Fintech to the (Worker) Rescue: Earned Wage Access, Financial Health and Employee Retention*

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Abstract

Using novel usage and survey data from a Mexican FinTech firm, we study the adoption by workers of earned wage access (EWA), an innovative financial service offered by firms to their employees as a benefit, and its potential effects on worker welfare. We find usage to be significant and concentrated towards the end of the pay cycle. We establish that such usage is associated with a higher employee retention for low rank workers, suggestive of improved welfare for financially constrained individuals. We consider possible underlying mechanisms for a causal effect, such as liquidity insurance, aligning the timing of income and expenditure, or catering to present-bias, and find empirical evidence supportive of different mechanisms being at play for different segment of users.

Keywords: Earned Wage Access, Consumption Smoothing, Employee Retention, FinTech

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Summary of Innovative Data

In our study, we harness an innovative and multifaceted dataset procured from Minu, a prominent provider of Earned Wage Access (EWA) services in Mexico. This dataset comprises several integral components, each contributing to its uniqueness and its capacity to illuminate the intricate dynamics of EWA adoption and its influence on employee retention. The combination of these diverse data sources enables us to assemble as comprehensive a view as possible, offering novel insights into this critical area of study. However, it's important to note that the process of harmonizing and executing a well-structured empirical analysis with this dataset presents a non-trivial challenge.

The first component of our dataset encompasses user activity data extracted from the Minu App. This dataset provides an exceptionally detailed perspective on all EWA-related transactions for a large set of users. It includes transaction-level information, such as timestamps, withdrawal amounts, and associated fees.

The second component derives from data shared by Minu's corporate clients, which provide us with information about the demographic characteristics and employment histories of their entire workforce, irrespective of their engagement with EWA. This demographic dataset encompasses essential details like employment start and end dates, gender, and, for a subset of employees, additional information such as birth year, work location, current and previous job positions, and hierarchical rank within the organization. By combining these first two datasets, we construct a comprehensive panel dataset that operates at the employee-pay-cycle level. This facilitates a nuanced examination of the intricate interplay between EWA adoption, employee attributes, and retention rates.

Lastly, to delve deeper into the motivations and behaviors of EWA users, we collaborated with Minu to conduct a survey in July 2023. Minu administered a concise 5-question survey via WhatsApp to approximately 9,700 users spanning 20 different companies. The survey aimed to uncover the primary purposes behind EWA utilization, any alternatives employees had explored before and after embracing EWA, typical withdrawal amounts, and comparisons with other company-provided benefits. Impressively, we garnered 1,435 responses within a mere two weeks of launching the survey, yielding a robust 15% response rate. This survey data enhances our capacity to delve into the underlying mechanisms fueling the demand for EWA access and its correlation with heightened employee retention.

In summary, our study capitalizes on an intricate and unique dataset, encompassing transaction-level EWA data, comprehensive employee demographic insights, and survey responses. This exceptional dataset empowers us to investigate the complexities of EWA adoption and its potential impact on employee retention and its underlying economic mechanism.

1 Introduction

According to the 2023 Fed survey on Economic Well-being of US Households, 37% of US households could not cover a $400 emergency expense completely sing cash or its equivalent. Such cash shortfalls can significantly impact households on several dimensions such as consumption (Shapiro, 2005), psychological standing (Haushofer and Fehr, 2014), or productivity at work (Kaur, Mullainathan, Oh, and Schilbach, 2021). A second stylized fact in developed economies is the decreasing tenure of employees, which stands at 3.7 year on average for private sector workers in the US as of 2023, and is even lower in services. Such short tenure might relate to employee financial well-being in several ways. First, employees facing a financial shock, even modest, might have to switch to positions paying them better in the short run, including informal ones. Second, engaging in moonlighting or reduced productivity in general might also lead their employers to end their employment.

A promising venue for improving employee retention and more generally employee welfare is therefore for employers to develop benefits that address worker financial strain, as a potential complement or lower cost substitute to increasing wages. An emerging tool for that purpose is earned wage access (EWA), a benefit facilitated by specialized FinTech firms that allows worker to withdraw at will a fraction of the wages they have earned from their employers but has not yet been paid. Proponent of this service argues that it can offer the same benefits as payday lending in terms of providing short term relief in economic hardship, without having the drawbacks of the latter, such as potentially predatory pricing and rollovers. Such service has gained traction in the US and in many emerging markets, typically for large employers that hire large numbers of low-skilled workers. For instance, Walmart, McDonalds, and Uber have adopted such programs. US workers made around 56 million withdrawals amounting to $ 9.5 billion from earned wage access in 2020, triple what it was in 2017.

This development raises the question of whether offering earned wage access does materially improve worker welfare, as well as significantly impact worker retention. If so,

what is the underlying economic mechanism that explains such an effect? And are there unintended costs to offering or using such products?

This paper tackles these questions by empirically investigating the usage patterns of earned wage access, and whether the introduction of EWA in a firm translates into higher employee retention. For this purpose, we exploit a novel data set from a leading provider of EWA in Mexico, Minu. This empirical setting is particularly suited to answering our research questions as we are able to access granular usage data, as well as worker demographics and employment history for a large sample of workers. The context of a developing economy is also of particular interest to investigate the benefit of such offer, as access to other tools for consumption smoothing might be particularly expensive, and safety nets are less protective in general.

Our results are as follows. We first document several stylized facts about the usage of this novel benefit offered to workers, typically via a partnership between a FinTech firm and a large employer. First, a significant fraction of workers adopt such a service within a short time frame. In the cross-section of workers, EWA appears to be more popular with workers that are male, young and have been employed at the firm for some time. In contrast to the widespread view that this product is targeted towards low income workers, tts adoption does not appear to vary significantly according to the level of skill or wages. Second, usage is concentrated towards the end of the pay cycle. Third, for the fraction of workers that use frequently the service, their withdrawn amount tends to increase over time, and such withdrawal happens progressively earlier in the pay-cycle.

Turning to studying the relationship between EWA usage and employee retention, we document that workers using EWA have a significantly lower probability of leaving their firm at any period than workers that do not, controlling for worker's age, gender, starting month and job position. We also find that such relationship is only present among lower-rank employees. We establish these results using a proportional hazard model applied to a worker panel data setting, but they are also robust to a cross-sectional analysis using OLS or logistic specifications.

In terms of underlying economic mechanism, we document empirical regularities consistent with several mechanisms at play among possibly overlapping sub-populations of users. First, earned wage access might act as a liquidity insurance, thereby alleviating short term financial strain which can be disruptive to workers. Second, EWA facilitates the alignment of the timing of income with expenditures. Both these mechanisms are supportive of an improvement of financial health resulting from EWA access. Last, some users exhibit behaviors suggestive of present-bias. Earned wage access may also raise the utility of such workers, by allowing them to consume earlier within the pay cycle, although the time inconsistency of such preferences suggests that the derived surplus should be more limited.

We further investigate underlying mechanisms for workers' demand for EWA using survey data collected by Minu from a large sample of users. First, we find that workers use EWA for both expected and unexpected expenses, confirming its dual function of providing liquidity insurance and consumption smoothing / timing alignment. Second, the majority of users reduce their usage of other financial products upon the availability of EWA. Regarding the use of other financial products, EWA first substitute out informal borrowing from family and friends and pawn shop, which are likely to create a high disutility in usage.

Our study relates to several streams for literature. First, our study contributes to the literature on cash shortfalls and their effects (see for instance Shapiro (2005) or Fink et al. (2020)). By studying a tool aiming at alleviating them, we speak to the existence of such effects and the value of insuring against them. Our work also connects with the literature that studies payday lending as potentially playing a liquidity insurance role (Morse, 2011), although these potential benefits might come with large unintended consequences (Melzer, 2011).

Second, our work adds to the literature on strategies to reduce firm turnover and foster retention, which include pay design (Oyer, 2004, Oyer and Schaefer, 2005), human resource management (Burks et al., 2015) or corporate culture, including CSR (see for instance Carnahan, Kryscynski, and Olson (2017), Bode, Singh, and Rogan (2015)). Earned wage

access represent a potentially cost-effective tool that can substitute with or complement other corporate actions targeting such effect.

Third, this study speaks to the effects of FinTech development for household welfare. This burgeoning literature has so far presented contrasting effects for household finances, such as overborrowing (Di Maggio and Yao, 2021, Chava et al., 2021) or improved asset allocation (Reher and Sokolinski, 2021). Our study, by taking a revealed preference approach and relating EWA usage with higher retention, provides a novel bright side of FinTech for households.

Last, by studying the mechanism that rationalizes the adoption of this innovation and its effects, our work also speak to the optimal frequency of pay (Parsons and Van Wesep, 2013), as well as the utility function of individuals, such as the well-documented existence of present-bias (Laibson, 1997, Parker, 1999, Stephens, 2003, Shapiro, 2005, Olafsson and Pagel, 2018), and how such non-standard preferences can influence financial product design (Calvet et al., forthcoming).

The remainder of the paper is structured as follows. Section 2 provides some background on earned wage access and describe the data we use for our study. Section 3 documents stylized facts about earned wage access usage. Section 4 establishes a significant relationship between earned wage access and employee retention. Section 5 discusses the economic mechanisms underlying the demand for EWA by confronting theoretical predictions with usage and survey data.

