The impacts of earned wage access on low income women workers*

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Abstract

Employer-provided digital financial services (DFS) can enhance the financial resilience of women earning regular but low wages. In a 12-month field experiment at a South Indian garment factory, we introduced an Earned Wage Access (EWA) application via tablets on the factory floor. This app allowed women in the treatment group to access up to 50% of their earned wages before payday, up to three times per month, with instant deposits into their bank accounts. Approximately one-third of the treatment group used the EWA app at least once. These women reduced their reliance on informal loans by 30% and were 20% less likely to cut back on monthly consumption compared to the control group, indicating improved liquidity. Worker retention increased significantly, with women in the intervention group being 4.2% more likely to be present at work on a given day. Overall earnings rose by 12% (significant at the 10% level), primarily due to women remaining in the labor force longer. Daily productivity also increased by 7.5% (significant at the 10% level), with the most significant gains among workers experiencing high financial stress, whose productivity rose by 17.5%, reflecting reduced financial strain. Importantly, improved liquidity through flexible pay did not lead to overspending but instead fostered confidence in mobilizing funds when needed. However, there were no significant changes in savings behavior or intra-household bargaining power. This study highlights the benefits of pay flexibility and workplace-based DFS solutions for financial well-being, women's empowerment, and workplace outcomes in developing countries.

** Preliminary findings - please do not cite **

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1 Introduction

Low and moderate-wage earners, despite having stable and predictable income streams, frequently encounter financial setbacks due to short-term liquidity constraints. Their tight budgets often cover only basic necessities, leaving little to no buffer for unexpected expenses, such as medical emergencies or urgent home repairs, as well as foreseeable irregular payments like school fees (Fitzpatrick 2014[17], Donner 2021[12], Murillo 2022[31]). In developing countries, these households often have minimal precautionary savings or liquid assets and lack access to affordable credit. They also face higher rates of income and expenditure shocks, making consumption smoothing more difficult during such times (Demirguc-Kunt et al., 2022)[11].

Households frequently resort to costly informal loans, rely on social networks, or liquidate assets to meet short-term needs and emergencies. In more severe circumstances, where liquidity is highly constrained, households may be forced to cut back on essential needs like food, healthcare, or timely payments on utilities and loans. The financial stress associated with these short-term liquidity constraints is often significant, leading to adverse outcomes including increased debt burden and financial instability. This, in turn, can impair physical and mental health (Field et al., 2012)[15], strain personal relationships, reduce workplace productivity (Kaur et al., 2021)[23], and impair cognitive function and decision-making (Mani et al., 2013)[28].

The life-cycle/permanent-income hypothesis (LCPIH) predicts that individuals who expect to be paid monthly should stretch their resources across the entire month to maintain a consistent level of consumption (Breza et al., 2017)[9]. However, research has shown that household consumption decisions often do not align with LCPIH predictions. For instance, households' spending patterns peak around paydays, without individuals delaying spending until their income arrives or spending immediately upon receipt (Olafsson and Pagel, 2018[32]; Baugh et al., 2021[6]; Gelman, 2022[19]). This deviation from LCPIH is often attributed to time-inconsistent preferences.

Another factor contributing to this is limited financial literacy and management skills (Lusardi, and de Bassa Scheresberg, 2013 [26]; Leary and Wang, 2016 [25]; Bhutta et al., 2023 [8]). Effective consumption smoothing requires households to manage both income inflows and expenditure outflows, but these often misalign—income may arrive at different times from when bills are due. (Zhang, 2023)[37]. Moreover, while various household members may receive their incomes at different times, they typically share common expenses like utility bills. Balancing these factors—timing of income receipts, expected payments (e.g., utilities, education), and unexpected shocks (e.g., health emergencies, funerals)—is crucial for maintaining consistent consumption. Without effective budgeting or saving strategies, households are more likely to face frequent liquidity crises. Research has also shown that lack of "mental bandwidth" or time for financial planning can also contribute to such situations (Schillbach et al., 2016)[34].

Added to this, the process by which financial decisions are made within households, particularly among married couples, also influences consumption smoothing and financial well-being of individual members of the household. Studies show that women, especially in developing countries, often have lower participation in household financial decision-making, including decisions about expenditures, savings, and investments (Doss, 2013[13]; Jayachandran, 2015[22]). While women who are employed tend to have more bargaining power compared to those not in the workforce (Majlesi, 2016[27]), significant gender disparities persist even among households where both spouses work, particularly in achieving economic independence and exercising agency in personal and household financial decisions. These are often dictated by distinct roles household members assume in generating and managing household finances prescribed by societal norms and the specific responsibilities within individual households.

Gender disparities also manifest in the reasons behind financial worries and in individual choices of spending. For instance, in India, a higher percentage of women express concern about insufficient funds for routine monthly expenses compared to men. Women are also more likely to cite children's school fees as their biggest financial worry (Demirgüç-Kunt, 2022)[11]. Women, in general, tend to have more difficulty accessing emergency funds, relying more on family support, which is often unreliable. Additionally, women generally have smaller social networks than men, making it harder for them to seek help during financial crises. Savings committed to Rotating Savings and Credit Associations (ROSCAs), which are popular among women, may also be inaccessible in emergencies.

Digital and financial services (DFS) have the potential to enhance financial resilience by providing liquidity during income and expenditure shocks. Research has shown DFS to increase household spending (Munyegera and Matsumoto, 2016[30]), promote saving (Suri and Jack, 2016[35]) and allow households to engage in consumption-smoothing when faced with idiosyncratic shocks (Batista and Vincente, 2020[5]). However, DFS initiatives may inadvertently perpetuate gender disparities due to structural and social constraints. For example, in countries like India, significant gaps in mobile phone ownership, higher illiteracy rates, limited awareness, and lower participation in market work among women contribute to lower adoption rates of digital banking technologies (Mariscal et al., 2019[29]).

One way to address short-term liquidity constraints and gender disparities in DFS among low-income salaried workers is through employer-enabled solutions, especially in industries that employ large numbers of women such as garment factories. Workplace access to DFS can help bridge gaps in mobile phone ownership and digital literacy by providing workers with on-site access to devices and internet, as well as training and support. Such solutions can economically empower women by improving their financial resilience and reducing financial stress (Fu and Salyanti, 2023)[18]. These benefits extend to employers as well, who may experience reduced absenteeism, lower turnover rates, enhanced productivity and can be cost effective due to lower transaction costs associated with digital payments.

We implemented an employer-enabled DFS solution using a full-scale Randomized Controlled Trial (RCT) in a garment factory in South India. Female workers were randomized into treatment and control groups, with the treatment group receiving access to a user-friendly Earned Wage Access (EWA) platform facilitated through tablets placed on the factory floor. Workers could withdraw up to 50% of their earned wages at any point during the month through the EWA app, which was instantly deposited to their bank accounts registered with the factory.

EWA, with its lower transaction costs compared to informal loans or high-interest credit, is expected to improve financial well-being by reducing defaults on payments, expenditure deferrals, and reliance on costlier informal credit, while also smoothing consumption. Furthermore, the expedited money transfers enabled by EWA can enhance women's ability to support their households during crises or enactment of their own preferences in household spending, and thereby potentially improving their bargaining power within the household. However, increased spending on women's preferred goods and services might lead to resistance or tension within households, impacting the tool's usage and impact (Fiala, 2018)[14]. Therefore, we also examine how prevailing social norms regarding household financial decision-making affect the usage of EWA and mediate its impact on women's empowerment and self-efficacy in household financial decision-making.

