Effects of Pandemic Unemployment Policies on Consumption, Savings, and Incomes of Workers: Evidence from Linked Survey-Transactions Data*

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Abstract

We present new results on the consumption, savings, and income effects of the introduction of the unusually generous unemployment insurance benefits during the COVID-19 pandemic in April, their abrupt expiration at the end of July, and their short-term partial reintroduction through August and September. We use a new dataset of administrative bank account balances and transactions 1.2 million workers and 258,065 recipients of UI. We link these administrative data with a large-scale survey (N = 24,671) of expectations and economic preferences. We find that account outflows fell by 20% among July UI recipients in the 12 weeks since expiration relative to non-recipients. We find that consumption drops around expiration were muted owing to accumulated savings out of the expanded UI over the March-July period; end of July savings were roughly three times as large as savings in January. The magnitude of the drop in savings following the expiration was larger in households with low expectations of continuing benefits, no children, low risk aversion, and high discount rates. We also find that the temporary Lost Wages Assistance program provided a small but temporary boost to savings and consumption, and the timing of this boost varied based on the staggered adoption by states.

JEL codes: D14, E21, G51, G52, J22, J65
Keywords: Unemployment insurance, COVID-19, CARES Act, Consumption, Household Saving, Labor Supply, Personal Finance

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1 Introduction

The Federal Pandemic Unemployment Compensation (FPUC) passed under the CARES Act added a \$600 boost to weekly UI benefits, an unprecedented increase in the income replacement rate. This large, temporary increase and its abrupt expiration provides a valuable lens through which we can better understand various behavioral responses to UI during a downturn. In this paper, we leverage a unique, large dataset which covers more than 200,000 UI recipients in the US along with administrative data on their daily bank account balances and financial transactions. Uniquely, we have matched this data to a large-scale survey ($N = 24,671$) conducted in August 2020 to provide new evidence on how the FPUC introduction and expiration affected consumption and savings behavior. We elicit theoretically important recipient behavioral characteristics such as risk aversion, time preference, and expectations in addition to basic demographics and household structure. Our sample of UI recipients captures a large sample of hourly wage workers disproportionately impacted by the economic fallout of the pandemic and is the first to include measures of key individual parameters that enter into the design of optimal UI policy.

In designing optimal unemployment benefits, the canonical Baily-Chetty approach trades off the social insurance value of UI with possible unintended consequences resulting from labor supply. One approach to estimating the social insurance value is through estimating the consumption response Δc to becoming unemployed (Gruber, 1997), and scaling this by the coefficient of relative risk aversion, γ, producing an estimated $(1 + \gamma\frac{\Delta c}{c})$. However, as Hendren (2016) shows, this estimate could understate the consumption response via expectations prior to becoming unemployed. Andrews and Miller (2013) also show this estimate is potentially incomplete by not accounting for the covariance between risk aversion and consumption declines. In past work, Ganong and Noel (2019) have documented the consumption response to UI checks and benefit expiration on consumption using rich, transactions-level data from JP Morgan Chase checking account holders during the Great Recession, and Farrell et al. (2020a) have used the same data to estimate the impact of the expiration of FPUC on consumption.

We build on this literature by using a new source of transactions data from a large sample of workers receiving UI (N=258,065) along with another million non-recipients from Earnin (a financial-management phone application providing wage workers early access to their paychecks). This dataset is potentially more representative of lower-wage workers for whom the consumption value of UI might be particularly important. We supplement the transactions with a large scale survey (N=24,671) where we collected information about consumption and employment expectations around the time of FPUC expiration and asked survey questions that we use to construct behavioral parameters of such as risk aversion or time preference from the same individuals for who consumption changes are observed. The combination of survey data with administrative transactions data provides a unique opportunity to evaluate and incorporate additional parameters into the canonical Baily-Chetty model as suggested by Hendren (2016) and Andrews and Miller (2013). We can also use the transactions data to measure employment response to the FPUC expiration which allows us to compare the behavioral responses related to labor supply (for evidence on unemployment duration responses to UI in the Great Recession, see Farber et al. (2015), Farber and Valletta (2015), Ganong and Noel (2019), Card et al. (2015), Rothstein (2011), and Johnston and Mas (2018)). This produces a single, comprehensive dataset that combines key information necessary for a full evaluation of UI policy, which has not been done previously.

In this preliminary draft, we use a difference-in-difference design to compare those who were receiving UI benefits in July prior to expiration to those who were not receiving UI in July. We find that while consumption and savings behavior of these two groups were moving in parallel between January and March, the introduction of UI led to a substantial build up of savings among recipients between April and July. Upon the expiration of FPUC, we find that recipients began drawing down savings, which protected against consumption drops (similar to findings in Farrell et al. (2020a)).

Following the expiration of FPUC at the end of July, consumption (as measured by outflows) fell sharply by around 20% for July UI recipients as compared to non-recipients. The short term implied marginal propensity to consume (MPC) based on the changes in income and consumption was around 0.7. UI recipients also drew down on a buffer savings that they had built up between March and July (worth around $1100 by late July, approximately three times as large as in January). By October, around 75 percent of the new savings were exhausted, and end of day balances were close to the April pre-FPUC levels for UI recipients. By October, the gap in savings between UI recipients and non-recipients had mostly disappeared.

We also find a temporary boost to incomes and consumption from a temporary (typically 5 week) $300/week supplement (Lost Wage Assistance) that was available during August and September during. The exact timing of implementation of LWA varied across states; when we consider early versus late-adopting states, we find the timing of the temporary income, consumption, and savings boost to be consistent with a causal effect of the policy. However, by October, the LWA-based benefits had wound down in almost all states, and savings in both early and late-adopting states among UI recipients were close to non-UI recipients levels. This indicates that we may be very close to a full draw-down of the buffer savings across the country.

In future work we plan to examine the detailed transactions data more closely, in particular dynamics of labor supply (via paycheck deposits) and more detailed consumption categories (via expenditure tags). Having behavioral parameters and 3 sources of large transfer policy variation (FPUC, its expiration, and staggered adoption and exhaustion of the LWA) will enable us to calibrate a rich model of consumption and earnings dynamics with quantitative roles for heterogeneous risk-aversion, expectations, and time-preferences.

2 CARES Act and Federal Pandemic Unemployment Compensation Program

The Coronavirus Aid, Relief, and Economic Security (CARES) Act was signed into law on March 27, 2020 and included $2.2 trillion in economic stimulus. The bill included one-time, untargeted cash payments of $1,200 to individuals, expanded unemployment benefits through the Federal Pandemic Unemployment Compensation (FPUC) program, forgivable small business loans through the Paycheck Protection Program, and hundreds of billions of dollars in aid to large corporations and state and local governments. In this paper, we are focused on the initial introduction of the FPUC program, its expiration in late July 2020, and the subsequent modified continuation of the expanded benefits which followed the FPUC payments in some states following an executive order.

FPUC provided an additional $600 per week for those receiving unemployment benefits. The supplementary benefits first arrived in unemployed workers bank accounts in early April and ran through through July 26, 2020. The $600 benefit is in addition to regular weekly unemployment compensation.

Following the expiration of the additional $600 per week from the FPUC program at the end of

July, President Trump authorized the Federal Emergency Management Agency (FEMA) to provide supplementary payments in the form of Lost Wages Assistance (LWA). Individuals who were eligible for unemployment payments of at least $100 per week after the expiration of the FPUC program were made eligible for LWA payments of up to $400 per week with $300 per week provided by up to $44 billion of funding allocated through FEMA.[1] The initial rollout of the LWA program produced some confusion, as it was unclear what was required of the states—many facing budget shortfalls as a byproduct of the pandemic—in order to access the additional funding from FEMA (Suderman et al., 2020). The resulting confusion led to staggered and delays rollouts of the supplementary LWA benefits, with some states forgoing the program entirely. We exploit the above variation to evaluate the effects of these policies on the consumption, income, and savings of Earnin's users in Section 4.

3 Data

We use a new dataset which includes the bank account balances and transactions of individuals disproportionately impacted by the pandemic's economic fallout, including 200,000 individuals who were receiving UI before the July 31st, 2020 cliff. In addition to the large sample of workers who receive UI benefits, we also implemented a large-scale survey of 25,000 individuals in August with linked bank account information that allows us to tie financial outcomes to welfare and policy-relevant factors that have not previously been observed in conjunction with administrative bank data of this scale. The survey collects information on demographics, economic preferences, and expectations.

Our de-identified transaction-level data comes from Earnin, a financial-management phone application that provides users who link their account information with products that include accessing their income before payday. The transactions include paychecks and unemployment insurance payments as well as purchases, allowing us to measure consumption in the aggregate and broken down by category. In addition to the transaction-level data, we also obtain daily readings of end-of-day bank account balances that allow us to easily monitor accumulated savings and net inflows and

[1] See FEMA's Lost Wages Supplemental Payment Assistance Guidelines for additional details: https://www.fema.gov/disasters/coronavirus/governments/supplemental-payments-lost-wages-guidelines.

outflows from the connected bank accounts. We make a number of sample restrictions to ensure the data observed by Earnin is representative of an individual's full financial picture including restricting the data to users for whom we can observe a minimum bank transaction date on or before January 1, 2020 and on or after September 30, 2020.[2]

Earnin users are not representative of the general population, but the data cover a large number of low-wage workers (Chetty et al., 2020). One key advantage of this dataset relative to other studies using similar data is that our sample appears to be more representative of workers affected by the economic disruptions of the pandemic. Ganong et al. (2020) use Current Population Survey data to show that mean pre-job loss earnings were $886. The time-series means in Figure 2 are close to this national benchmark which suggests the Earnin data may be more representative of the workers most affected by the expiration of FPUC. 174,022 of the million users we observe received UI payments in July 2020, and we see roughly 1,000 UI recipients in the median state. Our dataset covers 0.7 percent of the 30 million UI recipients nationwide, with that coverage growing to between 1 and 2 percent in the states where unemployment benefits are more commonly dispensed through direct deposit. See Appendix Table A1 and Appendix Figure A1 for state-by-state coverage of UI recipients. For additional details on the Earnin data, see Appendix A.

We supplement the transactions and end-of-day balance datasets with a survey of a subset of Earnin users which ran from August 19 through August 28, 2020. The survey asks questions about recent earnings, employment, unemployment benefits, and consumption for the month of July 2020. We also ask survey respondents about their expectations for each of those outcomes for September 2020.[3] In addition to these questions, we gather demographic information and elicit risk aversion and discount rates using questions from the Global Economic Preferences Survey (Falk et al., 2016, 2018). Potential respondents in the survey sample were offered an incentive of a $5 Amazon gift card.[4] The survey sample is composed of the universe of Earnin users who have received at least one unemployment insurance check between January and July 2020 and an equal-sized sample of

[2]We additionally restrict the data to Earnin users who signed up before June 28, 2020—the 180th day of the year—allowing us to observe transactions dating back to January 1, 2020. According to Earnin, the vast majority of banks and virtually all major banks provide precisely 180 days of account history when a user links a bank account. This makes only a marginal difference after restricting on the basis of transactions.

