Expanding Unemployment Insurance Coverage

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Abstract

I develop a quantitative framework to study the impact of Unemployment Insurance (UI) expansions to workers earning below eligibility thresholds. A model of UI is calibrated to replicate experiences of the eligible and ineligible, including consumption after job loss. Eligibility rules distort labor supply in costly ways and removing them would benefit workers across the income spectrum, even with consideration of funding costs. The model captures job-finding rates by eligibility that I document during the GFC and COVID-19 recessions. Although expanded eligibility during COVID-19 lowered job-finding rates, other changes in UI policy were more impactful.

1 Introduction

Unemployment insurance programs in the United States do not cover all workers. Eligibility generally requires the following three criteria to be met. First, the worker has had a sufficient amount of earnings in the last few quarters subject to an employer tax paid into the unemployment system. Second, the worker has been laid off at no fault of their own. Third, the worker is actively seeking employment. The specific parameters of these criteria are set by states but commonly ineligible groups include self-employed workers, contract or gig workers, workers with low earnings, and new entrants to the labor market. The group of ineligible due to their earnings history makes up over ten percent of the labor force and their share has been growing over time.

There are several arguments that rationalize an earnings requirement to qualify for unemployment insurance. One is to encourage work. Another is to insure only substantive declines in income. A third is to discourage fraudulent claims.[1] Yet there remains limited analysis of the impacts of earnings history requirements for unemployment insurance leaving little guidance as to whether these goals are being achieved or what exact requirements would best achieve them.

This paper provides a quantitative framework to study the effects of expansions in UI eligibility and provides an analysis of the near universal UI expansion during COVID-19. The research strategy is as follows. First, a theoretical framework is developed to establish the factors that affect an individual's value of the UI program and the impact of the UI program on

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[1]If it cannot be distinguished whether a worker was laid off at no fault of their own or if they quit voluntarily then conditioning benefits on work history can limit the incentive to quit a job in order to collect benefits (Hopenhayn and Nicolini (2009)).

labor supply. Second, facts about how ineligible workers differ from workers who are eligible for UI are documented using high-frequency panel data. These facts are used to calibrate the model to reflect actual labor supply decisions and consumption dynamics around unemployment. The calibrated model is next used for policy analysis. It provides predictions for what should happen if UI were permanently expanded and decomposes why incentives and welfare values differ for the current ineligible group compared to the eligible. Finally, the model is used to understand how changes in UI systems during two recessionary episodes affected employment and welfare. Machine learning techniques are used to track job-finding of eligible and ineligible unemployed workers during the Great Recession, and administrative UI data are used to study the newly eligible PUA workers and regular UI workers during the COVID-19 eligibility expansion. These applications also serve as model validation and confirm it's predictive power.

The theoretical framework includes two margins of how unemployment insurance affects labor supply. First, there is the typical moral hazard component on job search. Receiving unemployment benefits lowers the net value of leaving unemployment to take a job. This is quantitatively tempered by the types of jobs available to a worker. Workers with higher earnings (and higher earnings growth rates) or longer lasting jobs have higher surplus of looking for employment rather than remaining on UI. Second, unemployment eligibility rules affect labor supply decisions for those close to the earnings eligibility threshold. A worker who would choose hours that put earnings just below the threshold in absence of a UI program would have the extra incentive to raise those hours off of their labor supply curve in order to qualify for UI. Those working harder to exceed the threshold then have reduced job search incentives than those on their labor supply curve since the added disutility of work from their extra hours pulls the net value of employment down. This extra distortion of the eligibility rules amplifies the moral hazard of these marginally eligible workers which is not only economically costly but also biases standard regression discontinuity designs to measure of the impact of eligibility.

The magnitude of the impact that UI eligibility rules have on labor supply and workers' welfare is a quantitative question depending on several margins. Data from the PSID are used to calibrate the model in order to replicate key targets for both the eligible and the ineligible. The ineligible are found to have lower wages, higher job loss rates, and less earnings growth on the job. These work to lower the value of employment and increase the predicted moral hazard impact of a UI extension. The estimated model infers the ineligible have lower job finding efficiency and a lower extensive utility cost of working. These not-directly-measurable factors also affect moral hazard and search effort. The data also provide evidence affirming a positive effect on earnings, mostly through increased hours, in order to cross the eligibility threshold. Just as has been established with the EITC, low wage individuals have the ability to change hours to qualify for the program.[2] This behavior demonstrates their value of the program and the excess mass around the threshold helps pin down the elasticity of hours to the UI program.

I calibrate the model to an additional fact that I document: the decline in consumption

[2] Mortenson and Whitten (2020)

in the year of a job loss. Conceptually, workers who value insurance the most are those with the largest fall in consumption during unemployment in absence of the program. Consumption insurance, however, can be provided through other means such as precautionary savings or transfers from family and other government programs. I analyze PSID data and document that consumption declines more around unemployment for the UI ineligible than for the eligible, but by less than would be predicted from a standard precautionary savings model. This is in part from informal insurance: 20% of low-earning and UI ineligible workers live in families earning over $100,000 per year. For ineligible workers in low-income families, there is access to insurance through other programs. Nearly half of the ineligible receive non-UI government transfers over $1,000 per year in the year of a job loss. With these results in mind, I calibrate total additional resources and transfers available to unemployed workers to match their consumption declines. An assuring result is that the model exhibits a precautionary savings rate that well matches the low liquid asset holding in the data although it was not targeted in the calibration.

I provide several UI expansion experiments and find that the full removal of the earnings history eligibility requirements brings welfare gains to workers across the productivity distribution. Removing the earnings threshold increases the welfare of low-wage workers currently below and some just above the threshold by over 3% of lifetime consumption. This comes at a cost of raising unemployment by 80 basis points, lowering GDP, and raising the tax burden on higher income workers resulting in a welfare loss for them. Removing the duration threshold benefits both high and low income workers. If workers became eligible for UI benefits after one week of work instead of 26 weeks, the value of working would increase, unemployment would fall, GDP would increase, and more workers would be protected by unemployment insurance. The average welfare gain from removing either the duration threshold or removing both is around 0.88% of lifetime consumption but the gains are more equally distributed when just the duration threshold is removed.

The model is further validated by and used to understand the impacts of actual changes to the UI system in the Global Financial Crisis (GFC) and the COVID-19 pandemic. This requires to first establish facts about how job loss and finding rates changed for ineligible versus the eligible during each episode, but eligibility status is not readily available in most data. For the GFC, I apply a machine learning algorithm trained on the biannual Displaced Workers Survey (DWS) which includes a question on unemployment receipt. The algorithm shows good predictive power for the validation sample and so I use it to impute unemployment receipt in the months where the DWS is not available. I find that job finding rates for the UI eligible fell by about 50% in the GFC whereas they were unchanged for the ineligible. The model provides a good fit as it predicts only a small fall in job finding for the ineligible of 2.4 basis points. I then ask what would have happened if UI eligibility were expanded to universal eligibility in the GFC and find that UI benefits would cost 5.2% of the wage bill, up from 4.3% without the expansion, but would have brought average welfare gains equal to 5% of consumption to the newly eligible.

A second test of the model is on an actual UI expansion. The Federal Pandemic Unemployment Assistance Program (PUA) expanded unemployment insurance eligibility to virtually all workers in the wake of COVID-19, effectively removing both the duration and earnings eligibility thresholds. The expansion was significant. By the end of the summer of 2021, PUA recipients comprised over 40% of continued claims. I use the aggregated administrative claims data to provide real-time estimates of the mean unemployment duration of PUA workers and for those workers on regular plus extended UI. I find that the typical PUA claimant remained on the unemployment rolls around 20% longer than regular UI claimants.[3] The model is calibrated replicate observed job loss and job finding rates, on average, when the complete changes to UI policy including the FPUC supplement and longer duration of benefits are fed in. The resulting simulation well replicates the non-targeted difference in job finding rates between the PUA and regular UI claimants, and thus further validates the out of sample predictive power. I then provide policy experiments and find the PUA expansion, when added to the FPUC and extensions, accounted for 29% of the extra spending on unemployment insurance. The removal of the earnings threshold and duration thresholds under PUA were each equally as costly, but the duration threshold removal brought higher welfare gains. The extended duration of benefits and the FPUC supplement were the most costly change to UI during the pandemic. They accounting for 52% and 78% of the extra spending on UI, respectively (with interaction terms reducing the univariate effects and making the sum of all of these initiatives equal 100%).

Literature. There is a large literature on the work disincentive effects of unemployment benefits. Prior work has analyzed topics that this paper will also engage with: the replacement rate (Landais et al. (2018)), and the duration of benefits (Nakajima (2012), Hagedorn et al. (2013), Mitman and Rabinovich (2024), Goensch et al. (2024), Grindaker and Simmons (2024)).[4] This paper extends these studies by including those normally ineligible for UI, documenting their characteristics and analyzing how their job search tradeoffs differ when interacting with UI. Birinci and See (2023) study the UI system with emphasis on wealth heterogeneity.

Most research on the temporary changes to unemployment benefits during the COVID-19 pandemic focus on changes to the weekly amounts paid to an unemployed worker, also referred to as a replacement rate. The Federal Pandemic Unemployment Compensation (FPUC) and other programs increased weekly payments by \$300-\$600. This was a subject of intrigue because some workers now received more money through unemployment benefits each week than they had earned on their previous job. Boar and Mongey (2020), Petrosky-Nadeau and Valletta (2021), and Fang et al. (2020) use structural models to assess the expected impact of increased UI replacement rates on job finding rates. These papers emphasize that the choice to take a job is a dynamic one. The value of a job relative to unemployment is generally higher than the value

[3]This includes those workers entering through regular state unemployment and staying on through federal extensions either through the Extended Benefit (EB) or Pandemic Emergency Unemployment Compensation (PEUC). Including extensions implies an apples to apples comparison where total length of potential benefits was similar across both groups.

[4]This is, certainly, a non-exhaustive list of structural equilibrium analyses.

of a week of earnings on the job relative to a week of unemployment benefits. All three papers predict that many workers with replacement rates over 100% would still return to their old job.[5] Petrosky-Nadeau and Valletta (2021) provide some evidence this is true using variation in replacement rates across US states. Other empirical papers generally find higher replacement rates lowered return to work but also emphasize the unique context provided by the pandemic, (Finamor and Scott (2021)). Ganong et al. (2021) find smaller disincentive effects during the early months of the pandemic. They emphasize that a scarcity of job opportunities and expected recall, both unique in scope to the pandemic, likely tempered disincentive effects relative to a normal recession. By contrast, Arbogast and Dupor (2022) find significant disincentive effects later on, when analyzing the removal of the UI extensions. This paper focuses on newly insured PUA recipients who I show would not be predicted to return to work. My results for the increased replacement rates of workers entering through regular UI, however, are broadly consistent with these studies.

Normative research, and particularly quantitative normative research, studying expanding unemployment eligibility to workers with lower earnings or instable employment history has been rather scarce. Most studies focus on optimal benefit levels and duration for all workers and ignore eligibility. Hopenhayn and Nicolini (2009) provide a theoretical underpinning of the screening advantages of limiting eligibility using work history when quits cannot be distinguished from layoffs. Baker and Rea Jr (1998) find a substantial increase in moral hazard– that is unemployment duration– when eligibility was expanded in a natural experiment in Canada. Khoury et al. (2020) study work duration eligibility in matched French employee-employer data. They find that separations increase significantly after the eligibility threshold (indicating moral hazard concerns are real) and workers just on the other side of this threshold search significantly longer but do not have better job quality outcomes. The analysis in this paper does not address normative issues and no welfare calculations are provided. As a consequence moral hazard and a host of issues dealing with different notions of labor market equilibrium, dynamic contracting, mechanism design, etc. are justifiably ignored. The objective is instead to provide an understanding of how job search tradeoffs change from a worker's perspective across the earnings and job stability spectrum in order to set up a quantitative environment for normative study.