In the 12 months following the rollout of the EWA app, 33.6% of women in the treatment group used the app, generating 656 transactions with cumulative withdrawals amounting to USD 10,728[1]. These women, earning an average monthly income of USD 139, cited loan repayments, child-related expenses, and medical costs as their primary reasons for withdrawals. Analyses of EWA take-up and frequency of usage show that women with higher asset rankings were more likely to use the app. In contrast, those with lower financial resilience and higher financial stress in the baseline used the app more frequently. The app usage was 40% among the high-stress group compared to 20% in the low-stress group. Women with borrowing histories from informal, high-interest sources also showed higher app usage, indicating a shift away from these informal loans toward the EWA app.

Women in the treatment group were 9.6 percentage points less likely to borrow from informal sources, translating to a 32.9% reduction compared to the control group. EWA treatment led to a 20% reduction in the likelihood of cutting back on usual monthly expenditures due to cash shortages; we also find significant reduction in foregone food and health expenditures. Women in the intervention group also reported a 32% decrease in difficulty making ends meet, suggesting improved liquidity. However, the EWA intervention did not significantly affect savings or "regretful overspending." Further, the EWA intervention did not significantly affect women's empowerment in household financial decision-making. However, women using the app reported higher self-confidence in mobilizing funds.

The EWA intervention had a positive impact on workplace retention over time, as more women adopted and used the app progressively throughout the study period. By the final month, women in the intervention group were 4.2% more likely to be present in the factory on any given day. This improvement was largely driven by a 20% reduction in worker turnover, particularly among workers with low financial stress. We posit that the liquidity access facility effectively reduced the relatively higher reservation wage of low-stress workers, who initially exhibited higher turnover rates compared to their high-stress counterparts. Additionally, women's overall earnings increased by 21% as they remained in the labor force for longer periods due to factory employment. The EWA treatment also led to an 8.2% increase in daily productivity (significant at the 10% level), with effects being even more pronounced among workers with high financial stress at baseline, where productivity rose by 17.2%. These findings indicate that the EWA intervention simultaneously reduced turnover among low-stress workers and enhanced productivity among high-stress workers, creating a compelling business case for its adoption.

This study contributes to the literature on short-term credit solutions for low-income workers, with a particular focus on women in developing countries. Existing research largely examines payday loans and credit card debt in developed countries, especially the U.S (Fitzpatrick and Coleman-Jensen, 2014[17]; Donner and Siciliano, 2021[12]; Allcott et al., 2022[4]). In the U.S, these loans have become extremely controversial, leading to calls for regulation or even outright bans. Gomes et al., (2021)[20] review studies documenting both positive and negative effects. Payday loans are linked to higher bankruptcy rates, reduced job performance, and overdraft violations. Still, studies have also documented that it provides critical liquidity and improves expenditure smoothing, especially during financial emergencies. Documenting the welfare impacts of digital financial solutions like earned wage access, which reduce interest burdens associated with high-cost loans and enhance liquidity, is crucial in low-income, developing contexts.

We also contribute to the nascent strand of literature on staggering wage payments or payment frequency on household consumption decisions. Few studies find that higher payment frequency is associated with smoother expenditure paths (Aguila et al., 2017[3]; Berniell, 2018[7];

[1]Conversion rate being used: USD 1 is equal to INR 84.7.

Laamanen et al., 2019[24]). On the other hand, De La Rosa and Tully (2020) analyzed the impact of more frequent, smaller, paychecks on household wealth perceptions and spending and found that smaller, more frequent, paychecks increase individual wealth perception leading to higher discretionary spending. This experiment also adds to the growing literature of the impact of strengthening financial autonomy through access to DFS or formal sources of finance on the bargaining power of women and their labor supply decisions (Field et al., 2021[16]; Heath and Riley 2024[21]). As we are not altering the income of women (the salary remains unchanged), we isolate the impact of the provision of liquidity as opposed to the income effect. This adds nuance to the literature on women's empowerment in developing countries, specifically by highlighting how the timing of wages between pay periods influences women's spending decisions.

Finally, we add to the literature on how flexible pay options reduce financial stress, increase productivity, and cater to workers' preferences thereby reducing worker turnover. Kaur et.al., (2021)[23] found that workers paid earlier became 7.1% more productive due to reduced financial stress. Murillo et al., (2022)[31] analyzed earned wage access (EWA) usage in a Mexican fintech firm and observed higher usage near the end of the pay cycle, which correlated with higher employee retention. Chen et al., (2024)[10] conducted an RCT on gig workers at Uber, showing that switching from weekly fixed pay to on-demand, within-day withdrawals significantly increased work hours and earnings, driven by drivers' present bias. Similarly, Scarelli (2024)[33] ran a large-scale experiment with Brazilian rideshare drivers, revealing that most preferred immediate payment, even at the cost of a third of their potential earnings, due to liquidity constraints.

Finally, we add to the research and business case studies of non-salary work amenities and the return on such investments through their impact on workplace outcomes. Non-salary amenities in the workplace can have large impacts on worker productivity, retention and job satisfaction (Adhvaryu et al., 2023[2]; Adhvaryu et al., 2024[1]). We believe this experiment adds to the body of evidence of the business impact of worker wellbeing initiatives.

2 Context, program details and intervention design

2.1 Context

This study is conducted in one of the garment factories of Shahi Exports Private Limited, located in Karnataka, India. The garment manufacturing industry in India is a significant employment sector, comprising a workforce of approximately 13 million, with a substantial proportion being female workers. Shahi Exports, the largest exporter of readymade garments in India, employs over 100,000 full-time workers, three-fourths of whom are women, across its 63 factories, producing more than 144 million garments annually.

At Shahi, workers receive their monthly wages by the 7th of the subsequent month through direct transfers to their individual bank accounts. The company's wage processing system is automated, with certain stages requiring manual checks and authorisation. Worker attendance is tracked using a biometric authentication system, which is integrated with the payroll system to calculate monthly earnings, taking into account factors such as days worked, loan arrears, and wage advances. External auditors review the payment data, and once the necessary approvals are obtained from both auditors and Shahi management, the finalized payment details are submitted to the company's registered banking partner. The bank then transfers the wages directly into the workers' bank accounts by the 7th of the following month.

2.2 DFS Intervention

We developed an Android application, 'EWA,' which was deployed on tablets placed on the factory floor. This app is integrated with both Shahi's attendance management and payroll systems, allowing for real-time tracking of attendance and salary adjustments. A worker's monthly take-home salary is used to calculate earned wages up to any specific date, with compensation based solely on days worked, excluding leave, overtime, holidays, or weekends. For example, if a worker with a monthly take-home salary of INR 12,000 checks the app on the 20th of the month, having worked 17 days, she would have earned INR 6,400. The worker can choose to withdraw up to 50% of this amount, which is then transferred directly to her bank account.

The process is nearly instantaneous and takes only a few minutes of the worker's time: the worker logs into the app using a QR code linked to her identity card, views the maximum available withdrawal amount, and selects the desired amount. Once the worker confirms the withdrawal, the funds are transferred instantly to her registered salary bank account. Workers are permitted to make up to three withdrawals per month. Withdrawal data is then transmitted back to Shahi's payroll system through an integration managed by the IT team, where all transactions are recorded as "deductions" under the worker's employee code and they get their wages deducted by that amount in the next paycycle. In cases of resignation, these deductions are automatically included in the worker's final settlement, ensuring a fully automated system without the need for manual intervention.

A key factor in EWA's effectiveness is the instantaneous transfer of earned wages, made possible through a partnership with a fintech integrator. The integrator charges a transaction fee of USD 0.07 for transactions exceeding USD 11.9 and USD 0.05 for amounts below USD 11.9. Workers did not have to pay for the transaction charges, which were covered by the research team.

2.3 Experimental Design

The study is structured as a randomized controlled trial (RCT) with individual-level randomization. From a factory workforce of approximately 2600, we identified 1,492 eligible ever-married women who had been employed at the factory for at least six months. Our study sample consisted of 834 workers who were then randomized 1:1 into treatment and control groups following a stratified randomization procedure; our strata variables are household income and women's economic empowerment.