2 Background and Data

2.1 Background on Access to Earned Wages

Earned Wage Access (EWA) services, also referred to as on demand pay, allows users to withdraw wage earned during the pay cycle before the actual pay day. The service is typically offered in one of two ways by a FinTech firm: either it partners with employers and integrate the product with employer current payroll system that enables worker to trigger pay during the pay cycle, serving as a technology provider, or it serves as an intermediary: it

obtains information from the employer on the level of earned wages, transfers cash directly to worker bank accounts, and gets reimbursed by the employer on pay day. While these two models creates significant differences in the FinTech firm business model, ultimately they offer a similar product to the end user. Over the past few years, EWA became an increasingly popular benefit offered by employers for worker retention, especially among large services firms (e.g. Walmart, Target, Amazon, McDonald's, etc...). According to Payments Dive, US households made around 56 million withdrawals summing to $ 9.5 billion with withdrawn from EWA companies during 2020, triple what it was in 2017 (Marek, 2021). In a survey study by Visa in 2019, it reports that 95% of workers would be interested in working at companies who provide EWA (Visa, 2019). Crucially, earned wage access is not considered a loan under most juridictions, and therefore is also distinct from payday lending.[1] Earned wage access has raised some controversy and consumer protection discussions, mostly in the case where workers have to pay withdrawal fees that correspond to high APR.

2.2 Data

We obtain our dataset from Minu, a leading provider of EWA in Mexico. Minu follows the intermediated model with the employer and provides a mobile application that allows the employees of its corporate clients to immediately transfer from Minu already earned but not yet paid wage between pay cycles to the workers bank account. The service is offered via the employer as a benefit to its workers. Each transfer comes with a low fixed service fee of 39 pesos (around USD$2), and workers can make any amount of transfer for any number of times during the pay cycle. The next paycheck is automatically lowered by the amount withdrew during the past pay cycle. There is no cost in addition to the fixed fee, and therefore the paycheck adjustment exactly corresponds to the cumulative amount withdrawn during the pay cycle. As of 2022, the amount withdrawn is subject to a cap of

[1]Direct-to-consumer EWA, where the FinTech firm has no partnership with the employer and provide the advance based on past records of income, is conceptually very close to payday lending. An important distinction is that there is no roll-over possible.

50 percent of available earned wage at the time of withdrawal.

We obtain data covering the employees of three corporate clients of Minu, which are all services firms. For each company, we obtain two sets of data. The first set of data comes contains user activity data from the Minu App, which includes transaction-level details of all withdrawal activities, including time and date, amount and fees associated with every withdrawal of employees registered to use Minu. The second set of data comes from data shared by Minu corporate clients, which include basic demographic characteristics and work history information on all of their current employees, regardless of the use of Minu. In particular, we obtained start date, end date and gender for all employees. For a subset of employees, we also know their birth year, location of work, current and previous job positions and rank. We combine all of those types of information and construct a panel at the employee-pay-cycle level.

We also obtain survey data of Minu users, which we describe further in section 5.4.

2.3 Summary Statistics

There are a total of 51,543 workers in our sample, and about 7% of the sample workers use EWA during their employment. Panel A of Table 1 presents demographic characteristics of EWA users versus non users. The two groups have similar age distribution with mean age at 33 years old. The average worker also has about 2 years of tenure at the company. EWA users appear more likely to be male, have a somewhat longer tenure at their employer and are slightly higher ranked than non-users. In panel B, we present some statistics about EWA usage. Most users make less than 2 withdrawals per pay cycle, and the average withdrawal amount is 869 pesos (around USD$ 42).

[INSERT TABLE 1 HERE]

3 Stylized Facts about Earned Wage Access Usage

In this section, we present novel stylized facts about earned wage access adoption and usage.

3.1 Worker Characteristics and EWA adoption

First, we document that when an employer offers EWA to its employees, a significant share of workers use the service in a short matter of time. As shown in Panel A of Table 1, 7% of workers from our sample made withdrawals through EWA at least once after the introduction of the service. We also observe an upward sloping trend in the share of workers using Minu in pay cycles following the introduction, as shown in Figure A in the appendix, suggesting an increasing popularity as workers become more aware of the existence of this service.

We then explore what characteristics of workers predicts use of access to earned wages. Using a linear probability model, we regress an indicator for using EWA on worker characteristics, and report the coefficients in Table 2. We find that male and younger workers are significantly more likely to use the service. Given the baseline usage of 7%, the magnitudes of these coefficients appear particularly large: being male of being young increases the likelihood to use EWA by ca. half of the baseline. EWA also appears to be less popular with employees of lower rank. Starting after the introduction of EWA predicts significantly lower adoption, which could result both to lower exposition to communication on the benefit, as well as having had less time to use the service.

[INSERT TABLE 2 HERE]

3.2 EWA Usage Patterns

We now zoom in on the group of workers that use access to earned wages and investigate usage patterns. We first explore the distribution of user withdrawal frequency, amount, timing and numbers of withdrawals, and how they evolve in the next 7 months following their first adoption. Figure 1 presents the distribution of withdrawal timing (Panel A) and amount, scaled by 2-week pay cycle income (Panel B) and earned wage at the time of withdrawal (Panel C), all at the worker-pay cycle level and conditional on EWA usage by that user in that pay cycle.

We observe from Panel A that the majority of users use the service in the second week of the pay cycle, which corresponds to the period where the worker has accumulated wages that have been earned but not paid yet, and is also more likely to have exhausted its previous paycheck. From Panel B, we note that workers withdraw economically significant amounts: the average withdrawn amount is equal to 12.5% of the worker pay cycle wages. At Minu, the amount workers can withdraw is capped at 50% of the wages already earned but not yet paid. Panel C illustrates that most workers do not seem to maximize the amount they withdraw up to the cap, despite the fixed fee they pay when doing so.

[INSERT FIGURE 1 HERE]

Figure 2 documents how withdrawal activities evolve over pay cycles for an average user. We see that after their first use, around 40% of EWA users keep using the service at every period. Moreover, conditioning on making withdrawals in a given pay cycle, the users withdraw increasingly larger amounts: the proportion of earned wage an average user withdraws increase from 10% to 15% of the pay cycle wages 6 months after her first adoption. We also observe a trend towards making withdrawals earlier in the pay cycle, and a slight increase in the number of withdrawals per period.

[INSERT FIGURE 2 HERE]

We turn to exploring the potential heterogeneity of usage patterns across different groups of EWA users. In Figure 3, we group workers between low and high skill positions and plot the same graphs as in Figure 2. Overall, we observe comparable patterns between the two group, with low skill workers withdrawing a larger share of their wages, and doing so in less withdrawals. Interestingly, these differences are mostly in levels, as the two groups exhibit comparable evolutions of usage since their first use.

[INSERT FIGURE 3 HERE]

3.3 Frequent Users

In the top left panel of Figure 2, we identify a subgroup of users that exhibit a consistent use of the service after a few pay cycles. We therefore divide in Figure 4 the users into those who use EWA for less than 5 pay cycles during our sample period, and those who use it more than 5 pay cycles, and plot their usage pattern again.

We observe a large heterogeneity in the evolution of usage between these two groups. First, while the withdrawal amount as a share of income is roughly the same for the two groups of users at first, the frequent users show a clear pattern of withdrawing larger amount as time passes by. Infrequent users withdraw similar amount over the sample period. We also see different evolutions when looking at the timing of withdrawals: the frequent users are the ones driving the pattern of earlier withdrawals within the pay cycle previously documented. Last, for the number of withdrawals, the frequent users also make consistently more withdrawals within a pay cycle than its counterparts.

[INSERT FIGURE 4 HERE]

We now turn to studying the relationship between the usage of access to earned wages, and employee retention.

4 Effect of Earned Wage Access on Employee Turnover

Given the significant adoption by workers of EWA, its positioning as a benefit and the current low share of firms offering such a benefit, a natural question is whether offering EWA reduces employee turnover. Such an effect would further speak to the value workers put in accessing the service, and also identify a source of significant economic gain for employers offering such service.

4.1 Main Result

We first look at the unconditional relationship between the usage of EWA by a worker and their propensity to stay at their current employer. We thus plot the distribution of the

tenure length of users and non-users, conditioning on the worker having already left the company in Figure 5. The proportion of EWA users that stay at their companies for more than 3 months is significantly higher than that for the non-users. Moreover, when focusing on the employees who started working less than six months before the introduction date of EWA in Panel A Figure 6, and studying their likelihood of remaining employed at the firm from the introduction of Minu, we also observe that retention is significantly higher for EWA users. As of 8 months after the introduction of EWA, users have a 5 percentage point higher likelihood to still be at the firm that non-users. This relationship is even more pronounced for workers that joined after the introduction of EWA in Panel B. The two figures therefore suggest some association between the use of EWA and higher retention in the sample.

[INSERT FIGURE 5 AND 6 HERE]

This raw data correlation could however be driven by selection effects, for instance because characteristics that predict EWA adoption are correlated with turnover rate. To mitigate this concern, we estimate the relationship between using earned wages access and the likelihood of leaving the firm while controlling for observable characteristics of workers. We use a Cox proportional hazard model, with the following specification:

$$\lambda(t \quad | \quad X_{i,t}) \quad = \quad \lambda_{0,t} \quad \times \quad Exp(\beta_1 \, Used \; EWA_{i,t} \quad + \quad \gamma_{i,t} \quad + \quad \mu_f) \quad + \quad \varepsilon_{i,t}$$

where $Used\ EWA_{i,t}$ is an indicator that equals to 1 on and after the pay cycle t when the worker first uses EWA, and zero otherwise, $\gamma_{i,t}$ are worker characteristics including starting quarter fixed effect (to control for cohort effects), gender, age, and latest job rank of employee i, and μ_f are employer fixed effects.

Table 3 presents the coefficients (1-hazard ratio) for the explanatory variables. In column 1 and 2, it shows that when controlling for company and/or starting quarter fixed effects, EWA users on average have 12 to 15 percent lower probability of leaving the company in the next pay cycle comparing to the baseline of non-users. When also controlling

for the gender, job rank of workers in column 3, and age in column, we observe a reduction in the magnitude of the relationship, that however remains economically and statistically significant: EWA users still exhibit a 8 percent lower turnover likelihood once incorporating all these controls.