2 Background: Unemployment Insurance Eligibility in the United States.

Basic Unemployment Insurance systems in the United States are administered by state governments within guidelines provided by the Federal government. State governments levy taxes to fund the program and set program parameters determining eligibility and benefit schedules. A key exception is supplemental and emergency programs funded by the Federal government but

[5] Non-structural analysis, such as in Altonji et al. (2020), mostly reach a similar conclusion.

administered by states. These programs will be addressed later in this paper.

Eligibility criteria vary across states and have several dimensions. Often, a worker must have earned a sufficient amount of money (earnings threshold) over a sufficient amount of time (duration threshold). The ranges of these parameters are wide and have nuance. When including Alternative Base Periods (ABPs), a typical UI system in 2020 required $2500 of earnings in one of the last two quarters and a lower level such as 50% as much in another quarter.[6] Some states have hours requirements. Others only count certain types of earnings such as those above a minimum wage thus excluding labor exempt from minimum wages. Eligibility often excludes certain types of work such as the self employed or "gig" workers. Workers often need to have lost their job at "no fault of their own", log active job search while unemployed, and be immediately available for fulltime work to continue to receive unemployment benefits.

The complicated parameters of state UI policies make it impossible to construct exact eligibility in any data set.[7] This paper will focus on eligibility determined by earnings history and cause of job separation. Earnings, employment, hours, and reason for job separation are constructed at the weekly frequency using data from the Panel Study of Income Dynamics (PSID). The PSID provides earnings on many jobs and the reason for job separation, a key eligibility requirement, that is not available to researchers using administrative data like the LEHD. This data set also has the advantage in that consumption is also reported. Individuals are designated as being ineligible if they fail to meet their state's earnings history requirements for eligibility. State eligibility rules were hand-coded from the 2019 *Comparison of State Unemployment Insurance Laws* published by the Department of Labor Employment and Training Administration (DOLETA).[8] I critically include Alternative Base Period (ABP) qualification as well as qualification by standard base periods. Workers with only self-employment income or those who report they lost their job for a firing at fault or that they quit are coded as ineligible for all states. The sample is restricted to workers who have had some attachment to the labor force. They are either currently employed or have been non-employed for six months or less.

Table 1 provides summary statistics on individuals by the type of their current or most recent job. Workers in ineligible jobs make up approximately a quarter of all employed individuals and two-thirds of all individuals out of work for six months or less. Eligible workers generally work more than uncovered workers on both the extensive and intensive margins. Women are more likely to be ineligible but it does not seem this difference is due to child care as the presence of young children is statistically insignificant across eligible and ineligible workers. There is, however, a significantly different share of ineligible workers that are outside of the prime-age working years: 37.4% versus 9.7% for the eligible. Ineligible workers are also significantly less likely to have a college degree. The difference in the racial composition is not statistically

[6] Standard base periods look back up to 4 quarters starting in the quarter prior to job loss but all except 12 states allow workers to qualify under ABPs that include the quarter of job loss. ABPs are a primary pathway that low-earning workers qualify and it is critical to include them when studying earnings history-related eligibility.

[7] Complete administrative data such as the LEHD lack reason for dismissal.

[8] Accessible at https://oui.doleta.gov/unemploy/pdf/uilawcompar/2019/complete.pdf. Threshold criteria do not include more idiosyncratic criteria dealing with specific industries, seasonal employment, and other factors.)

mean or % of Group	Eligible	Ineligible
Months Employed	11.7	8.0*
Child age 0-6	15.5	11.7
Under age 25	3.0	8.7*
Over age 65	6.7	28.7*
White	88.1	86.9
Black	11.9	13.1
Female	50.2	62.8*
College	71.5	57.4*
% of Pop Employed in a year	89.8	10.2
% of Those Currently Working	91.5	8.5
% of Those Currently Not Working	60.0	40.0

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.

% of Group	Eligible	Ineligible
Poverty	1.4	15.9*
Food Insecurity	10.2	23.4*
Gov Transfers> $1k	22.5	49.3*
Fam Income > $100k	53.7	19.6*
Annual Fall in Food if Unemployment Spell	5.4%	14.7*%
Annual Fall in Total Spending if Unemployment Spell	3.9%	9.6*%

*Statistically different at 95% CI.

Table 2: **Characteristic of households in the PSID by workers' regular state unemployment coverage status.**

significant.

Table 2 presents statistics related to economic security at the household level. Households are put into the ineligible column if they contain an ineligible worker and into the eligible column if they contain an eligible worker. Thus households may appear in both columns. These data suggest that ineligible workers' households show higher economic need than those of eligible workers. They are significantly more likely to be in poverty, have food insecurity, and receive government transfers over $1,000 per year. There is, however, significant heterogeneity in the socioeconomic status within each group. For example, some eligible households struggle with food insecurity (10.2%) and some ineligible households are well-off. A share of 19.6% of ineligible workers have a total family income over $100k per year. In these households the ineligible worker is often not the sole earner in the household which provides some additional insurance in the case of job loss.

A measure of economic 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 food consumption in three categories: food prepared at home, food delivered to the home, and food consumed away from the home. 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. The methodology of Attanasio and Pistaferri (2014) is used to address this and other issues. The precise methodology is discussed in Section 4.1 but a main result to motivate the model is that the average fall in spending on annual food consumption in a year of an unemployment spell is two-and-a-half times larger for uncovered workers' households. The food spending of the ineligible, including the value of food stamps, falls 14.7%. A fall of this magnitude is likely associated with economic hardship if a job is lost. Eligible households also experience declines in food consumption associated with unemployment of 5.8% on average. Declines are decreasing in total household income for both covered and uncovered workers but remain significant into the middle class suggesting UI provides incomplete insurance even for the eligible.[9]

3 A Theory of Eligibility, Labor Supply, and Welfare

This section develops a structural model of the factors that determine the asset value of a job relative to non-employment. Such factors include the costs associated with job search and claiming UI benefits, and alternative sources of consumption insurance.[10] It will be calibrated to explore whether these factors can account for the differential unemployment duration of workers who do and do not meet the earnings requirements to be eligible for unemployment insurance; as well as the increased duration of ineligible workers when covered by the PUA program during the pandemic. Wages are determined in equilibrium in conjunction with profit maximizing firms.

The model will be described for a generic job type. In the quantitative section I will explain the difference in the parameter values across ineligible and eligible jobs.

Worker Types. There is a continuum of ex-ante non-identical workers. Workers are distinguished by a fixed permanent type $i \in \{1, 2\}$ each with share m_i in the population. A type will relate to the labor market productivity, and job finding and job loss rates for workers of that type. A share β^D of each type of workers die each period and are replaced by new labor market entrants of the same type.

Individual workers are further distinguished by ex-post and evolving individual states: their labor productivity z, labor market status q, weeks in their current state d, and asset holdings a. Labor force status takes two values: $q \in \{E, N\}$ or employed and non-employed, respectively. New entrants begin as non-employed and are endowed with an initial level of labor productivity from their type i's distribution $z \in \{z_{i1}, z_{i2}, ...z_{in}\}$ which will evolve stochastically during periods of employment and non-employment. The weeks in a state variable d will be used to calculate a worker's eligibility status for unemployment benefits. Assets are restricted to the bounded set $a \in [0, \bar{a}]$.

[9]A candidate explanation is differential access to credit markets as studied in Braxton et al. (2020) and Herkenhoff (2019).

[10]The dynamic tradeoffs to a worker typical in search models are discussed by Boar and Mongey (2020)

Preferences. Employed workers gain utility from consumption c, and suffer disutility in hours worked h and a fixed utility cost of work depending on individual fixed type, ϕ_i. Non-employed workers gain utility from consumption and suffer disutility from search effort s. These preferences are represented by the flow utility function $U(c,h,s) = u(c,h) - v(s) - \phi_i \mathcal{I}_{q=e}$. The function $u(\cdot)$ is increasing and concave in the first argument and decreasing and convex in the second. The disutility from search is separable and the function $v(\cdot)$ is increasing and convex in s.

Choices. Each period, individuals make consumption c and savings a' choices. Employed workers choose how many hours to work at their job $h \in (0, \bar{h}]$. Non-employed workers choose how much effort to put into searching for a job $s \in [0, \bar{s}]$. A non-employed worker who chooses $s = 0$ is classified as not in the labor force. A non-employed worker who chooses $s > 0$ is classified as unemployed. Newly unemployed workers choose of whether to pay a fixed utility cost κ_i to claim unemployment benefits $m = 1$, or not $m = 0$.

Constraints, Technologies, and Laws of Motion for Workers. The consumption resources available to an individual depend partially on their labor market status. All individuals have asset income from savings in the prior period $(1 + r)a$ and may have transfers: $T_i^q(z, h)$. Transfers capture government payments to individuals that are not unemployment insurance such as food stamps and welfare, as well as informal transfers within households or from non-governmental organizations.[11] Employed individuals collect labor income $(1-\tau)w_i zh$ each period after taxes τ are removed. Total labor income is a function of the wage per efficiency unit paid to the worker's fixed type w_i, her idiosyncratic productivity z, and her hours worked h. Labor income is taxed at a common rate τ for all workers. Newly unemployed and UI eligible individuals who chose to collect UI incur a one-time non-pecuniary cost κ_i. The UI payment schedule $b(w_i, z, d)$ depends on workers' fixed types and current productivity, and expire after a number of weeks unemployed: $\bar{d}$.

The law of motion for weeks in current state is somewhat complicated to match the complexity of UI determination. For the non-employed individual, the state d is used to track weeks of *remaining eligibility*. For the employed individual, it is used to track *accumulated weeks towards eligibility*. Formally, an individual who is non-employed and stays non-employed has the process $d' = d + 1$. An individual who is currently employed and becomes non-employed has the process $d' = \bar{d}$ if either they: (i) had not worked long enough with high enough income to be eligible ($d < \underline{d}^b$); (ii) they quit; (iii) they do not search $s = 0$; or (iv) choose not to pay the cost κ_i to collect. If they otherwise collect, then $d' = 0$. An individual who is employed and remains employed has the process $d' = d + 1$ if they earn above the threshold required for eligibility $w_i zh > \underline{earn}^b$ and $d' = d$ otherwise. An individual who was non-employed and becomes employed restarts their clock at $d' = 0$.

[11]These transfers will be calibrated to replicate falls in consumption during unemployment and are not part of the government budget balance since we cannot completely distinguish what percentage of the fall in consumption is buffered by government programs.

Idiosyncratic productivity z follows a sparse Markov chain dependent on labor market state. The function $\rho^z(z'|q,z)$ describes the probability a particular value is drawn for z' and is also conditional on the current value of z. It sums to one across all potential values of z' for a given q and z. Productivity is weakly increasing while employed akin to a theory of learning by doing. It is weakly decreasing while non-employed to replicate wage losses following job loss.