The control group continued with the standard salary processing method, where wages are transferred to workers' bank accounts on the 7th of the following month. The treatment group was given access to the digital platform for flexible salary withdrawals and received initial training on its usage. To onboard workers in the treatment group, QR codes for login to the EWA app were distributed to them and these could be attached to their ID cards, which they are required to carry to the workplace on a daily basis. We then conducted training sessions in groups of 5-10 workers, covering user navigation of the EWA app and various use-case scenarios drawn from qualitative pre-launch surveys. Recognizing that a single training session might be insufficient—especially for women unfamiliar with digital financial services (DFS)—we ensured that support staff or designated points of contact (POCs) were available near the tablets to assist with app navigation and address any queries.

3 Data and Summary Statistics

3.1 Human Resources Data

We accessed workers' demographic data, attendance records, tenure information, and salary details, all managed within a firm-maintained database. This dataset, linked by a unique worker ID, includes variables such as age, gender, native language, education, and date of employment. We combined this with two other datasets - daily attendance data and monthly salary data.

3.2 Hanger system data for productivity

In order to measure the impact on individual-level productivity, we use data from production lines which have a hanger system, a widely used production tracking mechanism in assembly-line manufacturing. The hanger system is an automated material handling system that uses hangers or carriers to transport semi-finished garments between workstations in a production line. Each hanger is typically equipped with an electronic tag or RFID (Radio Frequency Identification) chip that records production data. Each worker is assigned a specific task or operation in the garment production process (e.g., stitching, attaching buttons, hemming). As the garment piece moves through the production line, its progress is recorded at each workstation using the electronic tags on the hangers. The system logs which worker completed each task, how many units were processed, and the time taken for each unit. The system automatically collects real-time data on the number of units completed by each worker and the time spent on each unit or task. This data is uploaded to a centralized system for analysis. In the factory where we implemented the trial, the hanger system was available only on few production lines, and therefore all productivity analyses are restricted to workers observed on these lines during our study period.

3.3 Application Data

The backend of the EWA application provides transaction-level data, including unique worker ID, date and time of log-in, the amount available for withdrawal, the actual amount withdrawn, and the self-reported purpose of the withdrawal.

3.4 Survey Data

3.4.1 Baseline and Endline surveys

At the beginning of the study, baseline surveys were conducted to collect demographic and socio-economic information, such as age, education level, marital status, number of children, household income, savings, borrowing status, financial management practices, and intra-household financial decision-making. The endline survey collected the same data related to these outcomes.

3.4.2 High Frequency Surveys

These monthly surveys were administered to a sub-sample of workers from both the control and treatment groups at the end of each pay cycle, over the course of one year. This approach captured seasonality in workers' liquidity needs and measured their borrowings, savings and lending behaviour during the month, and the financial stress experienced over that month. Each worker was surveyed at least three times during the one-year period, providing repeated observations over time.

There are spillover concerns due to the provision of the EWA application to the treatment group and not the control group. For example, women workers are more likely to rely on informal networks at workplaces and outside for their borrowing needs. In such cases, the provision of the EWA intervention is expected to reduce the reliance on their co-workers for borrowing needs. On the other hand, participants in the treatment group can use the EWA intervention to lend to participants in the control group, leading to spillover concerns. Thus, we captured the borrowing and lending networks among co-workers and how this mediates the primary outcomes and is itself affected by the intervention using network elicitation surveys as part of our HFS and endline surveys. These surveys have questions around if a worker borrowed (lent) money from (to) a co-worker, the amount borrowed (lent), the co-worker from (to) whom they borrowed (lent) and the repayment schedule.[2]. This helps us to map borrowing and lending networks of workers within the factory and whether there were spillovers from treatment to control workers.

3.4.3 Phone surveys for attrited workers

Garment factories typically experience a monthly worker turnover rate of 6-8%, which poses challenges for maintaining statistical power in studies. To address this, we conducted phone surveys at the end of the study period with workers who had exited the factory during the study. These surveys, conducted at the end of the study period, explored their reasons for leaving, their employment status, and their earnings during the months they were not employed at Shahi. The timeline of the program rollout and data collection is presented in Figure 1.

3.5 Summary Statistics

Table 1 presents summary statistics of the main variables of interest, as well as balance checks for baseline values of age, years of education completed, and workplace outcomes like months of tenure with the firm, income from Shahi salary and attendance rates. Additionally, we check balance for several financial outcomes like borrowings, savings, knowledge of how to use debit cards and digital payments. We fail to reject that the difference between treated and control workers for any of these outcome means at baseline is statistically significantly different from zero. Average attendance rates are about 90%, and average tenure with the firm is about 2.8 years. The average worker is about 31-32 years old with an average of eight years of education. Nearly 60% of both samples had borrowed in the six months prior to the baseline survey and more than 80% had savings.

4 Empirical strategy

The empirical analysis proceeds in several steps, beginning with factors determining the take-up of the EWA app and the usage frequency among the treated group to understand if app users are more liquidity-constrained than non-users. We then proceed to test the impact of the program on financial resilience, well-being, and empowerment indicators of women workers and check for any treatment spillovers between the two groups. Given that we expect treatment impacts on retention resulting in differential attrition across treatment and control groups, we

[2]We use a specially designed BuddyApp, which streamlines and optimizes the process of identifying and mapping employee connections within the workplace, especially in large factory environments. The app allows us to search for employees across the entire factory workforce by linking the administrative database of the factory on the backend. This app is integrated to the SurveyCTO forms of high-frequency and endline surveys. In our study, when a survey respondent mentions that she borrowed from a coworker, we ask them that coworker's name. Once this name is entered into the app, it shows a list of all the workers in the factory with that name spelling as well as those with potential variations in spelling or partial information along with their profile photos and other administrative details. The respondent then identifies the right coworker based on his/her profile photo. Once the respondent identifies a coworker, the app has a built-in feature for the user to open the details of the coworker identified and to link their name and their unique ID to SurveyCTO. This allows the user to maintain a log of all the workplace networks nominated in a systematic manner.

use a weighting procedure to account for this in all our survey data analyses. Finally, we test for differences in workplace outcomes.

4.1 Financial resilience and empowerment of workers

We assess the impact of the EWA treatment on the financial resilience and well-being of women workers, drawing from data collected through three rounds of high-frequency surveys. Each worker can be surveyed up to three times, depending on their presence in the factory during the survey period. Each HFS round is conducted over 2-4 months, with only a sub-sample of workers (from both treatment and control groups) interviewed each month to account for potential seasonal variations in financial outcomes. However, measures of self-efficacy and empowerment are captured solely at the endline, as these indicators are not expected to fluctuate monthly or change rapidly. We estimate the EWA impacts on well-being and empowerment using (1):

$$Y_{it} = \delta T_i + X_{i0}^T \beta + \gamma M_t + \epsilon S_i + u_{it} \tag{1}$$

where Y_{it} can be one of the indicators – usual monthly expenses forgone or delayed, difficult making ends meet, savings, regretful overspending, informal borrowings and lendings. T_i indicates a worker's treatment status. M indicates month-fixed effects. Each month we survey a sub-sample of all the workers in the study and each worker is surveyed a maximum of three times over a year for high-frequency data, which helps to capture any seasonality in financial outcomes.

