Labor Market Responses to Unemployment Insurance: The Role of Heterogeneity

Online Appendix

Serdar Birinci
St. Louis Fed

Kurt See
Bank of Canada

A Data

In this section, we provide details about the SIPP data and our calculations of the empirical moments described in Section I. We also present additional results to supplement our discussion.

A.1 SIPP data

We use the SIPP data to discipline labor market flows, the distributions of income, assets, the asset-to-income ratio, and the unemployment spell duration, as well as UI-eligibility, take-up, and replacement rates. The SIPP is a longitudinal survey that follows individuals for a duration of up to five years. Until the 2014 panel, interviews were held in four-month intervals called waves. Each respondent was then assigned to one of four rotation groups. The rotation group determined which month within a wave a respondent was interviewed. Each interview covered information about the four months (reference months) preceding the interview month. For example, when a new SIPP panel started and Wave 1 (the first four months of the new panel) commenced, the first rotation group was interviewed in the first month of Wave 1, the second rotation group was interviewed in the second month of Wave 1, and so on. Once all four rotation groups had been interviewed by the end of the fourth month of Wave 1, Wave 2 began with the second interview of the first rotation group. This way, all four rotation groups would have been interviewed by the end of each wave. The SIPP changed the interview structure starting with the 2014 panel. While the four-wave structure was maintained, the frequency of interviews was reduced to once a year (as opposed to thrice) and the reference period was expanded to 12 months. Thus, each interview collected information for the 12 months in the preceding calendar year. In the end, the SIPP provides monthly data on demographics, income, and UI receipt, and weekly data on employment status. Importantly, the SIPP also provides data on asset holdings. In each panel, respondents provide information on various types of assets for two or three waves, usually one year apart. In the 2014 panel, this information is collected once every year.

We restrict our sample to individuals ages 25 to 65 who are not business owners. For respondents that have missing information on our variables of interest, we drop observations after the first missing observation.[1] The upcoming section supplements the discussion provided in the main text on the measurement of our findings from the SIPP data and reports additional results.

A.2 Details on the calculation of empirical moments

Labor market transitions Using the SIPP panels between 1996 and 2014 (covering data from 1996 to 2016), we calculate monthly EU and UE rates as follows. First, we classify an individual as employed (E) if he/she reports having a job and is either working or not on layoff, but is absent without pay during the first week of the month. We classify the individual as unemployed (U) if he/she reports either having no job and actively looking for work or having a job but is currently laid off in the first week of the month. Using these definitions, we construct monthly EU and UE transition probabilities using longitudinally matched individual-level data. In particular, for each month t, we calculate the average EU rate as the ratio of total EU transitions between t and $t+1$ to total employed at time t, and the average UE rate as the ratio of total UE transitions between t and $t+1$ to total unemployed at time t.[2] Once we obtain the monthly transition probabilities over time, we account for seasonality by removing monthly fixed effects.[3] When calculating the heterogeneity of EU and UE rates across the income distribution, we use monthly labor earnings data to obtain the current labor earnings of the employed and the previous labor earnings of the unemployed, which is measured as the average labor earnings three months prior to job loss.[4] We require positive labor earnings for the employed and positive previous labor earnings for the unemployed in order to focus on individuals who have sufficient attachment to the labor market. Given that SIPP data usually provide yearly information on the asset holdings of the respondent, when calculating the heterogeneity in EU and UE rates across the asset and asset-to-income ratio distributions, we approximate the respondent's asset holdings in each month using the SIPP wave with asset information closest to that month.

Asset and asset-to-income ratio distributions We focus on the net liquid asset holdings of individuals. The SIPP contains individual-level data on financial liquid assets such as interest-earning financial assets in banking and other institutions, amounts in non-interest-earning checking accounts, equity in stocks and mutual funds, and the face value of U.S. savings bonds. Moreover, for married individuals, the survey asks about the amounts of these assets in joint accounts. Only one spouse is asked about joint accounts; the response is then divided

[1] This is because, for example, it is not possible to correctly identify labor market flows of these individuals.

[2] Even if this EU flow measure incorporates both voluntary and involuntary separations, our UI program is able to filter out those who quit their jobs from being eligible for UI, as we observe the reason of unemployment.

[3] For our analysis in Section I.C, we calculate the EU and UE transition probabilities from the CPS between 1996 and 2016 using the same methodology.