[INSERT TABLE 3 HERE]

Next we run split sample regressions for company, gender, job rank and age group respectively to uncover potential heterogeneity in the relationship between access to earned wages usage and worker retention in Table 4. First, this relationship does not appear to vary by gender in a statisically significant way. On the other hand, when splitting the workers along their skill level, we see a stronger relationship between EWA usage and reduced turnover in column 3 and 4: among the low-rank employees, being a EWA user is associated with reduction of 24% in the likelihood of separating from the employer, a particularly large effect which contrasts with the lack of heterogeneity in adoption across that dimension. This estimate suggests that the benefit of EWA in terms of reduced turnover are concentrated among lower income workers, which are likely to be more financially constrained. However, the coefficient is positive and not statistically significant for mid-to-high rank employees, suggesting limited benefit in terms of turnover for such workers, despite their similar rate of adoption.

We also observe heterogeneity in the strength of the relationship between EWA usage and turnover by age: while young users are more likely to stay longer than young non-users, such a relationship does not hold for older workers.

[INSERT TABLE 4 HERE]

We then turn to exploring the intensive margin of the relationship between the use of EWA and turnover: are more intensive users more likely to stay? We first construct a measure of use intensity by summing the amount withdrawn by a user in the first 4 pay cycles (2 month) since their first usage, scaled by their income per period, and conditioning

on the user still working at the company 2 months after the first usage. In column 1 and 2 of Table 5, we regress the indicator variable for leaving the company on this measure of use intensity. We find that usage intensity is predictive of a reduction in turnover likelihood. The magnitude is also large: withdrawing one percent of a pay cycle wage is associated with one percent lower probability of leaving the company in the next period, controlling for full sets of worker characteristics. Table 6 replicates the split regressions in Table 4 with the use intensity measure as the predictor on the set of Minu users. Again, we found that the low-rank and young workers are more likely to stay longer when they use more intensively.

[INSERT TABLE 5 AND 6 HERE]

4.2 Robustness

For robustness purpose, we run OLS and logistic regressions in a cross-sectional setting at the employee level. Specifically, we regress an indicator for the worker having separated from the firm by the end of our sample period on an indicator variable for having used earned wages access. Importantly, we control for worker cohorts with starting quarter fixed effects, as well as for worker characteristics.[2] Table 7 presents the regression coefficients for the OLS specification. All columns show a EWA user is around 5 percent points less likely to separate from the firm than a non-user over our sample period, which represents a 20% reduction in baseline. The split OLS regressions in Table 8 also confirms that the relationship is particularly pronounced for low-rank employees and younger workers. In the appendix, we run the regressions with same predictors and outcome variable using a logistic specification, and find consistent results.

[INSERT TABLE 7 AND 8 HERE]

[2]Such regressions therefore identify a potential relation only from the extensive margin of employment, and ignore information on tenure length conditional on having left.

5 Economic Mechanism

In this section, we investigate the economic mechanisms that potentially underlie the demand for earned wage access, and its association with higher retention, which supports the hypothesis of improved worker welfare. We consider three main mechanisms through which offering access to earned wages might increase worker utility: that earned wage access plays the role of a liquidity insurance against unexpected expenses, that it allows workers to bridge systematic timing mismatch between revenues and expenses, or that it caters to worker's present-bias.[3] We contrast theoretical predictions derived from models capturing these mechanisms with our findings. In addition, leveraging on a survey Minu collected from its users, we provide empirical evidences for mechanisms at play.

5.1 Liquidity Insurance

Cash shortfalls often result from unexpected spending shock, such as a healthcare or car repair bill. Providing an insurance against such cash shortfalls should translate into an increase in utility for workers. The literature has abundantly documented the existence of these cash shortfalls, especially for low wage workers (Shapiro, 2005), and the detrimental effects of such cash shortfalls on worker standing, including its decision-making (Haushofer and Fehr, 2014) and productivity (Kaur et al., 2021). Such mechanism is also the motivation typically used for supporting the introduction of payday lending. Such a mechanism yields the following empirical predictions. First, earned wage access should be particularly attractive to financially constrained workers, which are more likely to be hit by a shock, and who do not have precautionary savings to absorb it. Second, its usage timing across pay cycle should be irregular, and within a pay cycle should be tilted towards the end. The amount withdrawn should be irregular too, as it should be matching the ones of spending shocks conditional on them being larger than the remaining balance from the last paycheck. Third, such a product should crowd-out costlier ways of accessing liquidity, such as payday

[3] As explained in O'Donoghue and Rabin (2015), any noticeable short-term discounting is evidence of present-bias, and cannot be reconciled with time-consistent impatience.

lending, and even potentially discourage precautionary savings.

Our previously documented stylized facts supports such a mechanism for a significant fraction of users. More specifically, the fact that effect on retention is concentrated among low-ranked workers, which are more likely to be financially constrained, is consistent with the predictions from this mechanism. The irregular nature of withdrawals in terms of timing and amount, and the notable fact that users only rarely withdraw up to the cap, is also consistent with this mechanism being at play.

5.2 Revenue and Expenditure Timing Mismatch

The literature shows that households might experience financial shortfalls even in the absence of uncertainty (Baugh et al., 2018). If a household's rent is due prior to pay date, this household might have issues making this payment because planning for it requires attention and effort. EWA might alleviate such systematic shortfalls by allowing a better alignment between expenditure and revenue timing.

Figure 7 is consistent with such a mechanism being at play. While the expenditure related to the celebration for Semana Santa in Mexico are largely predictable, whether it falls prior or after to a pay date might create a variation in shortfall. In 2021, it fell at the end of March, prior to the pay date, and we can observe the associated sharp increase in EWA usage.

[INSERT FIGURE 7 HERE]

5.3 Present-biased Workers

A last potential source of demand for earned wage access is that some workers are present-biased, as in Laibson (1997), and therefore derive significantly higher utility from consuming earlier within a short-term horizon. With present-bias, workers should exhibit demand for earned wage access even in the absence of uncertainty, as it allows them to increase their utility by shifting their consumption earlier within the pay-cycle.

Similar to the behavior modeled in Parsons and Van Wesep (2013), when payday lending is introduced for present-biased workers that are paid infrequently, and ignoring the fixed fee associated with a withdrawal, present-biased workers should withdraw all available earned wages on any day, to shift their consumption as early as possible within the pay cycle.

Some of the prediction of this second mechanism are aligned with the ones resulting from a liquidity insurance: there should be demand for EWA, and it should be used in priority to payday lending, given its lower cost. On the other end, present-biased workers are unlikely to have precautionary savings in the first place.

Such a mechanism however yields certain different empirical predictions regarding EWA usage. Under this framework, usage should indeed be regular and predictable. Usage should not necessarily be related to financial constraint.[4] Usage should happen earlier on average in the pay cycle than under the liquidity insurance prediction. Worker should also withdraw up to the maximal allowed amount. Because only a small fraction of users withdraw the maximal amount of earned wage they are allowed to, it is unlikely that present-bias, at least in its most extreme version where individual are not aware of it are not willing to have some commitment device, is the main driver for the demand for EWA.

A sub-group of users exhibit usage patterns that are consistent with such a mechanism being at play: the ones that regularly use the service, and withdraw increasingly earlier in the pay cycle. The fact that higher rank workers, which are less likely to be financially constrained, are likely to use EWA, also suggests that some among them exhibit this bias.

5.4 User Survey

To further investigate the mechanism underlying the demand for access to earned wages and its association with higher retention, we collaborated with Minu to collect survey data from its EWA users in July 2023. Minu sent a 5-question survey through WhatsApp to 9,700

[4]Earlier studies have shown that present bias is more frequent among low wage workers (Meier and Sprenger, 2015), but recent evidence (Olafsson and Pagel, 2018) documents significant present-bias behavior among mid to high income workers.

users in around 20 companies to better understand users' purpose and usage behaviors. We received 1,435 responses 2 weeks after the survey launched, which translated into a 15% response rate. The survey asks the main purposes of use, alternative products used before and after EWA adoption, typical withdrawal amount and comparison with other company benefits.

Figure 8 displays the frequency of various purposes of use of EWA. It shows that using EWA for unexpected expenses (unexpected bills and medical emergency) and expected expenses are equally likely. EWA thus appears to be used to smooth consumption in case of liquidity shortfall as well as solving mismatch between income and daily expenditures. Turning to financial products used for those purposes before EWA adoption, in panel A of Figure 9 we find that most workers first choose to turn to family and friends or tap into own savings, then borrow from credit card or other financial institutions, and rarely borrow from companies or use other non-financial products. Moreover, panel B plots the comparison of usage of alternative products after EWA adoption. Surprisingly, we find EWA substitutes out most informal borrowing from family and friends and pawnshops, whereas the use of credit card and instant loans reduce the least comparing with other means. This suggests that availability of EWA reduces loans that may create a pecuniary or non-pecuniary disutility. Financial products are not easily replaced possibly due to their convenience or higher amount allowed to borrow.

[INSERT FIGURE 8 and 9 HERE]

We now turn to investigate EWA proceeds usage by users withdrawing different amounts. Figure 10 plots the purposes of use for users who withdraw less than or exactly as needed and at maximum in two panels respectively. It can be seen that users mostly withdraw less than maximum allowed for daily and expected expenses, and withdraw as much as they can when meeting an unexpected expenditure. This fits our rejection of present bias being the main driver for using EWA, as they withdraw maximum amount only when in great shortfalls. Finally, Figure 11 further supports the role of EWA to

increase retention, as it is second most preferred company benefit after medical insurance.

