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

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Abstract

Using novel data from a Mexican FinTech firm, we study the usage by workers of earned wages access, an innovative financial service offered by firms to their employees as a benefit. We find usage to be significant and concentrated towards the end of the pay cycle. We document that such usage is associated with a higher employee retention, suggestive of improved welfare. We consider the possible underlying mechanisms for a causal effect, liquidity insurance and catering to present-bias, and find empirical evidence supportive of both being at play for different segment of users.

[PRELIMINARY VERSION]

*We are indebted to Minu for generously providing us access to their data. We thank seminar participants at Harvard Business School for their comments and suggestions. All errors are ours only.

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1 Introduction

Workers often experience cash shortfalls, which significantly impacts them on several dimensions such as consumption (Shapiro, 2005), psychological standing (Haushofer and Fehr, 2014), or productivity (Kaur, Mullainathan, Oh, and Schilbach, 2021). Recently, workers in the US and across the developed world are leaving their jobs at an unusually high rate, a phenomenon known as the Great Resignation. This episode is further fueling a growing awareness from employers to the benefits of improving employee welfare. A promising venue for doing so is therefore for employers to develop benefits that address worker financial strain, as a potential complement or substitute of increasing wages. An emerging tool for that purpose is earned wage access, which allows worker to withdraw at will a fraction of the wages they have earned but not yet obtained. 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. US workers thus 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 wages access improves worker welfare, with a possible significant impact on worker retention. If so, what is the underlying economic mechanism that explains such an effect? What would be potential costs associated with the product benefits?

This paper attempts to answer these questions by empirically investigating the usage patterns of earned wage access following its introduction within a firm, and in turn whether such usage translates into higher employee retention. For this purpose, we exploit a novel data set from a leading provider of such a product in Mexico. Such a laboratory is particularly suited 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, as access to other tools of 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. First, a significant fraction of workers adopt such a service within a short time frame. In the cross-section of workers, it appears to be more popular with workers that are male, young and did not recently joined the firm. Its 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 tend to increase, and such withdrawal happen earlier in the pay-cycle.

Turning to employee retention, we document that workers accessing earned-wages 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 the reduction in turnover is concentrated 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 interpret the empirical regularities we document as consistent with two mechanisms at play among possibly overlapping subpopulations 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, 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.

Our study relates to several streams for literature. First, our study contributes to the literature on cash shortfalls and their effects (see e.g. (Shapiro, 2005, Fink et al., 2020) , by studying a tool to alleviate them. In that sense, our work connects with the literature that studies payday lending as potentially playing a similar 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 mostly ambivalent or even detrimental effects for household finances, such as overborrowing (Di Maggio and Yao, 2021, Chava et al., 2021). Our study, by taking a revealed preference approach and relating EWA usage with higher retention, presents a bright side of such innovations.

Last, by studying the mechanism that rationalize the adoption of this innovation and its effects, our work also speak to 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.

2 Background and Data

2.1 Background on Access to Earned Wages

Earned Wage Access (EWA) services, sometimes called advanced wage access or on-demand pay, allow 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. Over the past few years, EWA became an increasingly popular benefit offered by employers for worker retention, especially among large retailers (e.g. Walmart, Target). 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).

2.2 Data

Our novel dataset is provided by Minu, a leader of EWA in Mexico. Minu follows the intermediation model 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 only comes with a small 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 will automatically deduct the amount withdrew during the past pay cycle. As transfers made on Minu is not a loan, there is no interest rate being carried over to future terms. Currently, the size of a withdrawal is subject to a cap of 50 percent of available earned wages at the time of withdrawals.

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, includes 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 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.

2.3 Summary Statistics

We obtain three data sets described above from each of two large companies in Mexico, where one is a retailer and the other is in telecommunications industry. There are in total 51,543 workers in our sample, and about 7% of the workers used Minu during their employment. Panel A of Table 1 presents some demographics of Minu users versus non-Minu 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. The Minu user groups has more males, slightly more senior and more higher-rank employees that the non-users group. In panel B, we present some statistics about user activities. Most users make less that 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 some stylized facts describing how and when do employees use the earned wage access service.

First, when access to to earned wages is offered through the employer, a significant share of workers use the service. As shown in Panel A of Table 1, 7% of workers from our sample made withdrawals through Minu 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 make them more likely to use access to earned wages. In Table 2, we run a logistic regression using worker characteristics to predict the probability of becoming a Minu user. We find that male and younger workers are more likely to use the service.