Jobs are destroyed with a type-specific hazard rate $\delta_i(d)$ that is weekly decreasing in the measure of job duration d. Job opportunities arrive for non-employed workers at a rate $\pi_i s$, proportional to the type-specific search efficiency π_i and chosen search intensity s.

The value of a job. The value of a job to a worker with fixed type i, earnings potential z, completed job duration d, and assets a is:

$$\begin{aligned}
J_i(z,d,a) &= \max_{h,a'} u(c,h) - \phi_i + \\
&\quad \beta \mathbf{E}_{z'|z}[(1-\delta_i(d))\max\{J_i(z',d'_e,a'),V_i(z',\bar{d},a')\} + \delta_i(d)V_i(z',d'_{ne},a')] \\
st &\quad c + a' = (1-\tau)w_i z h + T^q_i(z,h) + (1+r)a \\
&\quad a' \geq 0 \quad h \in (0,\bar{h}] \\
&\quad d'_e = d+1 \;\text{ if } w_i z h > \underline{earn}^b \;; \quad = 0 \;\text{ o/w} \\
&\quad d'_{ne} = 0 \;\text{ if } d > \underline{\mathrm{d}}^b \;; \quad = \bar{d} \;\text{ o/w}
\end{aligned}$$

The continuation value of a job is discounted at rate $\beta \in (0,1)$. With probability $\delta_i(d)$, the worker loses her job and her expected continuation value is the expected value of non-employment $V_i(z',d'_{ne},a')$. With probability $1-\delta_i(d)$, the worker keeps her job and her expected continuation value is the maximum of the expected value of employment $J_i(z',d'_e,a')$ and the expected value of quitting $V_i(z',\bar{d},a')$. If the worker quits, they will not be eligible for unemployment insurance and so $d' = \bar{d}$. Expectations are over possible values of z' tomorrow and are rationally consistent with the actual Markov transitions.

Claiming choice of a newly separated worker. The eligibility of a newly separated worker is summarized by her d; if $d = 0$ she has been determined to be eligible and if $d = \bar{d}$ she has been determined as ineligible. The eligible worker must now pay a non-pecuniary cost κ_i if she would like to claim unemployment benefits. This is interpreted as any fixed cost of the application process or stigma. Given $V(\cdot)$, the value of non-employment defined in the next section, her problem is summarized as follows:

$$\max\left\{ \underbrace{V_i(z,d,a) - \kappa_i}_{\text{apply for and collect UI}} \;,\; \underbrace{V_i(z,\bar{d},a)}_{\text{do not collect UI}} \right\}$$

The value of Non-employment. The value of non-employment to an individual with fixed type i, earnings potential z, completed weeks of eligible non-employment d, and assets a is as follows.

$$\begin{aligned} V_i(z,d,a) &= \max_{s,a'} u(c,0) - v(s) + \beta \mathbf{E}_{z'|z}[(1-\pi_i s)V_i(z',d'_{ne},a') + \pi_i s J_i(z',d'_e,a')] \\ st &\quad c + a' = b(w_i,z,d) + T_i^q(z,h) + (1+r)a \\ &\quad a' \geq 0 \quad s \in [0,\bar{s}] \\ &\quad d'_{ne} = d+1 \\ &\quad d'_e = 0 \end{aligned}$$

The asset value of non-employment includes the asset value of a job for workers who search. Workers who search for a job find one with probability $s\pi_i \in [0,1)$ where s is the worker's search effort and π_i is an exogenous linear search efficiency. Search has a convex, non-pecuniary cost $v(s)$. Workers who do not find a job or do not search remain unemployed. All workers' stochastic state z' may change next period while the assets evolve according to their chosen value. The "time in state" variable d' increases by one if the individual remains non-employed and resets to zero if the individual takes a job and moves to employment.

Firms. There is a single representative firm in the economy. Output is a function of total efficiency units of labor hired of each type of labor, $i \in \{1,2\}$: $Y = F(L_1, L_2)$. The market for labor is assumed to be competitive. Wages paid to each type of labor equal their marginal product: $w_i = \frac{dY}{dL_i}$.

Stationary Equilibrium. An equilibrium is a set of decision rules for the households: hours $g_i^h(z,d,a;q)$, savings $g_i^a(z,d,a;q)$, job search $g_i^s(z,d,a;q)$, whether to quit $g_i^Q(z,d,a;q)$, and whether to claim $g_i^m(z,d,a;q)$; a stationary distribution $\theta_i(z,d,a;q)$; labor demand L_1, L_2, and prices w_1, w_2 such that given all exogenous parameters the following hold true.

1. Households Optimize: $g_i^h(z,d,a;q)$, $g_i^a(z,d,a;q)$, $g_i^s(z,d,a;q)$, and $g_i^Q(z,d,a;q)$ are solutions to the dynamic programs above.
2. Labor Markets Clear: $L_i = \int_{izda} \theta_i(z,d,a;q=e) z g_i^h(z,d,a;q=e)$
3. Distribution $\theta_i(z,d,a;q)$ is consistent with policy rules and is stationary $\theta_i(z,d,a;q)' = \theta_i(z,d,a;q)$ for all i,z,d,a,q in their bounded ranges.
4. Government Budget Balance holds for UI. $\sum_i \tau L_i = \int_{izda} \theta_i(z,d,a;q=u) b(w_i,z,d)$

A few notes about the equilibrium concept. First, search frictions are exogenously given and the market for assets are partial equilibrium. The job destruction rate is partially endogenous as a worker may choose to quit. Second, the only government program considered is unemployment benefits. As in the US system, unemployment insurance taxes are levied on both on workers earning below and above the eligibility threshold.[12]

Comparative Statics. The quantitative part of this paper focuses on the nuances of the asset value of jobs and unemployment; and how they may account for differing behavior of eligible and non-eligible workers. If workers were myopic $\beta = 0$ then the value of unemployment and employment would be equal to the flow values of consumption alone. In this case, the search choice of a worker is easy. Her search effort is increasing in how much her earnings potential minus her utility cost of work exceeds the value of her unemployment benefits. This comparative static is still true in the full model, but is quantitatively tempered by variation in the asset values of employment and unemployment. Generally, the asset value of employment is higher than what would be provided by the present discounted current flow value for three reasons: productivity is weakly increasing in tenure (learning by doing); UI qualification requires working several periods; and having a job today increases the chance of having a job tomorrow (and at no extra search cost) compared to when unemployed. Conversely, the asset value of unemployment is generally lower than the present discounted value of the current flow value for three reasons: productivity is weakly decreasing in unemployment duration (wage scarring); any precautionary savings get drawn down; and UI benefits have an and date.

Formally, these claims are as follows.

Proposition 1 (Quitting Threshold): For a given i, z, d, a such that $J_i(z, d, a) > V_i(z, 0, a)$: the asset value of a job $J_i(z, d, a)$ is weakly increasing in:

- (i) the rate of productivity growth on the job; $(\hat{J}_i(z, d, a) - \hat{V}_i(z, 0, a)) \geq (J_i(z, d, a) - V_i(z, 0, a))$ for $\hat{\rho}^z(z; q = e) \succ_{FSD} \rho(z; q = e)^z$.
- (ii) the speed of gaining UI qualification; $(\hat{J}_i(z, d, a) - \hat{V}_i(z, 0, a)) \geq (J_i(z, d, a) - V_i(z, 0, a))$ for $\hat{\underline{\mathrm{d}}}^b < \underline{\mathrm{d}}^b$.
- (iii) the expected duration of the match; $(\hat{J}_i(z, d, a) - \hat{V}_i(z, 0, a)) \geq (J_i(z, d, a) - V_i(z, 0, a))$ for $\delta_i \hat{(d)} < \delta_i(d)$ for all d in the range.

Proposition 2: For a given i, z, d_e, a, the asset value of non-employment $V_i(z, d, a))$ is weakly decreasing in:

- (i) the rate of productivity decay while off the job; $\hat{V}_i(z, d, a) \geq \hat{V}_i(z, d, a)$ for $\hat{\rho}^z(z; q \neq e) \succ_{FSD} \rho(z; q \neq e)^z$.
- (ii) the speed of losing UI qualification; $\hat{V}_i(z, d, a) \geq \hat{V}_i(z, d, a)$ for $\hat{d} > \bar{d}$.

A corollary is that a comparison of flow earnings on a job to flow unemployment benefits is an insufficient determinant of job search intensity. Indeed, the latter can exceed the former and an unemployed worker can still want a job due to the comparison of asset values.

[12]UI taxes are complicated. There are both Federal and State taxes that tend to be highly regressive. For example, the standard 2025 Federal Unemployment Tax (FUTA) tax rate is 6.0% on the first $7,000 of taxable wages paid to each employee during the calendar year. Beyond this, employers are subject to state determined experience ratings.

4 Calibration and Quantitative Analysis.

The main quantitative assessment of the model is to see whether it can account for the differences in unemployment duration of eligible and non-eligible workers in three historical cases with varying UI payment durations, replacement rates, and eligibility criteria: (1) normal times (2014-2019); (2) the great recession (2008-2012); and (3) the COVID pandemic September 2020-May 2021.

The quantitative analysis includes two job types: eligible and threshold jobs. Eligible jobs are those with high enough earnings such that a worker will become eligible for unemployment insurance if they work for a sufficient duration. Threshold jobs include a range of jobs starting with earnings too low to qualify for unemployment insurance even if the worker is employed for the duration required to qualify and spanning to jobs that qualify with earnings double the threshold. Workers will be assigned to a job type and there is no switching probability in the baseline model. This is because, as documented in the appendix, switches between eligibility status are rare and primarily due to changes in job duration rather than earnings (less than 5% per year).

It is important to distinguish that the job type of a worker is distinct from their UI qualification status. An eligible worker is only qualified if they work for a sufficient duration. This distinction will be important later on when discussing the impact of the PUA program because PUA claims include all workers in threshold jobs and also workers in eligible jobs who are not yet qualified. Thus, the discussion of workers will include both their job types and qualification statuses.

4.1 Calibration.

The model period is one week. The discount factor is set to $\beta = 0.995$ and the interest rate to $r = 1.005$. The production technology is CES: $(\alpha_y L_1^{\rho_y} + L_2^{\rho_y})^{\frac{1}{\rho_y}}$. I set $\alpha_y = 1$ and $rho_y = 1$ since I calculate that the relative wages of the ineligible compared to the eligible are relatively constant over the business cycle in my PSID sample (2003-2019).

Technological parameters of the two job types differ but workers have the same preferences except for the flow cost of work. Preferences over consumption c, hours worked h, and search effort s take the following functional form:

$$u_i(c, h, s) = \frac{1}{1-\sigma}(c - \chi_h \frac{h^{1+\sigma_h}}{1+\sigma_h})^{1-\sigma} - \chi_i \mathcal{I}_{h>0} - \chi_s s^{\eta}$$

The utility specification is chosen to eliminate the impact of wealth effects on labor supply. This allows the model to replicate the positive relationship between hours and earnings that critically distinguish the eligible and ineligible groups in the data. The eligible group is high productivity (by definition) and works the longest hours. The threshold group is low productivity and works fewer hours. Further, a sizeable portion of the threshold group has high consumption in the data due to their status as secondary earners, adult children, or retirees. The model includes transfers above their own labor earnings to match their consumption and would have a hard time inducing them to work at all if there were significant wealth effects on labor supply.