[3]A smaller, unincentivized survey fielded from August 2 through 9, 2020 asked about expectations for August 2020.

[4]The survey was fielded over 5 days. The first 400 respondents on each day received an Amazon gift card.

users who had not received an unemployment insurance check in 2020.[5] Sampling Earnin users who received unemployment insurance payments enables us to analyze the effect of the expiration of the FPUC in late July. While half of the survey sample was drawn from Earnin users who had received at least one unemployment check in 2020, fewer than half of the users in the survey sample were still receiving unemployment when the additional benefits through the FPUC program expired. For additional details about the survey and survey instrument, see Appendix B.

4 Results

Our analysis focuses on three events. First, the initial onset of the $600 weekly FPUC payments in early April. Second, the expiration of these benefits at the end of July. For these first two events, we divide our sample by whether or not the user is confirmed to have received UI benefits in the month of July. The third event we focus on is the staggered and incomplete roll-out of the LWA benefits which partially replaced the FPUC payments. To analyze the LWA benefits, we split Earnin users based on whether they reside in a state that expanded LWA benefits early or in a state which adopted the benefits late or not at all. For this first set of analyses, we use the full set of 1,215,849 Earnin users and do not restrict to the subset who completed the survey. The figures in the main text all reflect mean weekly estimates, analogous time-series for using median weekly estimates are available in the appendix with similar results.

Figure 1 illustrates the timing and magnitude of these three events. The figure plots the mean weekly UI inflows based on transactions that are identifiable as unemployment benefit direct deposit payments. The timing of each of the three events is evidenced in the figure. The onset of FPUC payments climbed rapidly through April as the unemployment rate climbed and states resolved the technological hurdles to administering the additional payments. The payments we verify as definitely from unemployment benefits peak in July at just below $600. Given $600 per week would be the floor of UI benefits for those eligible for the FPUC benefits in addition to their weekly regular benefits, the magnitude of these weekly inflows are likely a result of false negatives in our ability to identify UI benefits from the information included in the transactions-level data. Nevertheless,

[5]The sample is additionally restricted on our ability to observe bank transactions on or before January 1, 2020 and on or after July 1, 2020.

the contours of the time-series variation are informative. While the increase in UI inflows from the FPUC increased rapidly and then decelerated from April through June, the expiration of the FPUC benefits dropped UI inflows by more than half in a single week, providing a stark change in total income. The magnitude of the differential drop in inflows from the peak in July to August is close to $600, suggesting limited offsetting labor supply increases. Finally, the staggered and short-term nature of the LWA benefits is also evident from Figure 1. Benefits begin to climb back toward the peak of the FPUC amounts as states distribute the funds from FEMA before falling off again when the program, which only had enough funding for a few weeks of supplemental benefits, exhausted its available funding.

Figure 2 presents the average weekly inflows from any source to Earnin users bank accounts from January 12, 2020 through October 9, 2020. The sustained income surplus for those who received UI in July relative to those who did not contextualizes the magnitude of the variation observed in Figure 1. While those who eventually received UI had roughly ten percent lower inflows preceding the onset of FPUC payments, they experienced sustained inflows roughly 50 percent higher than those not receiving UI from May through July. Total inflows for the July UI sample dip below those who did not receive UI briefly in August before the LWA program brought their income higher again. As the LWA payments were exhausted, we can see the unemployed sample falling below the non-UI sample again into early October.

Other features of the total inflow time-series in Figure 2 can also inform our understanding of this sample. First, those who would go on to receive UI in July had pre-job loss earnings of between $800 and $1,000 per week. This appears to be fairly representative of the mean pre-job loss earnings of $886 documented for workers who lost their jobs during the pandemic by Ganong et al. (2020) in the Current Population Survey. Second, we can observe two weeks where total inflows spiked. The first, in early March, is driven by tax refunds being deposited. The vast majority of workers on the Earnin platform are hourly workers, and this tax refund is likely to include money from the Earned Income Tax Credit. The second, in mid-April, is from the $1,200 economic impact payments allocated through the CARES Act. Income for those who did not receive UI in July is remarkably flat outside of these two spikes for the full sample period, and the two samples are largely on parallel trends prior to the onset of the FPUC payments.

Figure 3 shows the evolution of bank balances for the two samples. July UI recipients appear to build up a buffer stock of savings over the course of the FPUC payments, with mean bank balances at the end of July tripling their pre-tax refund balances of $400 and doubling their pre-economic impact payment balances of $600. Both samples saw peaks in their balances upon receipt of the economic impact payments. Those who received FPUC benefits were able to sustain this buffer stock of savings of around $1,100 on average, while those who did not receive FPUC benefits in July spent their bank balances between mid-April and early October back down to March levels. Following the expiration of FPUC benefits, however, these savings are being rapidly depleted with the two groups converging back to within $100 by early October. Appendix Figure A2 shows similar results in an analogous figure using the matched survey-bank balances sample and those who report no effect of the pandemic on their employment as the control group. These patterns are consistent with other early findings from Farrell et al. (2020b) that show a similar depletion of savings following the expiration of FPUC.

The analogous outflows presented in Figure 4 provide the last piece of the income, savings, and consumption picture. Outflows, which presumably provide a reasonable proxy for consumption (in some combination with potential debt payments),[6] were lower for those who received July UI before FPUC, were higher during the period of FPUC, but converged immediately back to the levels near those observed for those who did not receive UI. The fall in consumption among UI recipients from the expiration of FPUC was roughly 20% of their July levels. If we compare the size of the consumption drop following the expiration of FPUC to the size of the drop in incomes, it suggests a short term MPC of around 0.7, which is in line with prior work.

As we discussed above, UI inflows bounce back in August and September during the implementation period of the LWA benefits. To test whether LWA is driving this more explicitly, Figure 5 adds bank balances by July UI receipt along with a second split of the sample by whether the individual resides in state that expanded LWA benefits early versus late or not at all. There are no observable changes in balances for those who did not receive UI in July, an early spike in balances for UI recipients in states that were early adopters of LWA, and a later spike for the late-LWA-adopting

[6] Future versions of this paper will more carefully isolate consumption and break down how consumption changed across various spending categories

states. This supports the interpretation that this second bounce in balances for UI recipients is driven by the LWA program and reinforces the primacy of federal unemployment programs for the financial situations of individuals unemployed during the pandemic. The short term boosts in consumption also are consistent with a MPC around 0.7.

One unique feature of this paper is our ability to combine detailed administrative transaction data with a large-scale survey of 24,671 Earnin users, which we use for this second set of analyses. While the above results utilize the full 1,215,849 users for whom we have validated data, subsequent analysis utilize the sample for whom we collect data on demographics, self-reported income and employment, core economic preferences (discount rates and risk aversion), and expectations about future income and UI benefits. Table 1 provides summary statistics for the surveyed sample. Relative to the US population, the survey sample is disproportionately female (68%) and has higher representation of minority groups (24% black, 22% Hispanic). 74 percent of the survey sample has less than a Bachelor's degree, 73 percent report working full-time, and both the mean and median hourly wage is around $16. 42 percent of survey respondents report that the pandemic has had no effect on their employment, 24 percent report their hours and/or pay have been cut, while a further 33 percent were temporarily or permanently laid off.

We can also split the sample by the respondents' discount rates and risk aversion, which we elicit in the survey using the validated survey instruments presented in Falk et al. (2016). Risk aversion plays a central role in the models assessing optimal unemployment insurance benefits (Gruber, 1997; Chetty, 2006). While past studies have relied on plugging in a range of risk aversion inputs, by combining detailed transactions-level data with survey elicitations of core economic preferences and expectations about future income, we can build on these models with a full set of input parameters. Andrews and Miller (2013) build on the Baily-Chetty framework to show that the covariance of risk aversion and drop in consumption, which documents the degree to which risk falls on more or less risk-tolerant workers, affects the optimal level of social insurance. The ability to provide the first estimates of this covariance term is one example of the utility of the data we have collected.

Figure 6 and Figure 7 show how bank balances evolve differentially for UI and non-UI recipients, broken out by high and low risk aversion and discount rates, provide proof-of-concepts for these exercises. We find higher savings during benefit receipt and slower depletion of savings post-benefit expiration among those with low discount rates, with a less pronounced, but similar, effect among high risk aversion recipients.

Dynamic models of consumption imply that expectations of future income should affect current consumption. Because we also elicited expectations, we can see how income, consumption, and savings evolved separately by survey respondents expectations about future UI benefit receipt. Using the anticipated expiration of benefits as a negative shock to expected consumption, we can see whether savings decreased differentially among those who are relatively optimistic about the renewal of benefits.

Figure 8 shows how bank balances for UI recipients varied by expected level of benefits in August/September. Because of extreme policy uncertainty, where it was not clear if Senate Republicans and House Democrats would achieve a deal on a new round of fiscal relief, beliefs about future benefits would quite reasonably be heterogeneous. What Figure 8 shows is that respondents who expected benefits to be renewed drew down their savings at a faster rate than those who did not.[7]

Finally, as a descriptive exercise that might speak to the heterogeneous incidence of the FPUC on children and their families, we examine bank balances separately for respondents receiving UI reporting any children and those responding with no children. Figure 9 shows that families with kids may be more "hand to mouth" exhibiting a much more rapid drawdown of expanded benefits (which included an additional $500 dollars in child benefit which does not manifest in additional savings.[8] In future work, we hope to disentangle the sources of this heterogeneity (e.g. substituting for school closures or other increased care expenditures or avoiding means-testing thresholds e.g. in SNAP).

5 Next Steps

This draft is a preliminary, primarily visual, cut at our data. Moving forward, we will implement a variety of empirical strategies to provide causal evidence of the FPUC and LWA programs on con-

[7]The strength of the effect of future expectations on current consumption (and savings) should be larger where the discount rate is larger and the degree of risk-aversion (equivalent to inverse intertemporal elasticity of substitution in CRRA utility) is smaller. We plan on investigating these interactions in future work.

[8]As a validation check, one can see that the respondents with children report a larger income increase in March, when EITC receipts are realized.

sumption, savings, and labor market outcomes. The empirical strategies that we aim to implement in the next month include a variety of designs.

