Expanding Unemployment Insurance Coverage- Extended Appendix

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1 Panel Study of Income Dynamics

Employment and Earnings Histories. I construct monthly employment and earnings histories using two complementary modules from the Panel Study of Income Dynamics (PSID). For waves 2003-2019 (the "T-1" period), I use the standard PSID employment section, which tracks up to four jobs simultaneously for both household heads and spouses. This module provides detailed information on monthly employment status, hours worked per week, annual earnings, compensation time units, and self-employment indicators for each job. For waves 2001-2017 (the "T-2" period), I employ a the PSID supplement that records monthly labor force status (employed, unemployed, or not in labor force) along with annual weeks worked, hours per week, and total labor income. From these data, I create a monthly person-level panel that spans January 2001 through December 2019. Monthly earnings are calculated by converting job-specific compensation reported in various time units (hourly, weekly, biweekly, monthly, or annual rates) to consistent monthly figures, assuming four weeks per month. I sum across all jobs to generate total monthly earnings and hours worked, while maintaining separate measures for self-employed versus traditional employment.

Unemployment Insurance Eligibility Identification. I determine UI eligibility using state-specific rules as they existed in 2018, prior to pandemic-related expansions. For earnings, I follow a two-part eligibility test: sufficient work history (duration requirement) and adequate past earnings (monetary requirement). I merge state-level UI earnings criteria hand coded from the annual DOLETA report and convert all earnings to real 2018 dollars using the Consumer Price Index.

For the duration requirement, I calculate months and weeks worked in the year prior to potential unemployment and compare these to state-specific minimum thresholds, typically requiring work in at least two of the last five completed calendar quarters. For the monetary requirement, I compute quarterly earnings over the base period and apply state-specific formulas. These include: (i) minimum earnings in the highest quarter, (ii) minimum total base period earnings, (iii) minimum earnings outside the highest quarter, and (iv) state-specific combination

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mean or % of Group	Eligible	Ineligible All	Ineligible Level	Ineligible Duration
Over 65	6.4	20.9	22.8	15.6
Under 25	3.5	10.6	11.6	7.6
Monthly Hours when at Work	160.6	99.6	89.2	126.7
Annual Earnings	$56,151	$4,160	$2,378	$9,305
Months with Employment	12.0	8.0	7.9	8.5
Total Family Income	$120,700	$63,376	$62,566	$65,698
Transfer Income	$2,647	$6,294	$6,378	$6,055
College	70.1	59.6	57.0	67.8
Black	11.4	12.5	13.7	9.3
White	87.8	85.9	85.1	88.5
Female	47.5	63.1	65.3	56.7
Food Stamp Receipt	3.8	18.1	19.3	15.0
Food Secure	86.8	67.4	66.5	70.2
Tenure at Job Loss (months)	6.4	3.5	3.6	3.3
% of Pop Employed in a year	89.8	10.2	7.8	2.4
% of Those Currently Working	91.5	8.5	6.2	2.3
% of Those Currently Not Working	60.0	40.0	31.6	8.4

Statistically different at 95% CI.

Table 1: Characteristic of workers in the PSID by regular state unemployment coverage status. The lower panel restricts the sample to the population employed in a given year.

Earnings today	% in same state 6 months from now	% unemployed 6 months from now
Above threshold	97.1 (97.0-97.3)	0.5 (0.4-0.5)
Below threshold	81.8 (80.2-83.4)	2.4 (2.1-2.7)

Table 2: Persistence of Earnings: Share with earnings above eligibility threshold 6 months from now by earnings today.

rules such as earnings in the two highest quarters or North Dakota's "highest quarter plus half of second-highest quarter" formula.

With regards to non-monetary criteria, I exclude those solely engaged in self-employment, who were generally ineligible for traditional UI benefits before 2020. When studying experiences of eligible and non-eligible unemployed, I exclude those who report that they quit ("Quit; resigned; retired; pregnant; needed more money; just wanted a change"). This is not a perfect screen of the conditions of job loss required for eligibility. In most states, an individual is not eligible if they were fired for cause. I cannot distinguish this in the PSID because this would be coded as "Laid off; fired", the same response a lay-off at no fault would be coded. Conversely, some states do have provisions under which an employee who quits would be able to collect UI but these are rare cases that again are not identifiable in the PSID.[1]

Table 1 expands the statistics in the paper to show the means and percent of the group for each type of eligibility requirement.

Table 2 shows the persistence of the state of being above or below the earnings threshold in a given month.

[1] For example, Minnesota allows workers who quit for unsafe working conditions to collect UI.