The utility cost of job search takes a common form in the literature: $\chi_s s^\eta$. Studies using microeconomic time use data provide a range of estimates of η and I choose a central value $\eta = 3.0$.[13] The cost parameter χ_s is calibrated such that endogenous job search effort of unqualified workers matches the average search time of unqualified workers estimated in time use data by Krueger and Mueller (2010): 47 minutes out of a potential 4 hours for job search in a day.[14] The fixed flow utility cost of work $\chi_i \mathcal{I}_{h>0}$ is normalized to zero for ineligible jobs and, for eligible jobs, is calibrated to match the average search time of UI recipients in Krueger and Mueller (2010): 33 minutes a day.[15] The inter-temporal elasticity σ is set to 2, a standard value.

The remaining parameters are chosen to match estimates from the Panel Study of Income Dynamics.[16] The earnings process for each type of job are estimated from the PSID data for eligible and ineligible workers. Non-employed workers are only included if they have worked in the last twelve months. The earnings ladder for each job is chosen to match the median life-cycle income profile for each and include wage scarring targets for the non-employed. In the baseline calibration, workers in each job become unemployed with a weekly probability that replicates, on average, the monthly separation rate for each type of job in the PSID data. Individuals also receive government transfers which are calibrated to be equal to the median food stamp values in the PSID data of approximately \$60/week in 2019 dollars.

The UI program rules are set to replicate rules for New York state. The duration $\underline{\mathrm{d}}^b$ requirement for UI for workers in eligible jobs to become qualified is set to 26 weeks. The earnings threshold defining the maximum earnings in an ineligible job is set to \$2400 per quarter. The duration of unemployment benefits $\bar{d}^b$ is set to 26 weeks during normal times and will be extended to 99 weeks in the Great Recession. The duration of unemployment benefits is set to 75 weeks during the pandemic resulting in termination in mid-July 2021. This is to account for the states that ended the emergency federal programs early and I will provide evidence flows off of UI increased around this date.

Unemployed workers who are qualified for unemployment benefits receive benefits equal to the formula provided for New York state. This formula specifies a base rate of \$50 per week that increases at a linear rate for workers earning between \$950 and \$11,675 per month to a cap of \$480/week. Additional family income and/or informal transfers are chosen such that the average drop in consumption in the model equals a measure of the average drop in consumption in the PSID data. For the empirical targets, I first obtain an estimate of the change in household food consumption (not expenditure) during a year in which unemployment occurs. Food consumption is predicted with a regression controlling for age, family composition, share

[13] Gomme and Lkhagvasuren (2015); Faberman et al. (2017).

[14] Potential hours are set at 4 to match the range of typical job search per week in ATUS studies.

[15] The higher utility cost of work for eligible jobs is necessary because the other job-specific parameters of the model do not provide the difference in job search intensity seen in the data. A higher cost, however, is not unreasonable since eligible jobs have higher hours than ineligible jobs in the PSID data.

[16] The construction of this panel is mentioned in Section 2 and detailed in the Online Appendix.

of spending on each food category, the CPI of each food category, and individual family fixed effects in a similar manner to Blundell et al. (2008). Food consumption is adjusted to per-capita following the OECD formula for children and adults in household. I then regress annual changes in per capita food consumption on a dummy for unemployment in a year, including only those working continuously or with unemployment duration of six months or less. Second, I directly calculate the change in total expenditure on all goods and services in a year and conduct a similar regression to estimate the impact of unemployment on total spending.[17] The targeted change in consumption is the midpoint between the change in food consumption and change in total expenditure relative to predicted. The results of the second stage regression are reported in 3. To ensure a consumption floor, asset poor individuals also receive government transfers which are calibrated to be equal to the median food stamp values in the PSID data of \$60/week in 2019 dollars. Summary statistics, results of the first stage, and formal details of the regressions are available in the appendix.

	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 3: **The Effect of Unemployment on Household Consumption**

Notes: The dependent variables are log changes in OECD household size adjusted food consumption (column 1) and OECD household size 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.

Target	Covered	Uncovered
Annual earnings growth in E	2.6%	1.8%
Annual earnings loss in U	3.4%	5.7%
Median annual earnings	\$48k	\$8.6k
Monthly Hours (out of 240)	66.7%	41.5%
Search time	33 min	47 min
Monthly U to E	25%	25%
Monthly E to U	0.5%	2.5%
Consumption drop in U	4.9%	12.2%
UI Claiming rate (of eligible)	75%	

Table 4: Calibration Target Highlights

The model is exactly identified and the targets listed in Table 4 can be exactly matched. The

[17] I provide both of these concepts to give readers a sense of the change in actual spending for comparison with other studies. Change in spending is not a good measure of change in consumption due to things like durable goods and substitution of own time for purchased services.

only parameters that are internally calibrated after solving for policy rules are the fixed cost of applying for UI, and the two parameters for disutility of hours parameters, one search disutility parameter, the search efficiency of each type, the fixed cost of work, and informal transfers. While I do not have a proof, comparative statics show that the targets for these parameters are strongly monotone in one to two parameters which suggests that the calibration is locally unique within a broad scope.

Parameter	Value	Parameter	Value
Discount rate (β)	0.995	Interest rate $(1+r)$	1.005
IES parameter (σ)	2.0	Curvature on search cost (η)	3.0
Consumption Floor ($\bar{c}$)	\$60	Other Transfers (T)	(\$130,\$96)
Constant on search cost (χ_s)	80	Curvature on search cost (η)	3.0
Constant on hours disutility (chi_h)	1.8	Curvature on hours (σ_h)	3.5
Fixed Cost of Work	(0,0.3)	Fixed Cost of UI Application	7.0

Table 5: **Model Parameter Values (weekly)**. Values in brackets are for types (covered, uncovered).

Table 5 lists the calibrated parameter values. For context, the calibration implies that workers' endogenous search decisions provide a consumption equivalent flow utility cost worth 10.5 (9.1)% of flow employment consumption for the eligible (ineligible). The flow cost of work for eligible jobs is a welfare consumption equivalent to 14.1% of median eligible consumption. The one-time cost to collect UI benefits, if eligible, is a welfare consumption equivalent of 3.27 weeks of median eligible employed consumption.

Statistic	Model	Data
Aggregate Unemployment	5.5%	5.4^{a}%
Uncovered Share of U	37.3%	40.0^{b}%
Assets-to-Income	3.3 weeks	0.74 months^{c}
Replacement Rate of UI recipients	53.4%	52.0^{c}%
Hours jump, earnings threshold	19.1%	20^{b}%

[a] Data unemployment rate is the monthly median 2000-2019 in the Current Population Survey (CPS).
[b] Uncovered share of unemployed- author's calculation in PSID.
[c] Taken from Birinci and See (2023).

Table 6: **Non-targeted Statistics**

Table 6 presents some non-targeted statistics. While the average flows in each type of job are targeted using PSID data, it is a nice check to see that the equilibrium aggregate unemployment rate is in a good range when compared to the larger CPS survey[18] and that the share of uncovered workers in unemployment is nearly spot on as well. The assets-to-income ratio is also non-targeted but is strikingly close to the 3.1 weeks (0.74 months) found by Birinci and See (2023) in the Survey of Income Programs and Participation. Finally, the income replacement rate of UI recipients is nearly identical to that found in Birinci and See (2023), suggesting that the model's prediction for selection onto the program is a good approximation of reality. The hours jump around the earnings threshold for eligibility will be discussed in the next section.

[18]Data accessed via FRED.

As will become clear, the local elasticity of hours to the threshold greatly affects the moral hazard influence on search for unemployed workers who earned near the threshold. The model's excellent replication of this elasticity is paramount to the analysis of the impact of eligibility.

5 Mechanics of the Baseline Model.

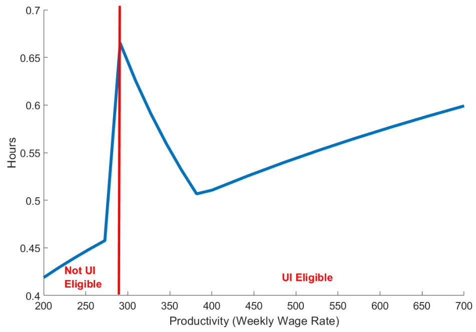
There are two main choices in the model: hours and job search effort. This section reviews how eligibility rules affect these decisions for threshold job holders in comparison to high earnings jobs away from the threshold. These choices are key for how eligibility policy affects individuals' welfare as well as total economic output and government expenditures.

Hours. Away from the earnings eligibility threshold, GHH preferences deliver strong increasing monotonicity of hours in individuals' productivity (wage) despite heterogeneity in wealth like assets or informal transfers/family income. The incentive provided by the earnings eligibility threshold interrupts this monotonicity. Workers who would be a bit below their threshold if they choose hours according to the pure wage incentives in their Euler equation (h^{euler}) instead choose to work additional hours off of this Euler equation in order to qualify (h^{qual}). This is because the additional hours worked have a discrete jump in their value due to the reward provided by qualifying for UI. Abusing notation to ignore other heterogeneity, let $g^a(h)$ refer to the asset choice given hours choice h. The decision of an agent then involves checking corners: whether the discrete jump in hours makes sense as shown in the equations below.

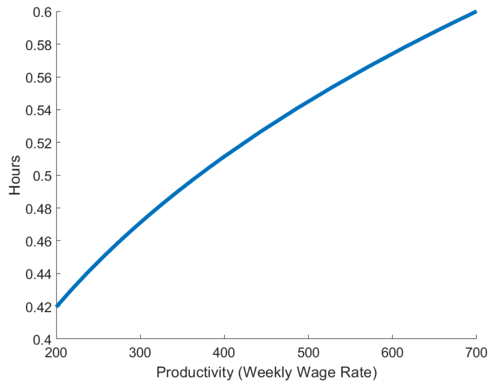
$$
\begin{aligned}
h^{euler} &= \left(\frac{w}{\chi_h}\right)^{\frac{1}{\sigma_h}} \\
g^h = h^{qual} &\text{ iff } \underbrace{\chi_h(h^{qual})^{\sigma_h} - \chi_h(h^{euler})^{\sigma_h}}_{\text{Cost of additional hours}} \\
&\leq \underbrace{w(h^{qual} - h^{euler})}_{\text{Additional Earnings}} + \underbrace{\beta E[V(z, d+1, g^a(h^{qual})) - V(z, d, g^a(h^{euler}))]}_{\text{value of progressing towards qualifying}}
\end{aligned}
$$

The effect of the threshold on hours produces a policy function shown in Figure 1 for a given state. What does this look like in the data? I look for evidence that workers are exhibiting effort to move above the qualification thresholds using weekly earnings histories constructed in the PSID.[19] I use the hand-coded state-specific qualifying rules for each worker and then compute the distance of their earnings from the qualifying threshold in their state at each point in time. Crucially, I include Alternative Base Periods (ABPs) when calculating eligibility. A typical base period ends in the quarter prior to employment termination but ABPs allow earnings in the current period of employment termination to be included. This is critical for low-earning

[19]As a side note, there is no excess mass in job separations above the threshold in US data. Based on these facts the model includes the impact of UI on the hours margin but not the impact of UI on the likelihood of separation.



(a) with earnings threshold



(b) with universal eligibility

Figure 1: Hours policy: with eligibility earnings threshold (left), and w/out (right).