[4] The result for the heterogeneity in UE rates across income groups is similar if we take previous employment income as the labor earnings from the month prior to job loss.

by two, and the divided amount is copied to both spouses' records. The SIPP also contains information about revolving debt on credit card balances at the individual level for both single and joint accounts in the same fashion. The summation of the amounts in liquid asset accounts net of revolving debt gives us the net financial asset holdings of the individual. Finally, the SIPP provides data on equity in cars at the household level. We split that amount between the members of the household and record that value as the amount of equity in cars for each individual within the household. Adding this value to net financial asset holdings of the individual gives us the measure of net liquid asset holdings for each SIPP wave with information on assets. Finally, dividing the net liquid asset holdings measure by monthly labor income gives us the ratio of net liquid assets to monthly income for each SIPP wave with asset information.[5] The asset-to-income ratio provides us with a useful metric of self-insurance in that it measures how many months of labor earnings net liquid assets can replace.

Unemployment spell duration We require positive previous labor earnings in order to focus on individuals with sufficient labor market attachment. Spells that are left-truncated and spells with missing information for which we cannot ascertain respondents' employment status are dropped. Finally, we define spells as uninterrupted months of unemployment and thus do not consider time spent out of the labor force, since we do not model the non-participation margin.

Eligibility, take-up, and replacement rates Again, we require positive previous earnings for the unemployed. If an individual's observations do not cover the entire base period but contain at least one quarter of information prior to unemployment, we approximate base period earnings with available information.[6] When calculating the second moment properties of the TUR in Table 3, we use data from SIPP panels 1996 to 2008, excluding the 2014 panel since we find that it underestimates UI take-up rates. As discussed above, interviews in the SIPP 2014 panel collect information about the (entire) calendar year preceding the interview, as opposed to the four-month horizon in previous panels. This survey redesign may have introduced additional measurement errors as it relies on individuals' ability to recall information for longer periods. In fact, Tables 7-9 in an assessment by the National Academies of Sciences and Medicine (2018) document that the SIPP 2014 panel underestimates the total number of individuals who report UI receipt when compared with the SIPP 2008 panel during all months of 2013, a period during which both panels overlap. The assessment discusses that since there were more individuals

[5] Here, if the individual is unemployed during the interview month, we use the individual's previous labor income associated with the last employment from earlier waves.

[6] Moreover, if earnings in the base period do not allow an individual to be eligible, some states also check earnings during the alternative base period, which is typically defined as the last four completed quarters preceding the applicant's claim for benefits. Furthermore, there are a few instances where our program classifies an unemployed individual as ineligible based on UI state laws but the respondent reports receiving UI benefits. In these instances, we consider the self-reported UI receipt as an indication of eligibility. Results remain similar when we consider these individuals as ineligible.

Table A1: Effect of available self-insurance on UI take-up decision

Dependent variable: UI take-up indicator		
	Coefficient estimate	Std. error
Asset-to-income ratio	-0.012	(0.004)
College	-0.200	(0.098)
Female	-0.121	(0.076)
Married	-0.079	(0.077)
Age	0.006	(0.004)
White	-0.086	(0.094)
Constant	0.498	(0.172)

Note: This table provides estimates of the effect of available self-insurance, measured as the ratio of net liquid assets to monthly labor earnings, on the UI take-up decision of UI-eligible unemployed individuals, using a non-recessionary wave with asset information from each SIPP panel before the Great Recession. Dependent variable is a dummy variable indicating if a UI-eligible individual takes up benefits. The sample includes UI-eligible unemployed individuals from our baseline sample of individuals ages 25 to 65 who are not business owners and who are in their first month of an unemployment spell. Values in parentheses denote the standard errors.

leaving the UI program each month than entering due to the recovery of labor markets in 2013, if the individuals who left the UI program early 2013 were less likely to report their UI receipt in an interview month after 2013 than those who left the UI program late 2013, then this would explain why the SIPP 2014 panel underestimates the number of UI recipients. For this reason, we do not use the SIPP 2014 panel when calculating the second moment properties of the TUR.