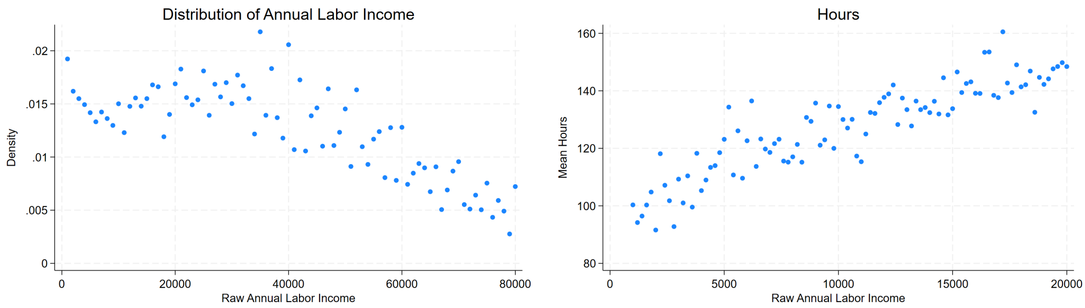


Figure 1: Density of total annual earnings and hours in the PSID.

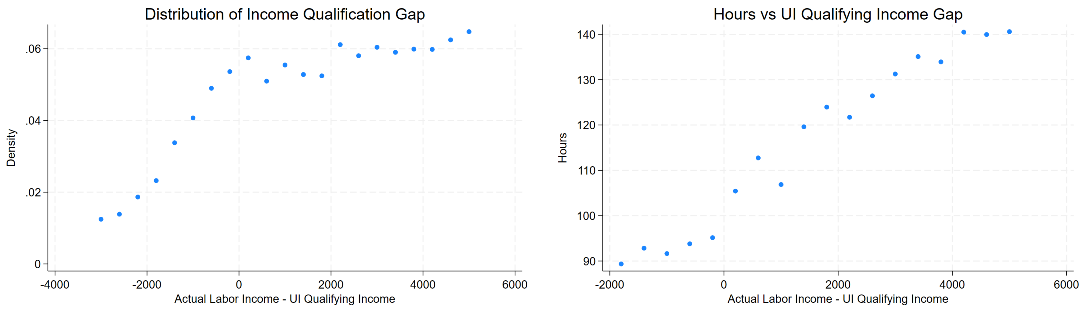


Figure 2: Density of earnings and mean hours around individuals' income - their state UI qualifying income threshold in the PSID

Testing for Manipulation Around Thresholds I now look for evidence that workers are exhibiting effort to move above the qualification thresholds. After coding each worker's state-specific qualifying rules, I compute their distance of their qualifying earnings from the qualifying threshold in each month using the state-specific rules. Figure 1 shows the regularities of the raw earnings and hours data. The right panel is the density of annual total earnings from $(1k, 80k)$ of individuals in jobs outside of self-employment. The left-panel shows the average annual hours worked in each earnings bin.

Figure 2 shows the density of earnings and mean hours of individuals this time with their gap from qualifying for UI on the x-axis. A positive number is how much over the threshold an individual earned and a negative number is how far below. There appears to be a kink in the density of earnings around the qualification threshold where the density flattens significantly. This is evidence that incentives to earn more flatten just over the threshold. A similar kink appears in hours. They increase steadily to the threshold and then jump. This suggests an extra incentive to work more to get over the threshold.

Figure 2 shows the density over qualifying gaps, restricting only to states that require a threshold to be met in two quarters during the look back period. This allows the x-axis to be extended to a greater range of outcomes below the qualifying gap and shows strong eye-ball evidence of manipulation around the threshold.

Interestingly, 4 shows an increased share of multiple job holding, defined as working two or more non-self-employed jobs in the same week in the past two quarters, for individuals earnings

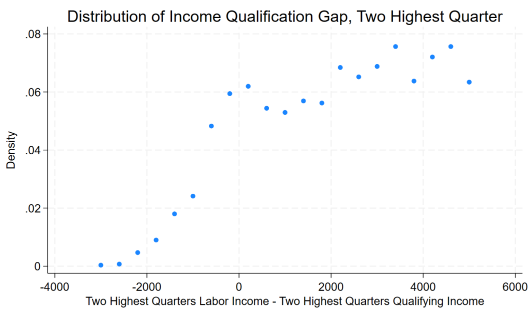


Figure 3: Density of individuals' income - their state UI qualifying income threshold for states using two highest quarters in eligibility rules

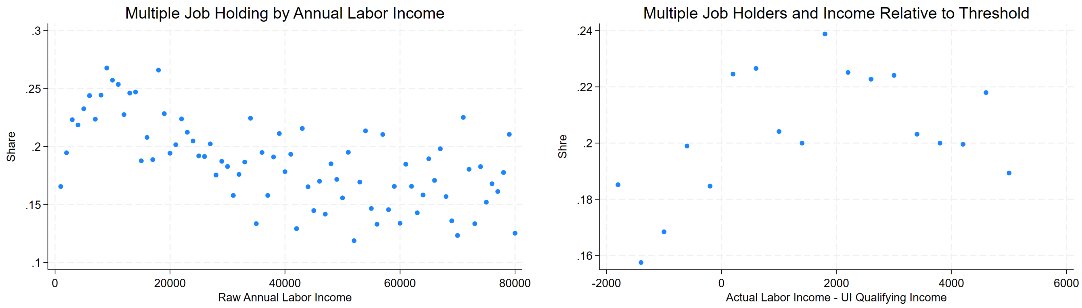


Figure 4: Share of multiple job holders by raw earnings and qualifying earnings gap

around \$10k in a year but the pattern around the qualifying threshold is much weaker. This not only suggests that multiple job holding isn't the modality of reaching over the threshold, it also demonstrates the qualifying gap metric is unlikely to be simply producing spurious relationships in the hours and density.

