Current assets
Treatment on Treated	-28792.61**	-34692.79	22527.18
	(12447.48)	(120492.47)	(61325.25)
Observations	285	285	285
Mean DV	30794.06	86209.45	91854.77
Std. dev.	47006.04	358728.17	191851.75

Notes: The dependent variables in this table are outcomes for investment and assets. Column 1 presents results for the magnitude of new investment made by a firm in the first three months of the study. Column 2 presents results for the total value of fixed assets. I define a fixed asset 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. Column 3 presents results for the total value of current assets. This is calculated as the sum of inventories, debt and cash in business. All variables presented in this table 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

Table 17: **Treatment effects on future business outcomes** :

	(1) Future business growth	(2) Future Customers	(3) Future Products
Treatment on Treated	-0.06	-28.75	-8.47*
	(0.10)	(18.71)	(4.96)
Observations	285	285	285
Mean DV	0.90	27.94	7.54
Std. dev.	0.30	69.43	16.62

Notes: The dependent variables in this table measure expectations on future firm outcomes. Column 1 presents results for the a dummy variable for whether a micro-firm owner expects their firm to grow in the future. Column 2 presents results for a variable that measures the number of new customers a firm expects to sell to in the future. Column 3 presents results for a variable that measures the number of new products a firm expects to sell in the future. Columns 2 and 3 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

E.3 Unsuitable technology

In Table 18, I find that firms report a positive experience while using the app. In Column 1, I document that treated firms are 67% (significant at 5%) more likely to recommend the MeraBills digital technology. As reflected in Column 2 they are also 280% more likely to teach family and friends how to use the digital technology (significant at 1%). As shown in Column 3, treated firms are also 82% more likely ((significant at 10%) to involve their family in using the digital technology. Lastly, Column 4 shows that treated firms are willing to pay more for use of 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 positive spillovers for family and friends.

Table 18: **Treatment effects on experience using app** :

	(1) Recommend DT	(2) Teach DT	(3) Involve HH in using DT	(4) Pay for DT
Treatment on Treated	0.35**	0.42***	0.31*	11.03
	(0.16)	(0.13)	(0.16)	(30.79)
Observations	289	289	289	289
Mean DV	0.52	0.15	0.38	45.24
Std. dev.	0.50	0.36	0.49	83.46

Notes: The dependent variables in this table measure a firm's experience using the MeraBills digital technology . Column 1 presents results for a dummy variable for whether a micro-firm owner would recommend the digital technology to others. Column 2 presents results for 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

F Separating treatment 1 and treatment 2

Since the treatment effect on adoption outcomes does not show a significant difference in the app usage between the two treatment arms, I expect the treatment effects on firm outcomes to also be similar. In Section 5, I present pooled treatment effects for the two hand holding treatments (Treatment Lite and Treatment Intense) while using survey data, for the purpose of power. In this section, I present results for individual treatment arms. Overall, while I have less statistical power in this specification, the results tell a similar story.

F.1 Business practices and firm outcomes

Looking at monthly revenue and profit data, I see negative effects on monthly revenue and profits. Again, I explore the two possible explanations for the decrease in firm revenue and profit.

Table 19: **Treatment effects on Firm Revenue and Profits** :

	Revenue			Profit		
	(1) Month 1	(2) Month 2	(3) Month 3	(4) Month 1	(5) Month 2	(6) Month 3
Treatment Lite	-1973.66	-1345.77	-6040.00**	-2290.35**	-1894.79*	-3485.35**
	(1860.66)	(1522.66)	(2751.54)	(1017.66)	(1007.33)	(1452.10)
Treatment Intense	-1717.80	-30.06	-4603.56	-1668.10	-771.87	-2406.41
	(1882.62)	(1780.59)	(3032.07)	(1066.17)	(1122.69)	(1529.12)
Observations	285	285	285	285	285	285
Mean DV	12405.95	11877.38	15553.57	6982.14	7136.90	8410.71
Std. dev.	14853.33	15132.61	25977.98	8934.02	10658.27	15222.48

Notes: The dependent variables in this table are outcomes for revenue and profit for firms. Columns 1 to 3 present results for firm revenue in months 1, 2 and 3 of the study while columns 4 to 6 present results for firm profit in months 1, 2 and 3 of the study. 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. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

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. In Tables 20 and 21, I find an overall improvement in financial management and inventory management practices. In Table 22, I find negative effects on new investments by the firm for both treatments (significant at 5%). In Table 23, I find reduced expectations of future firm growth.