[INSERT FIGURE 10 and 11 HERE]

6 Conclusion

Using novel usage and survey data from a Mexican FinTech firm, we study the usage of earned wage access by workers, an innovative service increasingly offered by employers as a benefit. We document that such product meets significant demand. The usage of earned wage access is associated with a higher employee retention, suggestive of improved welfare. We consider the possible underlying mechanisms for a causal effect, liquidity insurance, consumption smoothing and catering to present-bias, and find empirical evidence supportive of them being at play for different segment of users.

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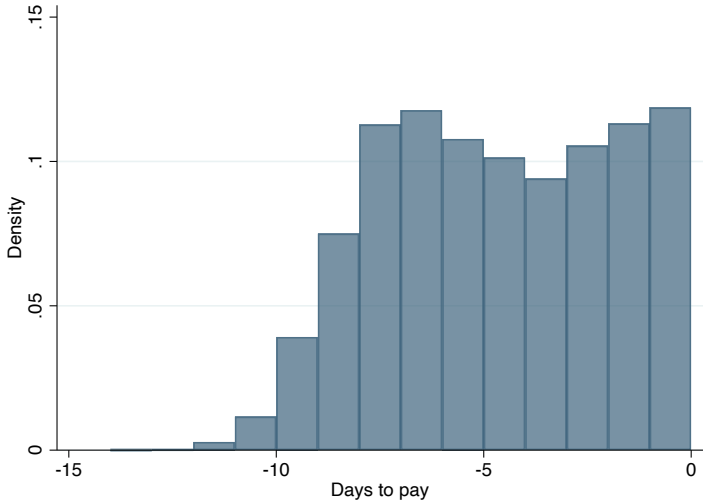
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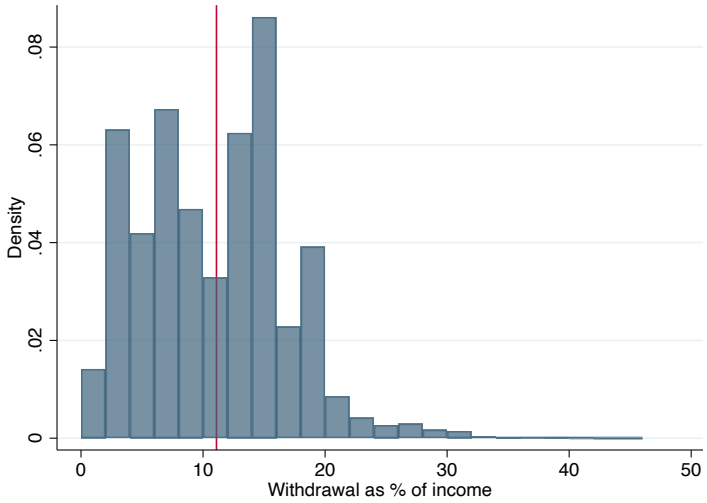
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7 Figures

Panel A: Average withdrawal timing



Panel B: Average withdrawal size



Panel C: Average withdrawal size relative to available income

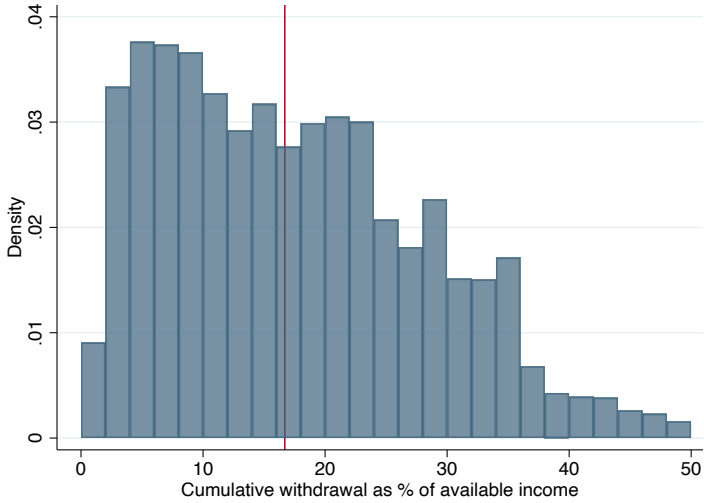


Figure 1: **Earned Wage Access: Withdrawal Timing and Size**

Notes: These figures present the distribution of timing and scaled amounts of EWA withdrawals. Panel A presents the distribution of numbers of days separating a withdrawal to the next pay check date. Panel B presents the distribution of cumulative withdrawal amount over a pay cycle, scaled by the pay cycle income, while panel C presents the distribution of the cumulative withdrawal in a pay cycle scaled by earned wage available for withdrawal minus the amount already withdrawn in the same cycle. Red vertical lines in panel B and C indicate median amounts.

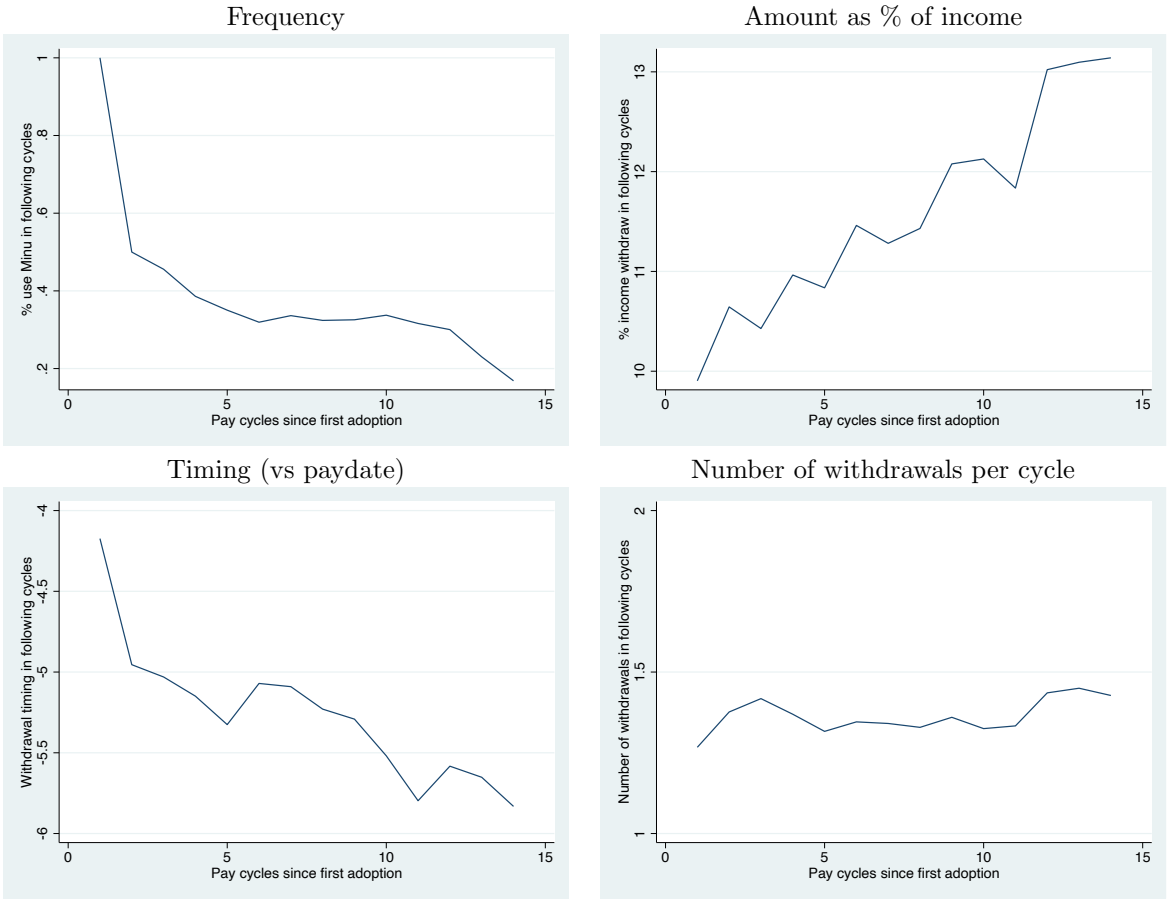


Figure 2: **Average withdrawal behaviors over time**

Notes: These figures present the evolution of the frequency, amount, timing and numbers of withdrawals over the following pay cycles for EWA adopters. Use frequency is calculated by the percentage of users who make withdrawals in the next cycles after their first usage. Number of withdrawals, withdrawal scaled by income and timing are calculated by averaging the measures over all users conditioning on users making at least one withdrawal in that pay cycle.