[INSERT TABLE 2 HERE]

We now zoom in on the group of workers that use access to earned wages and investigate usage patterns. To start with, we 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 and amounts averaging over all users and pay cycles for which there was at least one withdrawal. First, Panel A shows 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. In Panel B, the amount withdrawn are scaled by the worker income over the whole paycycle (two weeks). We observe that workers withdraw economically significant amounts: the average withdrawn amount is equal to 12.5% of the worker pay cycle wages. Importantly, the amount workers can withdraw is capped at 50% of the wages already earned but not yet paid, which increases within each pay cycle. We therefore repeat the same exercise, but scaling by the within pay-cycle wages up to the date of withdrawal in Panel C. We observe that 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 the users keep using Minu 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 from Minu 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 Minu 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]

In the top left panel of Figure 2, we identified 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 for less than 5 pay cycles and those who use more and plot their usage pattern again. We pick up a larger heterogeneity in the evolution of usage along this dimension. First, the withdrawal amount as proportion of income is roughly the same for the two groups of users at first, but as time goes by, the frequent users show a clear pattern of withdrawing larger amount, while the infrequent users withdraw similar amount comparing to the beginning. We also see this pattern in the timing of withdrawals: the frequent users are the ones driving the pattern of earlier withdrawals within the pay cycle. 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 Access to Earned Wages on Employee Retention

4.1 Main Result

We first look at the unconditional relationship between the usage of Minu and the propensity to stay at the firm. We first 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 Minu users that stay at the 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 Minu 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 Minu users. As of 8 months after the introduction of Minu, 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 Minu in Panel B. The two figures therefore suggest some association between the use of Minu and higher retention in the sample.

[INSERT FIGURE 5 AND 6 HERE]

We then estimate the relationship between using earned wages access and the likelihood of leaving the firm, controlling for observable characteristics of workers. We use a Cox proportional hazard model, with the following specification:

$$\lambda(t \mid Xi, t) = \lambda_{0,t} \times Exp(\beta_1 \, Used\ Minu_{i,t} + \beta_2 \, Start\ Quarter_i + \beta_3 Company_i + \beta_4 Demographics_i + \gamma) + \varepsilon_{i,t}$$

where $Used\ Minu_{i,t}$ is an indicator that equals to 1 on and after the pay cycle t when the worker first use Minu, and zero otherwise, γ are the set of other explanatory variables including gender, age and latest job position of employee i, and $Company_i$ are firm 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 start quarter fixed effects, Minu users on average have about 12 percent lower probability of leaving the company in the next pay cycle comparing to the baseline of non-users. When controlling for the gender and job rank of workers in column 3, we still see a 8 percent lower chance for the worker to leave when she is a Minu user.

[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 significantly by gender. On the other hand, when splitting the workers along their skill level, we see a stronger relationship between Minu usage and retention in column 5 and 6: among the low-rank employees, being a Minu users is associated with a significantly lower likelihood of terminating their employment at any period, while there is not such a relationship for mid-to-high rank employees. We find that use of Minu is associated with 20 percent lower probability for low-ranked employees to leave their employment in any next pay cycle compared to the baseline likelihood among this type of workers. We also observe heterogeneity in the strength of the relationship 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]

On the extensive margin, we find that the average user is 10 percent less likely to leave the company comparing to a non-user. We then turn to exploring the intensive margin of the use of the service on turnover - are more intensive users more likely to stay? We construct a measure of use intensity by cumulating the amount withdrawal by a user in the first 4 pay cycles (2 month) since her first adoption scaled by her income per period, conditioning on the user work at the company beyond 2 months. In column 1 and 2 of

Table 5 , when regressing this measure of use intensity on indicator of leaving the company, we find that a 10 percentage point increase in scaled withdrawal size is associated with 0.1% 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.[1] Table 7 presents the regression coefficients for the OLS specification. All columns show a Minu user is around 5 percent points less likely to separate from the firm than a non-user over our sample period, which represents . The split OLS regressions in Table 8 also confirm this positive effect on retention, and the effect is especially announced for the low-rank and young employees. Furthermore, in the appendix, we run the regressions with same predictors and outcome variable using a logistic specification, and the results are also consistent with the findings in the OLS specification.

[INSERT TABLE 7 AND 8 HERE]

5 Economic Mechanism

In this section, we investigate the economic mechanisms that potentially underly the demand for earned wage access, and its association with higher retention, supportive of improved worker welfare. We consider three main mechanisms through which offering access

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

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.[2] We contrast theoretical predictions derived from models capturing these mechanisms with our findings. In addition, we plan on exploiting survey data collected by Minu from its users to further investigate these mechanisms.