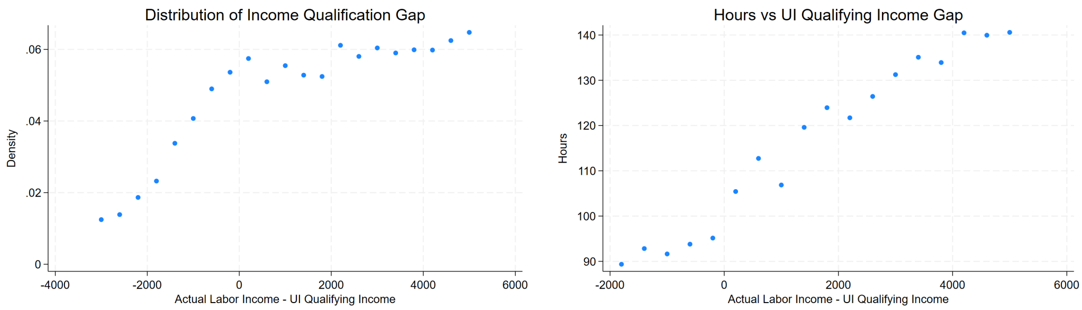


Figure 2: **Density of earnings and mean hours around individuals' income - their state UI qualifying income threshold in the PSID.**

workers. It is estimated that over 58% of those qualifying under an ABP are in the first earnings quartile (Stettner et al. (2005)).

Figure 2 shows the density of earnings and mean hours of individuals 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 a manipulation of

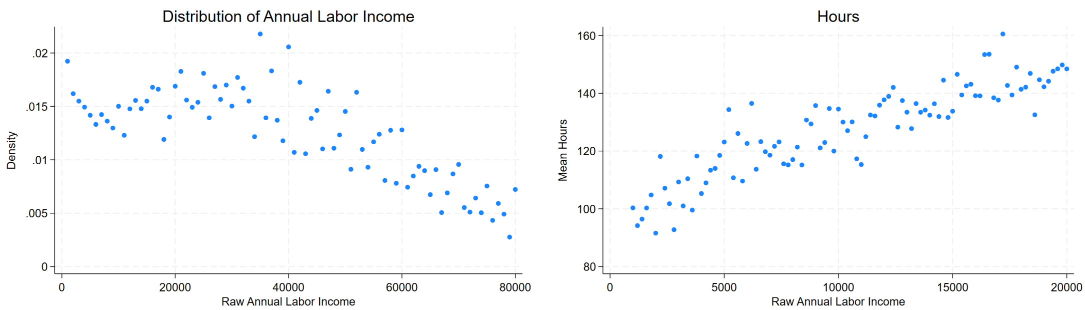


Figure 3: **Density of total annual earnings and hours in the PSID.**

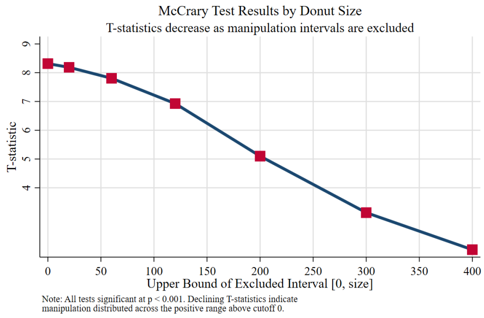
hours to earn more to get over the threshold.

The appendix contains additional data cuts that reveal even stronger jumps in states with more well-defined rules, placebo tests, and additional McCrary Tests verifying this result. An eye-ball view of the placebo test is shown by the regularity of hours and earnings shown in Figure 3. The left panel is the density of annual total earnings of individuals in jobs outside of self-employment. The right-panel shows the average annual hours worked in each earnings bin. The jumps in Figure 2 are not present in this graph, indicating the state-specificity of the earnings threshold is driving them and not an unrelated feature of the earnings distribution.

More formally, Table 4a and Figure 4b show the results for a 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 ($p < 0.001$), indicating density manipulation. 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 1.848 ($p = 0.065$). The progressive reduction in test statistics reinforces that the earnings threshold is meaningful despite potential rounding-bunching in self-earnings reports, while also providing evidence of potential overshooting.[20]

Excluded Range	Obs.	P-val	T-stat	Reduction (%)
Base	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

(a) **One-Sided Donut McCrary Test Results**



(b) Visual outcome of the donut test

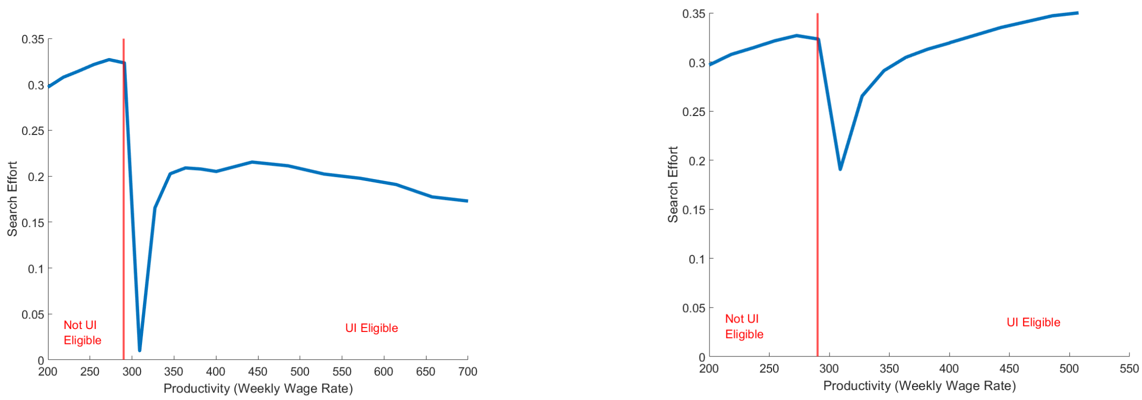
Figure 4: **Donut McCrary Test Analysis**

Based on this evidence, there is a jump in hours of approximately 20% around the earnings threshold. In the model, the peak jump in $h^{qualify}$ relative to h^{euler} is 31.8% but the average is 19.1% within a 10% earnings range above the threshold. This is an excellent non-targeted fit that both validates the model and suggests the model has a realistic key elasticity of hours relative to the earnings eligibility rule.

Search Effort. In a world without an UI program, search effort would be increasing in productivity, all else equal. The presence of a UI program, especially one with an earnings threshold for eligibility, disrupts this pattern and does so even for the long-term unemployed who have exhausted their benefits.

[20]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.

Figure 5 depicts the search policy for jobs near the threshold. The left pane shows search effort before the eligible unemployed exhaust their benefits and the right shows search effort when the eligible unemployed have exhausted their benefits and are no longer able to collect UI. The search policy is normal for workers who are not eligible for UI and would be earning below the threshold if employed. It is qualitatively similar to if there were no UI at all.[21] Further above the threshold, search effort is climbing when UI is exhausted (b) and falling in the first period of UI claiming when many weeks remain (a). This decline is purely due to the UI benefit replacement rate specification which is regressive at first and then progressive at much higher earnings levels. If panel (a) were extended we would see an increase in search effort after the maximum benefit level is reached and the replacement rate falls. The difference between the two panes is as expected for these workers: search effort increases when benefits are exhausted.



(a) before benefit exhaustion

(b) after benefit exhaustion

Figure 5: **Search policy: while collecting UI (left), and after UI benefits are exhausted (right).**

The unusual precipitous drop in search effort just over the threshold is due to the eligibility threshold design of the program. These workers would be off of the normal Euler equation for hours if they were working. They are working harder than what is justified by the wage in order to qualify for UI. The extra disutility of hours pulls down the value of employment relative to both those with low enough or high enough productivity to be back on their Euler equation, and the ability to collect UI pulls up the value of unemployment relative to those just below the threshold. This causes the net benefit of employment to be lowest for the marginally eligible. The right panel shows that this effect persists even when UI is exhausted. This isolates the pure effect of working hours off of the normal Euler equation in pulling down the value of work.

The results in Figure 5 are important for the evaluation and design of UI threshold policies. First, the drop in search effort just above the threshold stands as a caution against empirical threshold design, such as used in a difference-in-difference estimator, to study the impact of UI receipt. The PSID analysis showed that there may not be a sharp break in earnings and

[21] The search effort is a bit above what it would be if there were no UI at all. Due to the job ladder dynamics in the model even a worker below the threshold has extra incentive to work in order to climb the ladder and UI eligibility is a bonus that makes that climb a bit more valuable.

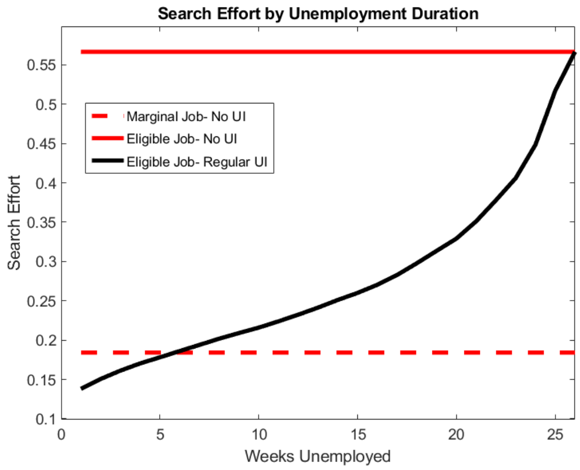


Figure 6: **Search effort dynamics over unemployment spell.**

hours worked around the threshold due to measurement error or overshooting while the donut approach corrected for this and found significant evidence that individuals do work harder to get above the threshold. In this case, these individuals have a sharply lower incentive to search for a job than those farther up beyond the threshold and are not representative of the impact a UI extension would have on search disincentives. Indeed, they are a worst case scenario. Secondly, the fall in search effort illustrates that UI earnings eligibility thresholds have a welfare cost. Those who work harder to qualify ameliorate the value of UI eligibility with the marginal, lowest productivity UI recipient being indifferent between having the program around or not. These workers "pay" more than others for the program with their added disutility of work and this payment, as well as the added moral hazard it creates, should be considered when evaluating the cost of the program.

Figure 6 shows how search effort evolves over an unemployment spell. The movement from search effort in week one of unemployment (panel (a) of Figure 5) to the week of benefit exhaustion (panel (b) Figure 5) does not happen suddenly in the week of benefit exhaustion. Agents are forward looking and the search effort of those collecting UI increases gradually over time as the final week of eligibility draws near. The pace at which their search effort increases over time depends on several factors including whether there is a net positive surplus of being employed while collecting UI and how easy it is to find a job. The difference between the search effort of the threshold jobs with no UI (those not meeting the earnings threshold) and the search effort of the eligible job with no UI (those not meeting the duration threshold) reflect how these factors are different in the different job types. Absent UI payments, the high productivity workers search more than twice as hard as the low productivity workers, and even after 6 weeks high-productivity workers who are receiving UI search harder than the low productivity threshold job workers.

