

Online Appendix

Early Withdrawal of Pandemic Unemployment Insurance: Effects on Employment and Earnings

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APPENDIX A: DATA CONSTRUCTION

1. Data

We receive anonymized data containing user tags with information about each user, bank account transactions (for all transactions), account balances, and a subset of transactions Earnin identifies as earnings. Transactions data include information on the amount of each transaction, a memo describing the source or destination of a transaction, and a categorization of the type of transaction from Plaid, a third party that connects users' bank accounts to Earnin's database. We measure state based on the location of the most recent job when present, or based on smartphone location when the location of the most recent job is missing.

2. Creating Proxy User IDs Using Tags

While the datasets we received do not contain user identifiers, each dataset does contain Earnin's "tags" that allow us to categorize users across datasets. We use these tags to construct panels based on the sign-up date, gender estimated by first name, and confidence in that estimate—which are included in each dataset. Using these tags, we construct "proxy IDs" and measure the panel outcomes for each proxy ID in each dataset. For simplicity, we sometimes refer to each proxy ID as a "user" or an "individual".

3. Identifying UI Payments

We identify UI payments based on transaction memos. Earnin maintains a list of transaction memos that indicate that an inflow is a UI payment, and we supplement this list with other memos that we identify as attached to UI payments.

We define an individual as a *UI recipient* in week t if they received any UI benefits in weeks t through $t + 2$.

4. Identifying Earnings

In order to identify transactions as earnings, we leverage multiple aspects of the transactions and observed earnings data. Our first stage involves matching Earnin's observed earnings database to the transactions database to flag potential earnings transactions. Ideally we could treat all transaction memos matched to observed earnings as earnings for a single user, but there are potential false positives and negatives. To account for this, our second stage supplements these transaction matches with information about the bank transactions themselves including their exact date, memo line, and categories provided by Plaid to remove some false positives and negatives.

We start by removing transaction memos that are almost surely not job-related memos using regular expressions. These pre-dropped memos relate to routine bank activity, interest payments, Child Support Payments, refunds for goods and services, one-off payments for services, and financial tech apps like Earnin, Ibotta, Coinbase, Roundup Savings, Keep Your Change, Chime, Venmo, PayPal, and other person-to-person payment platforms. This pre-dropping improves processing time for the code and increases our ability to match

transactions uniquely to Earnin-reported earnings. A potential downside is these regular expressions may include a handful of false negatives. We minimize the number of false negatives by checking this list of pre-dropped memos based on the match rate process described below. Additionally, we keep any memos that contain a regular expressions related to payroll, direct deposit, earnings, or a handful of miscellaneous regular expressions even if they do contain “dropped” regular expressions. A list of the exact regular expression patterns is available upon request.

After pre-dropping memos, we clean transaction memos to remove any non-alphabetic characters. This helps make it possible to track earnings from the same source, even where memos include dates of payment.

We match the remaining transaction amounts to Earnin’s observed earnings database at the user-week-dollar amount level. The rows in Earnin’s observed earnings database are dollar amounts linked to a pay date associated with each user. In a given week, there are up to four amount rows, representing different sources of earnings. Any matched transaction is considered a candidate earnings memo.

Additionally, we flag and unmatch candidate transactions that are definite false positives surviving the initial pre-drop screen. Definite false positives include child tax credit, stimulus, and tax refund payments. We identify child tax credits (CTC) as those transactions with a memo line containing the regular expression “CHILD[[^]A-Z]*TAX,” “CHILD[[^]A-Z]*CTC,” “IRS,” “TAX,” “INTERNAL.*REV,” or “CTC,” (but not “DIRECT.*CA”), and with an amount of money that matched the child tax credit payment schedule. We follow a similar process to flag American Recovery Program (ARP) stimulus payments with the regular expressions “ECONOMIC.*IMPACT,” “EIP,” and using the payment schedule, additionally only dropping mentions occurring between March 1, 2021 and April 30, 2021 – the dates when the majority of payments hit bank accounts. Finally, we flag all mentions of “IRS[[^]A-Z]*TREAS,” “ST[[^]A-Z]*TAX[[^]A-Z]*RFD,” “STATE[[^]A-Z]*OF[[^]A-Z]*MICHIGAN.*REFUND,” “TAX[[^]A-Z]*REFUND” as a last catch for any other IRS payments.