5.1 Liquidity Insurance

A first source of cash shortfall is that a worker is hit with an expected spending shock. Providing an insurance against such cash shortfall should translate into an increase of the utility of 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 lending, and even potentially discourage precautionary savings.

Our previously documented stylized facts supports such a mechanism for a significant fraction of users.

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

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 TABLE 7 HERE]

5.3 Present-biased Workers

A second 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.[3] 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.

Again, a sub-group of users exhibit usage patterns that are consistent with such a mechanism being at play.

5.4 Next Step: Leveraging Survey data

To further disentangle the mechanism underlying the demand for access to earned wages and its association with higher retention, we plan on exploiting user survey data provided by Minu.

6 Conclusion and Next Steps

Using novel 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 and catering to present-bias, and find empirical evidence supportive of both being at play for different segment of users.

To gain causal identification for the relationship between using access to earned wage and increased retention, we plan on exploiting a natural experiment provided by the stag-

[3] 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.

gered implementation of the service across different establishments of one of Minu large corporate client. We are currently working on obtaining this additional dataset.

To further pin-down the mechanism(s) driving the demand for EWA, we will implement a survey with Minu users and target users.

Last, to value the utility derived from the use and access of the service, we will exploit a quasi-natural experiment resulting from a change in the pricing policy.

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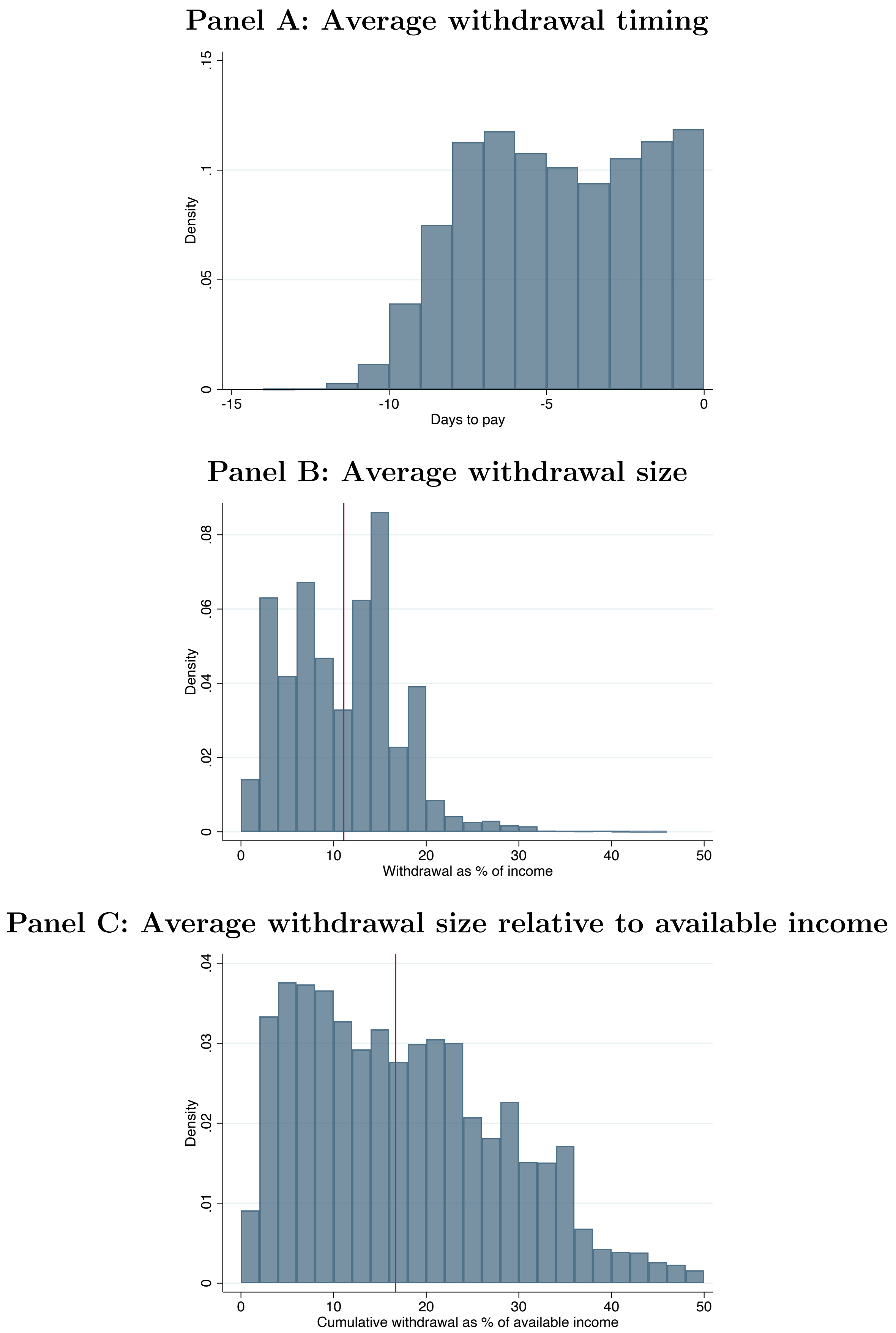