4.2 Workplace outcomes: Retention, earnings, and productivity

We estimate the impact of EWA treatment on workplace outcomes like present and working on a particular day in the factory (a binary variable that takes the value 1 if present in the factory and 0 if she left the factory or is absent or on leave on a particular day), earnings from the factory (conditional on working in the factory), and earnings from any job. We use administrative data spanning six months of the pre-intervention period and 12 months of the intervention period. We employ panel Difference-in-Differences (DiD) models as shown below:

$$Y_{it} = \gamma(T_i * Post_t) + \eta_i + \psi_t + u_{it} \tag{2}$$

Where the outcome Y_{it} is one of the workplace outcomes. $Post_t$ takes value 1 if the observations are made after the launch of the intervention (12 months) and 0 for the pre-intervention period. i absorbs the worker-fixed effects and t absorbs the time-fixed effects (date or monthly depending on the frequency of observation of workplace outcome).

We estimate productivity impacts using equation (3), accounting for the dynamic nature of production line assignments. Workers may handle different types of items and may also shift between production lines within the same day or across multiple days. To capture these variations, our estimation includes type of item (ϕ_j) and line fixed effects (μ_l), along with individual and date fixed effects. Additionally, we control for the cumulative number of days a worker worked on a particular item as of time 't', X_{jit}, as prolonged engagement with the same item typically leads to greater efficiency over time.

$$Y_{jilt} = \gamma(T_i * Post_t) + \beta X_{jit} + \phi_j + \eta_i + \mu_l + \psi_t + u_{it} \tag{3}$$

4.3 Dealing with Potential Bias from Selective Attrition

Garment factories often experience high turnover rates, which leads to workers leaving the study as they exit the factory. Additionally, some workers may remain on the attendance roster but be absent on the day of the survey, resulting in missing survey measurements. When evaluating conditionally observed outcomes, such as financial resilience and stress from HFS and endline surveys—recorded only when a worker is still retained and present—there is a risk of selective attrition or observation bias. This occurs when treatment influences whether an outcome is measured, potentially generating bias in impact estimates. To address this, we apply weighting to all observations based on the probability of measuring the outcome at each time point, thereby recovering population average treatment effects for conditionally observed outcomes over the observation period. Following Adhvaryu et al., (2023)[2], who adapted an approach proposed in Wooldridge (2010)[36], we estimate a probit specification for the probability of being observed, which is a dummy variable that takes the value 1 if the worker is in the sample on any given month and 0 otherwise on the treatment indicator interacted with HFS round fixed effects and baseline characteristics. The inverse of the predicted probabilities from the probit model are used as probability weights in equations (1) and (2) with the conditionally observed outcome variables as the dependent variable.

5 Results

5.1 App take-up and usage

Individual adoption of financial products is driven by personal needs and preferences. During the EWA intervention period between Sept-2023 and Sept-2024, 34.3% of women in our treatment group used the app at least once, generating a total of 721 transactions. The cumulative withdrawals amounted to USD 11,943, with an average withdrawal of USD 16.5 and the average number of withdrawals was 5.2 per user over a year. Monthly transaction volumes and values fluctuated (Appendix Table A1), with a marked decline in November, coinciding with the disbursement of their annual statutory bonus, which is equivalent to one month's salary for workers who have completed at least a year of service. We also collected primary reasons for the withdrawals from the app users and we find that the most frequently cited reasons were loan repayments, child-related expenses, and medical costs (Appendix Table A2).

We employ a logistic regression model to estimate the likelihood of app usage (defined as whether a woman in the treatment group used the app) and a Poisson regression model to examine the frequency of app usage. Key independent variables include demographic and economic indicators, financial autonomy, and borrowing history, all measured at baseline. The results suggest that women with higher rankings on the asset index were less likely to use the app and had a lower number of transactions on EWA (Table 2). Conversely, women reporting lower financial resilience (i.e., difficulty raising emergency funds) and higher levels of financial stress were significantly more likely to use the app. Additionally, women with a history of borrowing from high-interest informal sources, such as moneylenders or Self-Help Groups (SHGs), showed higher rates and frequency of app usage. Mothers with younger children were also more likely to engage with the app, underscoring the heightened liquidity constraints they face. The convenience of using the app and the instantaneous availability of money that is transferred to their bank accounts were the most rated features of the app by the users.

In summary, EWA app usage is concentrated among the most financially vulnerable individuals in the treatment group—particularly those experiencing higher financial stress levels. Furthermore, these users may be substituting away from high-cost informal borrowing sources like moneylenders and SHGs in favor of the app, especially for addressing urgent financial needs.

5.2 Financial resilience and well-being

Results from the high-frequency surveys We begin by estimating the impact of access to the

EWA on the financial outcomes of women workers as measured through high-frequency and endline surveys. Our first outcome of interest is whether women in the treatment group borrowed less, particularly from informal sources. On average, the treatment led to a reduction in borrowing, especially from informal lenders. Compared to 28.3% in the control group, women in the treatment group were 9.3 percentage points less likely to borrow from informal sources, translating to a significant 32.9% reduction (Table 3). The amount borrowed from these informal sources also decreased by 32 percentage points. Conditional on borrowing from informal sources, the total amount borrowed reduced by 32 percentage points as well (Appendix Table A3).

As noted, access to earned wage advances between pay cycles may help smooth consumption. We measured this by asking workers if they had to cut back on their usual monthly expenditures in the survey month and how difficult they found it to make ends meet. The results indicate that women in the treatment group were 6.3 percentage points less likely to reduce their usual monthly expenditures due to a shortage of funds, compared to the control group (Table 4). In the control group, 30.9% of women reported cutting back, indicating more than 20% reduction in the treatment group. This is also reflected in the total amount of foregone expenditure. However, conditional on reporting a reduction, the amount of foregone expenses did not differ between the two groups. Additionally, women in the treatment group were 8.8 percentage points less likely to report difficulties in making ends meet, a 32% reduction compared to the control group.

Research on payday loans and earned wage access suggests that increased liquidity between pay cycles or increase in pay frequency might lead to overspending or discretionary spending, especially in cases where annual expenditure is almost equivalent to annual incomes. On the other hand, research also predicts that easing liquidity constraints may improve savings for households. However, we do not find any significant effect of the EWA treatment on regretful overspending among the treatment group (Table 5). We also do not find any difference in savings between control and treatment group participants. The results hold true even if we consider the amount of monthly savings in different sources as well as the amount of regretful overspending done by workers in the month of the survey.

In this RCT, given the individual-level randomization of the treatment, there are potential spillover concerns, as workers in the treatment group may lend money to coworkers in the control group or reduce their reliance on informal loans from them. It is also interesting to know how access to workplace DFS influences lending and borrowing among social networks outside workplaces as well. To explore this, we used network elicitation surveys to identify lending and borrowing pairs among coworkers across both groups (Tables 6 and 7). Table 6 presents the results of our analysis of coworker borrowing, showing a 35% reduction in both borrowing from coworkers as well as from family and friends outside the workplace, compared to the control group. This suggests that workers are decreasing their reliance on informal sources as they gain access to workplace DFS. Conversely, we find that workers in the treatment group are more likely to lend to family members and friends outside the workplace (Table 7).

5.3 Results from the endline surveys

Our endline survey, conducted a year after the intervention's launch, captures information on respondents' borrowings and savings during the six months prior, as well as women's self-efficacy in mobilizing money and empowerment in financial decision-making. Consistent with our monthly survey findings, workers in the intervention group were less likely to borrow from informal sources, particularly from coworkers, family, and friends (Table 8). The magnitude of this reduction aligns with our earlier results from the HFS. Similarly, we observe no significant effects of the intervention on respondents' savings behavior, which mirrors our findings from the HFS.[3]

5.4 Women's empowerment in financial decision-making and self-efficacy in mobilizing money

Access to DFS has the potential to enhance women's bargaining power within their households. However, as previously noted, the intervention does not alter women's income (as their salaries remain unchanged). Thus, our analysis focuses on the provision of liquidity and its impact on women's economic empowerment, which is different from the income effect. To measure women's empowerment in financial decision-making, we asked them about their income sharing with spouses or other household members, permission-seeking for personal or children's expenses, decision-making on emergency expenses, participation in regular household expenditures, and authority in decision-making during financial conflict situations. Our findings reveal no significant differences between the intervention and control groups across these dimensions, nor in the aggregate empowerment index (Table 9).