A.3 Additional empirical results

Effect of wealth on UI take-up decision In light of the results presented in Section I.B, we conclude that eligible individuals who take up UI possess less self-insurance than those who do not. In this section, we estimate an empirical model to provide further evidence on this finding. In particular, we use a non-recessionary wave with asset information from each SIPP panel before the Great Recession and consider a sample of UI-eligible unemployed individuals from our baseline sample of individuals ages 25 to 65 who are not business owners and who are in their first month of an unemployment spell.[7] To understand the effect of wealth holdings on the UI take-up decision, we estimate the following regression for the unemployed in our sample:

$$\text{Take-up}_i = \alpha + \beta_1 X_i + \beta_2 \text{Asset-to-income ratio}_i + \epsilon_i,$$

where i indexes individuals; Take-up$_i$ is an indicator variable with a value of 1 if individual i takes up UI benefits; Asset-to-income ratio$_i$ is the level of self-insurance, measured as the ratio of net liquid assets to monthly labor earnings, available to individual i; and X_{it} is a vector of demographic characteristics including age, gender, marital status, race, and education.

[7] To isolate the effect of wealth holdings upon unemployment, we focus on individuals at the start of their unemployment spell.

Table A2: Heterogeneity in unemployment spell duration

	p10	p25	p50	p75	p90	Mean
Unemployed	1	1	2	4	6	3.13
Eligible	1	1	2	4	7	3.31
Take-up	1	2	3	5	8	3.81
Non-take-up	1	1	2	3	5	2.42

Note: This table documents the distributions of the completed unemployment spell durations across different groups within the unemployed, using the SIPP 2004 panel. Our sample requires positive previous labor earnings to focus on individuals with sufficient labor market attachment.

Table A1 presents the results. Even after controlling for various demographic and economic characteristics, eligible individuals with higher self-insurance are significantly less likely to take up UI. In particular, we find that a one-unit increase in the asset-to-income ratio, i.e., an increase in asset holdings such that it covers one more month of previous earnings, decreases the probability of take-up by 1.2 percent. Put differently, an increase in asset holdings that covers one year more of previous earnings decreases the probability of take-up by around 15 percent.

Heterogeneity in unemployment spell durations Section I.B documents results on the heterogeneity of EU, UE, FEU, TUR, and replacement rates across quintiles of income, assets, and the asset-to-income ratio. Here, we provide results on the distributions of the completed unemployment spell durations across different groups within the unemployed, using the SIPP 2004 panel. Table A2 shows that the eligible unemployed who do not take up UI have significantly shorter unemployment spell durations than those who do. This is an important empirical finding because it allows us to further understand the characteristics of those who do not claim UI despite being eligible: in addition to holding much higher liquid wealth, they also experience much shorter unemployment spells, both of which diminish the insurance benefits of UI transfers.

Joint distribution of hourly income and assets Table 2 in Section I.B documents features of the joint distribution of monthly income and asset holdings. In order to understand whether these results are driven by the correlation between wages and assets or between hours worked and assets, we now provide results for the joint distribution of hourly income (wages) and assets. The SIPP provides information on respondents' usual number of hours worked per week at each job. Using this information, we first calculate the total usual hours worked in a month in all jobs. We then calculate the hourly income (wages) of employed individuals by dividing monthly labor earnings by monthly total usual hours worked. For unemployed individuals, we use their previous labor earnings and hours worked three months prior to job loss to obtain hourly income. We then calculate the joint distribution of hourly income and assets for our entire sample.

Table A3 provides the results. A comparison of the results in Table 2 and the results in Table A3 reveals that the joint distribution of income and assets and the joint distribution of hourly

Table A3: Joint distribution of hourly income and asset holdings

	Assets				
Hourly income	Q1	Q2	Q3	Q4	Q5
Q1	0.18	0.35	0.24	0.14	0.09
Q2	0.21	0.27	0.25	0.17	0.10
Q3	0.23	0.18	0.22	0.21	0.16
Q4	0.21	0.12	0.18	0.24	0.24
Q5	0.15	0.07	0.13	0.23	0.43

Note: This table documents the joint distribution of hourly income and asset holdings for all individuals, using the SIPP 2004 panel. Rows represent quintiles of hourly income and columns represent quintiles of assets. Hourly income is calculated by dividing the monthly labor earnings of the respondent from their current job (for employed) or the average monthly labor earnings in their previous job (for unemployed) by the monthly hours worked in their current job (for employed) or the average monthly hours worked in their previous job (for unemployed). Assets are measured as net liquid wealth holdings.

income and assets are very close to each other. Thus, we conclude that the results presented in Section I.B are driven by the correlation between wages and assets. This finding is consistent with our model where the variation in income is driven by wage differences in the model.