Figure 1: **Withdrawal statistics**

Notes: These figures present the distribution of timing and scaled amounts of user withdrawals. Panel A presents the distribution of the day of withdrawal measured by number of days to the next pay check. Panel B presents the distribution of withdrawal amount of a pay cycle scaled bi-week income, while panel C presents the distribution of the cumulative withdrawal in a pay cycle scaled by earned income available for withdrawal minus the amount already withdrawn in the same cycle. Red vertical lines in panel B and C indicate median withdrawal.

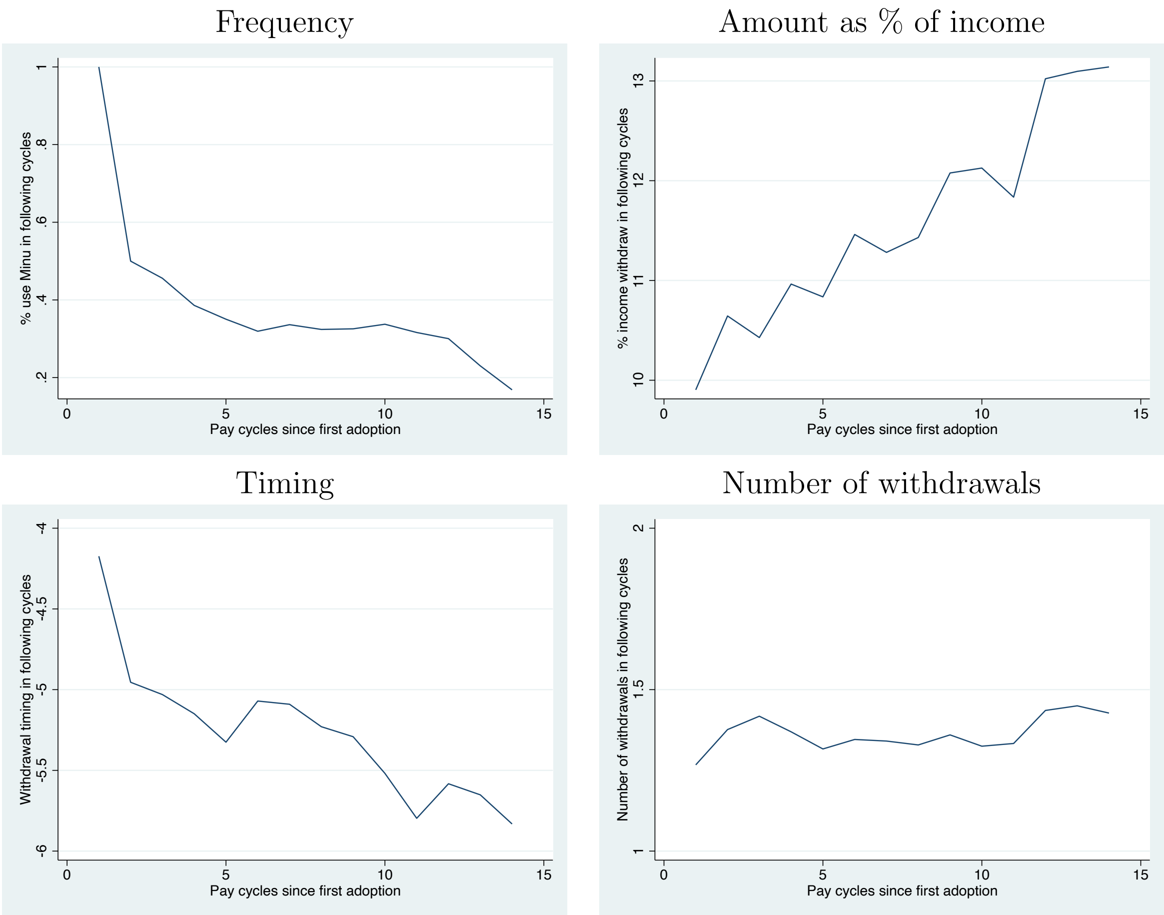

Figure 2: **Average withdrawal behaviors over time**