To explore these dynamics, we asked women if they generally mobilize money during times of need, whether doing so improved their self-confidence and respect within the household, or if it led to conflicts or financial exploitation. Interestingly, we find that women in the intervention group report higher self-confidence in themselves to secure finances compared to those in the control group (Table 10). However, there is also an increased possibility of financial exploitation within the household among the treatment group, though this effect is statistically significant only at the 10% level.

5.5 Workplace outcomes

5.5.1 Worker turnover, earnings and productivity

Using administrative data spanning six months of the pre-intervention period and 12 months of the intervention period, we employ panel Difference-in-Differences (DiD) models to estimate the impact of the EWA intervention on worker retention, earnings, and productivity. Column (1) in Table 11 presents the effects of the EWA intervention on daily worker presence in the factory. The outcome variable is binary, taking a value of 1 if the worker is present on the factory floor on a given day and 0 if the worker has left the job or is on leave/absent. Our findings indicate that workers in the treatment group are 4.2% more likely to be present in the factory on any given day during the study period compared to the control group. This effect is primarily driven by higher retention rates of the treatment group workers in their current jobs rather than a reduction in absenteeism. We also assess the monthly impacts of EWA treatment on worker turnover (whether exited the factory job) and not working (either exited factory job or absent from work) (Appendix table A5). In the initial months following the EWA app roll-out, we do not observe significant treatment effects on retention. However, six months after the implementation of the intervention, we detected a significant effect of treatment on the reduction in worker turnover. By the end of the study period, a treatment group worker is 4.6 percentage points less likely to exit the factory job (significant at 10% level) or less likely to be not working. This translates to a 21% reduction in worker turnover compared to the control group.

Next, we capture the impact of EWA on productivity. The key measure of productivity we study is efficiency. The factory has some production lines connected to the hanger system. On a particular day, workers can be rotated across lines and across workstations within each line.

[3]Results are not shown here for the sake of brevity.

Therefore, a worker's productivity may be observed for specific tasks in a day or on specific days of the year depending on if they worked on stations that were connected to the hanger system.[4] Given this, we calculate efficiency as the total SAM[5] of produced pieces divided by the total time taken for the pieces on a particular day.[6]Since workers are randomly observed on different days during the study period, depending on whether they worked or not in the hanger system lines, we run a probit model of whether a worker is observed on a particular day and use this to calculate the IPW weights. These weights are then included in our outcome regression analysis (Column 2 in Table 11). Over the intervention period, we find that the daily productivity of the workers went up by nearly 7.5% (4.4 percentage points), albeit at the 10% level of significance.

Further analysis of monthly earnings from factory jobs, conditional on being employed in factory work, reveals no significant effect of the intervention on earnings for those who remained in factory employment (Column 3 in Table 11). We also assess whether the intervention resulted in higher overall earnings due to prolonged participation in the labor force by continuing to work in the factory. The outcome is monthly earnings from any job during the study period (Column 4), incorporating data from phone surveys with workers who exited the factory. The phone surveys captured employment status and earnings since their departure from factory work, reducing the study attrition to 4% for all earnings related information. Among those who left the factory, only 30% reported being employed at any point thereafter, thus, women are more likely to leave the labour force altogether after exiting their factory job[7]. Given this, we find that the EWA intervention resulted in a 12% increase in overall earnings during the study period, albeit at a 10% level of significance, attributable to the extended duration that women remained in the labor force due to continued factory employment. This highlights the role of the EWA intervention in enhancing women's labor force participation and earnings sustainability over time.

5.5.2 Heterogeneity checks

We posit that treatment effects are mediated by baseline financial stress levels. Kaur et al. (2021)[23] argue that the inability to meet expenses creates mental burdens for workers, termed as financial strain, which negatively impacts workplace productivity through distraction or errors. Our data shows that EWA app usage is higher among workers with high financial stress levels (41% in the high-stress group compared to 28% in the low-stress group). Based on this, we hypothesize that the productivity gains from the intervention will be greater for workers with higher financial stress at baseline.

In contrast, the impact of the treatment on worker turnover across financial stress groups is less straightforward. Although app usage is higher among the high-stress group, turnover rates are higher in the low-stress group (19% versus 13%, in low- and high-stress groups respectively).

[4]To ensure our analysis is not biased by sample selection, we conduct a series of balance tests on baseline characteristics. We compare workers who appear in the hanger system production lines to those who do not and find no significant differences, except that workers in the hanger system data have lower tenure and a higher ability to raise emergency funds within a week. Additionally, within the hanger system sub-sample, we confirm that treatment and control groups are balanced on all baseline characteristics.

[5]SAM is the benchmark for each task, comparing a worker's actual performance to the standard. SAM is defined as the number of minutes required for a single garment of a particular style to be produced. That is, a garment style with a SAM of 30 is deemed to take half an hour to produce one complete garment. This measure at the line level is then decomposed into worker or task-specific increments. As the name suggests, it is standardized across the global garment industry and is drawn from an industrial engineering database.

[6]We have also trimmed the data at the 2.5% and 97.5% levels, to avoid extreme values owing to mismeasurement in the hanger system.

[7]Out of 147 workers who left the factory job during the study period, we were able to track 114 workers through phone surveys, thus, we were able to limit the study attrition to 4% for earnings related outcomes. 83% of women left their factory jobs due to sickness or care responsibilities.

This can be attributed to workers with lower financial stress—often associated with higher asset rankings or household income—having higher reservation wages. These workers are more likely to leave low-paying jobs, such as those in garment factories, for better-paying jobs or leave the labour market altogether if their basic needs are met. Workplace amenities like the EWA app can effectively reduce the reservation wages of these workers by helping them address essential financial needs without requiring a direct wage increase. On the other hand, for workers with higher financial stress, the priority is often income stability, making them more likely to remain in their jobs irrespective of the EWA intervention. Thus, the effectiveness of the treatment on turnover may differ significantly between these groups.

Figure 2 shows the treatment effects for overall and high- and low-financial stress samples. The impact of EWA treatment on worker retention is entirely driven by the low financial stress group, with the treatment leading to 5.2% increase (4.1 pp increase) in the likelihood that a worker is present on the factory floor, while it is not significant for the high-stress sample. Thus, a workplace amenity like EWA leads to effectively lowering the reservation wage for those who were financially better off in the baseline. Further, as expected, the impact of EWA treatment on productivity is entirely driven by the higher financial stress group. The intervention leads to 17.5% increase in productivity among this group while having no impact on the lower financial stress group.

6 Discussion

The implementation of the EWA intervention enabled women garment workers to access liquidity throughout the month, leading to significant reductions in informal borrowing and financial stress while facilitating smoother consumption between paychecks. This intervention addresses critical gaps in the scant literature on employer enabled DFS and their impact on women's financial strength, well-being, and empowerment in developing countries.

This study highlights the intricate link between financial stress, workplace outcomes, and women's labor market continuity. Women's participation in the labor force in countries like India is often precarious due to domestic responsibilities that force them to move in and out of employment. The EWA intervention demonstrates how ongoing liquidity access creates cumulative benefits. Workers experienced a 4.2% increase in retention, translating into prolonged labor force participation and a 12% rise in overall earnings (albeit at 10% level of significance). By directly linking financial stress relief with women's ability to remain in formal employment, this study shows a critical pathway to economic empowerment, particularly in low-income contexts. By isolating the liquidity effect rather than wage increases or cash infusion, we show how flexible pay options can stabilize employment and address systemic barriers that disproportionately limit women's economic participation.