To formally test for manipulation of workers to earn income over the qualifying threshold, I implement both standard and one-sided donut MacCrary tests and further perform placebo validations. Typical McCrary tests examine density discontinuities at a single point, but studies suggests that individuals may overshoot income thresholds related to public programs to ensure qualification rather than clustering precisely at thresholds and risk missing the threshold (Kleven and Waseem, 2013). The one-sided donut test allows for this overshooting by intervals above the qualification cut-off and re-estimates the McCrary density test at the original cutoff of zero. I consider progressively larger intervals [0, size] above the qualification cutoff of sizes ranging from 20 to 400 dollars to show this is not random bunching. If manipulation is concentrated within the excluded interval, one would expect the test statistic to decrease substantially as the manipulation window is removed.

Table 3 present the results for the baseline and donut McCrary tests around the qualification threshold. The data pass the baseline McCrary test with a highly significant T-statistic of 8.315 ($p < 0.001$). The donut tests are passed as well. The T-statistic consistently declines as larger intervals above the cutoff are excluded: excluding [0,120] reduces the T-statistic by 16.7% to 6.928, excluding [0,200] reduces it by 38.7% to 5.100, and excluding [0,400] reduces it by 77.8% to

Excluded Interval	Excluded Obs.	P-value	T-statistic	Reduction (%)
Full Sample	0	0.0000	8.315	–
[0, 20]	36	0.0000	8.187	1.5
[0, 60]	115	0.0000	7.807	6.1
[0, 120]	240	0.0000	6.928	16.7
[0, 200]	425	0.0000	5.100	38.7
[0, 300]	654	0.0017	3.136	62.3
[0, 400]	856	0.0646	1.848	77.8

Table 3: One-Sided Donut McCrary Test Results

Notes: McCrary density test at policy cut-off measured as distance in earnings from threshold. One-sided donuts exclude observations in intervals [0, size] above the cutoff.

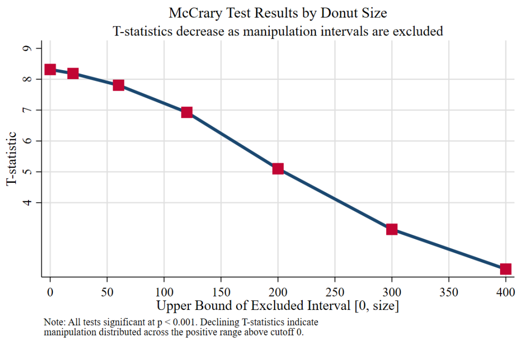


Figure 5: Visual outcome of the donut test

1.848 (p = 0.065). The progressive reduction in test statistics reinforces that the zero threshold is meaningful despite potential rounding-bunching in self-earnings reports, while also providing evidence of overshooting. The rounding-bunching is less problematic when looking at distance from the qualification thresholds because the thresholds differ across states and the look back period also eliminates some rounding-bunching.

I conduct placebo tests at fake cutoffs below the true qualification rule to further distinguish policy-driven manipulation from measurement error. 4 shows no significant manipulation in either baseline or donut tests at cutoffs \$200 or \$100 below the true policy rules. Only the true policy cutoff (0) exhibits the result that donut exclusion eliminates manipulation evidence entirely, with the p-value increasing from less than 0.001 to 0.238.

Cutoff	Baseline McCrary Test		Donut McCrary Test	
	T-statistic	P-value	T-statistic	P-value
−200	−1.028	0.304	−0.403	0.687
−100	−0.348	0.728	0.107	0.915

Table 4: Placebo Tests for Policy Cutoff

Notes: Placebo tests below actual eligibility threshold rule. Baseline McCrary tests use the full sample. Donut McCrary tests exclude observations in the interval [cutoff, cutoff + 100].

Consumption Dynamics around Job Loss A measure of insurance need surrounding an unemployment spell is how much consumption declines. In models of perfect insurance the decline should be zero. The PSID contains annual reports on total spending and on food spending in three categories: food used at home, food delivered to the home, and food consumed away from the home. Summary statistics on spending are displayed in Table 5. Workers who are employed in covered jobs (those eligible if they lost their job) generally live in richer households with higher per capita spending than workers employed in uncovered jobs or with an unemployment spell in any year. Interestingly, workers in all situations allocated the same share of their total spending on food but the households of uncovered workers and unemployed who are ineligible spend more on food at home and less on food away and delivery. This suggests that total spending is not the same as total real consumption of food.