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

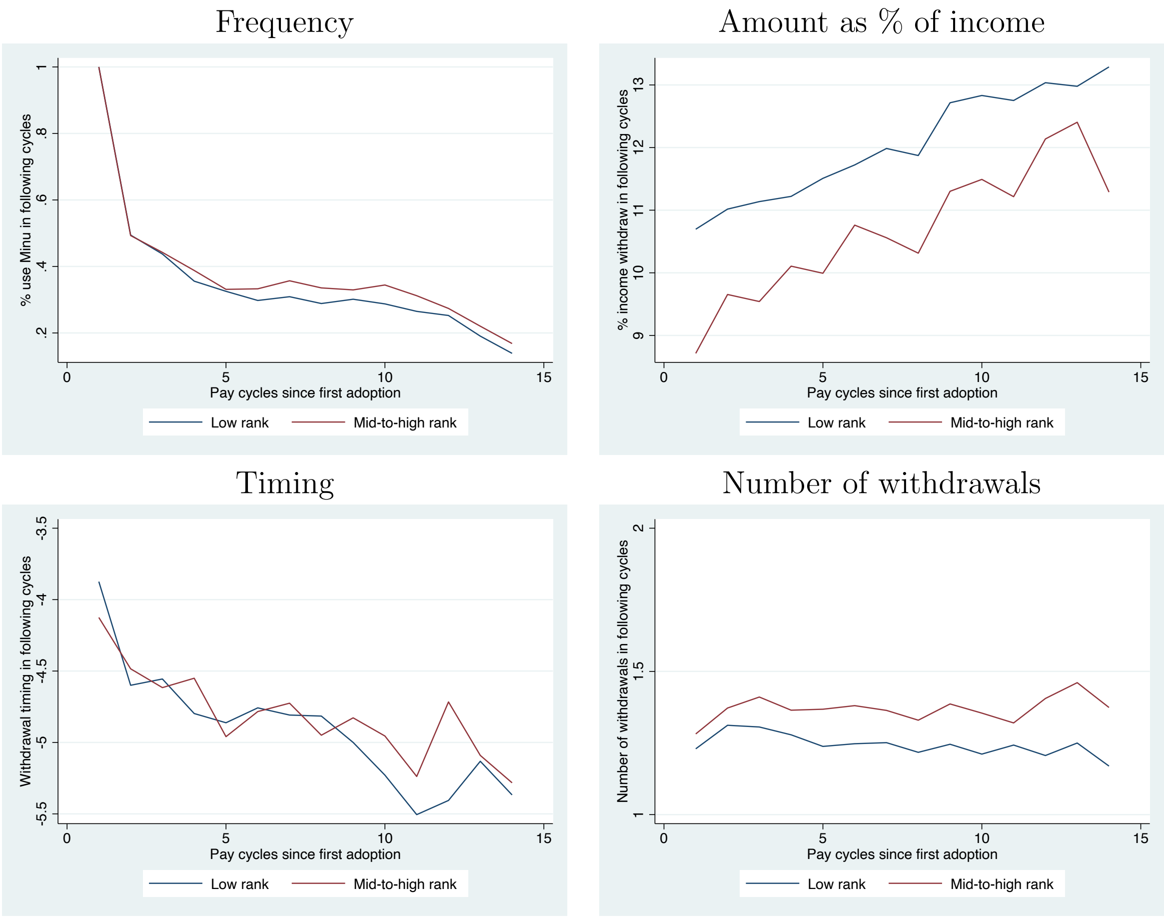

Figure 3: **Withdrawal behaviors over time by job ranks**

Notes: These figures present the evolvement of the frequency, amount, timing and numbers of withdrawals over the following pay cycles after first adoption, for users lower in job rank versus users of mid and high rank. Use frequency is calculated by the percentage of users who make withdrawals in the next cycles after the first adoption. Number of withdrawals, withdrawal scaled by income and timing are calculated by averaging the measures over all users conditioning on making withdrawal in that pay cycle.