Table 20: **Treatment effects on financial planning practices** :

	(1) Biggest expense	(2) Income Expense Statement	(3) PnL_statement
Treatment Lite	0.09	0.09	-0.02
	(0.06)	(0.07)	(0.07)
Treatment Intense	0.16***	0.12*	0.10
	(0.06)	(0.07)	(0.06)
Observations	285	289	285
Mean DV	0.70	0.65	0.73
Std. dev.	0.46	0.48	0.45

Notes: The dependent variables in this table are outcomes for financial planning practices for firms. Columns 1 presents results for a dummy variable that measures whether firms know their biggest expenditure category. Columns 2 and 3 present results for dummy variables for if firms maintain an Income and Expense statement and a Profit and Loss statement respectively. "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 second survey round is currently underway in the field.

Table 21: **Treatment effects on inventory management practices** :

	(1) Negotiate with supplier	(2) Info. from supplier	(3) Attract customer
Treatment Lite	0.19**	0.18**	0.13*
	(0.08)	(0.08)	(0.08)
Treatment Intense	0.07	0.09	0.12
	(0.07)	(0.08)	(0.07)
Observations	285	285	285
Mean DV	0.48	0.49	0.45
Std. dev.	0.50	0.50	0.50

Notes: The dependent variables in this table are outcomes for business practices around dealing with suppliers and customers. Columns 1 presents results for a dummy variable that measures whether firms negotiated prices with their suppliers. Columns 2 presents results for a dummy variable for whether firms' obtain information from their suppliers regarding which products sell best. Column 3 presents results for a dummy variable for whether firms attract customers with special discounts. "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 second survey round is currently underway in the field.

Table 22: **Treatment effects on Firm Assets and Investment** :

	(1) New Investment	(2) Fixed Assets	(3) Current assets
Treatment Lite	-11769.84**	35779.28	33810.79
	(5643.45)	(63239.30)	(31529.05)
Treatment Intense	-11499.39**	-58792.02	-12658.75
	(5042.18)	(43956.67)	(25379.28)
Observations	285	285	285
Mean DV	30794.06	86209.45	91854.77
Std. dev.	47006.04	358728.17	191851.75

Notes: The dependent variables in this table are outcomes for investment and assets. Column 1 presents results for the magnitude of new investment made by a firm in the first three months of the study. Column 2 presents results for the total value of fixed assets. I define a fixed asset 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. Column 3 presents results for the total value of current assets. This is calculated as the sum of inventories, debt and cash in business. All variables presented in this table 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

Table 23: **Treatment effects on future business outcomes** :

	(1) Future business growth	(2) Future Customers	(3) Future Products
Treatment Lite	-0.04	-13.57*	-2.64
	(0.05)	(7.35)	(2.26)
Treatment Intense	-0.01	-9.81	-4.04**
	(0.05)	(8.42)	(1.98)
Observations	285	285	285
Mean DV	0.90	27.94	7.54
Std. dev.	0.30	69.43	16.62

Notes: The dependent variables in this table measure expectations on future firm outcomes. Column 1 presents results for the a dummy variable for whether a micro-firm owner expects their firm to grow in the future. Column 2 presents results for a variable that measures the number of new customers a firm expects to sell to in the future. Column 3 presents results for a variable that measures the number of new products a firm expects to sell in the future. Columns 2 and 3 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.

F.3 Unsuitable technology

In Table 24, I find that firms report a positive experience while using the app for both treatment arms.

Table 24: **Treatment effects on experience using app** :

	(1) Recommend DT	(2) Teach DT	(3) Involve HH in using DT	(4) Pay for DT
Treatment Lite	0.13*	0.13**	0.09	11.23
	(0.07)	(0.06)	(0.07)	(16.52)
Treatment Intense	0.15**	0.21***	0.16**	-1.70
	(0.07)	(0.06)	(0.07)	(13.53)
Observations	289	289	289	289
Mean DV	0.52	0.15	0.38	45.24
Std. dev.	0.50	0.36	0.49	83.46

Notes: The dependent variables in this table measure a firm's experience using the MeraBills digital technology . Column 1 presents results for a dummy variable for whether a micro-firm owner would recommend the digital technology to others. Column 2 presents results for 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 results are pooled for the follow-up survey rounds. Currently, the results only include one round of survey data. The second survey round is currently underway in the field.