B Model

Here, we first lay out the recursive problem of the ineligible unemployed. Next, we provide definitions of the recursive equilibrium and BRE, as well as a proof of the existence and uniqueness of a BRE. Finally, we discuss the computational algorithm used to solve for the BRE.

B.1 Problem of ineligible unemployed

The recursive problem of the ineligible unemployed is given by

$$\begin{aligned} V^{NB}(a,y;\mu) \quad = \quad & \max_{c,\, a'\geq a_l,\, s} \quad u\left(c\right)-\nu\left(s\right)+\beta\left(1-\omega\right)\mathbb{E}\Bigg[\max_{\tilde{w}}\Big\{sf\left(\theta\left(\tilde{w},y';\mu'\right)\right)V^{W}\left(a',\tilde{w},y';\mu'\right) \\ & +\left(1-sf\left(\theta\left(\tilde{w},y';\mu'\right)\right)\right)V^{NB}\left(a',y';\mu'\right)\Big\}\Big|y,\mu\Bigg] \end{aligned}$$

subject to

$$\begin{aligned} & c+a'\leq\left(1+r\right)a+h \\ & \Gamma'=H\left(\mu,p'\right),\quad p'\sim F\left(p'\,|\,p\right),\quad y'\sim Q\left(y'\,|\,y\right). \end{aligned}$$

Compared with the eligible unemployed, the ineligible unemployed do not receive benefits and are unable to gain eligibility if their job search fails.

B.2 Equilibrium

Definition of recursive equilibrium Given UI policy $\Big\{b\left(w,p\right),e\left(p\right),g\left(w,p\right),\,\tau\Big\}_{w\in\mathcal{W},\ p\in\mathcal{P}}$, a recursive equilibrium for this economy is a list of policy functions for asset, wage, search effort, and UI take-up decisions; a labor market tightness function $\theta(w, y; \mu)$; and an aggregate law of motion $\mu' = (p', \Gamma')$ such that

1. Individuals' policy functions solve their respective problems.
2. Labor market tightness is consistent with the free-entry condition (6).
3. The government budget constraint (7) is satisfied.
4. The law of motion of the aggregate state is consistent with individuals' policy functions.

Definition of BRE A BRE is an equilibrium in which value functions, policy functions, and labor market tightness depend on the aggregate state of the economy μ, only through the aggregate productivity p and not through the aggregate distribution of agents across states Γ.

Proposition: *If i) utility function $u(\cdot)$ is strictly increasing, strictly concave, and satisfies Inada conditions, and $\nu(\cdot)$ and $\phi(\cdot)$ are strictly increasing and strictly convex; ii) choice sets $\mathcal{W}$ and $\mathcal{A}$, and sets of exogenous processes $\mathcal{P}$ and $\mathcal{Y}$ are bounded; iii) matching function M exhibits constant returns to scale; and iv) UI policy is restricted to depend on the aggregate state only through aggregate labor productivity, then there exists a unique BRE for this economy.*

Proof: The proof presented here follows from Herkenhoff (2019) and Karahan and Rhee (2019), which are extensions of Menzio and Shi (2010, 2011). We extend the proof to a model in which the government finances time-varying UI benefits.

<u>Existence</u>: Let $\mathcal{J}(\mathcal{W}, \mathcal{Y}, \mathcal{P})$ be the set of bounded and continuous functions J such that $J : \mathcal{W} \times \mathcal{Y} \times \mathcal{P} \to \mathbb{R}$, and let T_J be an operator associated with Equation (4) such that $T_J : \mathcal{J} \to \mathcal{J}$. Using Blackwell's sufficiency conditions for a contraction and the assumptions of the boundedness of the sets of exogenous processes $\mathcal{Y}$ and $\mathcal{P}$ and choice set $\mathcal{W}$, we can show that T_J is a contraction and has a unique fixed point $J^* \in \mathcal{J}$. Thus, the firm value function satisfying Equation (4) depends on the aggregate state of the economy μ only through aggregate productivity p. This means that the set of wages posted by the firms in equilibrium $\mathcal{W}$ for each productivity level in the set $\mathcal{Y}$ is determined by aggregate productivity as well. Plugging J^* into Equation (6) yields

$$\theta^*(w, y; p) = \begin{cases} q^{-1}\left(\kappa / J^*(w, y; p)\right) & \text{if} \quad w \in \mathcal{W}(p) \quad \text{and} \quad y \in \mathcal{Y}(p) \\ 0 & \text{otherwise,} \end{cases}$$

implying that equilibrium market tightness does not depend on the distribution of agents.[8]