The study also examines longer-term impacts compared to the short-term effects of liquidity infusions on workplace outcomes, such as productivity. For instance, Kaur et al. (2021)[23] found that providing early wage payments reduced financial stress and increased productivity, but their findings were limited to a few weeks of observation. While such studies capture the immediate relief liquidity provides, they miss the sustained behavioral and workplace efficiency benefits observed in this research. Over the year-long intervention period, high-stress workers in the EWA group achieved a 17.5% increase in productivity, emphasizing that reducing financial stress drives significant gains in workplace performance over a longer period.

Interestingly, the study reveals a dual benefit of workplace amenities like EWA: while high-stress workers experienced substantial productivity improvements, low-stress workers showed higher retention rates. This suggests that such interventions serve a dual role—stabilizing the most vulnerable workers and retaining those with greater economic alternatives by effectively lowering their reservation wages. This duality adds nuance to the discussion on how financial stress, productivity, and labor force participation intersect, offering practical insights for employers and policymakers.

7 Conclusion and Future Work

This research demonstrates the transformative potential of workplace financial interventions in reducing financial stress for women workers while enhancing their labor force continuity. The study also makes a compelling case for employers: offering tools like EWA not only improves worker well-being but also boosts productivity and retention, delivering tangible returns on investment. This dual benefit—enhancing workers' financial resilience while driving employer profitability—establishes a strong business case for implementing similar interventions.

The literature on DFS and their impacts on women's financial strength, well-being, and empowerment in developing countries is still maturing. As more employers, especially those in the gig economy, adopt DFS tools like flexible pay options, understanding their broader implications is crucial. While some proponents argue that such tools can ease short-term financial stress by improving liquidity, critics highlight the risks of overspending and poor financial planning. Our study contributes to this debate, demonstrating how thoughtfully designed tools, such as the EWA app with limits on withdrawal frequency (three per month) and amounts (50% of earned wages), can mitigate risks of overspending. Future research should explore whether integrating DFS with financial literacy or budget management features can promote better long-term financial decisions as compared to relying on usage restrictions.

Addressing gender disparities in the adoption and impact of DFS is another critical avenue for future work. While this study tackled structural barriers by providing workplace access, training, and support, these efforts alone were insufficient to overcome deeply entrenched norms. For example, 10% of non-users cited the lack of decision-making power in their households or discouragement from spouses as reasons for non-participation, while 5% expressed concerns about misuse or appropriation of funds. These findings underscore the need for deeper exploration into how social norms mediate women's trust, confidence, and autonomy in using DFS.

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8 Tables

Table 1: Summary statistics and balance checks

	(1) Full sample	(2) Treatment	(3) Control	(4) Difference
Age (years)	31.8	31.7	31.8	0.11
	(4.12)	(4.05)	(4.20)	(0.29)
Years of completed schooling	8.72	8.79	8.65	-0.14
	(2.77)	(2.84)	(2.71)	(0.19)
Tenure (months)	34.5	34.3	34.7	0.40
	(14.3)	(14.3)	(14.3)	(0.99)
Respondent Income	138.0	138.0	138.0	0.0081
	(3.71)	(3.73)	(3.70)	(0.26)
Proportion of days present in the last six months	0.94	0.94	0.94	0.0032
	(0.059)	(0.060)	(0.058)	(0.0041)
Household size	4.84	4.84	4.84	0.0045
	(1.47)	(1.52)	(1.42)	(0.10)
Currently married	0.81	0.81	0.82	0.010
	(0.39)	(0.39)	(0.39)	(0.027)
Household borrowed in the last six months	0.57	0.56	0.58	0.014
	(0.50)	(0.50)	(0.49)	(0.034)
Total borrowings (in USD)	319.4	370.2	270.7	-99.4
	(1247.1)	(1614.3)	(740.3)	(86.4)
Household saved in the last six months	0.85	0.87	0.84	-0.030
	(0.36)	(0.34)	(0.37)	(0.025)
Total savings (in USD)	209.7	233.6	186.8	-46.9
	(469.1)	(566.5)	(350.7)	(32.5)
Knows how to withdraw money from the ATM using a debit card	0.48	0.49	0.48	-0.0089
	(0.50)	(0.50)	(0.50)	(0.035)
Knows how to make digital payments on the mobile phone	0.15	0.13	0.16	0.032
	(0.35)	(0.34)	(0.37)	(0.024)
Observations	834	408	426	834

Table 2: Determinants of application usage

	(1) Used the app	(2) Frequency of using the app
Fin. stress quartile: lowest		
Fin. stress quartile: low	0.12*	0.60
	(0.069)	(0.50)
Fin. stress quartile: medium	0.16***	0.59
	(0.061)	(0.61)
Fin. stress quartile: high	0.14**	1.00*
	(0.067)	(0.59)
Currently married	0.084	0.36
	(0.058)	(0.49)
HH size: 2-3 members		
HH size: 4-5 members	0.016	-0.35
	(0.074)	(0.72)
HH size: more than 5 members	0.0025	-0.32
	(0.082)	(0.79)
Has children under the age of five	0.15**	-0.041
	(0.074)	(0.64)
HH assets group: poor		
HH assets group: middle	-0.042	-0.86*
	(0.054)	(0.51)
HH assets group: rich	-0.15**	-1.32***
	(0.060)	(0.44)
Respondent indulged in regretful expenditure	0.029	-0.69*
	(0.054)	(0.38)
Find it difficult to raise USD 59 in a month	0.12**	0.47
	(0.048)	(0.48)
Borrowed from a money lender	0.24**	3.32**
	(0.11)	(1.56)
Borrowed from a MFI/SHG	0.094	2.33***
	(0.058)	(0.77)
Borrowed from friends/family/neighbours	-0.080	-0.68
	(0.057)	(0.43)
Observations	408	408
Mean	0.340	1.770
Controls	Yes	Yes

Note: Only select control variables have been reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Impacts of FSA treatment on loans taken in the month prior to the survey

	(1) Whether taken a loan from any source	(2) Whether taken loan from informal sources	(3) Log(1+loan amount) - any source	(4) Log(1+loan amount) - informal sources
Treatment	-0.096***	-0.093***	-0.28***	-0.32***
	(0.021)	(0.021)	(0.078)	(0.070)
Observations	2061	2061	2069	2069
Control Mean	0.310	0.280	33.25	15.23
Controls	Yes	Yes	Yes	Yes

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors in parentheses are clustered at the worker level. Regressions control for baseline characteristics like marital status, age, education, current marital status, tenure, household bargaining power, financial resilience (difficulty to raise INR 5000), financial stress index quartile groups, asset tertile groups, borrowings from various sources. Probability weights have been assigned to account for survey attrition.

Table 4: Impacts of FSA treatment on consumption smoothing: Results from high frequency surveys

	(1) Whether worker reduced usual monthly expenses	(2) Whether worker found it diff to make ends meet	(3) Log(1+amount of expenses reduced)
Treatment	-0.063***	-0.088***	-0.21***
	(0.021)	(0.020)	(0.065)
Observations	2061	2069	2069
Control Mean	0.310	0.270	8.300
Controls	Yes	Yes	Yes

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors in parentheses are clustered at the worker level. Controls used are the same as reported in Table 3. Probability weights have been assigned to account for survey attrition.

Table 5: Impacts of FSA treatment on savings and overspending

	(1) Whether saved any money	(2) Whether regretted spending	(3) Log(1+amount saved)	(4) Log(1+amount of regretful spending)
Treatment	0.023	-0.011	0.12	-0.018
	(0.022)	(0.018)	(0.090)	(0.047)
Observations	2069	2061	2069	2069
Control Mean	0.710	0.190	26.86	2.920
Controls	Yes	Yes	Yes	Yes

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors in parentheses are clustered at the worker level. Controls used are the same as reported in Table 3. Probability weights have been assigned to account for survey attrition.