Next, we flag potential false positive transactions. These include transactions that posted on a different day than the observed earnings database payday and those with memo lines or a Plaid category indicating that the transaction is an internal account transfer, person-to-person transfer, or generic memo. For each user-week-Earnin amount, we sum the number of memo matches and the number of unlikely memo matches to earnings. If the sum total of matches exceeds the sum total of likely false positives, then there is at least one match that is not a likely false positive, so we remove all the likely false positive candidate matches for that user-week-amount. If the sum of total matches equals the sum of false positives, we keep all the candidate matches.

After removing likely false positives, there remain instances in which there are multiple candidate matches within a single user-week-observed earning amount bin. There can be multiple matches if a user frequently receives earnings in a checking account and automatically moves that earnings to their savings account on the same day with a non-standard bank transfer memo line. We break ties between candidates matches by comparing the count of distinct user-weeks in which a candidate memo matches observed earnings. If a candidate memo’s user-week match count is the maximum number of matches for a user-week-amount bin, then we assume all other transactions with that memo line are earnings. If a candidate memo’s user is never the maximum user-week match count for any user-week-amount bin, then we do not assume all other mentions of that memo are also earnings.

The process described above limits the number of false positive matches before broadcasting matched memos to all those memos that Earnin’s observed earnings does not track. Using these broadcasted memos, we then track memos over the entirety of Earnin users and consider a given memo to be earnings if it is tracked as earnings more than 5 times

globally and is tracked as earnings over 90% of the time it appears.

After matching memos to observed earnings, we perform straightforward searches of transaction memos; we flag any transaction with a memo containing the regular expressions “PAYROLL,” “ACH[[^]A-Z]*PAY,” “PAY[[^]A-Z]*RL,” or “SALARY” as earnings.

Finally, we use Plaid’s categorization of transactions as Payroll or Income. Upon inspection, we find Plaid’s categorization of Earnings and Income to be susceptible to false positives. To account for this, we require the memo to occur in more than two unique weeks and with a modal frequency once every one or two weeks *and* not be identified as unemployment benefits *and* either include the phrase “DIRECT DEPOSIT” (or derivatives), or “EARNINGS” or have a median amount between \$50 and \$5,000.

We define someone as *employed* in week t if they received any earnings in weeks t through $t + 2$.

5. Sample Restrictions

We start with an unbalanced panel from Earnin that includes 2.5 million active users⁷ and impose restrictions that result in a balanced panel of 362,000 users before selecting our analysis sample of 16,253 users that are unemployed and insured in the week of April 30, 2021. We detail the full set of restrictions below.

AT LEAST ONE TRANSACTION IN 2020 AND 11 CONSECUTIVE WEEKS WITH AT LEAST TWO
TRANSACTIONS, NO DUPLICATES

To get a baseline sample into a more manageable size, we initially drop users without at least one transaction in 2020 and at least 11 weeks between their first and last transaction. We also drop users that may be a possible duplicate based on their proxy ID.

TRANSACTION COVERAGE

We require that each individual in our sample have transaction data coverage for the full period of our analyses spanning January 1, 2021 through September 17, 2021. This restriction further reduces our sample.

UNINFORMATIVE TRANSACTION MEMOS

Uninformative transaction memos (e.g., ‘CREDIT’ or ‘DEBIT’) make it difficult to identify earnings so we remove users for whom more than one percent of their bank memos are of this uninformative type. This restriction drops roughly half a million users out of our base sample.

OUTFLOW FREQUENCY

Some individuals may hold other bank accounts not linked to Earnin where they do most of their banking. To ensure our banking data represents a reasonably comprehensive picture of the individuals’ banking activities, we require that the user has five or more outflows from their bank account during this period in each month from January through August 2021. This restriction drops another approximately half-million users out of our base sample.

⁷As of November 2, 2021, per <https://www.earnin.com/press>. Accessed January 21, 2022.