Table 7 provides experiments to measure the impacts various factors have on the search intensity of the marginal job holders. The contribution of each factor is studied by assigning, one at a time in isolation, the characteristics of eligible jobs to marginal job workers. The lower

Threshold Job Search Effort	
Baseline	**0.196**
Decomposition of Threshold Job Search Effort	
If had eligible's...	
Job finding efficiency	0.288
Job loss rate	0.273
Earnings Process	0.259
Fixed utility cost of work	0.140
*** Matched data value in baseline calibration**	

Table 7: **Decomposition of differences in search intensity across job type.**

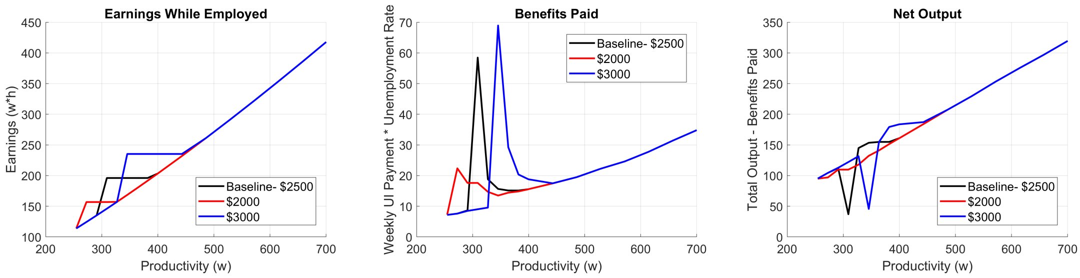


Figure 7: **Changing the earnings threshold.** Left: monthly earnings while employed. Middle: total UI payments to unemployed Right: Net output = wage bill of employed − total UI payments to unemployed.

efficiency of search χ for marginal jobs has the largest impact on lowering search effort compared to if it held the same value as eligible jobs, a decline of 32%. Next is the higher job loss rate, which lowers the asset value of a job and reduces search effort by 28%. The difference in the earnings process reduces search effort by 24%. One factor increases search effort in marginal jobs relative to eligible jobs. Workers in eligible jobs have a higher fixed utility cost of work. The lower utility cost for workers in marginal jobs increases their search effort by 40%. The conclusions of this analysis are that there are many differences in incentives affecting the search effort of workers in marginal jobs versus the eligible and we should not expect them to behave the same as currently eligible workers if UI eligibility were expanded to them.

6 Expanding Unemployment Insurance.

The model is now used to analyze what would happen to individual's welfare and to the economy as a whole if UI were to be expanded on a permanent basis. All experiments maintain the equilibrium assumptions: agents optimize in response to the new policies; and wages and taxes adjust to clear markets and balance the government budget.

Figure 7 illustrates responses to a changes in the earnings threshold for eligibility, zooming in on marginal jobs near the earnings threshold. The leftmost panel shows earnings while employed, the product of productivity (x-axis) and hours. We see the positive bump to earnings of workers around the threshold who work additional hours to clear the threshold. This is a boost to aggregate output but is costly in terms of these workers' added disutility of work. These extra hours reduce the benefit of working relative to the value of unemployment, and even more so

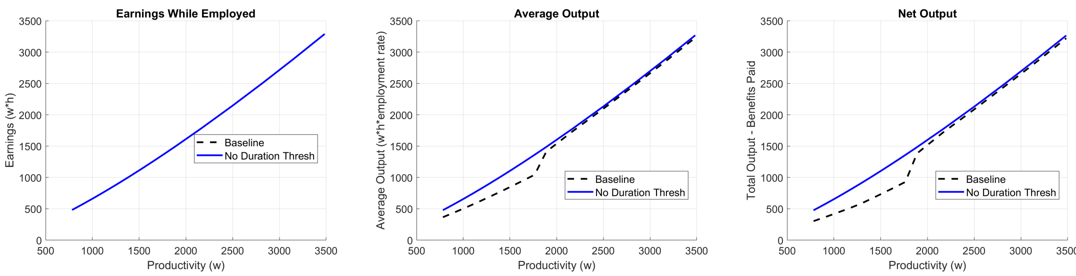


Figure 8: **Removing the duration threshold.** Left: monthly earnings while employed. Middle: total wages of employed. Right: Net earnings = wage bill of employed − total UI payments to unemployed.

prior to the exhaustion of benefits. This contributes to the added fiscal cost of UI benefits for workers near the threshold, shown in the middle panel, as they stay on unemployment longer. The cost is higher when the threshold is raised because UI benefits are increasing in past wage. They become much lower when the threshold is reduced because low productivity workers have lower returns to working harder to get over the threshold because (i) they get less additional wages for their extra effort, and (ii) they have larger streams of need-based transfers via welfare programs and thus lower marginal utility of UI. The third panel adds these two opposing effects together to provide a net effect. Those who only had to work a little harder to qualify for UI generate a net output surplus while those who had to work a lot harder have strong disincentives to go back to work and stay on UI much longer. Not shown in the graphs are the higher earning eligible jobs who are only affected by the differential tax burdens of these policies. In sum, these figures emphasize that the distortions created by the earnings threshold can be very different depending on where the threshold is placed, and the distribution of productivity in the economy (pdf along the x-axis) is important for determining whether the distortions result in a net positive or negative effect on output and the fiscal situation of the government.

Figure 8 illustrates responses to a removal of the duration threshold, zooming out to higher paying jobs which are impacted the most. The dashed line shows the baseline with the duration threshold in place. The kink in the baseline is where the cap in the benefit formula is hit and the effective replacement rate starts falling. The leftmost panel shows earnings while employed are unchanged by this rule because, due to GHH preferences, hours only depend on wages for workers away from the earnings threshold. The middle panel shows average output: the product of the employment rate and earnings while employed. Since earnings while employed are unchanged, average output increases solely due to a reduction in the unemployment rate when the duration is removed. The third panel shows the net impact on output. Lower unemployment both increases output and lowers spending on unemployment insurance. Why does the removal of the duration threshold increase search effort? It does so by raising the value of employment since the added value of becoming eligible for UI happens in just one week instead of being discounted 26 weeks out by both the discount factor β and the probability of maintaining a job.

Table 8 shows there are net welfare gains from the removal of the eligibility threshold rules,

	Base	Removal of Eligibility Threshold Rule Earnings	Duration	Both
Unemployment	4.9%	5.7%	4.6%	4.7%
GDP	49295	49088	49533	49355
UI % of Labor Income	2.08%	2.16%	2.06%	2.21%
Asset-to-Income	3.3	3.3	3.4	3.4
Workers eligible	83.4%	85.2%	91.1%	100%
Δ C year of U	-8.77%	-11.08%	-7.76%	-8.15%
Δ Welfare				
Marginal Jobs		+3.40%	+2.94%	+4.64%
Eligible Jobs		−0.11%	+0.65%	+0.47%
Total		+0.24%	+0.88%	+0.89%

Table 8: **Policy experiments: removal of eligibility threshold rule.**

	Base	Change in Eligibility Threshold Rule Earnings −$500	 +$500	 Duration − 6 wks	 + 6 wks
Unemployment	4.9%	5.1%	4.8%	4.8%	5.2%
GDP	49295	49233	49340	49400	49110
UI % of Labor Income	2.08%	2.10%	2.00%	2.07%	2.26%
Asset-to-Income	3.3	3.3	3.3	3.4	3.3
Workers eligible	83.9%	84.7%	83.0%	87.5%	80.1%
Δ C year of U	-8.59%	-8.48%	-9.12%	-8.10%	-9.21%
Δ Welfare					
Marginal Jobs		+2.07%	−0.28%	+1.45%	−3.46%
Eligible Jobs		−0.02%	0.00%	+0.11%	−1.60%
Total		+0.19%	−0.03%	+0.24%	−1.79%

Table 9: **Policy experiments: incremental changes in eligibility threshold rule.**

and that removing the duration threshold benefits workers in all jobs.[22] The removal of the earnings threshold benefits those in marginal jobs, both those previously below the threshold and those who worked off of their intra-temporal labor supply curve to be above the threshold. Their welfare gains come with a cost of raising unemployment and raising UI spending as a percent of labor income. This results in added UI taxes and reduced welfare for everybody else. Removing the eligibility threshold benefits all workers without the need to increase UI taxes. In fact, unemployment falls and output rises. The net welfare gain is equivalent to a 0.88% increase in lifetime consumption, with workers in marginal jobs seeing a gain of 2.94% and everybody else seeing a gain of 0.65%. Removing the earnings threshold in conjunction with removing the duration threshold induces a higher UI tax burden, borne mostly by those who were previously eligible, and reduces their welfare gain. The previously ineligible gain the most in this scenario, equivalent to a 4.64% increase in lifetime consumption.

Table 9 shows the results of smaller-scale permanent policy changes: changing the earnings threshold by $500 (about 20 percent) or changing the duration threshold by 6 weeks (the baseline

[22]For practical purposes, I set the earnings threshold at $100 and the duration threshold at 1 week, and I also maintain the requirement that the worker becomes unemployed due to layoff or else the 26 week duration of benefits has no bite and UI essentially becomes universal basic income which is not the topic of study here.

is 26 weeks). Qualitatively, the results confirm that changes in the duration threshold tend to benefit/disadvantage workers in both types of jobs while the earnings eligibility threshold tends to benefit workers in one type of job at a cost to workers in the other. There are also asymmetries in tightening or loosening the thresholds. Raising the earnings threshold is less costly in terms of welfare than lowering it from the status quo. The opposite is true for the duration threshold. Raising the number of weeks required to qualify from the status quo is more costly than reducing them. To caveat: this is a local quantitative result and need not be true for other thresholds that could be considered.

7 Interpreting the Great Recession and the COVID-19 Pandemic.

The model is used to understand the impact of changes in the structure of UI eligibility and benefits during Great Recession and the COVID-19 pandemic. This also serves as a validation of the model to see whether it can replicate differences in job finding rates across eligibility groups. The Great Recession serves as a benchmark where unemployment benefits where extended for the eligible but not expanded to include the ineligible. This tests whether the model can replicate elasticity of behavior to a recession (higher job loss rates and lower job finding rates) for workers with and without UI coverage. The COVID-19 recession serves as an example of when unemployment insurance was expanded to include all workers ineligible due to failure to meet the earnings threshold or duration requirement. This tests whether the model is a good predictor of what occurs when UI benefits are increased, extended, and expanded.

Facts around unemployment exit rates of each group must first be established for each recession. Each section will proceed by first developing methodologies to identify workers of each eligibility type in data. Next, these data are used to estimate unemployment exit rates for workers of different eligibility categories. Finally, experiments will be run in the model to test it's replication ability and analyze the episode.

7.1 The Great Recession.

Worker Outcomes by Eligibility in the Data. Data from the monthly outgoing rotational group (MORG) of the Current Population Survey (CPS) are commonly used to estimate variation in monthly flow rates from unemployment to employment at the business cycle frequency. To use this data set for my analysis, I need to first develop a method to categorizing workers as either eligible or ineligible for regular state unemployment. A difficulty in doing so is that the MORG is a short panel. Workers are interviewed in each month for four months, removed from the sample for eight months, interviewed for another four months, and then dropped from the sample. Thus eligibility based on earnings history cannot be constructed directly in accordance with the two quarter reference qualification period allowed by most states. Some eligibility can be categorized directly, such as for the self-employed who are not eligible, and in these cases I categorize workers directly.

To categorize workers as eligible or ineligible based on earnings history criteria, I implement a least absolute shrinkage and selection operator (LASSO) trained on data from the Displaced Workers Supplement (DWS). The DWS includes supplemental questions to workers who experience a job loss and asks them questions about whether they are receiving Unemployment Benefits but it is insufficient on its own because it only occurs once every two years.

I train the algorithm to predict unemployment receipt on variables including an array of demographic and employment characteristics available in both the MORG and the DWS, as well as my own constructed eligibility variable. 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 my best attempt at determining UI eligibility status with the limited earnings history available as well as the reason for separation. I also designate a variable for self-employment income.