The initial results presented suggest that event study and difference-in-differences designs are likely to be successful approaches for some of our policy variation. See, as an example, the flat pretrends in Panel (b)Figure 4. These unadulterated time-series also mask some underlying staggered implementation of the pandemic UI policies. Figure 5 demonstrates the type of staggered rollout that can provide quasi-experimental variation. There were similar delays in the initial rollout of the FPUC payments. These delays within eventually treated individuals (i.e., individuals that eventually receive UI) by past income (or predicted income) percentiles or income levels can help address selection concerns. Beyond this state-level variation in policy over time, there are additional dimensions of heterogeneity across individuals within states. For instance, we can use variation in the replacement rates (based on pre-pandemic wages) crossed with state and national policy changes (e.g., FPUC expiration) to better isolate causal effects of replacement rates. We can also use variation in asset-test thresholds across states in safety net programs (e.g., SNAP) to assess if SNAP-eligible UI recipients limited savings accumulation in order to maintain eligibility. these policies for consumption, savings, and labor supply decisions. In addition, by using expectations information from the survey we can assess how expectations about the future policies affect labor supply decisions.

In addition to exploiting heterogeneity to estimate average treatment effects, we also plan to assess heterogeneity in the consumption and labor supply responses to UI. This will include estimating quantile effects, and estimating effects by observed characteristics such as pre-crisis outcomes and demographic characteristics.

With reduced-form estimates from these various identification strategies, we aim to calibrate a model of household consumption and labor supply—potentially augmented with home production/children—that allows heterogeneity in discount rates, risk-aversion, and policy expectations to quantitatively and holistically evaluate welfare implications and the design of optimal UI policy. This will include incorporating the insights of Hendren (2016) and Andrews and Miller (2013) to extend the Baily-Chetty framework and account for the rich potential of our data linking administrative bank account information with elicitations of core economic preferences and expectations.

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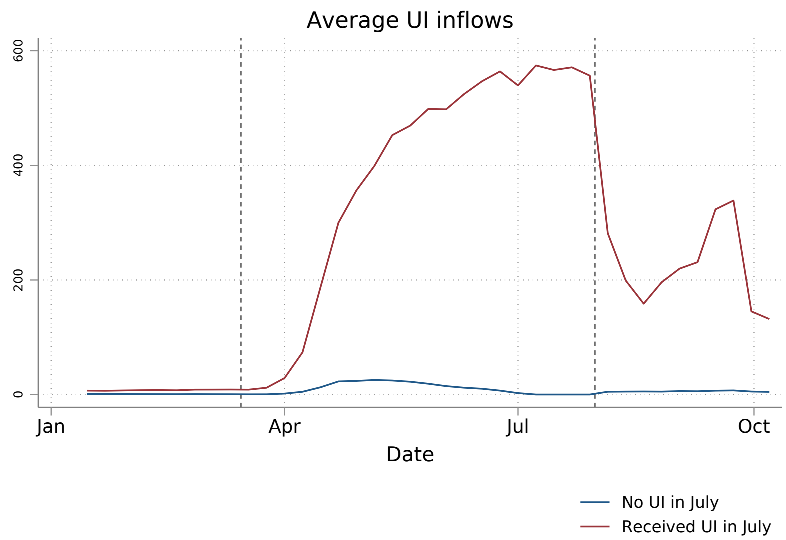
Table 1. Survey Summary Statistics

	Mean	SD	Median	90th Pct
Female	0.68	0.47	1	1
Children in Household	0.95	1.17	1	3
Race				
White	0.43	0.50	0	1
Black or African-American	0.24	0.43	0	1
Other Race	0.34	0.48	0	1
Spanish, Hispanic, or Latino	0.22	0.42	0	1
Education				
Less than High School	0.01	0.12	0	0
High School Diploma or GED	0.18	0.38	0	1
Some College, No Degree	0.36	0.48	0	1
Vocational Training	0.06	0.24	0	0
2-Year Degree	0.12	0.33	0	1
Bachelor's Degree or More	0.26	0.44	0	1
Employment Status				
Working Full Time	0.73	0.45	1	1
Working Part Time	0.12	0.32	0	1
Not Working, Looking for Work	0.11	0.31	0	1
Not Working, Not Looking for Work	0.05	0.21	0	0
Hourly Wage at Main Job	$17.64	$4.62	$16	$25
Hourly Wage at Last Job	$15.96	$4.58	$16	$22.5
Effect of Pandemic on Employment				
No Effect	0.42	0.49	0	1
Hours and/or Pay Cut	0.24	0.43	0	1
Furloughed or Temporarily Laid Off	0.24	0.43	0	1
Permanent Job Loss	0.09	0.29	0	0
Observations	24,671			

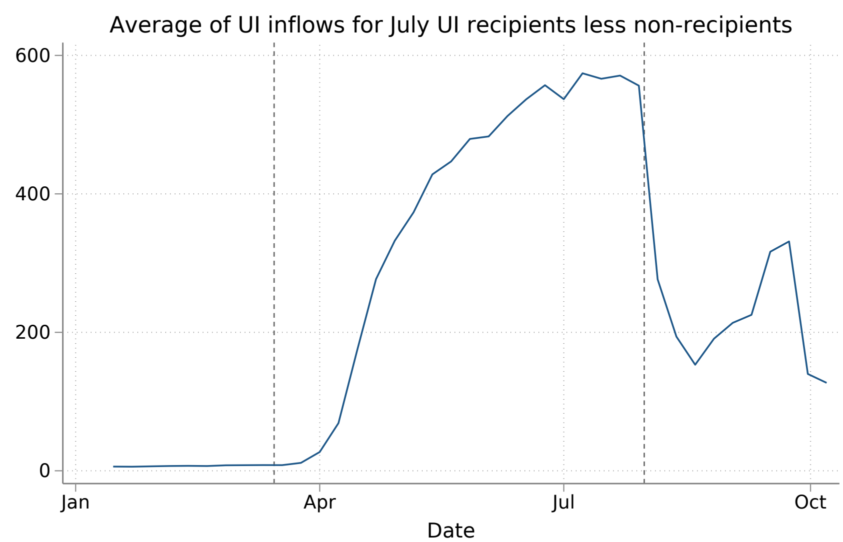
Notes: The sample for the above table includes all Earnin users who completed the survey.

Figure 1. Average Weekly UI Inflows

(a) UI Inflows by July UI Receipt



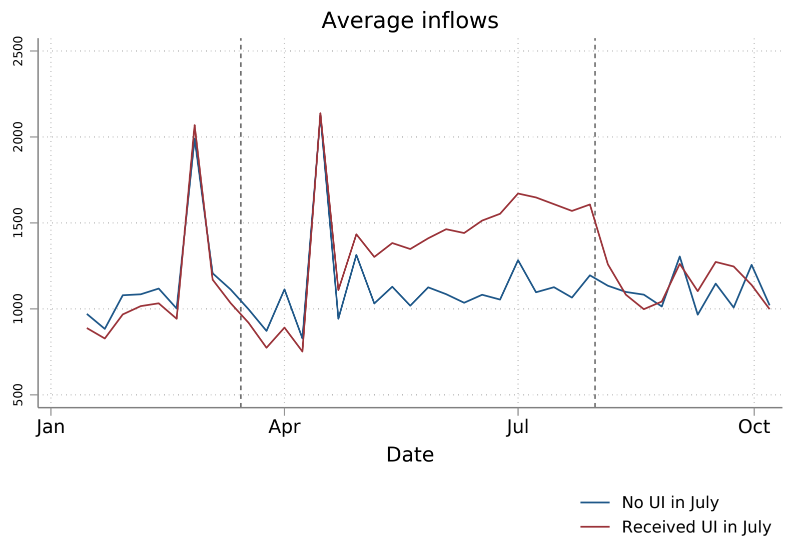
(b) UI Inflows Differenced by July UI Receipt



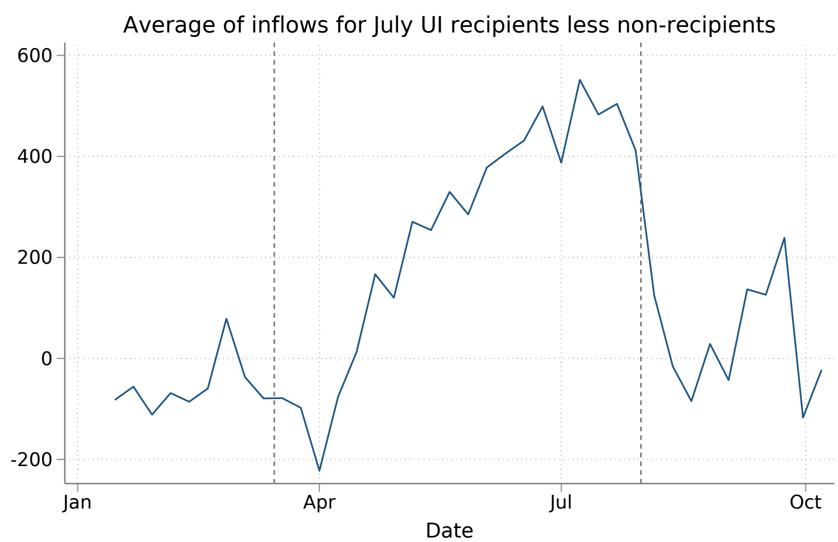
Notes: The sample includes all Earnin users and is split by whether the user received unemployment benefits in July. Panel (a) shows average (winsorized) weekly inflows of unemployment insurance payments for each of these two groups from January 12, 2020 to October 9, 2020, and Panel (b) shows average (winsorized) weekly inflows of unemployment insurance for those receiving July UI less those not receiving July UI for the same period. Vertical dotted lines are included at March 15th and July 31st to indicate the start of lockdowns and the end of FPUC payments, respectively.