	Emp Covered	Emp Uncovered	U Uncovered	U Covered
Total Spend ($)	34591.86***	24515.60***	24167.47***	25408.35***
Total Food Spend ($)	6122.22***	4812.34***	4595.87***	5174.52***
Food at Home	3632.64***	3100.99***	2978.15***	3671.15***
Food Away	2110.25***	1330.12***	1449.68***	1416.78***
Food Delivered	379.33***	381.28***	168.04***	86.59
Share Food of Total Spend	0.19***	0.21***	0.20***	0.22***
Share Food at Home of Food	0.64***	0.66***	0.64***	0.71***
Share Food Delivered of Food	0.06***	0.07***	0.08*	0.01
Share Food Awy of Food Spend	0.31***	0.26***	0.28***	0.28***
Share w/ any Food Stamps	0.04***	0.13**	0.20***	0.22*
Share Food Secure	0.88***	0.58***	0.72***	0.70***
Observations	25901	1252	1294	483

Spending statistics as annual per-capita according to OECD household size adjustment. $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$.

Table 5: Mean Food Expenditures and Security by Employment Status

Total spending on food is an imperfect measure of tangible consumption. Newly unemployed workers may report a fall in food spending as they substitute more expensive convenience products towards similar products from the grocery store now that they have a less busy schedule. A methodology simlar to Attanasio and Pistaferri (2014) is used to address this issue. Real food expenditure in each category is estimated from nominal expenditure, including food stamps, by controlling for the category-specific deflator in the Consumer Price Index, education, age, and individual fixed effects. This estimate of real food expenditure is then adjusted for household size and composition (ages of members) according to OECD standards. Formally, this is defined in the following equations.

$$\begin{aligned} RealFoodConsumption_{it} \quad &= \beta_1 Col_{it} + \beta_2 lessHS_{it} + \textstyle\sum_j \gamma_j AgeB_{jit} + \beta_3 cpiFoodAway_t + \\ &\beta_4 cpiFoodHome_t + \beta_5 OECDsize_{it} + \beta_6 sFoodHome_{it} + \\ &\beta_7 sFoodDlvr_{it} + \beta_8 sFoodAway_{it} + \beta tFoodSpend_{it} + \alpha_i + \varepsilon_{it} \end{aligned}$$

The variables with "sFood" are shares of total food spending on each category and "tFood-Spend" is total spending on food. The predicted values for a household i in year t are denoted with hats and provide our measure of real consumption. The annual change in food consumption is measured as the long change in this real estimate, year over year, divided by the OECD definition of household size to get a measure of per capita real consumption.

Changes around unemployment are predicted from a regression with a dummy each for the presences of an unemployment spell in the past year for eligible and ineligible workers; as well as controls for education interacted with the life-cycle profile, year fixed effects, and individual fixed effects. This sample is limited to workers who have been in the data set for more than two years prior to their unemployment spell.

$$\Delta \ln(FoodAdj)_{it} = \beta_1 u\_ineligible_{it} + \beta_2 u\_eligible_{it} + \sum_{t=2004}^{2018} \delta_t \mathbf{1}[year = t] + \alpha_i + \varepsilon_{it}$$

The variables $u\_uncovered_{it}$ and $u\_covered_{it}$ are dummies indicating an unemployment spell, by whether the individual was eligible, in year t.

	Dependent Variable	
	Δ ln(Food) (1)	Δ ln(Total Spending) (2)
UI Ineligible Unemployment	-0.147^{***}	-0.096^{***}
	(0.027)	(0.021)
UI Eligible Unemployment	-0.058^{***}	-0.039^{***}
	(0.012)	(0.011)
Year FE	X	X
Observations	43,895	57,015
Number of Groups	10,340	14,979

Table 6: The Effect of Unemployment on Household Consumption

Notes: The dependent variables are log changes in OECD-adjusted food consumption (column 1) and OECD-adjusted raw total nominal spending (column 2). The sample is restricted to households with unemployment duration less than 7 months and positive employment in the base period. Standard errors are reported in parentheses. Statistical significance: *** p<0.

The results shown in Table 6 provide evidence of heterogeneous consumption responses to unemployment based on insurance coverage. An uncovered unemployment spell generates a 14.7 percentage point decline in OECD-adjusted annual food consumption at the household level, while covered unemployment produces a significantly smaller 5.8 percentage point reduction.[2] This 8.9 percentage point differential represents a 61 percent attenuation in the consumption response when eligible for insurance through the unemployment benefit system. Similar to the findings of Blundell et al. (2008), I find that total annual spending falls less at 9.6 percentage

[2]The decline for the eligible shows that unemployment insurance does not provide full insurance. The replacement rate of UI is less than 100% plus take up is incomplete and credit markets do not make up the difference (Braxton et al. (2020) and Herkenhoff (2019)).

points for those ineligible for UI and 3.9 percentage points for those who are eligible. The differential, however, is similar: a 59 percent attenuation in the spending decline for the eligible.