Table 6: Spillover concerns: Impacts of FSA treatment on borrowing from coworkers and social networks outside workplace

	(1) Whether taken a loan from a coworker	(2) Whether taken a loan from family/friends outside of work	(3) Log(1+loan amount) - coworker	(4) Log(1+loan amount) - friends/family
Treatment	-0.039***	-0.064***	-0.10***	-0.22***
	(0.014)	(0.018)	(0.034)	(0.064)
Observations	2061	2061	2069	2069
Control Mean	0.110	0.190	1.220	10.93
Controls	Yes	Yes	Yes	Yes

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors in parentheses are clustered at the worker level. Controls used are the same as reported in Table 3. Probability weights have been assigned to account for survey attrition.

Table 7: Spillover concerns: Impacts of FSA treatment on lending to coworkers and social networks outside workplace

	(1) Whether lent to a coworker	(2) Whether lent to family/friends outside of work	(3) Log(1+amount lent to coworkers)	(4) Log(1+amount lent to friends/family)
Treatment	-0.0069	0.028**	-0.0059	0.064**
	(0.011)	(0.012)	(0.023)	(0.032)
Observations	2069	2061	2069	2069
Control Mean	0.0500	0.0400	0.460	1.530
Controls	Yes	Yes	Yes	Yes

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors in parentheses are clustered at the worker level. Controls used are the same as reported in Table 3. Probability weights have been assigned to account for survey attrition.

Table 8: Impacts of FSA treatment on informal borrowing: Endline survey results

	(1) Whether taken loan from informal sources	(2) Whether taken a loan from a coworker	(3) Whether taken a loan from family/friends outside of work	(4) Log(1+loan amount) - informal sources	(5) Log(1+loan amount) - coworker	(6) Log(1+loan amount) - friends/family
Treatment	-0.078**	-0.060**	-0.070**	-0.39*	-0.13*	-0.21
	(0.036)	(0.030)	(0.033)	(0.20)	(0.076)	(0.13)
Observations	665	665	665	665	665	665
Control Mean	0.560	0.240	0.290	179.6	3.130	30.58
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$. Standard errors in parentheses are clustered at the worker level. Controls used are the same as reported in Table 3. Probability weights have been assigned to account for survey attrition.

Table 9: Impacts of FSA treatment on women's empowerment in financial decision-making: Endline survey results

	(1) Needs to seek permission for expenses on self/children	(2) Needs to seek permission for emergency expenses	(3) Spouse/others make decisions on regular expenses	(4) Respondent gives all her salary to the spouse/other HH members	(5) Spouse/Others opinion prevails during dis-agreements on financial decisions	(6) Aggregate WEE Index scores
Treatment	0.00077	-0.029	0.029	-0.0037	0.052	0.043
	(0.030)	(0.035)	(0.034)	(0.032)	(0.037)	(0.11)
Observations	665	665	665	665	665	665
Control Mean	0.200	0.280	0.270	0.250	0.410	-0.0100
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors in parentheses are clustered at the worker level. Controls used are the same as reported in Table 3. Probability weights have been assigned to account for survey attrition.

Table 10: Impacts of FSA treatment on women's self-efficacy in mobilizing money for emergencies: Endline survey results

	(1) Resp. mobilizes money for emergency	(2) Mobilizing money builds confidence	(3) Mobilizing money builds respect with family	(4) Mobilizing money leads to conflict	(5) Mobilizing money leads to exploitation	(6) Aggregate Efficacy Index Scores
Treatment	0.0059	0.048**	0.035	0.016	0.056*	0.13
	(0.019)	(0.023)	(0.032)	(0.023)	(0.032)	(0.10)
Observations	665	665	665	665	665	665
Control Mean	0.930	0.890	0.760	0.0700	0.190	-0.0800
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors in parentheses are clustered at the worker level. Controls used are the same as reported in Table 3. Probability weights have been assigned to account for survey attrition.

Table 11: Impact of FSA on worker attendance and earnings: Panel DiD estimates

	(1) Present on the factory floor	(2) Efficiency	(3) Log(1+factory earnings)	(4) Log(1+any earnings)
Treatment x Study Period	0.030**	0.044*	-0.0091	0.12*
	(0.013)	(0.025)	(0.0094)	(0.062)
Observations	483720	41666	14668	15604
Control Mean	0.790	0.590	117.7	117.4
Date FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Line and itemtype FE		Yes		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the individual level.

9 Figures

Figure 1: **Timeline of experiment and data collection**

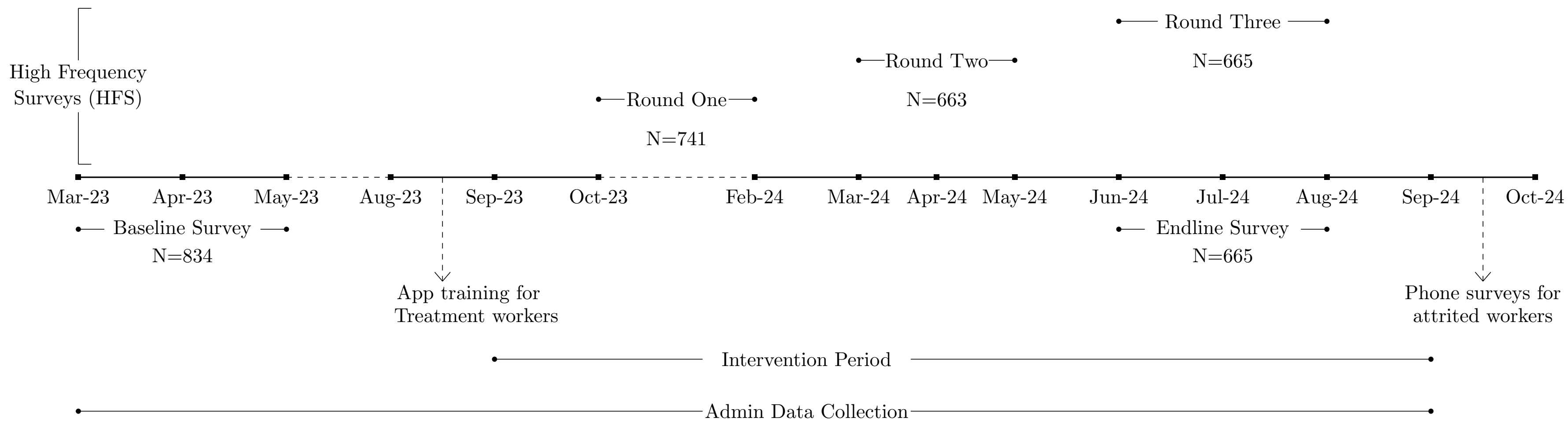
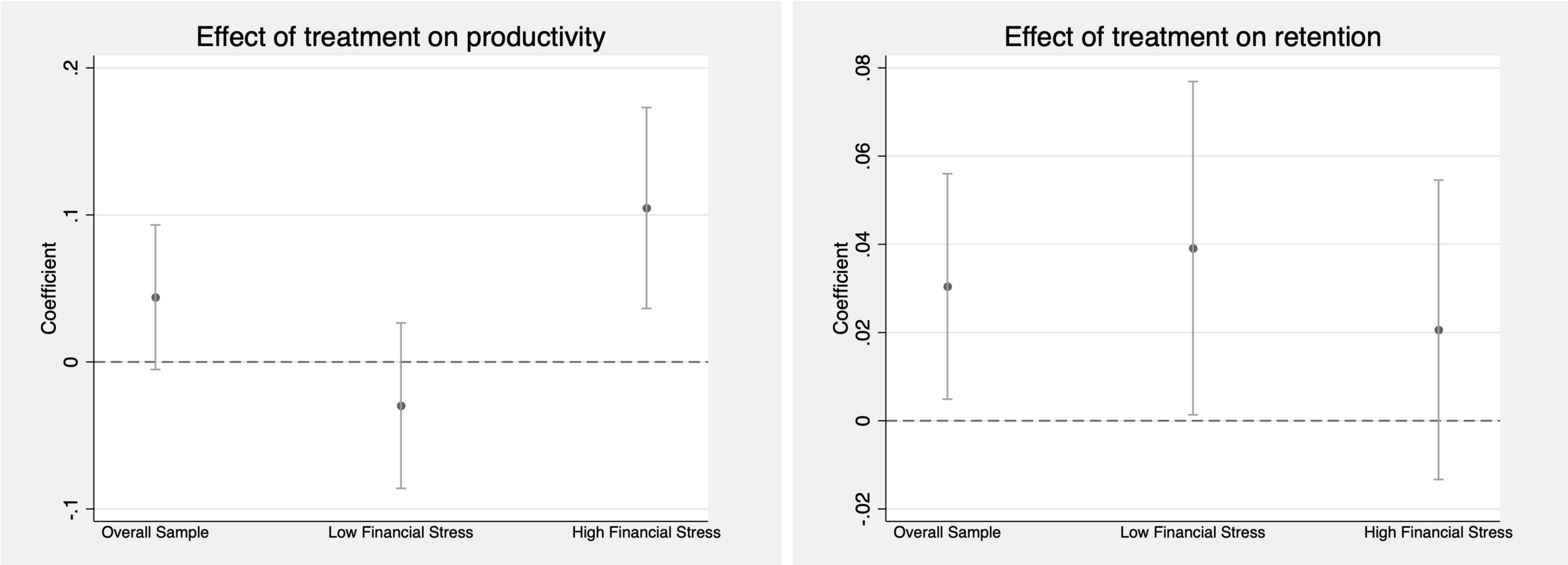