Figure 2. Average Total Weekly Inflows

(a) Weekly Inflows by July UI Receipt



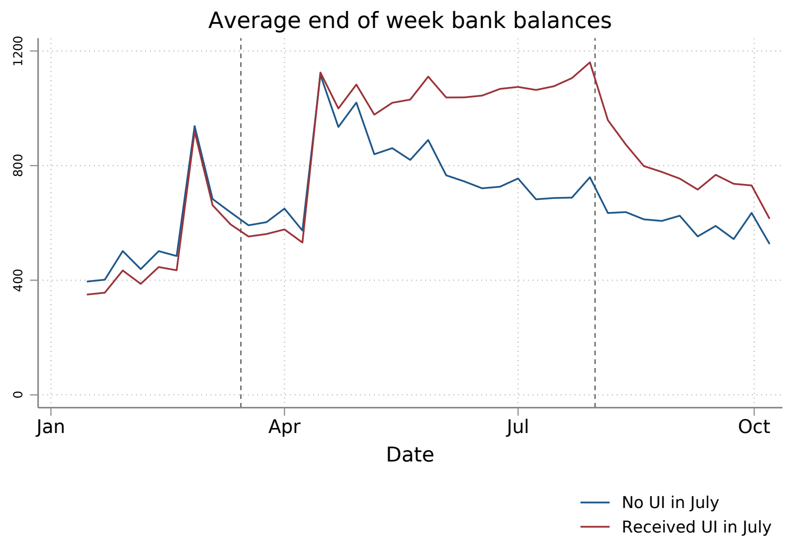
(b) Weekly Inflows Differenced by July UI Receipt



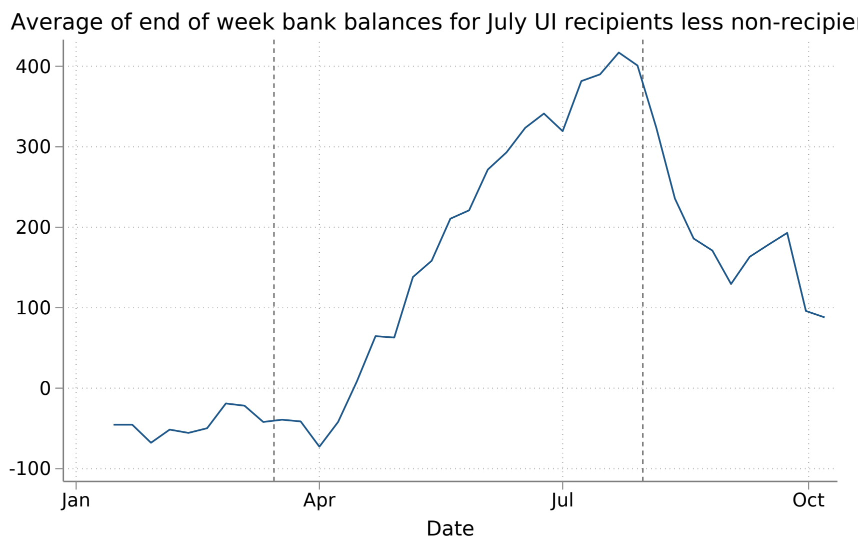
Notes: The sample includes all Earnin users and is split by whether the user received unemployment benefits in July. In Panel (a), the lines show average (winsorized) weekly inflows of all payments (including UI) for each of these two groups from January 12, 2020 to October 9, 2020. In Panel (b), the line shows average (winsorized) weekly inflows of all payments (including UI) for those receiving July UI less those not receiving July UI for the same period. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of FPUC payments, respectively.

Figure 3. Average End-of-Day Bank Balance

(a) Bank Balance by July UI Receipt



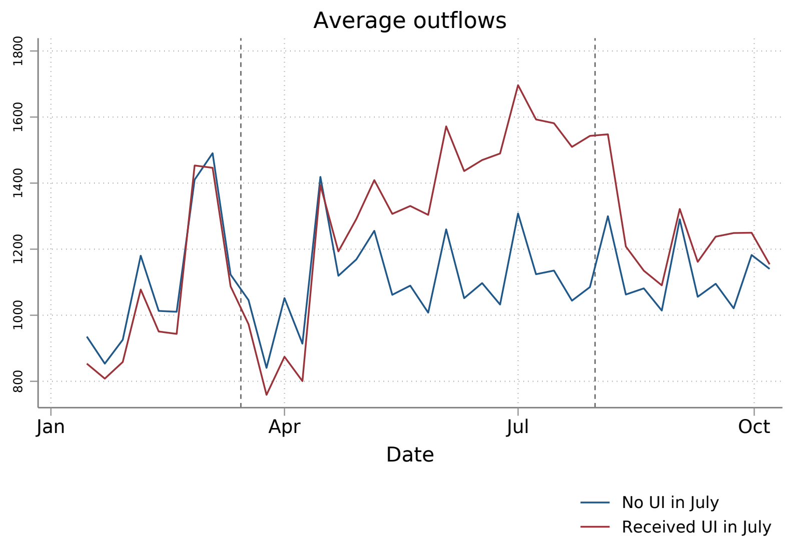
(b) Bank Balance Differenced by July UI Receipt



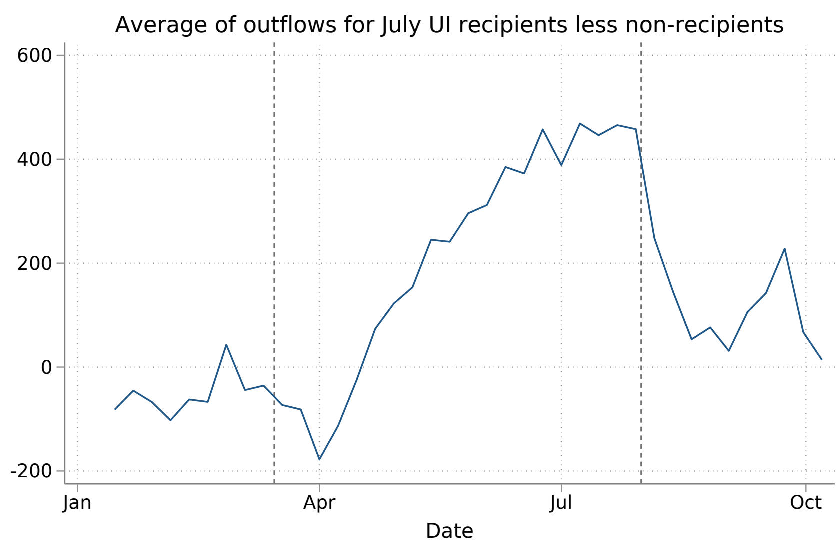
Notes: The sample includes all Earnin users and is split by whether the user received unemployment benefits in July. In panel (a), the lines show average (winsorized) weekly end-of-day bank balances for each of these two groups from January 12, 2020 to October 9, 2020. In panel (b), the line shows average (winsorized) weekly end-of-day bank balances for those receiving July UI less those not receiving July UI for the same period. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of FPUC payments, respectively.

Figure 4. Average Total Weekly Outflows

(a) Outflows by July UI Receipt

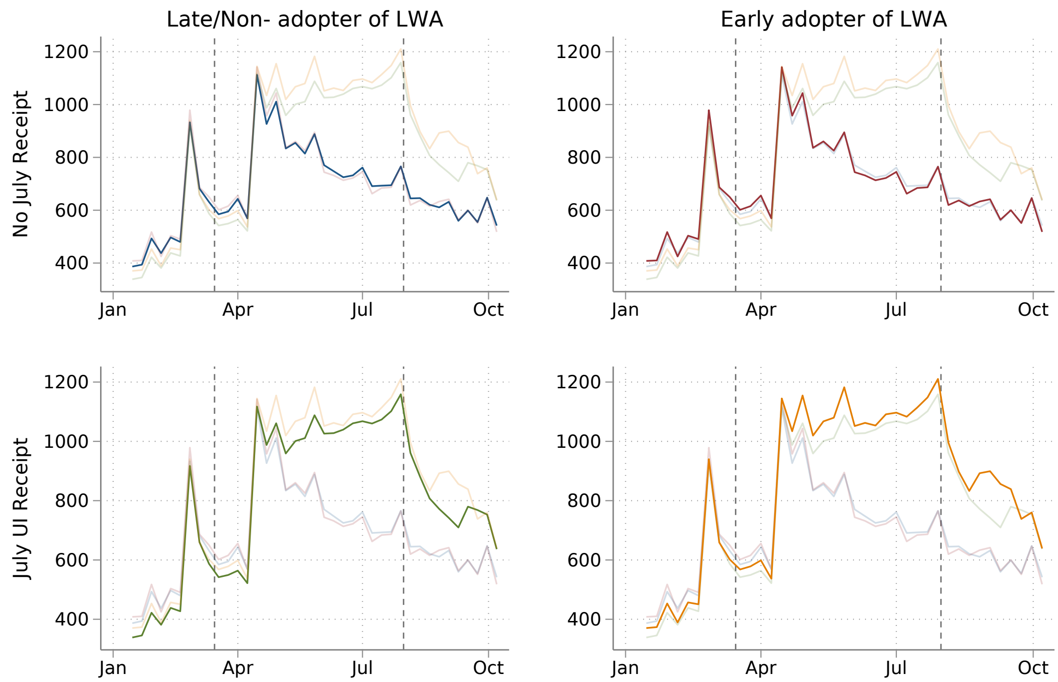


(b) Outflows Differenced by July UI Receip



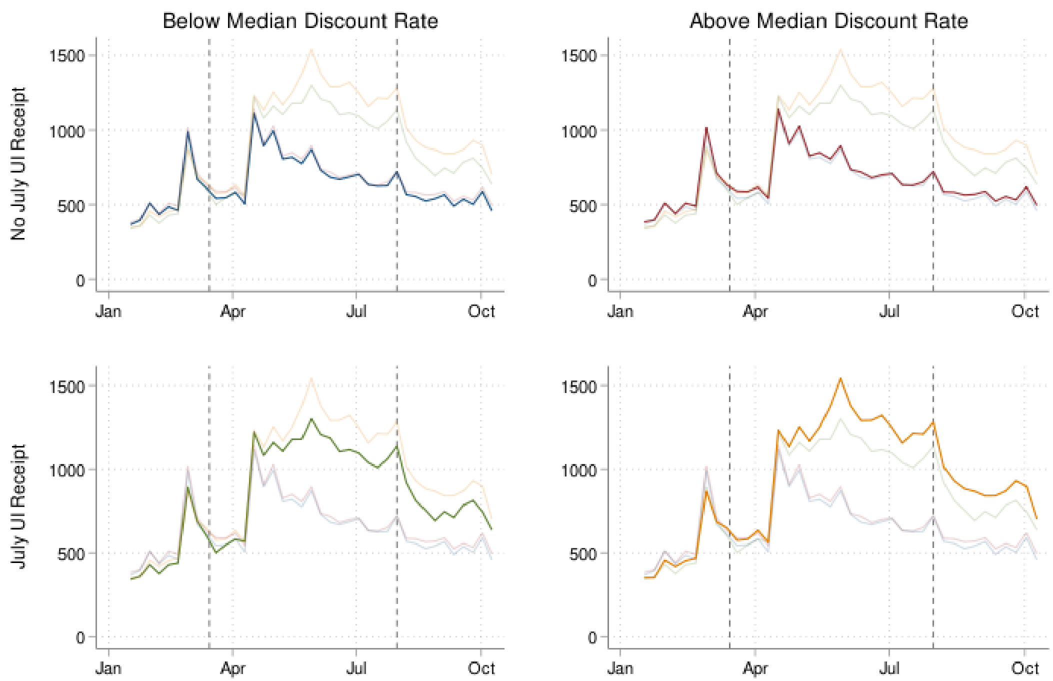
Notes: The sample includes all Earnin users and is split by whether the user received unemployment benefits in July. Panel (a) shows average (winsorized) weekly inflows of all payments (including UI) for each of these two groups from January 12, 2020 to October 9, 2020, and panel (b) shows average (winsorized) weekly inflows of all payments (including UI) for those receiving July UI less those not receiving July UI for the same period. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of FPUC payments, respectively.