The algorithm is similar to propensity score matching but with using the LASSO algorithm to perform 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. All continuous variables are discretized and represented by a collection of dummy variables for each bin as a quasi-non parametric approach. The optimal lasso estimator selected 58 out of the more than 100 provided variables. It returned a low lambda (0.00573), 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.

Table 10 shows the predictive power of the independent variables in the lasso regression.[23] 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.[24] 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.

I use the LASSO model to predict the probability each worker is eligible for UI in sample months where the DWS is unavailable. Individuals with low predicted UI claiming probabilities

[23] Characteristics of the predicted sample versus the PSID sample can be found in the appendix.
[24] State and region are known to be important determinants of eligibility (Skandalis et al. (2022)).

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 10: **Variable Importance in Lasso Regression**

(less than 40%) are classified as ineligible. Those with high predicted UI claiming probabilities (more than 60%) are classified as UI eligible. Finally, a monthly panel of labor market flow rates is constructed by aggregating employment transitions (unemployment-to-employment, employment-to-unemployment, etc.) separately for each eligibility group and applying time aggregation bias corrections (Shimer (2012)) to calculate accurate transition rates.

Figure 9 depicts labor market flows from unemployment to employment. The key result is that the job finding rates are less cyclical for the ineligible. The exit rate from unemployment falls more for eligible UI claimants than the ineligible during the Great Recession. The unemployment to employment rate falls approximately in half for the eligible from peak to trough and is virtually unchanged for the ineligible.[25]

The behavior over the time series of the CPS sample is consistent with a work disincentive effect of unemployment insurance. Unemployment insurance was more generous and lasted longer during the Great Recession but was not expanded to the ineligible. The job finding rate of those estimated to be likely eligible for unemployment falls more than those estimated to not be eligible during this time but the gap between the rates closes to a constant and stable gap after the more generous UI programs are ended.

Model fit. The model is applied to analyze whether the theory can replicate job finding behavior across eligibility that I estimated for the Great Recession. The unemployment insurance program is adjusted to include the 20 week increase in the duration of benefits that was enacted during this time. Next, the efficiency of search technology, χ_i is adjusted downwards for the workers in eligible jobs such that the endogenous job search response to both changes replicates

[25]This pattern is qualitatively similar if I used instead flows from non-employment (unemployment and non-participation combined) to employment for the working age population excluding retirees.

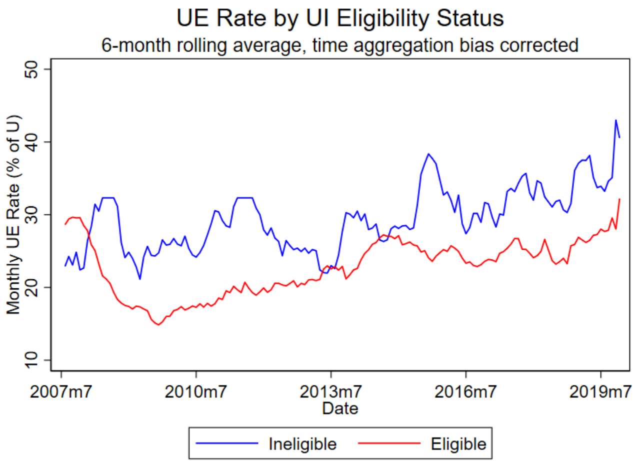


Figure 9: **Unemployment to Employment Flow Rates by ML-predicted UI Eligibility Status in the CPS (2007-2019)** *Note:* All rates shown as 6-month rolling averages with time aggregation bias correction. Blue lines represent UI-ineligible individuals, red lines represent UI-eligible individuals.

their lower job finding rate estimated in the CPS data. The search efficiency for ineligible jobs is then adjusted downwards by the same proportion and the job type specific employment to unemployment rates are fed in as changes in separation shocks δ_i. The implicit assumption here is that eligible and ineligible jobs became equally more difficult to find during the Great Recession. To be clear, the recession is a surprise ("MIT") shock but once the shock occurs agents know the complete forward path of UI policies and a linear recovery in job loss and job finding rates.

This model does well in matching the gap in job finding rates across eligibility status during the Great Recession. It is calibrated to exactly match the decline of eligible workers and predicts a decline of 2.4 ppt for earnings ineligible workers. The actual decline for this group is essentially zero. Still, I conclude that the model well captures the fact that recessionary changes in job loss and job finding rates have only small impacts on the search effort and unemployment duration of workers in low-earning jobs below the UI eligibility threshold.

The model can also be used to assess what would have happened if a PUA like program extending coverage to workers not qualifying for regular state UI had been put in place during the Great Recession. Table 11 presents the findings. If they had been granted access to the same UI benefits, the model predicts job finding rates for the newly covered workers would have fallen 41% and would have been below the job finding rates of the previously eligible workers.[26] The job finding rates for the workers in eligible jobs go down a little bit as well because this exercise includes expanding the program to workers in higher earning eligible jobs who have not met the two-quarter duration requirement. Removing the extension to 99 weeks only affects the previously eligible workers and increases their job finding rate. Interestingly, a hypothetical

[26] Same benefits means the same duration of payments but the benefit rates would be calculated using the same formula which results in lower payments for lower income workers.

	Data	Baseline	Expansion	No extension
Job Finding Rate				
Ineligible Jobs	0.245	0.221	0.091	0.221
Eligible Jobs	0.146	0.146	0.138	0.152
Total	0.150	0.163	0.124	0.167
UI % of Wage Bill		4.3%	5.2%	4.1%
Δ Welfare vs Baseline*				
Marginal Jobs			+5.50%	0%
Eligible Jobs			+0.91%	−0.85%
Total			+1.38%	−0.77%

Table 11: **Policy experiments during the GFC.** Averages, Jan 2008-Dec 2010. (∗)Welfare is calculated as percent consumption equivalents but holds fix tax rate and so excludes welfare losses from funding costs their distortions.

expansion to duration ineligible would have had a greater impact on job finding rates than the 20 week UI extension. Welfare changes are calculated as the percent of consumption an agent would give up or have to receive to be indifferent between the change and the baseline. These changes do not include the fiscal burden of the program because it could be funded in different ways with different welfare implications, but the average monthly benefits paid as a share of the wage bill are presented in the final row to give a sense of the fiscal burden/rebate a hypothetical change would have had.

7.2 The COVID-19 Pandemic.

Worker Outcomes by Eligibility in the Data. Unemployment insurance was expanded during the COVID-19 pandemic through the Pandemic Unemployment Assistance Program (PUA). PUA was a temporary Federal program that extended unemployment benefits eligibility to workers not meeting states' earnings history criteria. I perform a stock flow analysis of aggregated claims data to deduce how the claim duration of PUA recipients differed from those whose initial claims met regular state unemployment insurance eligibility. Administrative data has flaws that I attempt to accommodate but they also have advantages over survey data. Standard large surveys did not collect data on PUA claimants consistently. This stock-flow methodology uses the universe of claims and not subject to selection bias or surveying lags. None-the-less, the newness of the program and the decentralization of its administration across states present several hurdles to any methodology and I detail how I deal with them in the following paragraphs.

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. 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.[27]

The PEUC and EB programs are federally funded and extend the duration of benefits for claimants in the regular state programs.[28] 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.[29]

The PUA program provided up to 79 weeks of federally funded payments to workers with reduced income who are not eligible for 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 at different times across different states during 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 a stock-flow analysis. I deal with the first two issues by simply starting the analysis on July 15, 2020. The analysis is ended on May 1, 2021 which a month prior to when a subset of states withdrew from federal programs including PUA and PUEC. To deal with the second issue, I categorize states into three groups: those that require an applicant to apply for PUA by first 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.[30] The states in the third category are dropped.

For the states that take PUA applications indirectly through regular state programs, both the initial PUA and regular state claims data must be adjusted to reflect true flows onto each program. I do this by using the time series of rejection rates of initial claims due to insufficient work history which is available for each state from the Department of Labor. These are the true rejection rates for claims made to and intended for regular state UI program in the states that process PUA claims separately from regular ones. I extrapolate these rejection rates to the states that took PUA and regular claims together by assuming that the mean rejection rate due to insufficient work history of claims intended for the regular state program is the same in each set of states. I apply the mean rejection rate to regular initial claims from these states to

[27] These are approximate measurements. For example, some initial claims are rejected and never result in payment and some programs allowed retrospective claims during the pandemic. Both of these issues will be addressed in the analysis.

[28] 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.

[29] This is because we are interested in the stocks of claimants by eligibility type and not the state versus federal funding distinction.

[30] 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. We 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%) based on insufficient work credits than those that take PUA applications directly and separately.

those states that did not take PUA claims directly and assign any excess rejections as initial applications to the PUA program.

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

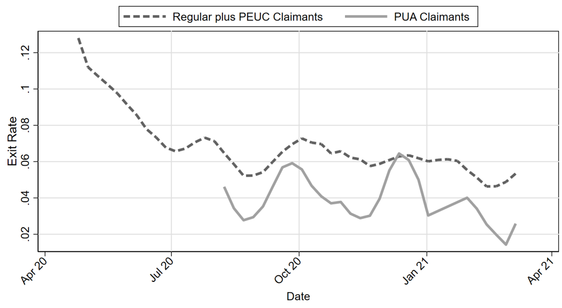
Table 12: **PUA Application Protocol by State**

In specific notation, 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 and regular claims separately, the observed objects reported by DOLETA should be the actual ones, subject perhaps to measurement error. For the states that require PUA claims to be filed first as regular claims and then rejected, the approximation of the true values are:

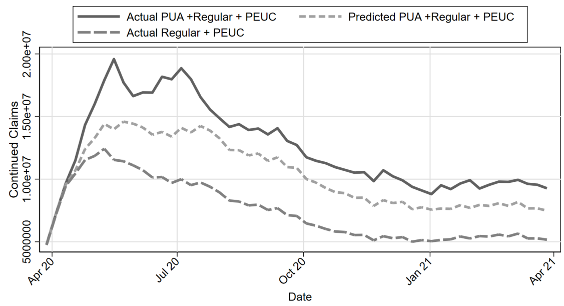
$$
\begin{aligned}
\tilde{r}_t^j &= mean_{j \in \{direct\}}(\hat{r}_t^j) \\
\tilde{a}_t^{regularj} &= \hat{a}_t^{regularj} * (1 - (\hat{r}_t^j - \tilde{r}_t^j) \\
\tilde{a}_t^{PUAj} &= \hat{a}_t^{regularj} * (\hat{r}_t^j - \tilde{r}_t^j) \\
\tilde{c}_t^{pj} &= \hat{c}_t^{pj}
\end{aligned}
$$

The data are cleaned in a third and final way by removing four states with swings in PUA continued claims data that exceed 200% starting in July 2020. Altogether this sample contains 718 million weekly continued claims on regular UI including EB, plus 473 million weekly continued claims assigned to PUA.

Results The stock-flow estimates of the weekly exit rate from unemployment programs are shown in Figure 10. PUA claimants had lower exit rates from unemployment insurance than those entering through regular state program eligibility. 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%).



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



(b) Continued Claims

Figure 10: **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.

A basic accounting impact of the longer duration of PUA claimants on total claims paid is in Panel (b) of Figure 10. It 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 10. This reduces the additional contribution of PUA claims to total continued claims by 42.5% and total continued claims by 17.9%. This difference amounts to approximately 225 million additional claim weeks. The increase in claims caused by the lower PUA exit rates grew larger in 2021 because PUA exit rates fell further behind those of regular claimants as the Pandemic recovery progressed.