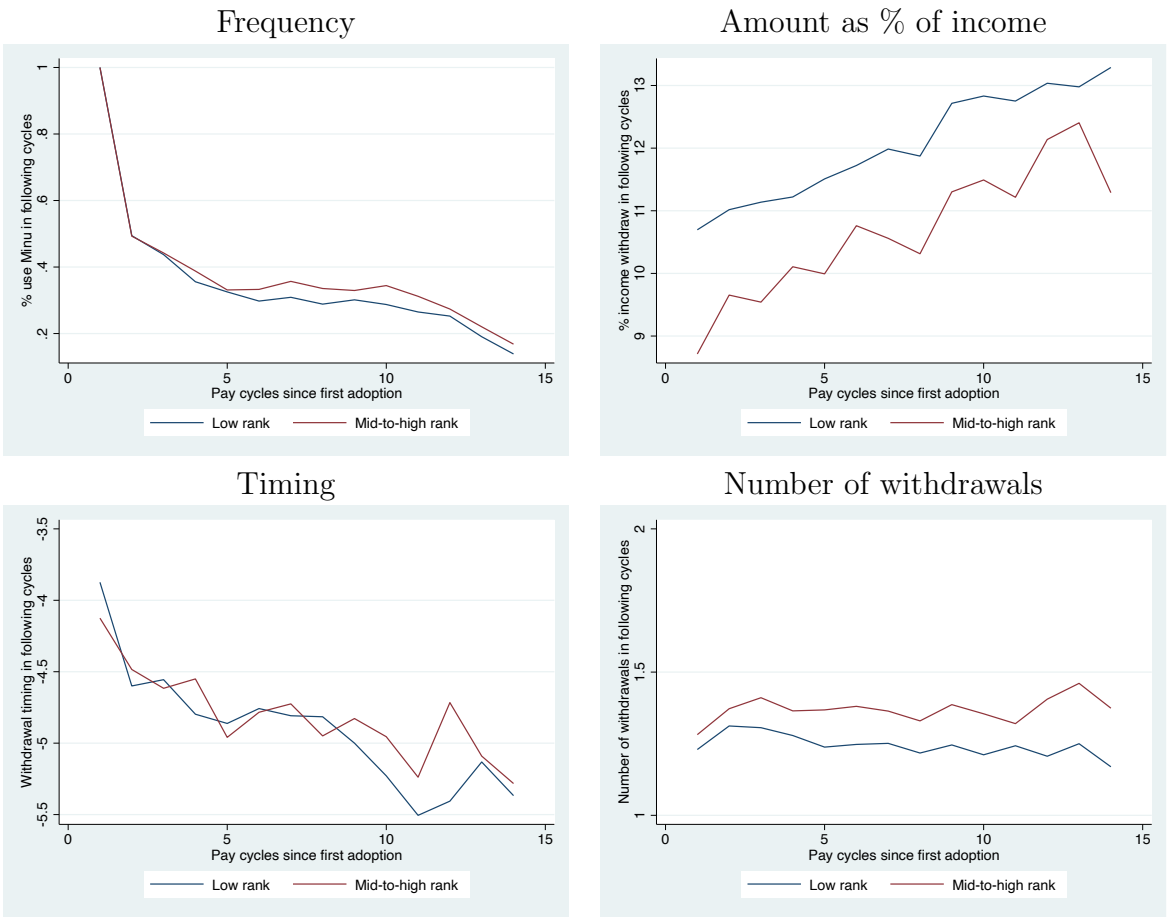


Figure 3: **Withdrawal behaviors over time by job ranks**

Notes: These figures present the evolution of the frequency, amount, timing and numbers of withdrawals over the following pay cycles for EWA users split between the ones holding a lower job rank and users of mid and high rank. Use frequency is calculated by the percentage of users who make withdrawals in the next cycles after their first usage. Number of withdrawals, withdrawal scaled by income and timing are calculated by averaging the measures over all users conditioning on users making at least one withdrawal in that pay cycle.

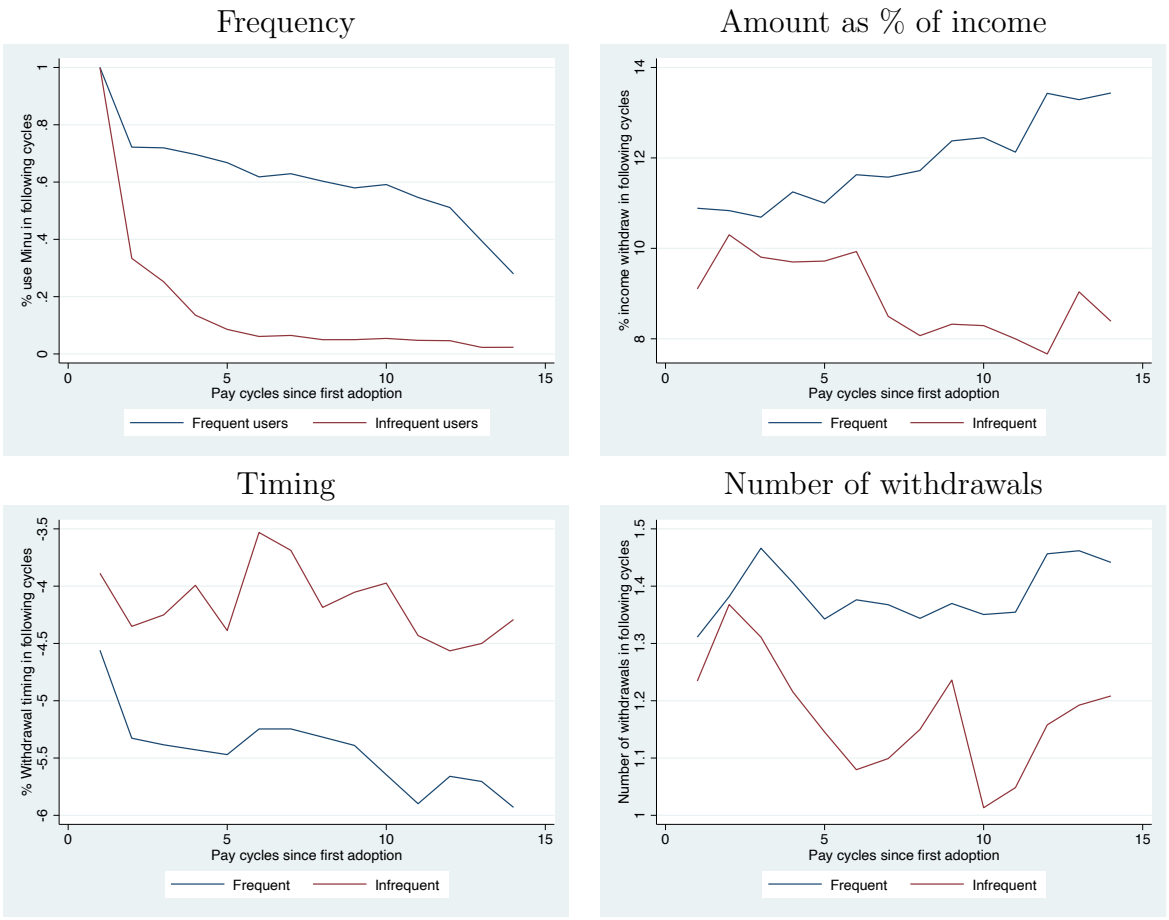


Figure 4: **Withdrawal behaviors over time by user types**

Notes: These figures present the evolution of the frequency, amount, timing and numbers of withdrawals over the following pay cycles for frequent users (who use the service in five or more cycles), versus less frequent users. Use frequency is calculated by the percentage of users who make withdrawals in the next cycles after their first usage. Number of withdrawals, withdrawal scaled by income and timing are calculated by averaging the measures over all users conditioning on users making at least one withdrawal in that pay cycle.

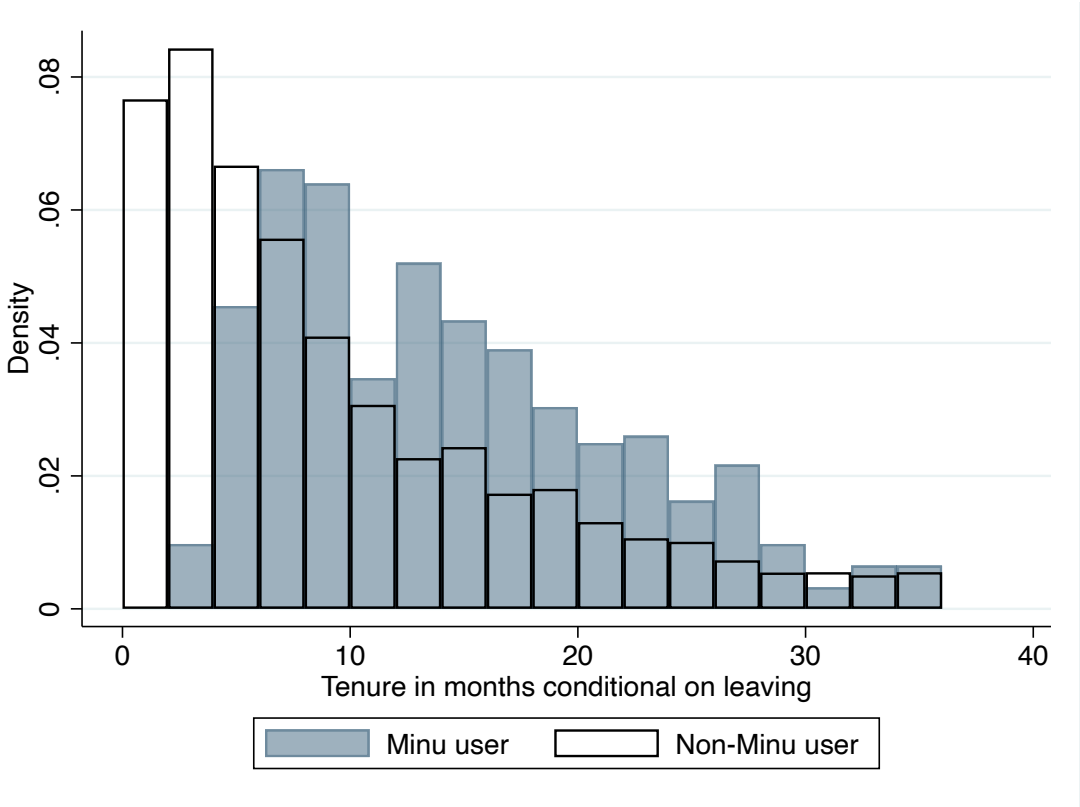
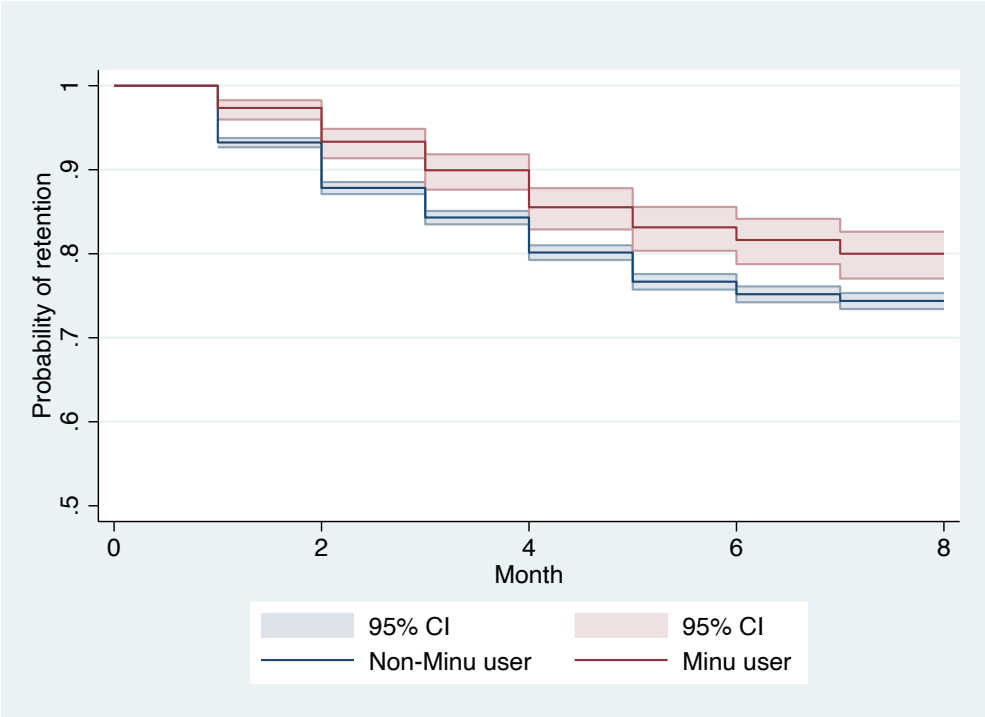