Figure 2: **Heterogeneous impacts of FSA treatment on worker retention and productivity**



(a) Productivity (b) Retention

Note: The coefficients are derived from the linear combination of the estimates of Table A6.

A Appendix

Table A1: Month wise transactions on FSA

	Transactions	Unique users	Average transaction per user	Total amount with-drawn*	Mean amount withdrawn	Min. amount withdrawn	Max. amount withdrawn
September 2023	53	46	1.15	766.26	14.46	.59	41.32
October 2023	59	45	1.31	884.93	15	.59	37.78
November 2023	34	25	1.36	576.15	16.95	2.36	35.42
December 2023	49	33	1.48	821.08	16.76	2.36	41.91
January 2024	69	58	1.19	1207.26	17.5	1.18	40.14
February 2024	72	57	1.26	1110.42	15.42	.59	42.5
March 2024	62	45	1.38	855.36	13.8	2.36	35.42
April 2024	52	36	1.44	804.05	15.46	1.18	35.42
May 2024	59	39	1.51	956.29	16.21	2.36	41.32
June 2024	44	30	1.47	807.58	18.35	3.54	47.23
July 2024	49	36	1.36	977.61	19.95	5.9	47.23
August 2024	54	34	1.59	949.28	17.58	3.54	41.32
September 2024	65	43	1.51	1214.71	18.69	3.54	44.86

*All amounts are in USD.

Table A2: Reasons for withdrawal

	(1) Count	(2) Percentage
Children	91	12.62
Festival	36	4.99
Food	62	8.60
Lending	8	1.11
Medical	82	11.37
Not reported	94	13.04
Remittance	47	6.52
Repay loans	301	41.75
Total	721	100.00

Table A3: Impact of FSA treatment on informal borrowing amounts conditional on taking a loan

	(1) Log(loan amount) - informal sources, conditional on borrowing	(2) Log(loan amount) - coworkers, conditional on borrowing	(3) Log(loan amount) - friends/family, conditional on borrowing
Treatment	-0.32**	-0.35*	-0.15
	(0.15)	(0.20)	(0.18)
Observations	492	195	322
Control Mean	0.280	0.110	0.180
Controls	Yes	Yes	Yes

Note: *** p< 0.01, ** p< 0.05, * p< 0.1. Standard errors are clustered at the individual level.

Table A4: Impact of FSA on worker attendance and earnings: Simple DiD estimates

	(1) Present on the factory floor	(2) Efficiency	(3) Log(1+factory earnings)	(4) Log(1+any earnings)
Treatment	-0.0039	0.0063	-0.0068	-0.0038
	(0.0043)	(0.024)	(0.0053)	(0.017)
Study Period	-0.12***	0.035*	0.018***	-0.39***
	(0.0096)	(0.019)	(0.0052)	(0.047)
Treatment x Study Period	0.030**	0.031	-0.0095	0.13**
	(0.013)	(0.025)	(0.0080)	(0.063)
Observations	483720	41682	14668	15604
Control Mean	0.789	0.594	117.7	117.4
Controls	Yes	Yes	Yes	Yes
Line and itemtype FE		Yes		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the individual level.

Table A5: Monthly treatment effects on worker turnover and absenteeism

	(1) Absent	(2) Left the factory	(3) Absent or left the factory
Treat x March 2023	0.00046	0.00091	0.0014
	(0.0052)	(0.0042)	(0.0070)
Treat x April 2023	-0.0056	0.00091	-0.0046
	(0.0049)	(0.0042)	(0.0067)
Treat x May 2023	0.00035	0.00091	0.0013
	(0.0056)	(0.0042)	(0.0071)
Treat x June 2023	-0.0078	0.00091	-0.0069
	(0.0051)	(0.0042)	(0.0067)
Treat x July 2023	-0.0053	0.00091	-0.0044
	(0.0052)	(0.0042)	(0.0067)
Treat x August 2023	0.0056	0.00091	0.0065
	(0.0054)	(0.0042)	(0.0066)
Treat x September 2023			
Treat x October 2023	-0.0013	-0.0019	-0.0032
	(0.0047)	(0.0071)	(0.0076)
Treat x November 2023	0.0052	-0.0035	0.0017
	(0.0050)	(0.011)	(0.012)
Treat x December 2023	0.00099	-0.0096	-0.0086
	(0.0061)	(0.015)	(0.015)
Treat x January 2024	-0.0068	-0.017	-0.023
	(0.0057)	(0.017)	(0.017)
Treat x February 2024	-0.0021	-0.028	-0.030
	(0.0058)	(0.019)	(0.019)
Treat x March 2024	-0.0095	-0.042**	-0.051**
	(0.0065)	(0.020)	(0.020)
Treat x April 2024	-0.0085	-0.045**	-0.054**
	(0.0068)	(0.022)	(0.022)
Treat x May 2024	-0.0085	-0.050**	-0.059**
	(0.0067)	(0.024)	(0.023)
Treat x June 2024	0.000061	-0.040	-0.040*
	(0.0055)	(0.025)	(0.024)
Treat x July 2024	-0.0086	-0.040	-0.048*
	(0.0059)	(0.025)	(0.025)
Treat x August 2024	-0.0027	-0.052**	-0.055**
	(0.0051)	(0.026)	(0.026)
Treat x September 2024	0.00020	-0.046*	-0.046*
	(0.0057)	(0.027)	(0.026)
Observations	483720	483720	483720
Individual FE	Yes	Yes	Yes
Month and Date FE	Yes	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Impacts of FSA on produvtivity and worker retention: Heterogeneity

	(1) Efficiency	(2) Present on the factory floor
Treatment x Study Period	-0.025	0.039**
	(0.029)	(0.019)
Treatment x Study Period x High Stress	0.13***	-0.019
	(0.045)	(0.026)
Observations	41666	483720
Control Mean	0.607	0.788
Date FE	Yes	Yes
Line and itemtype FE	Yes	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at the individual level.