Model Fit. The model is applied analyze the Pandemic Recession following a similar method as for the GFC. First, the unemployment insurance program is adjusted to look like enacted measures. The duration of benefits for regular UI workers and coverage for PUA workers are each extended to match the full extension from March 2020 until July 2021.[31] To be clear, regular UI workers in the model are workers who earned qualification for UI in eligible jobs. PUA workers in the model are those in jobs below the earnings threshold or that did not yet work long enough to earn qualification for regular UI. The level of benefits is also increased by \$600 per week for the first five months and \$300 per week for the next 11 months to replicate the supplement provided by the FPUC program. Second, the efficiencies of search technology, χ_i is adjusted such that the change in the endogenous job search of the workers in always eligible jobs induces a job finding rate equal to the approximate 20% decline from normal times as estimated in the DOLETA administrative data for the sample period of September 2020-May 2021 versus 2019.[32] The resulting search technology is an improvement in efficiency of 16%. This means

[31] PEUC and PUA were terminated early in a subset of states and, without a doubt, there was uncertainty all along about coverage duration. These choices serve as a benchmark. Adding greater uncertainty or changing the expected length of coverage does not greatly change the duration of PUA workers *relative* to regular UI workers in the model which is the primary focus here. It would change the duration for both groups.

[32] This sample period avoids the higher incidence of recall early in the recession.

that the observed job finding rate was higher than the disincentives provided by both changes in the UI program and also disincentives provided by higher job loss rates. I will assume the increase in search efficiency is the same across job types as this assumption generated a good model fit for the Great Recession. Finally, the pandemic is a surprise ("MIT") shock but once the shock occurs agents know the complete forward path of UI policies and a linear recovery in job loss and job finding rates.

The model predicts a decline in job finding rates for the newly PUA eligible of 55.1% of the baseline rate. The actual finding rate in the data declined on average 53% relative to 2019 over the months the program was in place. This is a non-targeted result and again provides confidence in the model's predictive power.

Table 13 considers how job finding and welfare would have been different if select components of the UI system had not been changed. The columns under "No PUA Expansion" remove expanded eligibility by reinstating the earnings threshold alone, duration threshold alone, and then both. The expansion to low-earning workers has a large impact on their job finding rates. They would have been 77% higher which would have cut their unemployment duration nearly in half. The duration threshold has a smaller impact on job finding rates because if affects low-tenure workers higher up in the earnings distribution who already have strong incentives to search. The duration expansion does have a larger impact on welfare in part because there are more duration ineligible workers, especially given the spike in layoffs at the beginning of COVID. The no extension scenario has the largest impact on job finding rates of all workers. Without the extension, many of the unemployed would have lost benefits in the fourth quarter of 2020. Removing the FPUC, or extra $300-$600 per week has a large effect on search effort, particularly for low earners. Turning to welfare, FPUC had the largest effect for the low marginal earners because it is large relative to their incomes, but the extension was more important for eligible jobs. Fiscally, the FPUC had the largest impact on the budget. UI payments as a share of the wage bill would have been over 75% lower without it. This is unsurprising because the maximum benefits paid in the model under the benefit formula calibrated to California in 2019 is $479/week. This gives an average of $320 in normal times and so the FPUC is more than doubling UI payments.[33]

Conclusions of this analysis are two-fold. First, the extension of UI benefits combined with FPUC had a large impact on unemployment duration and the fiscal cost of UI during the pandemic. Second, the full expansion of UI through PUA had a lesser impact on unemployment duration but the largest welfare gain relative to it's fiscal cost (assuming the extension and FPUC remained in place). In other words, if one is going to extend the duration of UI benefits and add an FPUC type of program, then expanding it through a PUA type program is a relatively small additional cost.

Further Evidence: Anticipated Expiry in December 2020. The CARES act created the PUA program which extended UI to those previously not eligible, and the PEUC which

[33] The actual national average paid in 2019 was $378.

	Data	Baseline	No PUA Expansion Earn	Duration	Both	No extension	No FPUC
Job Finding Rate							
Marginal Jobs	0.160	0.165	0.292	0.198	0.305	0.439	0.307
Eligible Jobs	0.240	0.240	0.240	0.274	0.278	0.486	0.392
Total	0.170	0.171	0.256	0.250	0.285	0.467	0.365
UI % of wage bill		21.3%	17.8%	17.5%	15.2%	10.3%	4.6%
Δ Welfare vs Baseline*)							
Marginal Jobs			-7.5%	-21.2%	-23.6%	-7.0%	-35.2%
Eligible Jobs			0%	-0.8%	-2.5%	-3.2%	-1.8%
Total			-0.8%	-2.8%	-4.6%	-3.6%	-5.1%

Table 13: **Policy experiments during COVID.** These are averages over March 2020-May 2021. (∗)Holds fix tax rate and so excludes funding costs and distortions.

extended the duration of claims to regular programs from 26 to 39 weeks. Both programs were temporary measures. PUA, PEUC, and also the full federal funding of Extended Benefits (EB) were originally slated to expire on December 26, 2020. As of the first week of December 2020, there were 9.7 million PUA continued claims and 5.0 million PEUC continued claims representing unemployed persons at risk of losing coverage if the programs were to have ended on December 26.[34] On December 21, 2020 the text of a bill that would extend PUA and PEUC for an additional 11 weeks was made public. The provision was signed into law by President Trump on December 27, 2020.

The model predicts that UI claimants would start looking for work in anticipation of their benefits expiring and increase the rate at which they exit unemployment before they are actually terminated. This, however, is only the case if the presence of the UI program had a negative causal impact on job search behavior to begin with. The exit rate estimates shown in Panel (a) of Figure 10 provides evidence that the UI programs did have negative impacts on job finding rates. The exit rate of both PUA and combined regular UI and PEUC claimants rise in December 2020 before falling sharply at the end of the month when the extension is announced. There could be other factors at play such as seasonal work and so this is only suggestive evidence but the magnitude is significant and this all occurred during the largest spike in measured virus cases thus far in the pandemic.

7.2.1 Robustness to Omitted Pandemic Features.

This section discusses three features absent to the baseline calculations. All three features would exacerbate the inability of the baseline model to explain the unemployment duration of PUA claimants and thus strengthen the results of this paper.

Expanded government transfers. Prior literature has presented mixed results on whether work disincentive effects of UI are stronger for households with higher or lower access to liquid

[34] All claims data published by the Department of Labor.

assets.[35] Government transfers increased during COVID and could have been thought of as an increase in liquid assets. This would have disincentivized job search but due to the parameterization of the model, it would have disincentivized job search more for those in eligible jobs which could improve the model fit as it predicts a gap between eligible and PUA that is a bit too low.

Recall. The COVID pandemic was unique in that recall of unemployed workers to their former employer was much higher than in both normal times and during previous recessions. Hall and Kudlyak (2021) show that temporary unemployment accounted for more than three-quarters of all unemployment in early 2021 but declined to 26 percent by November 2020. The November statistic is close to normal times if compared with the finding of Fujita and Moscarini (2017) that 30% of unemployed workers return to a previous employer. Given these facts, I consider that my stock-flow analysis partially addresses this concern by focusing on the period from September 2020-May 2021. Further, the estimates in 10 show that the exit rate of regular claimants plus PEUC had stabilized from the initial burst of recall before the time period of analysis in this paper starting in September 2020.

Duration Dependence. The model implicitly includes duration dependance through the earnings potential process. Duration dependence is an empirical phenomenon whereby workers who have been unemployed for a longer duration have a lower monthly probability of returning to employment. The model generates this through both a composition effect and a causal duration effect. The composition effect is that lower wage workers choose lower job search effort and so make up a larger portion of long-term unemployed. This mechanically lowers the average job finding rate of long-term unemployed workers. The causal duration effect is that, if we construct panel data on model workers, workers who are unemployed longer are more likely to have moved down the earnings potential ladder relative to where they were before. This reduces their job search effort relative to where it was in the beginning of their unemployment spell.

Match Quality. There is no match quality in this analysis. Studies considering match quality conjecture that the longer unemployment durations accompanying more generous UI policies yield better matches through longer and pickier search. Multiple studies refute this conjecture and find the opposite: workers take worse jobs after longer unemployment spells induced by more generous UI (Schmieder et al. (2013), Schmieder et al. (2012)).[36] Studies that do find better match quality after longer unemployment spells induced by more generous UI find this effect to be quantitatively trivial (Griffy and Rabinovich (2022)).

[35] Meyer and Mok (2014) present evidence that disincentive effects are not dependent on liquid assets. Chetty (2008) find the opposite.

[36] Similarly, Rebollo-Sanz and Rodríguez-Planas (2020) finds no decline match quality when benefits are made less generous.

8 Conclusion.

The near universal expansion of eligibility for unemployment benefits during the COVID-19 pandemic sparked the question of whether UI eligibility should be expanded in general or cyclically during future economic downturns. It also provided an interesting experiment where outcomes of a UI expansion could be observed. Yet the pandemic was an unusual context and context must be taken into consideration when extrapolating findings to more normal scenarios.

This paper provided a quantitative framework to contextualize the PUA expansion and understand the impact an UI expansion would generally have both in normal times and in a typical recession like the GFC. The focus was on modelling the eligibility rules in detail and calibrating the model to newly documented facts on how workers' experiences in the labor market differ based on their eligibility in normal times, and in the GFC and COVID recessions. The model matched aspects of the data critical for policy evaluation, like consumption dynamics by UI eligibility following job loss; and predicted well the differences in job finding rates of each group of workers during the GFC and the COVID-19 episode.

The main lesson is that removing both the earnings and duration eligibility requirements would benefit workers across the income spectrum. Both requirements distort the economy in different ways. Removing the duration requirement actually reduces unemployment and raises GDP. It expands coverage to insure more workers but does not require an increase in the UI tax rate. Removing the earnings requirement alone benefits low-income workers at the cost of higher unemployment, lower GDP, and higher taxes on higher-income workers, but the average welfare gain in the population is still positive.

Applying the model to the COVID-19 expansion reveals a caveat to this lesson: expanding UI eligibility becomes much more costly in deep recessions and especially if benefits are raised through a supplement (FPUC) or extended in duration. In these cases, removing the duration eligibility threshold does not pay for itself and requires a higher UI tax rate. The same is predicted to would have been true if eligibility requirements had been removed during the GFC. These results suggest that the clear positive results on UI eligibility expansion during normal times could also bring elevated costs during crises with potential to turn the results to net negatives.

While this research made progress in documenting facts about UI eligibility and understanding the effects of eligibility rules, it abstracted from two factors policy makers should also consider. First, it did not consider how changes in UI eligibility would interact with and change other governmental and informal transfers. Second, it did not consider how changes in UI eligibility would change job creation. This is because the impact of UI program rules on job creation is also complicated and not currently well understood. A good avenue for future research would be to treat the employer side of UI funding with the same detail this paper treated the eligibility side. This would involve study of the details of employer experience rating and the peculiar funding of UI. For example, the Federal Unemployment Tax Act (FUTA) tax levies on employers a flat tax rate or 6% on the first $7,000 of wages paid to each employee annually but only for employees over a liability threshold, which includes both an earnings and duration component. It would be interesting to quantify how the experience rating and the tax only on initial wages would interact with incentives to create jobs, especially short-term or low paying jobs.

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