Figure 5: **Tenure of employees conditioning on ending the employment**

Notes: This figure displays the distribution of tenure lentgh of employees that have left the company as of the end of the sample (2021), split between EWA users and non-users.

Panel A: Employees starting 6 months or less before EWA is offered



Panel B: Employees starting after EWA is offered

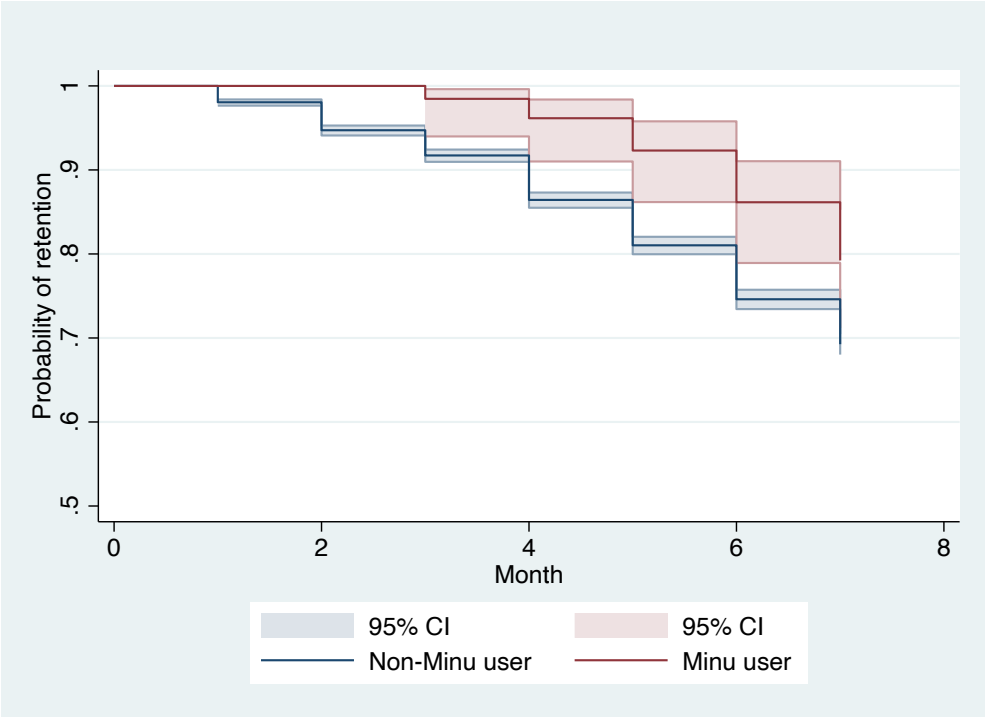


Figure 6: **Turnover and EWA use**

Notes: These figures displays the share of employees who are still working at their initial employer in a given month since they, for EWA users and non-users. Panel A restricts the sample to the group of employees who started 6 months or less before EWA was initially introduced at the employer level, and panel B restricts to the employees who started working at the company after EWA is introduced.

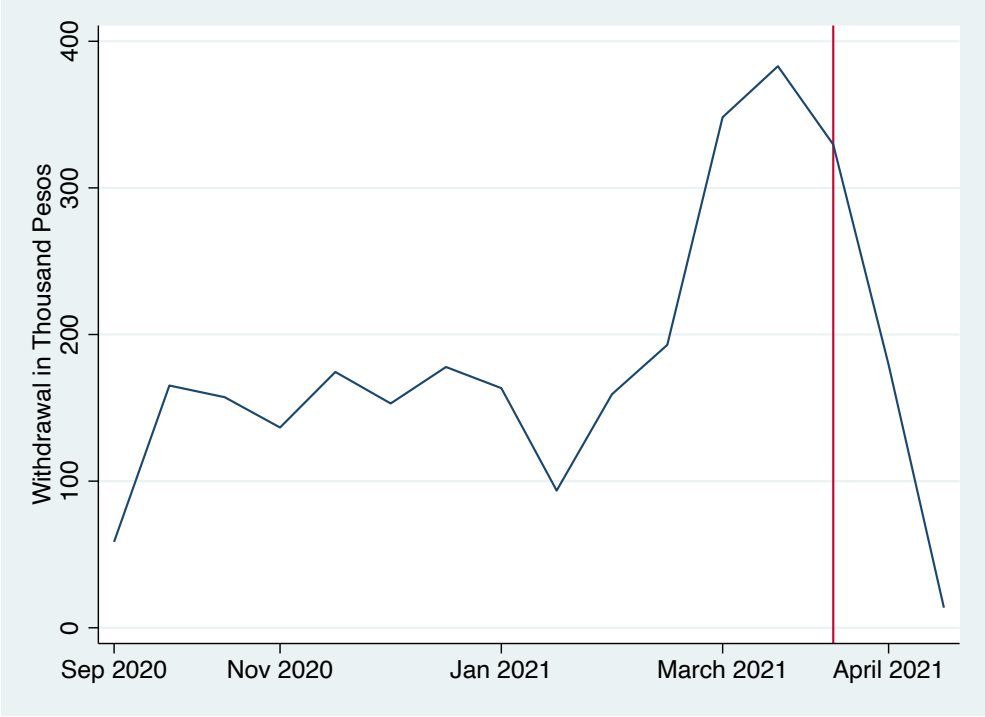


Figure 7: **Total withdrawal across time**

Notes: This figure plots the aggregate withdrawal amount on Minu in thousand Pesos from September 2020 to April 2021 in our sample. The red line indicates the week of 'Semana Santa', a major holiday in Mexico.

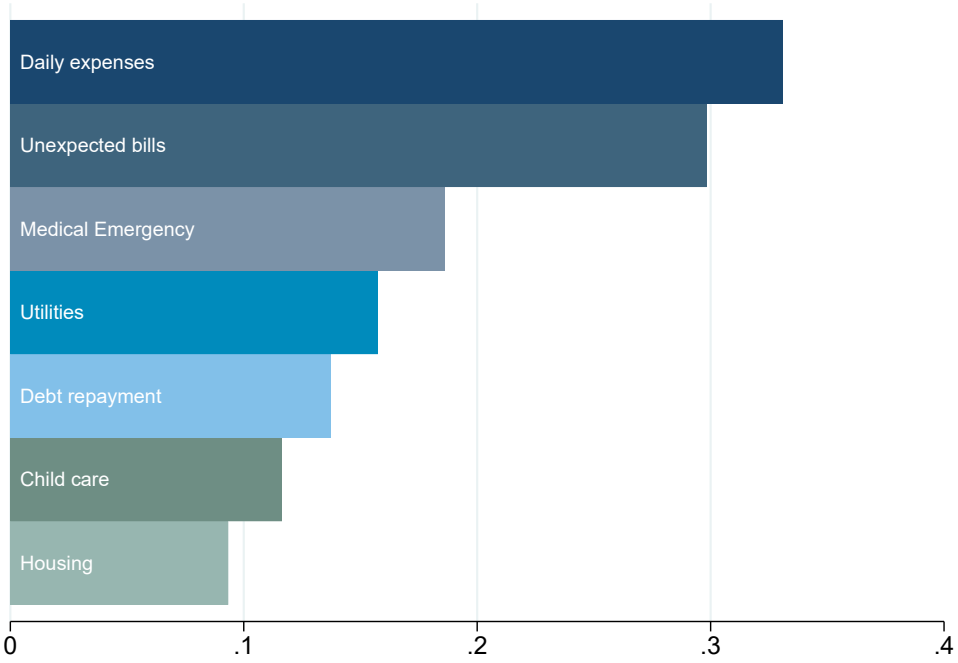


Figure 8: **EWA Purpose of use**

Notes: This figure plots the proportions of top three answers chosen by respondents to survey question: "What are the main purposes that you use Minu EWA for?" .