Figure 5. Average Bank Balance by July UI Receipt and Timing of Lost Wage Assistance Approval



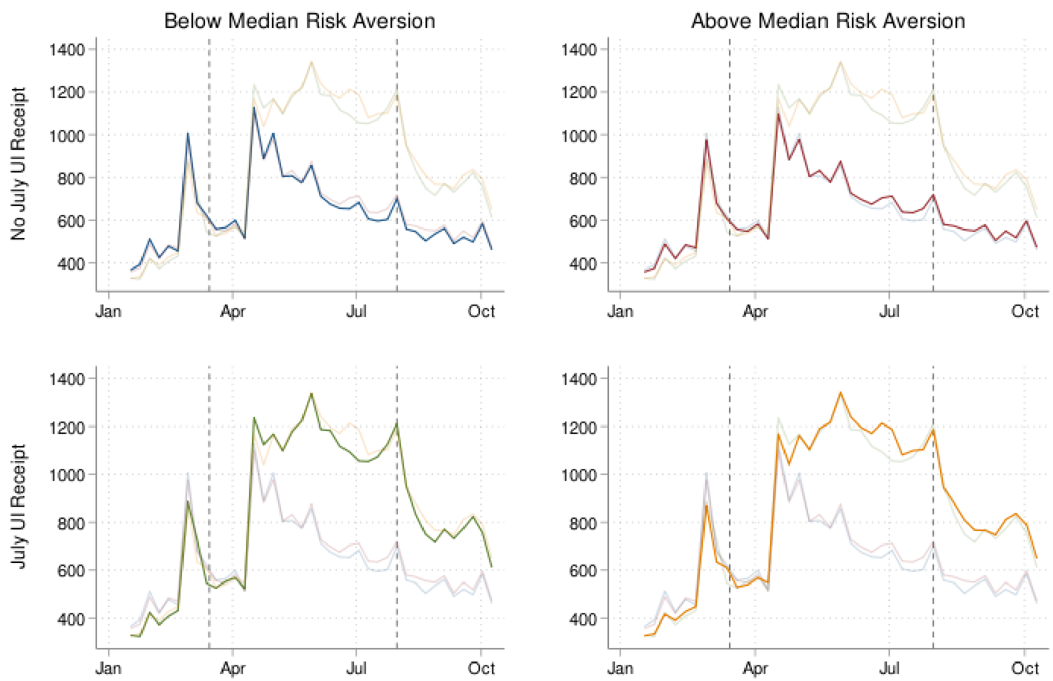
Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and being in a state that approved lost wage assistance early or late. The lines show average (winsorized) weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure 6. Average Bank Balance by July UI Receipt and Discount Rate Measure



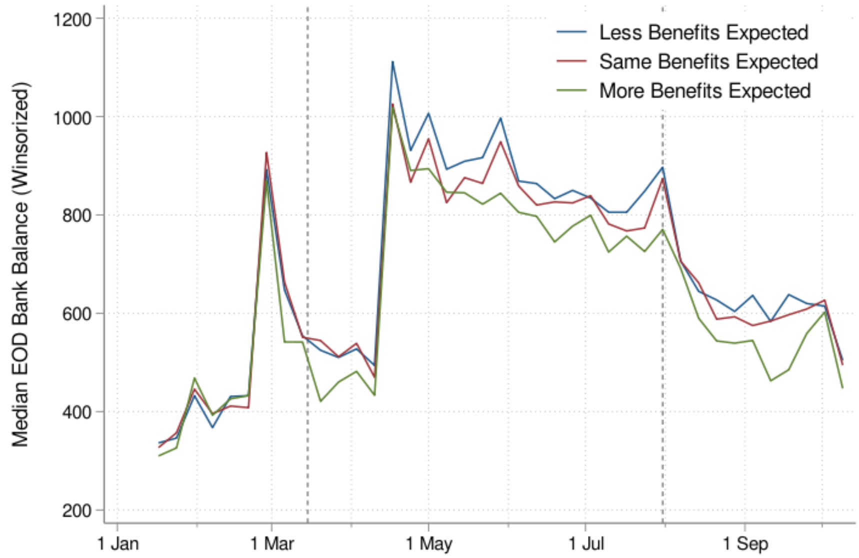
Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and having an estimated discount rate above and below the median among survey respondents. The lines show average (winsorized) weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure 7. Average Bank Balance by July UI Receipt and Risk Aversion Measure



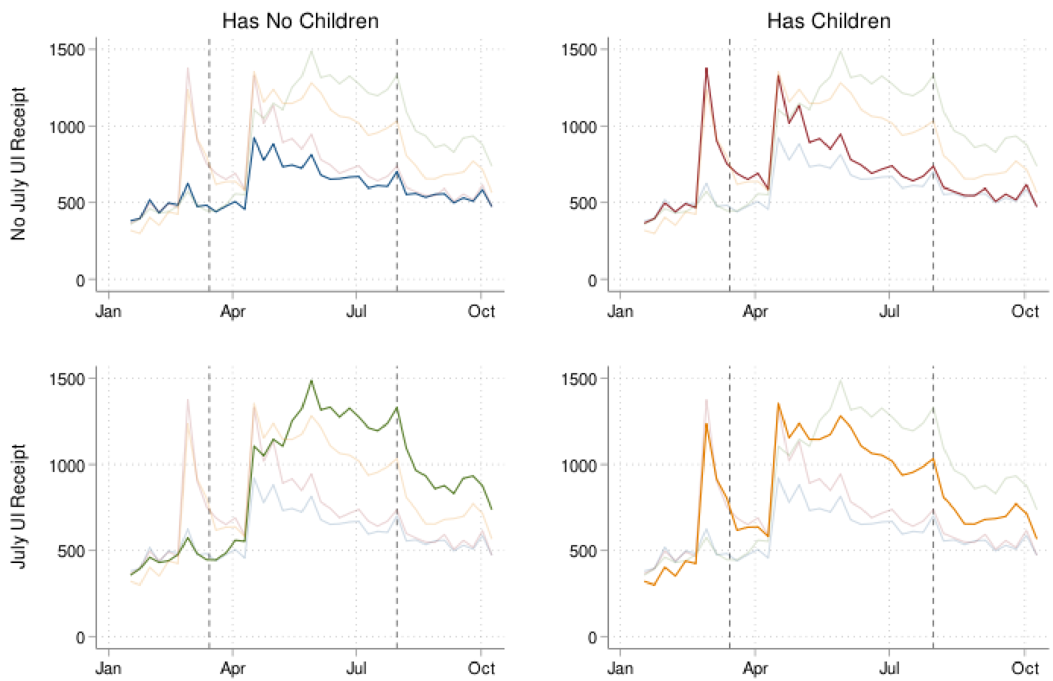
Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and having estimated risk aversion above and below the median among survey respondents. The lines show average (winsorized) weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure 8. Average Bank Balance by Expected July-to-September Change in Benefits



Notes: The above plot shows bank balances for those receiving UI in July who expect their benefits in September to be less than, the same as, and greater than their benefits in July. Each line shows the average (winsorized) weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure 9. Average Bank Balance by July UI Receipt and Parental Status



Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and those reporting having kids or not having kids. The lines show average (winsorized) weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

A Data Appendix

For the full sample of Earnin users, we do not have identifiers that allow us to track individuals across days; however, we do collect information, which tag users. This information can be divided into 16 fixed and 16 time-varying tags from January 2020 to the present. Fixed tags include user sign-up date, date they gave Earnin access to their bank, the dates of their first and last transactions of any type and specifically flagged as unemployment, the user's January 2019 and 2020 earnings, GPS-tracked work hours, and implied wage, the date and amount of their stimulus payment, the average unemployment and number of unemployment payments received during the sample period, their home ZIP, and whether they responded to the survey. Time-varying tags include, workplace ZIP, industry, firm size decile, firm size NAICS code, if the employer receive a PPP loan based on a crosswalk to the Small Business Administration and amount of the PPP loan, the type of earnings from the user's "primary" job, the pay cycle frequency and worker earnings, hours, and wages over the last 7, 14, 21, and 28 day. Tags are often missing, but together allow us to track a user over time. Each combination of these tags creates a unique cell containing one or more users of Earnin.

We use four separate data sets. The first is a tags data set, which includes a fixed panel of all Earnin users with all the tags listed over time. The second is a transactions-level data set, which lists user's bank account transaction amounts along with their associated tags, memo line, and an Earnin-assigned transaction category. The third has End-Of-Day Bank Balances, which is at the user level and contains end-of-daily bank balance levels for a user's bank account connected with Earnin. Fourth, we have linked survey data, which are at the respondent level and contain responses to a survey administered to Earnin users.

In all four data sets, we first restrict our analysis to a sample of those with first transactions occurring before January 1, 2020 and final transaction occurring after September 30, 2020. This provides a more balanced sample. Second, we drop any rows for which the minimum bank connection time is after June 28, 2020. June 28, 2020 is 180 days into the year and most major banks only provide transactions data going back six months, thus any transactions observed for accounts with a bank connected after June 28, were a data error. Third, we flag a user's account or bank transaction as receiving unemployment in July if the July falls in the range between the first and last unemployment transaction dates. Last, we merge on states to job ZIP using a ZIP to state crosswalk and use that to merge on a data set of LWA adoption dates that we built using Forbes news reports.[9]

While each row uniquely identifies a user in the End-Of-Day Balance, Tags, and Surveys data, that is not the case for the bank transactions data. We flag unemployment payments using regular expressions provided by Earnin applied to the memo line associated with the transaction. Then we collapse outflows, non-UI inflows, and UI inflows at the level of the tag cells and the following Friday of the transaction. These cells may contain multiple users, so we turned to the tags and bank balance datasets to confirm that 94 percent of the tag cells uniquely identify a single person in a given week. Unfortunately merging issues prevent us from matching the number of people receiving across these datasets. We instead assume that each cell identifies a single person, which suffices for initial analysis. Going forward, we plan to confirm cell counts and troubleshoot merge issues with Earnin.