2 CPS

The Displaced Workers Survey (DWS) is a biannual supplement to the Current Population Survey (CPS), usually conducted in January or February. The (DWS) samples individuals who have involuntarily lost their jobs and includes specific questions about whether respondents received UI benefits. These questions are not available in other months and so the goal of this section is to predict receipt using the DWS as a training sample for machine learning techniques.

I use a least absolute shrinkage and selection operator (lasso) regression to identify the most predictive factors of UI receipt in the DWS samples. The lasso methodology addresses the challenge of high-dimensional prediction by simultaneously performing variable selection and coefficient estimation, automatically shrinking less important coefficients toward zero while setting irrelevant variables to exactly zero. The optimal regularization parameter (lambda) is selected using a cross validation procedure on a 80-20 training-validation random split of the data. The model is trained on data spanning 2009-2013.

The set of potential predictors I provide the algorithm include demographic and economic characteristics provided in the CPS, and variables related to the UI system which I create. Demographic variables are: age group, sex, race, educational attainment, marital status, census region, metropolitan designation, and citizenship status. Economic characteristics include detailed family income categories, occupation and industry classifications, and constructed labor income quintile indicators. Household composition is captured through variables indicating the presence of a spouse, children of various ages, and the number of children in the household. The main variables I construct are attempts at determining UI eligibility status with the limited earnings history available in CPS as well as the reason for separation. I also designate a variable for self-employment income.

The results of the lasso approach are shown in Table 7. The lasso approach handled the multicollinearity of the demographic and geographic variables well, selecting 58 out of the more than 100 provided. The low lambda (0.005732) shows minimal shrinkage, meaning the coefficients on the remaining variables are not being forced towards zero. The r-squared achieved on the validation sample is 70% of that on the training sample.

Statistic	Value
Optimal Lambda	0.005732
Variables Selected	58
Training Sample Size	4597

Table 7: Lasso Regression Summary Statistics

Notes: Model trained on 80% random sample of data from 2009-2013. Lambda selected via cross-validation; 58 variables selected from candidate set.

Table 8 shows the predictive power of the dependent variables in the lasso regression. All variables are 0 or 1 dummies. To measure the total predictive contribution of each variable category, I simply sum their coefficients to get an "importance" statistic. Region (importance = 0.327) and age group (importance = 0.314) are the most influential variable categories. Labor market characteristics also prove highly predictive, as occupation (0.261), family income (0.250), and industry (0.240) rank among the top five predictors. Author constructed variables of eligibility show moderate importance highlighting the difficulty of constructing eligibility in the CPS and accounting for take-up. Traditional demographic characteristics such as sex, race, and marital status show relatively low importance scores which is inline with the similarity in these characteristics across eligibility groups in the PSID.

Group	Importance	Categories	Max abs(Coef)
Region Dummy	0.327	7	0.124
Age Group Dummy	0.314	4	0.222
Occupation Dummy	0.261	7	0.069
Family Income Group Dummy	0.250	7	0.096
Industry Dummy	0.240	6	0.065
Citizenship Dummy	0.223	2	0.168
Number of Children Dummy	0.215	5	0.114
Unemployment Dummy	0.200	1	0.200
Education Dummy	0.122	4	0.079
Self Employment Dummy	0.102	1	0.102
Individual Income Quintile Dummy	0.064	1	0.064
Eligible Ever Dummy	0.040	1	0.040
Any ADL Dummy	0.030	1	0.030
Metro Status Dummy	0.029	3	0.017
Marital Status Dummy	0.021	2	0.013
Child under age 6 Dummy	0.016	1	0.016
Sex Dummy	0.012	1	0.012
Race Dummy	0.012	1	0.012
Respondent Dummy	0.006	1	0.006

Table 8: Variable Importance in Lasso Regression

This lasso model is used to predict claiming behavior for additional months in the CPS. Individuals with low predicted UI claiming probabilities (less than 40%) are classified as PUA-eligible, representing those who would typically be ineligible for traditional unemployment insurance but might qualify for Pandemic Unemployment Assistance. Those with high predicted UI claiming probabilities (more than 60%) comprise are classified as regular UI eligible.

Table 9 presents summary statistics of the demographic characteristics of the predicted eligible and predicted ineligible. The demographics show some similarities and some differences compared to the PSID sample that was constructed directly from weekly earnings histories. In both samples the ineligible are less educated but similar in gender, racial, and marital demographics. The CPS sample has a much lower share of older workers coded as ineligible and the share White has a larger gap across eligibility.