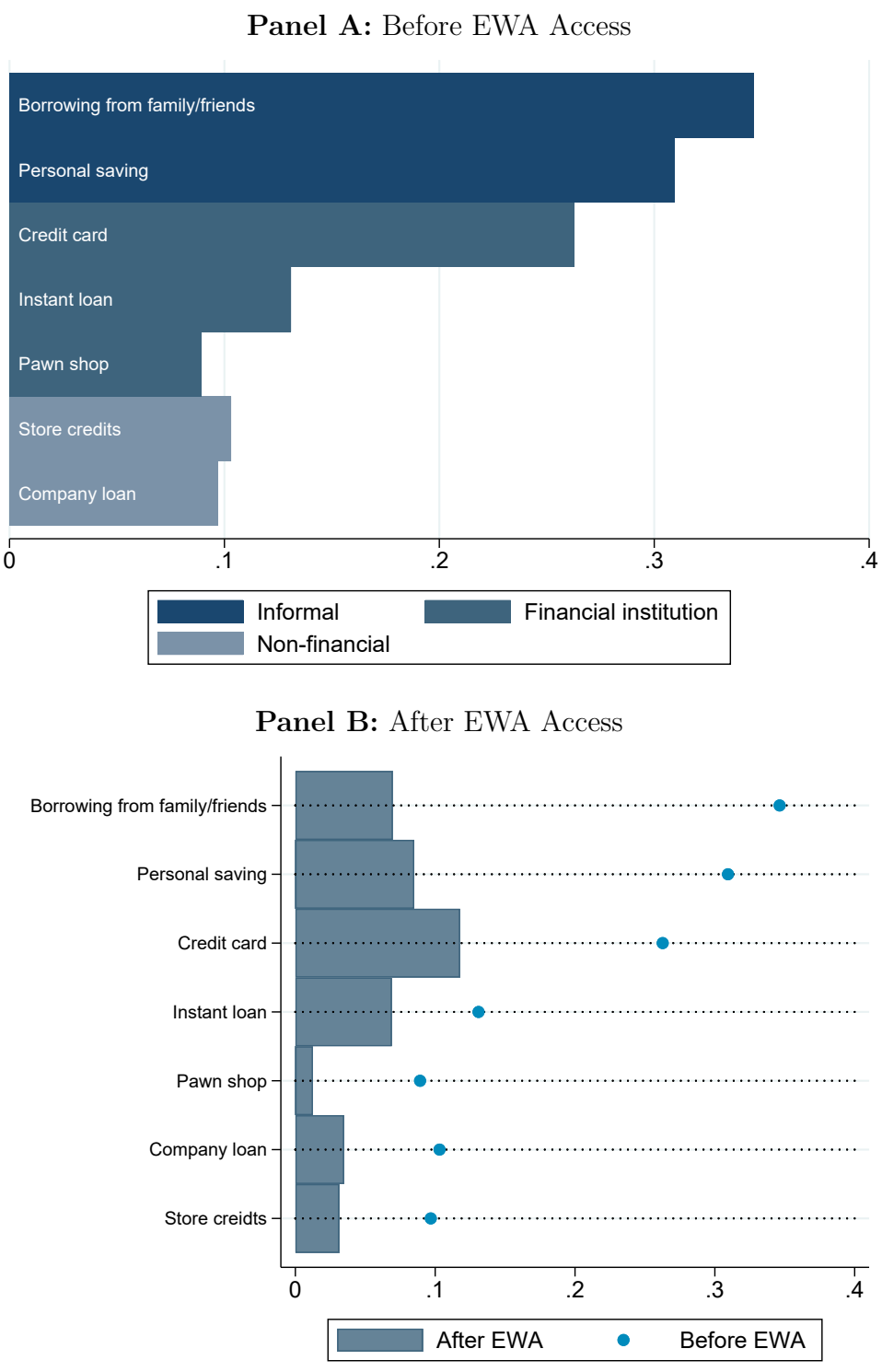
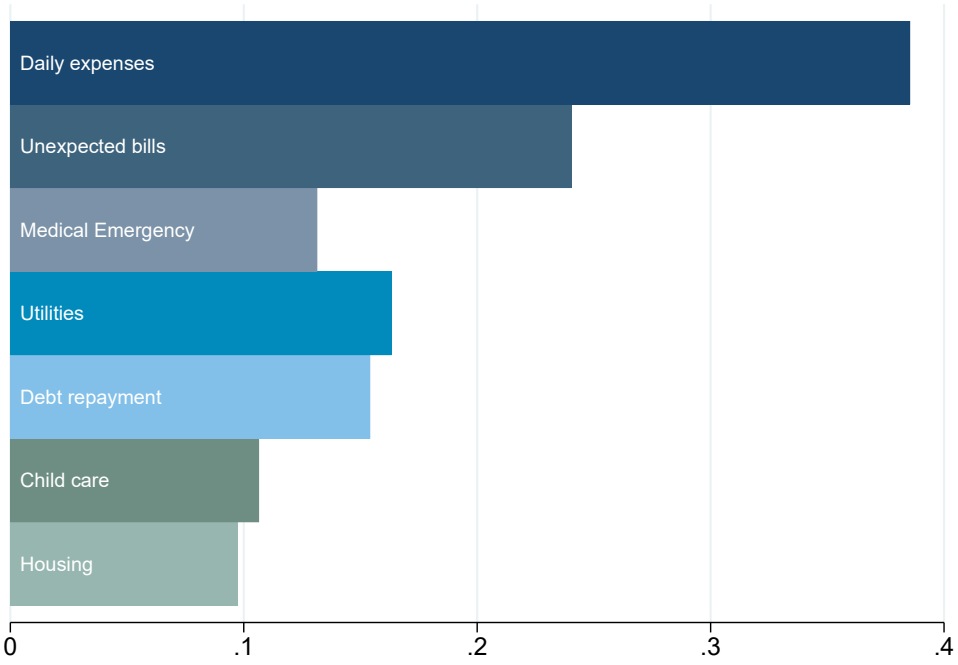


Figure 9: **Financial Products Used before and after EWA Access**

Notes: These figures displays the proportions of financial products that respondents chosen for their main purposes of use. Panel A plots their answers to survey question "What are the financial products that you have used before minu SoD was available to you for such purpose(s)?" . Panel B plots the proportion of uses of financial products other than Minu EWA after it was available among those who still uses multiple financial products.

Panel A: Less than or exactly as needed



Panel B: Maximum allowed

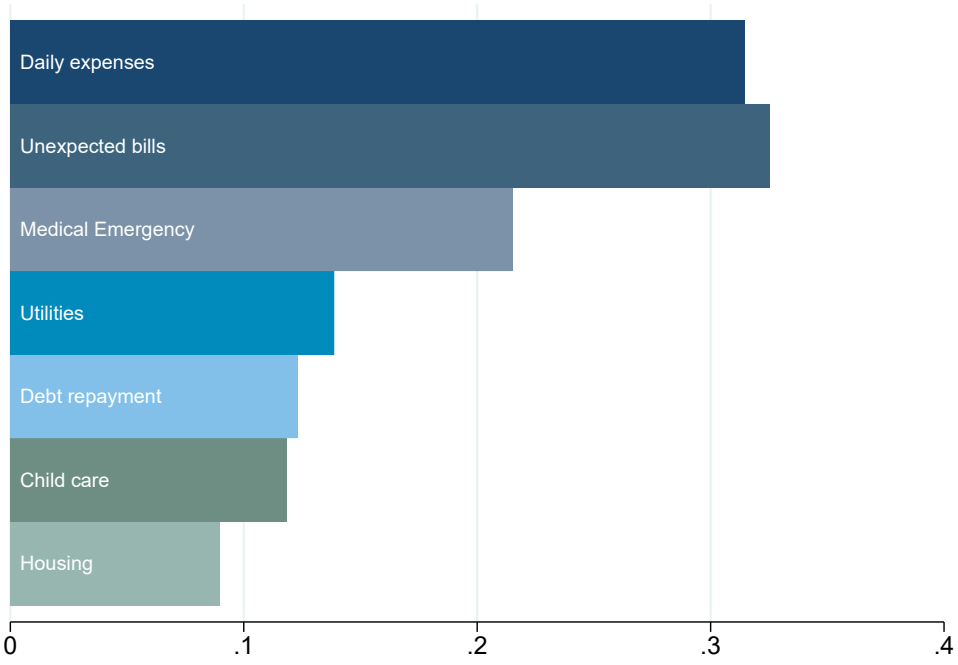


Figure 10: **Proceeds Usage by Amount Withdrawn**

Notes: These figures displays the proceeds usage by amount withdrawn selected by respondents when answering question "How do you choose the amount you withdraw from minu SoD when you use it?". Panel A plots the usage of withdrawal from Minu EWA among users who withdrew less than or exactly as needed, and plot B plots that for workers who withdrew at maximum.