B Survey Design

Earnin offered the opportunity to complete the survey to the full set of users who received any unemployment insurance benefits between January and July 2020 and to a equal-sized randomly drawn sample of the remaining users who had not received an unemployment insurance check in 2020. The sample size was 267,768 UI recipients (of whom 253,036 received UI for the first time after March 15th 2020) and a random sample of 267,768 non-recipients. The initial, unincentivized survey was fielded from August 2 through 9, 2020. To increase the sample size, the survey was fielded again from August 19 to August 28, 2020. For the incentivized survey, the first 400 respondents on each day were sent a $10 Amazon gift card. We received 24,671 responses to the incentivized survey.

The survey instrument included eight modules: Employment, Bank Accounts, Income, Expenditures, Savings, Risk Preferences, Time Preferences, and Demographics. The employment questions collected information on employment status, hourly wage at current or most recent job, hours worked in July and expected hours in September, and how the respondent's employment had been

[9] https://www.forbes.com/advisor/personal-finance/lwa-unemployment-benefits-by-state/

affected by the pandemic. The bank account questions asked whether the respondent had multiple bank accounts and if so, whether the account linked with Earnin was their primary account. The income and expenditures questions asked users to recall their income (separately for earnings and benefits) and spending in July and to report their expected income and spending in September. The savings questions asked whether the respondent had savings outside the observed account with Earnin and asked the respondent for an estimate of their total savings.

Risk preferences were elicited with the qualitative and telescoping questions designed by Falk et al. (2016). They ask users to choose between a 50-50 chance of $450 or a sure payment of varying amounts, and respondents answer a series of questions that pins down their risk aversion. In the interests of keeping the survey time short, we asked the qualitative question from Falk et al. (2016) for time preferences and asked the respondent directly how much money they would require in 3 months to forgo $40 one week from today. Finally, we collected a series of standard demographic characteristics including age, gender identity, ethnicity, race, household composition, and education.

C Appendix Tables

Table A1. UI Coverage by State

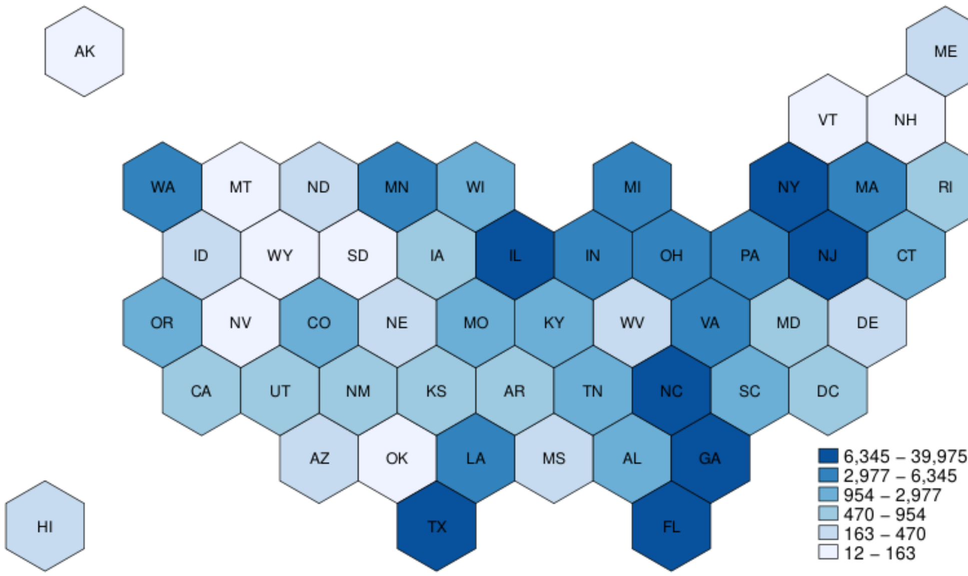
	Earnin UI Rec	Total UI Rec	Earnin UI/Total UI (%)	2019 Pop
AK	163	58,447	0.28	731,545
AL	2,081	197,461	1.05	4,903,185
AR	905	212,775	0.43	3,017,804
AZ	470	1,005,874	0.05	7,278,717
CA	473	6,581,066	0.01	39,512,223
CO	2,977	311,547	0.96	5,758,736
CT	2,140	327,494	0.65	3,565,287
DC	681	88,825	0.77	705,749
DE	461	54,139	0.85	973,764
FL	17,760	691,070	2.57	21,477,737
GA	13,438	1,014,857	1.32	10,617,423
HI	266	220,055	0.12	1,415,872
IA	686	140,300	0.49	3,155,070
ID	379	32,557	1.16	1,787,065
IL	7,636	816,063	0.94	12,671,821
IN	3,316	378,777	0.88	6,732,219
KS	693	183,162	0.38	2,913,314
KY	1,625	199,073	0.82	4,467,673
LA	3,505	483,367	0.73	4,648,794
MA	4,147	1,036,167	0.40	6,892,503
MD	726	505,265	0.14	6,045,680
ME	353	92,393	0.38	1,344,212
MI	6,345	1,576,585	0.40	9,986,857
MN	3,035	391,804	0.77	5,639,632
MO	1,564	258,613	0.60	6,137,428
MS	325	167,433	0.19	2,976,149
MT	15	94,225	0.02	1,068,778
NC	7,303	725,285	1.01	10,488,084
ND	192	34,017	0.56	762,062
NE	382	76,184	0.50	1,934,408
NH	99	85,477	0.12	1,359,711
NJ	7,607	943,050	0.81	8,882,190
NM	954	186,359	0.51	2,096,829
NV	137	500,053	0.03	3,080,156
NY	17,866	2,913,805	0.61	19,453,561
OH	5,533	810,842	0.68	11,689,100
OK	62	127,617	0.05	3,956,971
OR	1,419	279,116	0.51	4,217,737
PA	5,259	2,027,992	0.26	12,801,989
RI	850	122,816	0.69	1,059,361
SC	2,567	286,596	0.90	5,148,714
SD	124	20,220	0.61	884,659
TN	2,434	478,636	0.51	6,829,174
TX	22,809	1,636,547	1.39	28,995,881
UT	850	83,146	1.02	3,205,958
VA	4,761	812,815	0.59	8,535,519
VT	12	48,698	0.02	623,989
WA	4,648	508,344	0.91	7,614,893
WI	1,384	315,919	0.44	5,822,434
WV	377	68,800	0.55	1,792,147
WY	69	17,259	0.40	578,759
Missing	39,975	0	0.00	0
Total	203,852	30,228,987	0.67	331,433,217

Notes: The above table gives the total number of Earnin users who received unemployment benefits through direct deposit during the month of July 2020 by state. Included also is this total as a percentage of total estimated UI recipients by state as estimated by Chetty et al. (2020) and the 2019 population estimates from the American Community Survey (U.S. Census Bureau, 2019)

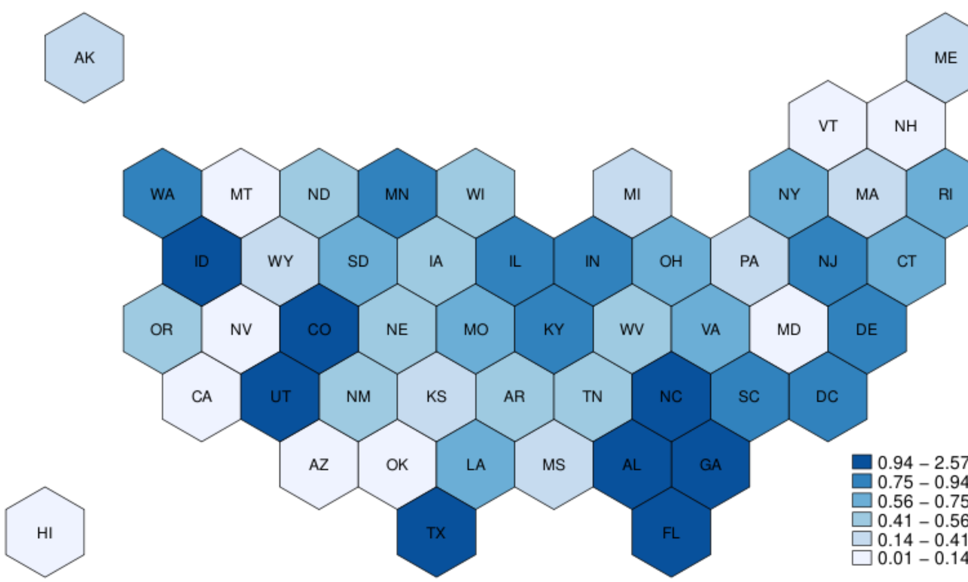
D Appendix Figures

Figure A1. Earnin UI Recipient Coverage

(a) Number of UI Recipients on Earnin

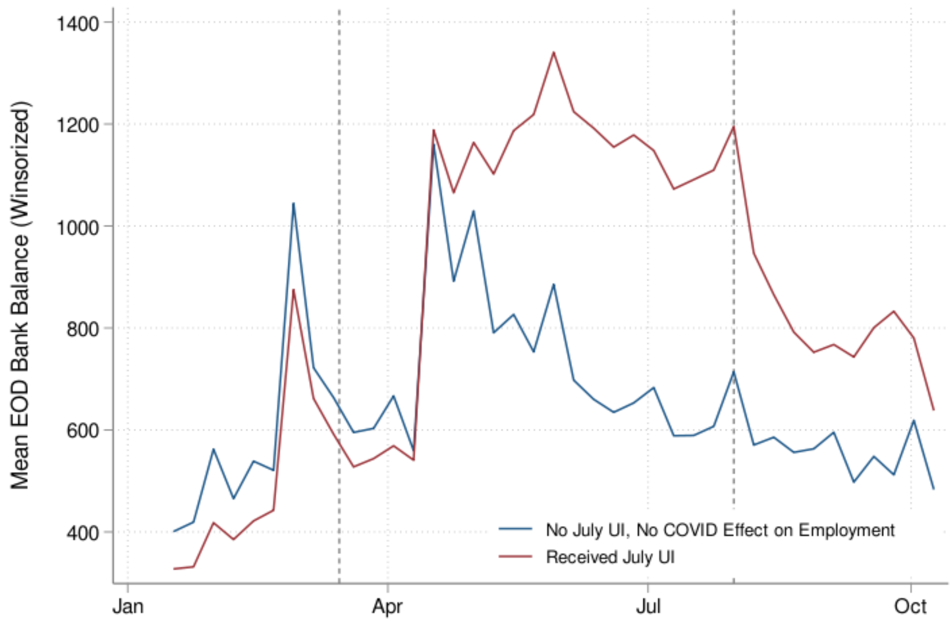


(b) Fraction of All UI Recipients on Earnin (%)