EARNINGS FREQUENCY

To reduce false positives in our earnings categorization, we additionally drop users who we track as having more than five earnings inflows in a single week through 2019 using our earnings classification algorithm described above. This restriction drops roughly 30 thousand users out of our base sample.

STATE

There are five states for which our coverage of UI receipt is considerably lower than in other states due to a lack of direct deposit UI disbursement. These states are California, Maryland, Nevada, Arizona, and Oklahoma. These states account for one million users in our base sample.

We also exclude from this analysis users from states who withdrew from additional federal unemployment benefits in July and August. These states are Arizona, Louisiana, Maryland, and Tennessee; additionally we drop users from Indiana, since that state withdrew from additional federal unemployment benefits in June but subsequently restarted those benefits in July due to a court order. These states account for roughly 100,000 of our base sample.

The product of applying these restrictions is a sample of approximately 362,000 Earnin users from states with well-tracked UI payments who have fewer than five transactions categorized as earnings in any given week, more than five outflows in each month of our study, few uninformative transaction memos, and transaction data coverage from January 1, 2021 through September 17, 2021.

6. Unemployed and Insured

We further restrict this analysis sample of 362,000 to 16,253 users who are both unemployed and insured in the week of April 30, 2021 per the definitions of unemployed and insurance provided in the general body of the paper.

7. Final Sample for Analysis of June UI Withdrawals

We additionally compare the characteristics of our unemployed population to those in the Current Population Survey. Specifically, we compare the pre-pandemic earnings distribution of those who were unemployed in January and February of 2021; as expected, Appendix Figure A3 shows that our Earnin sample has lower earnings than the estimates from the CPS.

APPENDIX B: ADDITIONAL RESULTS

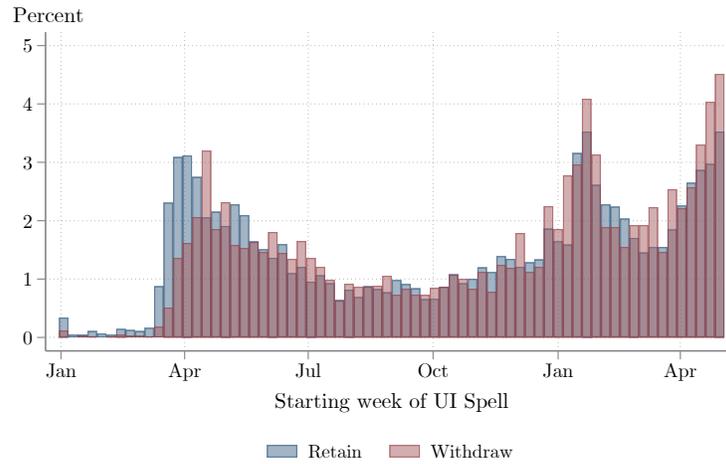


Figure A1. Histogram of Starting week of UI spells in April by State Withdrawal Status

Note: The above figure plots the histograms of the starting week for each users' unemployment insurance reciprocity spell that runs through the end of April by retain and withdraw states. The sample is restricted to those 16,253 Earnin users whom we track as receiving UI benefits and no earnings in the final week of April. In our sample, the Retain cohort contains 23 states and the Withdraw cohort contains 19. Within this sample, 58.4 percent of users in Retain states started this spell in 2020, while the analogous share in Withdraw states is 53.2 percent.