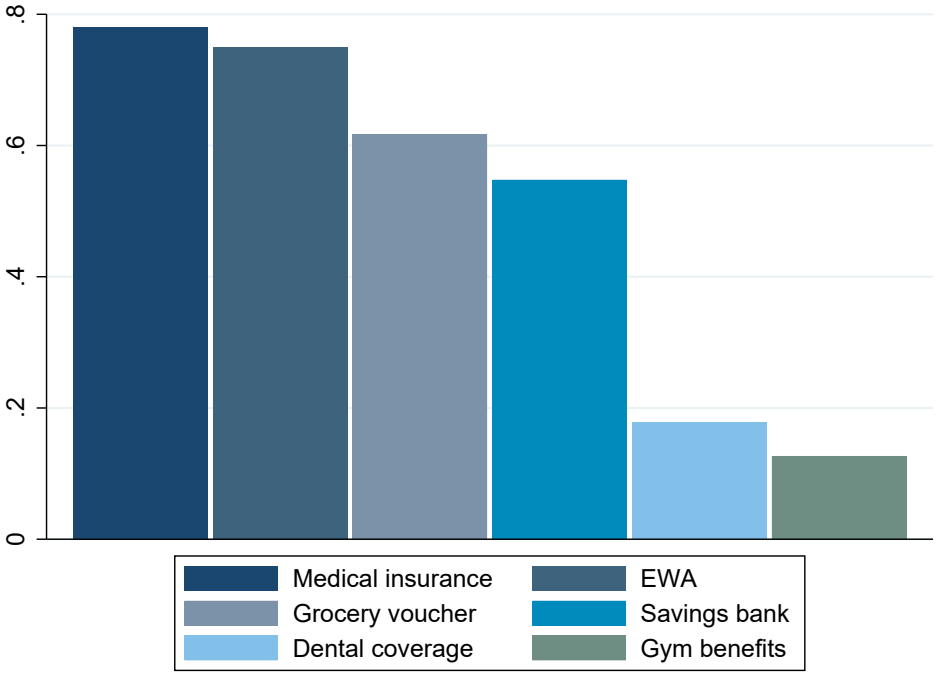


Figure 11: **Preferences for Company Benefits**

Notes: This figure plots the proportions of top three answers chosen by respondents to survey question: "What are the main purposes that you use Minu EWA for?" .

8 Tables

Table 1: **Summary statistics**

Panel A. Employee Characteristics						
	EWA users (N = 3,787)			Non-EWA users (N = 47,756)		
	Mean	**p25**	**p75**	**Mean**	**p25**	**p75**
Age	33.1	27	38	33.7	26	40
Male	0.70	0	1	0.60	0	1
Start year	2018.0	2017	2019	2018.4	2018	2020
% Low-rank employees	59.2	-	-	62.4	-	-
% Mid-rank employees	31.1	-	-	32.0	-	-
% High-rank employees	9.7	-	-	5.6	-	-
Leaves Firm (1/0)	0.13	0	0	0.19	0	0

Panel B. EWA User Activity				
	Obs	**Mean**	**p25**	**p75**
Avg. withdrawals per pay cycle	17,903	1.35	1	1.5
Avg. withdrawal amount per pay cycle	17,903	868.5	404.8	975

Notes: This table reports summary statistics for the main variables used in the analysis. Panel A reports worker age (as per 2021), gender, start year, proportion of ending the employment and job ranks, separately for EWA users and non-users. Panel B displays summary statistics of EWA usage (conditional on using EWA in that pay cycle). Amounts are in Mexican pesos.

Table 2: **Earned Wage Access Adoption and Worker Characteristics**

	EWA user=1 (1)
Male=1	0.035*** (0.004)
Young=1	0.029*** (0.004)
Low rank=1	-0.011** (0.004)
Start two year or less before EWA introduction	0.027*** (0.010)
Start after EWA introduction	-0.102*** (0.010)
Company B	-0.012*** (0.004)
Observations	23,472
R^2	0.041

Notes: This table presents the OLS coefficients from regressing an indicator variable for using EWA on worker's gender, age group, job rank, groups of start time and company which she works at to predict the probability of becoming a Minu user. Standard errors are robust.

Table 3: **Hazard model - EWA use and turnover**

	Leaves firm=1			
	(1)	(2)	(3)	(4)
EWA User	-0.117**	-0.157***	-0.110**	-0.085*
	(0.046)	(0.047)	(0.050)	(0.050)
Male=1			-0.002	-0.017
			(0.027)	(0.027)
Low rank=1			1.035***	1.180***
			(0.032)	(0.031)
Age				0.004**
				(0.001)
Company FE	Y	Y	Y	Y
Start quarter FE	N	Y	Y	Y
Number of Employees	44,139	44,139	27,617	22,942
Observations	684,888	684,888	394,701	333,016

Notes: This table presents the coefficients (1-hazard ratio) from Cox proportional hazard regressions that uses the indicator for EWA usage to predict the probability of a worker leaving their firm. The set of controls include worker's gender, age and job rank. Standard errors are clustered at starting-quarter level.

Table 4: **Hazard Model: Heterogeneity**

	Leaves firm=1					
	Gender		Job Rank		Age	
	Female	Male	Low	Mid-to-High	Below median	Above median
	(1)	(2)	(3)	(4)	(5)	(6)
EWA User	-0.131	-0.062	-0.242***	0.134	-0.203***	0.077
	(0.087)	(0.062)	(0.060)	(0.085)	(0.068)	(0.074)
Company FE	Y	Y	Y	Y	Y	Y
Start quarter FE	Y	Y	Y	Y	Y	Y
Age	Y	Y	Y	Y	N	N
Gender	N	N	Y	Y	Y	Y
Rank	Y	Y	N	N	Y	Y
Number of Employees	8,605	14,337	13,324	9,894	12,782	10,160
Observations	118,004	215,012	167,942	165,074	182,321	150,695

Notes: this table presents the coefficients (1-hazard ratio) from Cox proportional hazard regressions that uses the indicator for EWA usage to predict the probability of a worker leaving their firm. The sample is split on worker gender (column 1 and 2), worker job rank (column 3 and 4), and worker age (column 5 and 6). The set of controls include worker's gender, age and job rank. Standard errors are clustered at starting-quarter level.

Table 5: **EWA use and turnover - Intensive Margin**

	Leaves firm=1	
	(1)	(2)
Withdrawal as % of income	-0.010*	-0.010*
	(0.006)	(0.006)
Male=1	0.126	0.082
	(0.235)	(0.236)
Low rank=1	2.325***	2.452***
	(0.334)	(0.326)
Age		0.022**
		(0.011)
Company FE	Y	Y
Start quarter FE	Y	Y
Number of Employees	2,504	2,065
Observations	35,014	29,396

Notes: this table presents the coefficients (1-hazard ratio) from Cox proportional hazard regressions that uses the EWA cumulative withdrawn amount over the two pay cycles following the first usage (scaled by pay cycle wage) to predict the probability of a worker leaving their firm. The sample is restricted to EWA users. Standard errors are clustered at starting-quarter level.

Table 6: **Heterogeneity for Hazard Model - Intensive margin**

	Leaves firm=1					
	Gender		Job Rank		Age	
	Female	Male	Low	Mid-to-High	Below median	Above median
	(1)	(2)	(3)	(4)	(5)	(6)
Withdrawal as % of income	-0.028*	-0.007	-0.010*	-0.001	-0.017**	-0.001
	(0.015)	(0.006)	(0.006)	(0.030)	(0.007)	(0.009)
Company FE	Y	Y	Y	Y	Y	Y
Start quarter FE	Y	Y	Y	Y	Y	Y
Age	Y	Y	Y	Y	N	N
Gender	N	N	Y	Y	Y	Y
Rank	Y	Y	N	N	Y	Y
Number of Employees	545	1,520	1,153	939	1,292	773
Observations	7,724	21,672	15,926	13,470	18,536	10,860

Notes: this table presents the coefficients (1-hazard ratio) from Cox proportional hazard regressions that uses the EWA cumulative withdrawn amount over the two pay cycles following the first usage (scaled by pay cycle wage) to predict the probability of a worker leaving their firm. The sample is restricted to EWA users. The sample is split on worker gender (column 1 and 2), worker job rank (column 3 and 4), and worker age (column 5 and 6). Standard errors are clustered at starting-quarter level.

Table 7: **EWA use and turnover - OLS model**

	Has left firm=1			
	(1)	(2)	(3)	(4)
EWA user	-0.073***	-0.083***	-0.056***	-0.048***
	(0.018)	(0.015)	(0.016)	(0.013)
Company FE	Y	Y	Y	Y
Start quarter FE	N	Y	Y	Y
Gender	N	Y	Y	Y
Job position	N	N	Y	Y
Age	N	N	Y	Y
Observations	51,530	51,521	32,299	27,466
R^2	0.065	0.103	0.321	0.451

Notes: This table presents OLS coefficients from regressions that use an indicator variable for the worker being a EWA user to predict the probability of the worker leaving the company before the end of the sample period. Standard errors are clustered at starting-quarter level.

Table 8: **Heterogeneity for OLS model**

	Has left firm=1					
	Gender		Job Rank		Age	
	Female	Male	Low	Mid and High	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
EWA user	-0.051**	-0.046***	-0.146***	-0.009	-0.061***	-0.039***
	(0.020)	(0.012)	(0.022)	(0.012)	(0.020)	(0.009)
Company FE	Y	Y	Y	Y	Y	Y
Start quarter FE	Y	Y	Y	Y	Y	Y
Gender	N	N	Y	Y	Y	Y
Job position	Y	Y	N	N	Y	Y
Age	Y	Y	Y	Y	N	N
Observations	10,068	17,226	14,271	9,172	13,585	13,747
R^2	0.395	0.490	0.131	0.438	0.426	0.461

Notes: This table presents OLS coefficients from regressions that use an indicator variable for the worker being a EWA user to predict the probability of the worker leaving the company before the end of the sample period. The sample is split on worker gender (column 1 and 2), worker job rank (column 3 and 4), and worker age (column 5 and 6). Standard errors are clustered at starting-quarter level.