Table 10 extends the sample to include COVID modules from 2020 and presents summary statistics of economic characteristics of the predicted eligible and predicted ineligible. The ineligible are lower tenure, as expected, and there are more eligible workers in recessions. The COVID module shows that ineligible workers are 20% more likely to be unable to work due to

Table 9: Summary Statistics- Mean Demographics by Eligibility

	UI Eligible	UI Ineligible
Over 65	0.038	0.045
Under 25	0.020	0.202
Age of Youngest Child	10.028	7.711
Has Child under 5	0.193	0.240
Has Child under 12	0.127	0.086
Female	0.461	0.510
White	0.870	0.766
Black	0.067	0.074
Married	0.675	0.573
Urban	0.283	0.380
US Citizen	0.992	0.755
High School or Less	0.315	0.275
Any ADL	0.026	0.033

Note: UI eligibility is predicted using machine learning methods based on demographic and economic characteristics. Sample includes individuals aged 16-75 in the CPS. Data covers the period 2007-2019. ADL = any difficulty with daily living, a measure of disability.

Table 10: Summary Statistics- Mean Economic Characteristics by Eligibility

	mean	mean
Tenure	9.894	6.949
Recession	0.186	0.154
Worked remotely for pay due to COVID-19 pandemic	0.398	0.406
Unable to work due to COVID-19 pandemic	0.050	0.060
Received pay for hours not worked due to the COVID-19 pandemic	0.302	0.251
Prevented from looking for work due to COVID-19 pandemic	0.177	0.296

Note: UI eligibility is predicted using machine learning methods based on demographic and economic characteristics. Sample includes individuals aged 16-75 in the CPS. Data covers the period 2007-2020.

COVID-19 if they are currently employed, and they are much more likely to be unable to work due to COVID-19 if they are without a job (29.6% versus 17.7% for the eligible.)

I construct labor market flow data by aggregating employment transitions (unemployment-to-employment, employment-to-unemployment, etc.) separately for each PUA eligibility group, applying time aggregation bias corrections (Shimer (2012)) to calculate accurate transition rates.

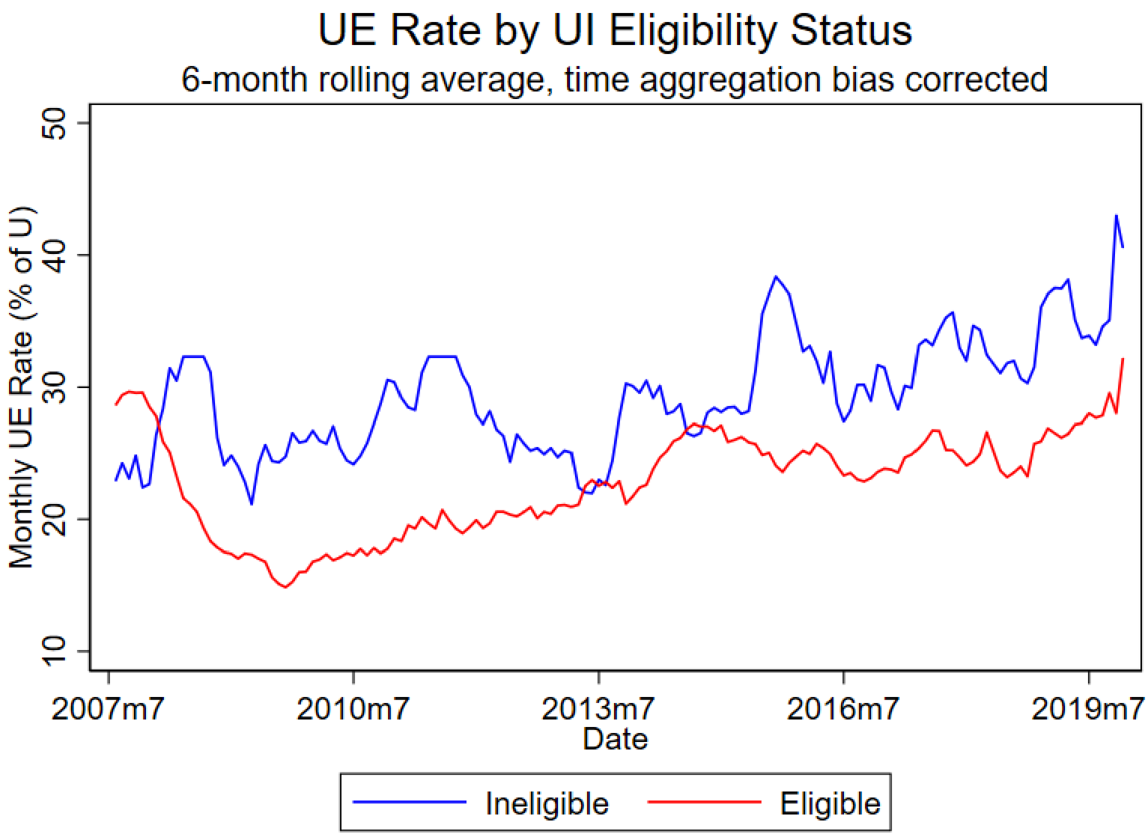


Figure 6: Unemployment to Employment Flow Rates by ML-predicted UI Eligibility Status in the CPS (2007-2019)

Note: All rates shown as 6-month rolling averages with time aggregation bias correction. Blue lines represent UI-ineligible individuals, red lines represent UI-eligible individuals.