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

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

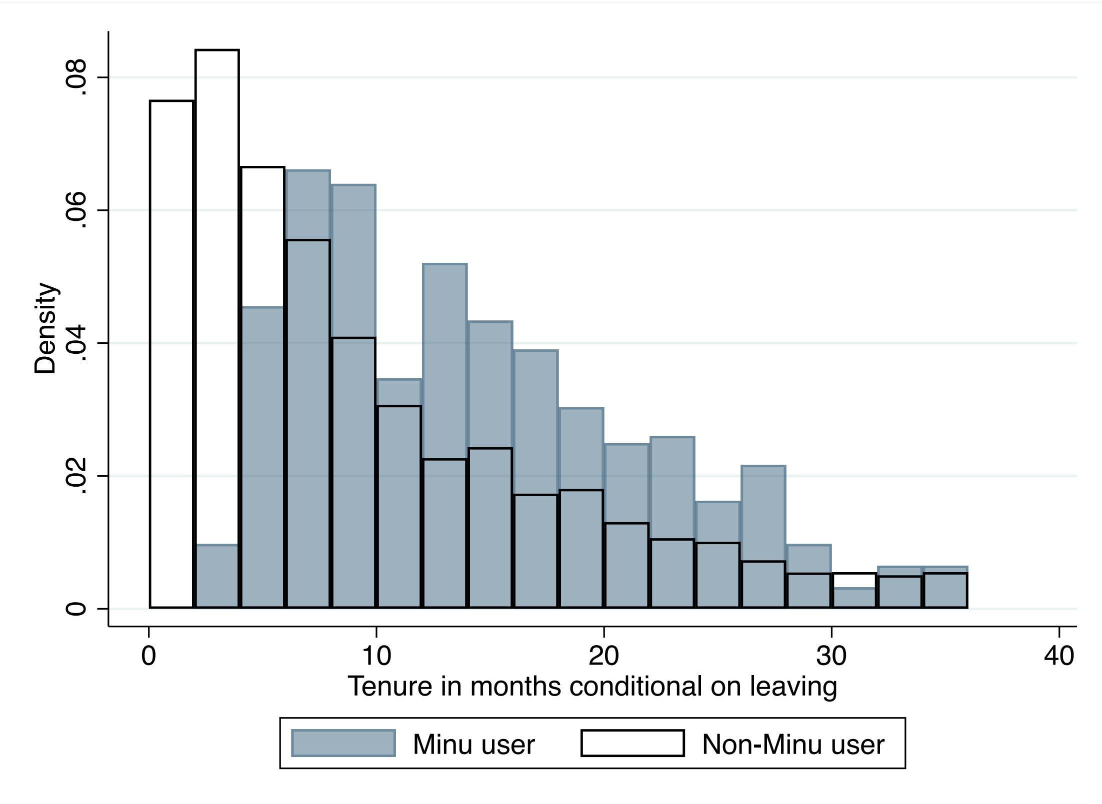

Figure 5: **Tenure of employees conditioning on ending the employment**

Notes: This figure compares the distribution of tenure of employees for those who left the company who are Minu users and non-users.