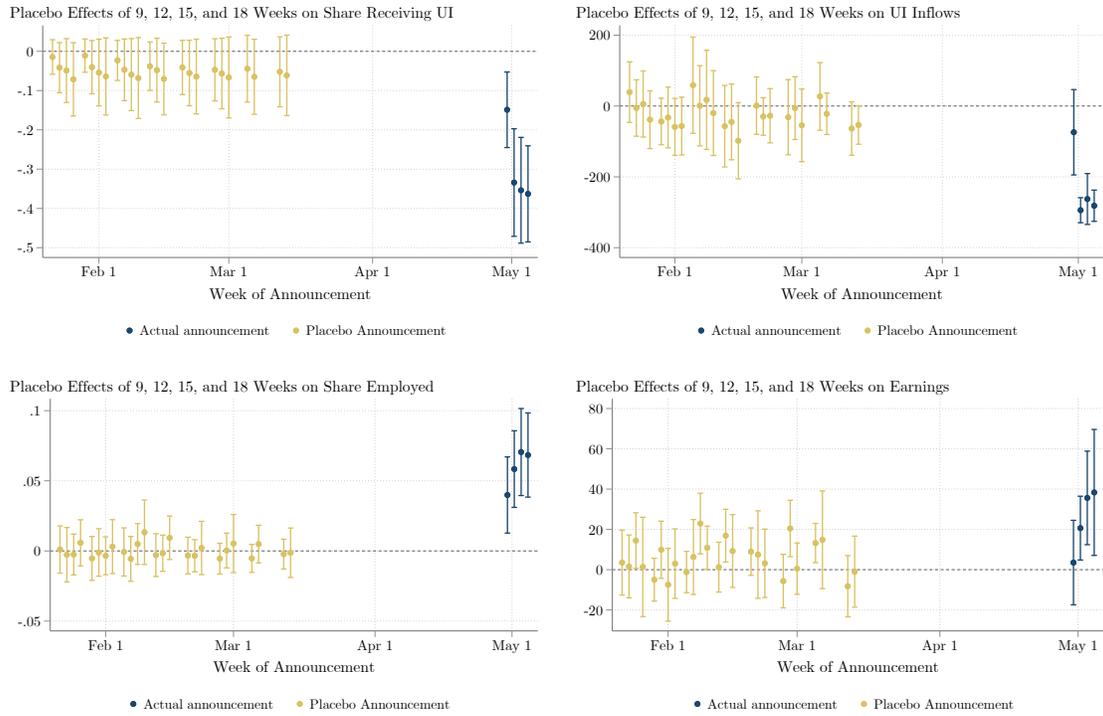


Figure A2. Assessing Pre-existing Trends: Effects of Actual versus Placebo Treatments

Note: The figures above present placebo estimates on the effect of federal benefit withdrawal on state share employed, share insured, average earnings, UI inflows, and spending in the 9th, 12th, 15th, and 18th week after placebo announcements in each week from January 22nd to March 12th and the actual week before the announcement, April 30. The 18th week placebo estimates are omitted for placebo announcements after February 12th, as these weeks occur after the June withdrawal dates. The 15th week placebo estimates are also omitted for March 5th and 12th for the same reason. Placebo estimates with 95% confidence intervals are shown in yellow, and the true estimate with 95% confidence intervals are shown in blue.

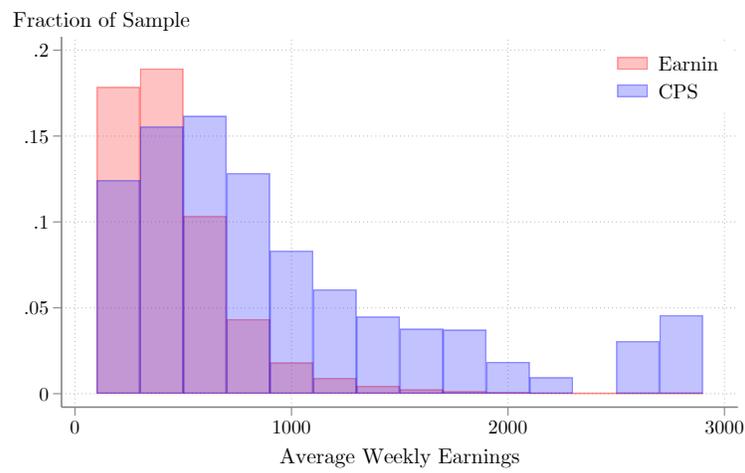


Figure A3. Earnings Distributions

Note: Figure compares distributions of the average weekly earnings in January and February of 2020 for Earnin users and estimates from the CPS. We restrict both samples to those who were unemployed in January and February of 2021. The Earnin sample additionally requires the user to have transactions from January 2020 through March 2021.