Figure 6 depicts labor market flows between employment and unemployment (looking for a job), and between employment and non-employment (regardless of looking for a job). Retirees are dropped from the samples. The top panels shows that separation rates are higher for ineligible. They also follow a longer business cycle compared to the short spike for eligible workers. The second row shows that job finding rates are usually a bit higher for ineligible. More importantly, the job finding rates are less cyclical for the ineligible.

3 Department of Labor Employment Training Administration (DOLETA) Claims Data

The United States Department of Labor provides data on initial and continued claims for the Pandemic Unemployment Assistance (PUA) and regular state unemployment systems, as well as continued claims for the Pandemic Emergency Unemployment Compensation (PEUC) and the Extended Benefits (EB) programs.[3] An initial claim is a request for determination of UI eligibility from an unemployed individual who recently was separated from his or her employer. A continued claim is a claim for an additional week of unemployment from an individual who has already filed an initial claim. The former approximates a flow onto an unemployment program and the latter is the stock of individuals continuing prior claims.[4]

The PEUC and EB programs are federally funded and extend the duration of benefits for claimants in the regular state programs.[5] Moving from a regular state program to PEUC or EB constitutes a continued claim. I will define total continued claims in regular state programs as the sum of continued claims across the regular program, PEUC, and EB. This is because we are interested in the stocks of claimants by eligibility type and not the state versus federal funding distinction.

The PUA program provides up to 79 weeks of federally funded payments to workers with reduced income not covered by total regular state programs. The program initially provided payments through December 31, 2020 but was extended by President Trump on December 28, 2020 to last until March 14, 2021. In January 2021, it was extended again by President Biden through September 6, 2021. Additionally, the program provides retrospective payments for reduced income events beginning on or after January 27, 2020. Administration of the PUA program began in different times across different states in April-June 2020.

The retrospective payments, staggered start dates, and the requirement of some states that PUA claimants first file a regular unemployment claim all present hurdles for our stock-flow analysis. I deal with the first two issues by simply starting my analysis on July 15, 2020. I end my analysis on May 1, 2021 to avoid states withdrawing from federal programs. To deal with the second issue, I first categorize states into three groups: those that require an applicant to apply for PUA through being rejected from the regular state program; those that accept PUA applications directly, and those that either changed protocol at some point or whose protocol cannot be determined.[6] The states in the third category are dropped. The complete

[3] I use GeoFRED to access these data and would like to thank the staff at FRED for making these data available.

[4] These are approximate measurements. For example, some initial claims are rejected and never result payment. The results presented assume that this rejection rate is the same across program type.

[5] PEUC provided up to an additional 13 weeks of federally funded insurance due to special actions dealing with the pandemic. The EB program is automatic and provides up to 13 additional weeks if a state is experiencing high unemployment. The EB program may extend duration in eligible states after a claimant's PEUC weeks run out.

[6] I find that roughly half of the sample, 25 states plus the District of Columbia, require PUA applicants to first file for regular benefits and be denied. I check this categorization by comparing rejection rates to regular state programs in each group. Indeed, the group that requires PUA applicants to file for regular benefits and be rejected has a 12.6 percentage point higher rejection rate of initial claims to state programs (44.3% versus 31.7%)

categorization of states is shown in Table 11.

Apply Direct to PUA	**Apply to Regular UI First**	**Uncertain or Changing Protocol**
Arizona, Arkansas, California, Colorado, Florida, Georgia, Hawaii, Iowa, Maine, Massachusetts, Montana, Nebraska, New York, North Carolina, North Dakota, Ohio, Oregon, Pennsylvania, Rhode Island, Utah, West Virginia, Wisconsin, Wyoming	Alabama, Alaska, Connecticut, Delaware, District of Columbia, Idaho, Illinois, Indiana, Kansas, Kentucky, Maryland, Minnesota, Mississippi, Missouri, New Hampshire, New Jersey, New Mexico, Tennessee, Texas, Vermont, Virginia, Washington	Louisiana, Michigan, Nevada, Oklahoma, South Carolina, South Dakota

Table 11: PUA Application Protocol by State

Altogether this sample contains 718 million weekly continued claims on regular UI including EB, plus 473 million weekly continued claims assigned to PUA.

For the states that take PUA applications indirectly through regular state programs, I must adjust both the initial PUA and regular state claims data. I do this by assuming the mean rejection rate due to insufficient work credits on claims for the regular state program is the same in each set of states. That means I make the adjustment by first calculating the mean rejection rate of initial claims to state programs in states that take PUA claims directly. These data are available from DOLETA.[7] I then apply this mean rejection rate to regular initial claims in the states that don't take PUA claims directly and assign any excess rejections as initial applications to the PUA programs.