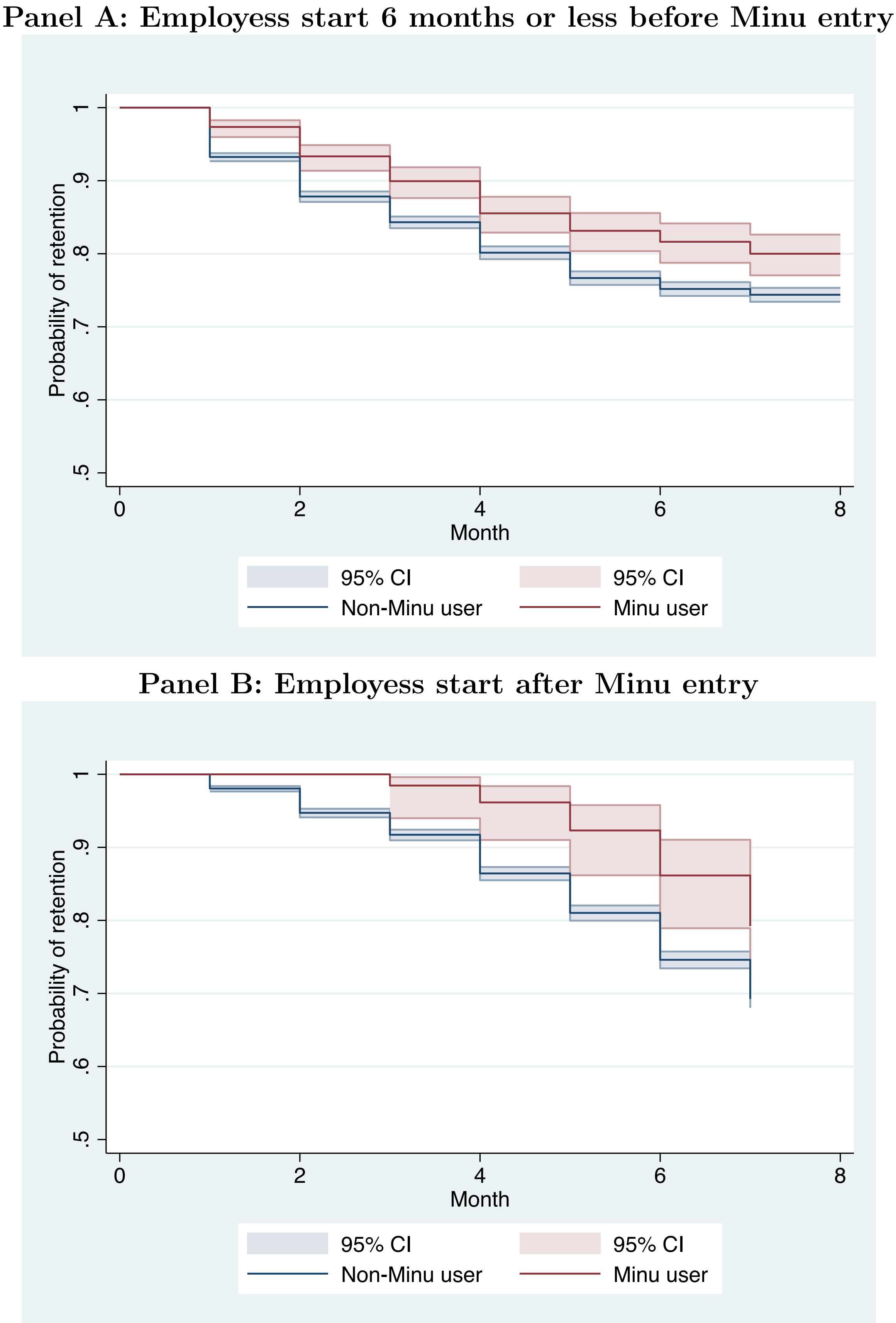

Figure 6: **Turnover and Minu use**

Notes: These figures track the proportion of employees who remain working at the company up to 8 months in the sample of Minu users and non-users using survival analysis data. Panel A restricts the sample to the group of employees who started 6 months or less before Minu entry, and panel B restricts to the employees who started working at the company after Minu is introduced.