Notes: Panel (a) gives the total number of Earnin users who received unemployment benefits through direct deposit during the month of July 2020 by state. Panel (b) gives this total as a percentage of total estimated UI recipients by state as estimated by Chetty et al. (2020)

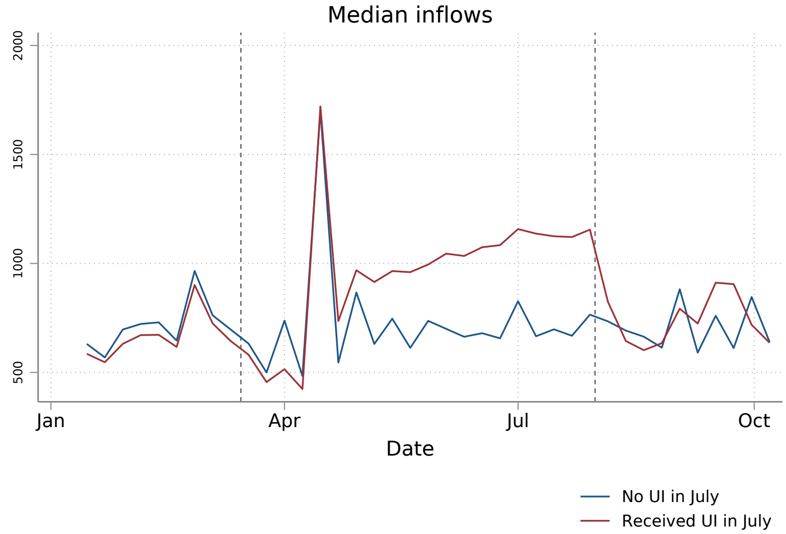
Figure A2. Average Bank Balance by July UI Receipt and COVID Effect on Employment



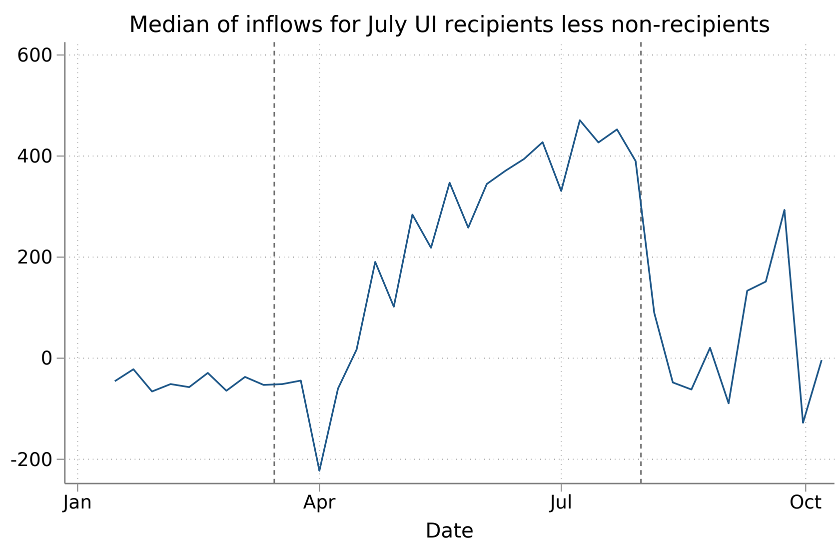
Notes: The above plot shows bank balances for those receiving UI in July who received UI benefits in July and for those who did not receive UI benefits in July and for whom COVID-19 did not affect their employment. Each line shows the average (winsorized) weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure A3. Median Total Weekly Inflows

(a) Weekly Inflows by July UI Receipt



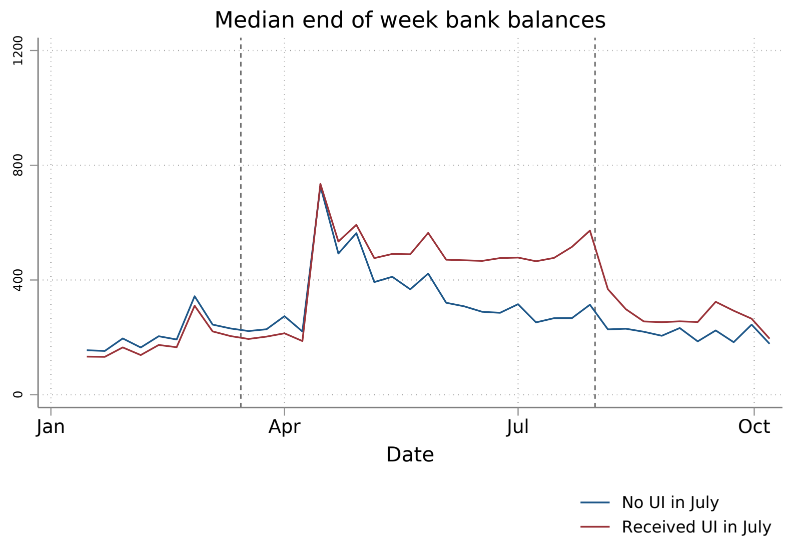
(b) Weekly Inflows Differenced by July UI Receipt



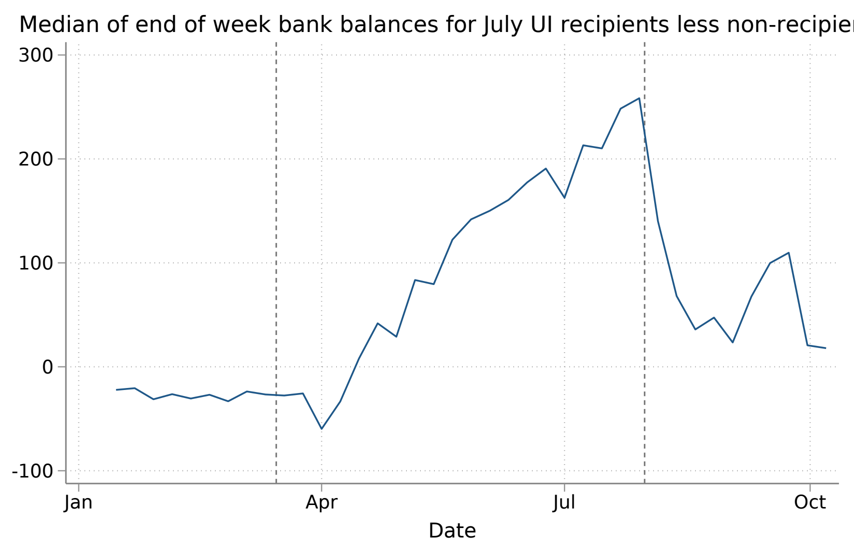
Notes: The sample includes all Earnin users and is split by whether the user received unemployment benefits in July. In Panel (a), the lines show median weekly inflows of all payments (including UI) for each of these two groups from January 12, 2020 to October 9, 2020. In Panel (b), the line shows median weekly inflows of all payments (including UI) for those receiving July UI less those not receiving July UI for the same period. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of FPUC payments, respectively.

Figure A4. Median End-of-Day Bank Balance

(a) Bank Balance by July UI Receipt



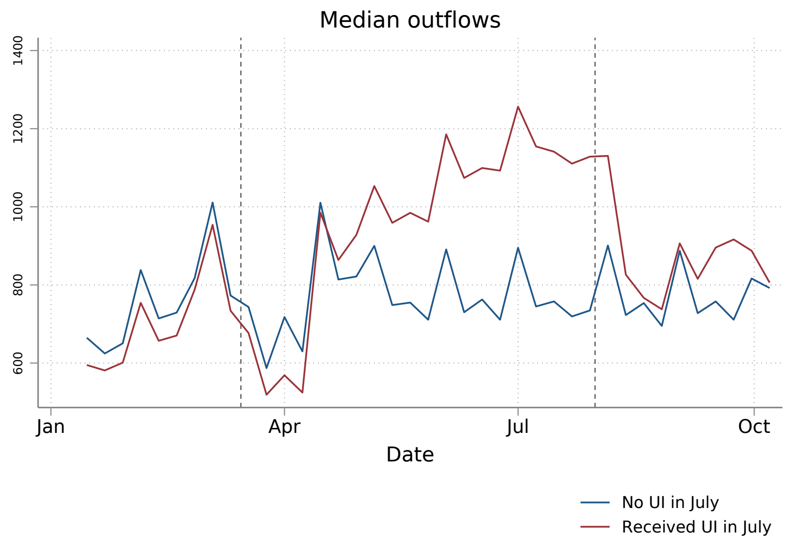
(b) Bank Balance Differenced by July UI Receipt



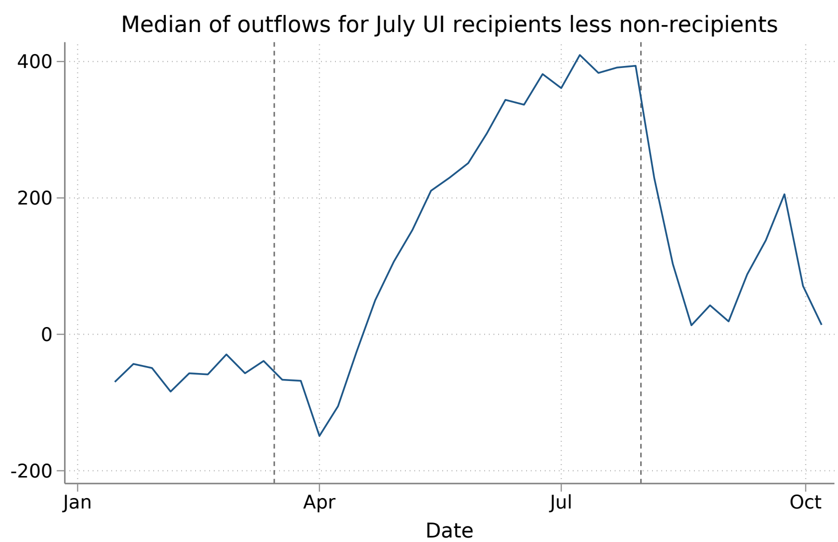
Notes: The sample includes all Earnin users and is split by whether the user received unemployment benefits in July. In panel (a), the lines show median weekly end-of-day bank balances for each of these two groups from January 12, 2020 to October 9, 2020. In panel (b), the line shows median weekly end-of-day bank balances for those receiving July UI less those not receiving July UI for the same period. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of FPUC payments, respectively.