Let $\{a_t^{pj}, c_t^{pj}, r_t^j\}$ be the true initial claims, continued claims, and rejections to program p in state type j at time t. Let $\{\hat{a}_t^{pj}, \hat{c}_t^{pj}, \hat{r}_t^j\}$ be the same objects reported in the DOLETA data. For states that take PUA claims directly, the observed objects reported by DOLETA should be the actual ones, subject perhaps to measurement error. For the states that do not take PUA claims directly, the approximation of the true values are:

$$
\begin{aligned}
\tilde{r}_t^j &= mean_{j\in\{direct\}}(\hat{r}_t^j) \\
\tilde{a}_t^{regular j} &= \hat{a}_t^{regular j} * (1 - (\hat{r}_t^j - mean_{j\in\{direct\}}(\hat{r}_t^j)) \\
\tilde{a}_t^{PUA j} &= \hat{a}_t^{regular j} * (\hat{r}_t^j - mean_{j\in\{direct\}}(\hat{r}_t^j) \\
\tilde{c}_t^{pj} &= hatc_t^{pj}
\end{aligned}
$$

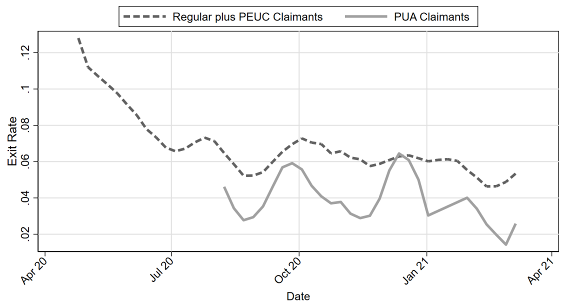
Lastly, I clean the data in a third and final way by removing states with swings in PUA continued claims data that exceed 200% starting in July 2020. This step removes Arkansas, California, Colorado, District of Columbia, Florida, Illinois, Kentucky, Minnesota, New Jersey,

based on insufficient work credits than those that take PUA applications directly and separately.

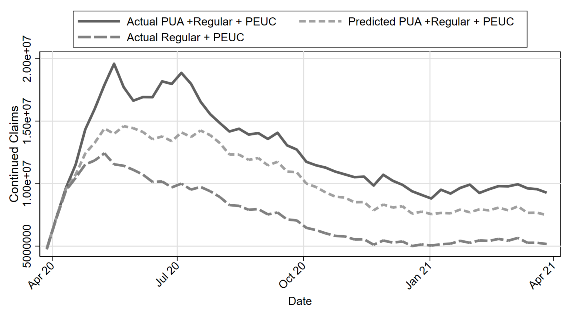
[7]https://oui.doleta.gov/unemploy/DataDownloads.asp has details on applications and rejections at the state level.

Ohio, and West Virginia.[8]

I also perform an arithmetic counterfactual: how many weeks of PUA continued claims would there have been if PUA claimants had the same estimated exit rate as regular UI claimants? I calculate this number by iteratively constructing a time series of the stock of PUA claimants generated from the actual PUA claims but with the time series of exit rates from the regular UI claims. I find that the actual total weeks of PUA claims is 23.3-42.6% higher than would have been provided if the PUA claimants had the higher exit rate that the regular claimants had, and overall UI benefit weeks paid were 10.3-18.0% higher. The higher figure is from the subset of states that had direct PUA applications, the lower figure is imputing the share of PUA applicants to regular UI programs in the states where PUA applications were not separate from Regular UI.



(a) UI exit rate, September 2020 - June 2021



(b) Continued Claims

Figure 7: UI Claiming Behavior by Program.

Note: PUA sample are states with direct application to PUA program. Predicted continued claims in (b) is the series generated with regular UI exit rates and the PUA initial claims series.

Figure 7 shows the main results of the stock-flow analysis. Left panel (a) of Figure 7 compares the deduced rate of exit off the UI rolls for regular UI, including extended benefits, and PUA. The average (median) exit rate from PUA across weeks is 6.4% (5.8%) per week which is 17% (15.7%) lower than the rates for regular UI at 7.6% (7.0%). The right panel (b) of Figure 7 shows the actual stock of regular UI continued claims, including extended benefits, on the bottom. The top line shows the total continued claims when adding PUA claims in. These numbers are taken directly from the DOLETA reports. The middle line of predicted total claims shows what the total claims would have been if the exit rate from PUA was the same as for regular plus EB as in panel (a) of Figure 7. This reduces the additional contribution of PUA claims to total continued claims by 42.5% and total continued claims by 17.9%.

[8]Some of these states had known issues. For example, UI fraud was so bad in California that the state temporarily paused processing new claims in 2021.

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