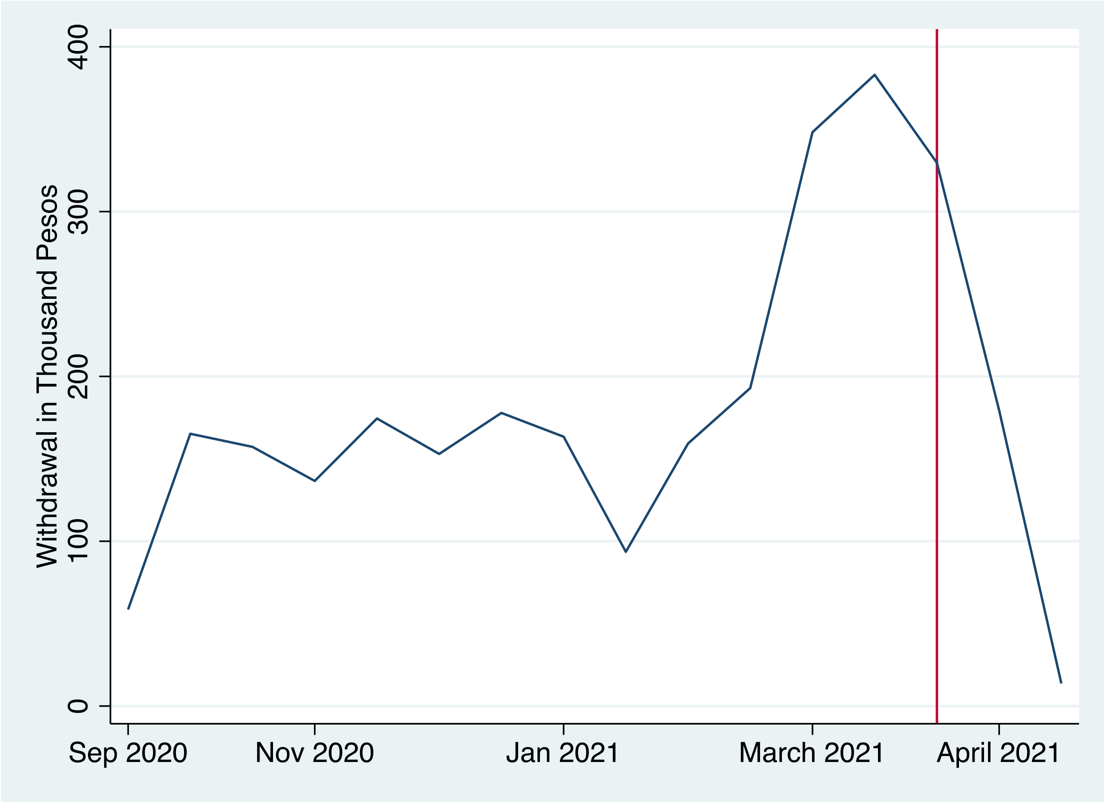

Figure 7: **Total withdrawal across time**

Notes: This figure plots the total withdrawal 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.

Table 1: **Summary statistics**

	Minu user N = 3,787			Non-Minu user N = 47,756		
	Mean	**p25**	**p75**	**Mean**	**p25**	**p75**
	Panel A. Employee Characteristics					
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
Ind. of ending employment	0.13	0	0	0.19	0	0
% Low-rank employees	59.2	-	-	62.4	-	-
% Mid-rank employees	31.1	-	-	32.0	-	-
% High-rank employees	9.7	-	-	5.6	-	-

	Panel B. Minu 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 main variables used in the regressions. Panel A reports the distribution of age, gender, start year, proportion of ending the employment and job ranks by Minu users and non-users. Panel B displays summary statistics of user activities by average number of withdrawals made and average withdrawal amount per pay cycle. The average withdrawal amount is in Mexican pesos.

Table 2: **Probability of using Minu and worker characteristics**

	Indicator for becoming Minu user
	(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 Minu introduction	0.027***
	(0.010)
Start after Minu introduction	-0.102***
	(0.010)
Company B	-0.012***
	(0.004)
Observations	23,472
R^2	0.041

Notes: This table presents an OLS regression that uses 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 - Minu use and turnover**

	Indicator for not being employed anymore			
	(1)	(2)	(3)	(4)
Minu 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 Cox proportional hazard regressions that uses the indicator for use of Minu to predict the probability of a worker ending the employment in the next pay cycle. The set of controls include worker's gender, age and job rank. Standard errors are clustered at starting-quarter level.

Table 4: **Heterogeneity for Hazard Model**

	Indicator for not being employed anymore					
	Gender		Job Rank		Age	
	Female	Male	Low	Mid-to-High	Below median	Above median
	(1)	(2)	(3)	(4)	(5)	(6)
Minu 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 Cox proportional hazard regressions in split samples that uses the indicator for use of Minu to predict the probability of a worker ending the employment in the next pay cycle. Standard errors are clustered at starting-quarter level.

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

	Indicator for not being employed anymore (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 Cox proportional hazard regressions that uses the cumulative withdrawal amount scales by bi-week income of the users first 2 months since adoption to predict the probability of a worker ending the employment in the next pay cycle. Standard errors are clustered at starting-quarter level.

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

	Indicator for not being employed anymore					
	Gender		Job Rank		Age	
	Female (1)	Male (2)	Low (3)	Mid-to-High (4)	Below median (5)	Above median (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 Cox proportional hazard regressions in split samples that uses the cumulative withdrawal amount scales by bi-week income of the users first 2 months since adoption to predict the probability of a worker ending the employment in the next pay cycle. Standard errors are clustered at starting-quarter level.

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

	Indicator for not being employed anymore			
	(1)	(2)	(3)	(4)
Minu 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 regressions that use the indicator for employee being a Minu user to predict the probability of a worker eventually left the company. Standard errors are clustered at starting-quarter level.

Table 8: **Heterogeneity for OLS model**

	Indicator for not being employed anymore					
	Company		Gender		Job Rank	
	Female	Male	Low	Mid and High	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
Minu 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 regressions in split samples that uses the indicator for employee being a Minu user to predict the probability of a worker eventually left the company. Standard errors are clustered at starting-quarter level.