Figure A5. Median Total Weekly Outflows

(a) Outflows by July UI Receipt

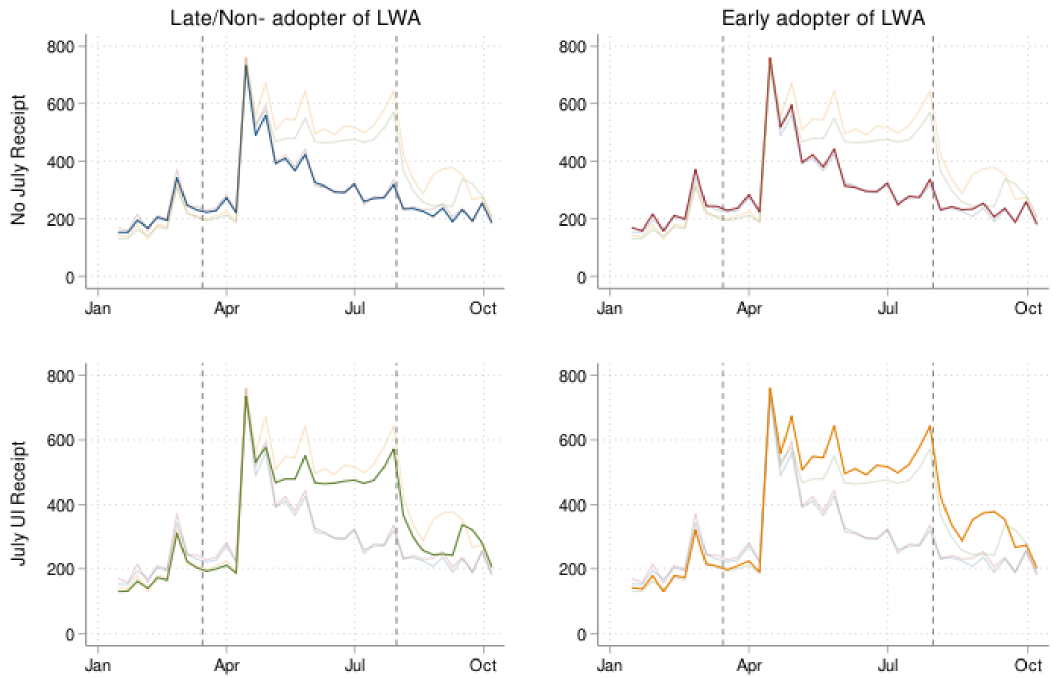


(b) Outflows Differenced by July UI Receip



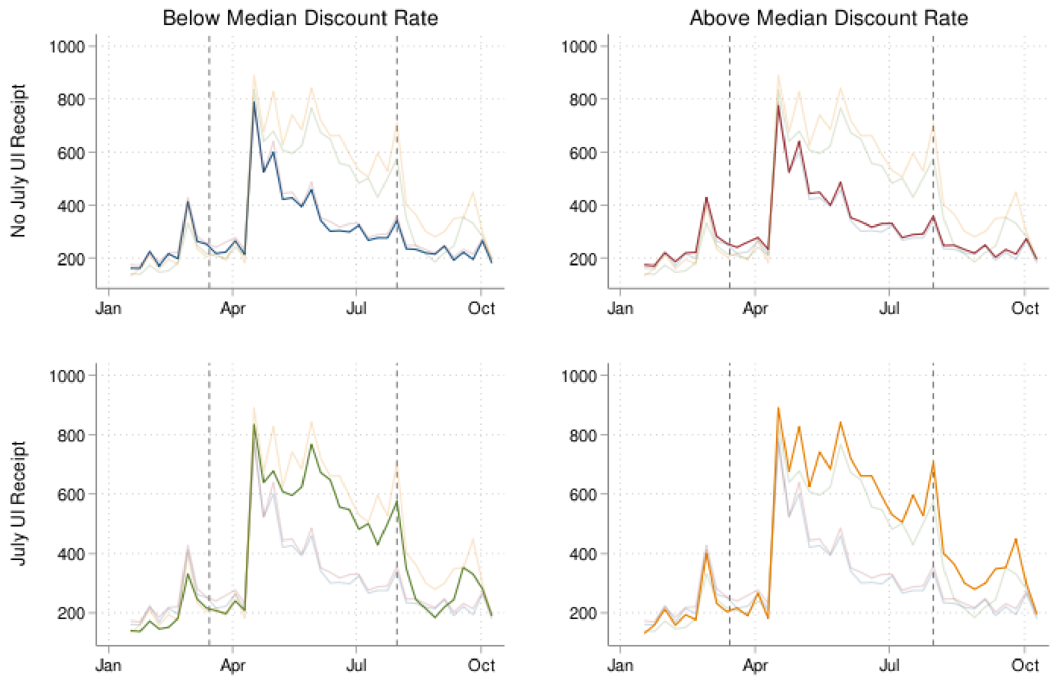
Notes: The sample includes all Earnin users and is split by whether the user received unemployment benefits in July. Panel (a) shows median weekly inflows of all payments (including UI) for each of these two groups from January 12, 2020 to October 9, 2020, and panel (b) shows median weekly inflows of all payments (including UI) for those receiving July UI less those not receiving July UI for the same period. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of FPUC payments, respectively.

Figure A6. Median Bank Balance by July UI Receipt and Timing of Lost Wage Assistance Approval



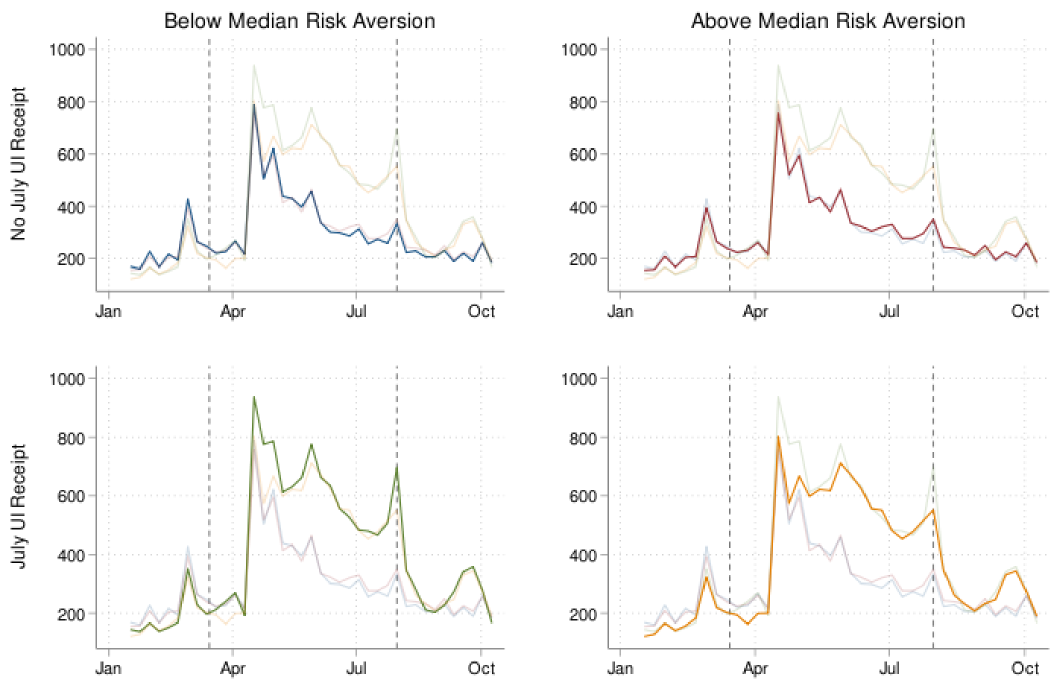
Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and being in a state that approved lost wage assistance early or late. The lines show median weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure A7. Median Bank Balance by July UI Receipt and Discount Rate Measure



Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and having an estimated discount rate above and below the median among survey respondents. The lines show median weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure A8. Median Bank Balance by July UI Receipt and Risk Aversion Measure

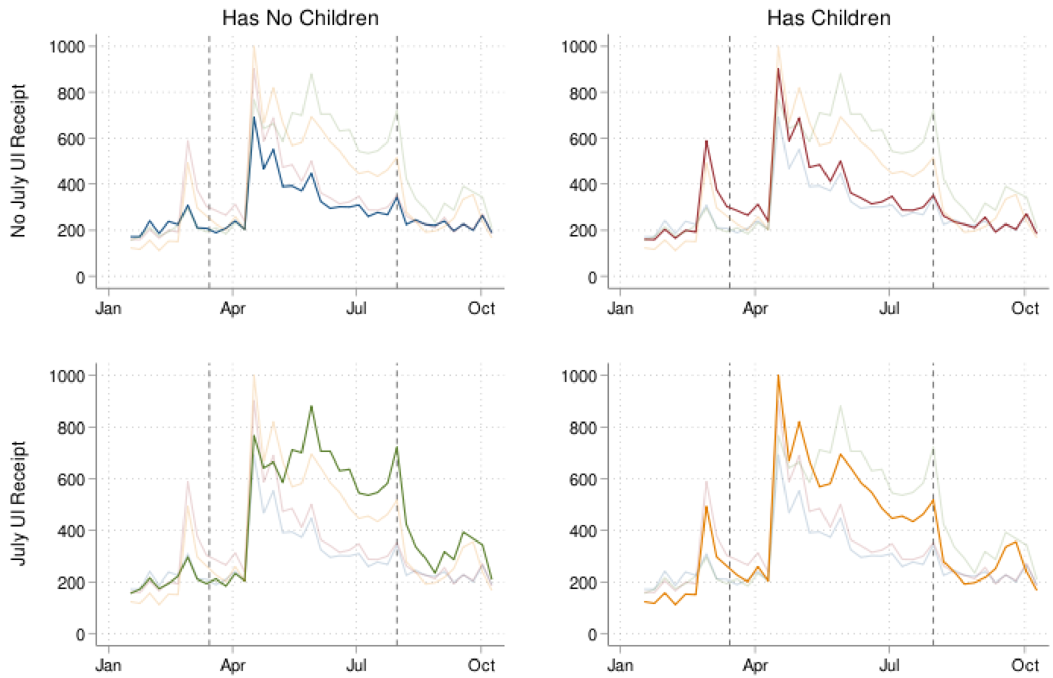


Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and having estimated risk aversion above and below the median among survey respondents. The lines show median weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure A9. Median Bank Balance by Expected July-to-September Change in Benefits

Notes: The above plot shows bank balances for those receiving UI in July who expect their benefits in September to be less than, the same as, and greater than their benefits in July. Each line shows the median weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.

Figure A10. Median Bank Balance by July UI Receipt and Parental Status



Notes: Each panel highlights one of the combinations of having received unemployment benefits in July and those reporting having kids or not having kids. The lines show median weekly end-of-day bank balances for each of these four groups from January 12, 2020 to October 9, 2020. Vertical dotted lines are included at March 15th and July 31th to indicate the start of lockdowns and the end of PUA, respectively.