Next, let l be an indicator of being employed or unemployed and n be an indicator of being eligible or ineligible for UI. Let Ω denote the possible realizations of the aggregate state μ and define a value function $R : \{0,1\} \times \{0,1\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{Y} \times \Omega \to \mathbb{R}$ such that

[8] Notice that the constant-returns-to-scale property of the matching function M is crucial here so that we can write the job-finding rate and vacancy-filling rate as functions of θ only. The free-entry condition (6) is also important to pin down market tightness.

$$
\begin{aligned}
R\left(l=1,n=0,a,w,y;\mu\right) &= V^{W}\left(a,w,y;\mu\right)\\
R\left(l=0,n=1,a,w,y;\mu\right) &= V^{B}\left(a,w,y;\mu\right)\\
R\left(l=0,n=0,a,w,y;\mu\right) &= V^{NB}\left(a,y;\mu\right).
\end{aligned}
$$

Then, we define the set of functions $\mathcal{R} : \{0,1\} \times \{0,1\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{Y} \times \mathcal{P} \to \mathbb{R}$ and let T_R be an operator such that

$$
\begin{aligned}
\left(T_R R\right)\left(l,n,a,w,y;p\right) = l\Bigg[&\max_{c_{1,0},\,a'}\; u\left(c_{1,0}\right) + \beta\left(1-\omega\right)\mathbb{E}\Big[\delta\left(y',p'\right)\Big(\left(1-g\left(w,p'\right)\right)R\left(l=0,n=1,a',w,y';p'\right)\\
&+ g\left(w,p'\right)R\left(l=0,n=0,a',w,y';p'\right)\Big) + \left(1-\delta\left(y',p'\right)\right)R\left(l=1,n=0,a',w,y';p'\right)\Big]\Bigg]\\
&+\left(1-l\right)n\Bigg[\max_{d}\; -\phi\left(d\right) + d\Bigg(\max_{c^{T}_{0,1},\,a',\,s}\; u\left(c^{T}_{0,1}\right) - \nu\left(s\right)\\
&+\beta\left(1-\omega\right)\mathbb{E}\Big[\max_{\tilde{w}}\Big\{sf\left(\theta\left(\tilde{w},y';p'\right)\right)R\left(l=1,n=0,a',\tilde{w},y';p'\right)\\
&+\left(1-sf\left(\theta\left(\tilde{w},y';p'\right)\right)\right)\Big[\left(1-e\left(p'\right)\right)R\left(l=0,n=1,a',w,y';p'\right)\\
&+e\left(p'\right)R\left(l=0,n=0,a',w,y';p'\right)\Big]\Big\}\Big]\Bigg)\\
&+\left(1-d\right)\Bigg(\max_{c^{NT}_{0,1},\,a',\,s}\; u\left(c^{NT}_{0,1}\right) - \nu\left(s\right)\\
&+\beta\left(1-\omega\right)\mathbb{E}\Big[\max_{\tilde{w}}\Big\{sf\left(\theta\left(\tilde{w},y';p'\right)\right)R\left(l=1,n=0,a',\tilde{w},y';p'\right)\\
&+\left(1-sf\left(\theta\left(\tilde{w},y';p'\right)\right)\right)\Big[\left(1-e\left(p'\right)\right)R\left(l=0,n=1,a',w,y';p'\right)\\
&+e\left(p'\right)R\left(l=0,n=0,a',w,y';p'\right)\Big]\Big\}\Big]\Bigg)\Bigg]\\
&+\left(1-l\right)\left(1-n\right)\Bigg[\max_{c_{0,0},\,a',\,s}\; u\left(c_{0,0}\right) - \nu\left(s\right)\\
&+\beta\left(1-\omega\right)\mathbb{E}\Big[\max_{\tilde{w}}\Big\{sf\left(\cdot\right)R\left(l=1,n=0,a',\tilde{w},y';p'\right)\\
&+\left(1-sf\left(\cdot\right)\right)R\left(l=0,n=0,a',w,y';p'\right)\Big\}\Big]\Bigg]
\end{aligned}
$$

subject to

$$
\begin{aligned}
& c_{1,0} + a' \leq \left(1+r\right)a + w\left(1-\tau\right)\\
& c^{T}_{0,1} + a' \leq \left(1+r\right)a + b\left(w,p\right)w\left(1-\tau\right) + h\\
& c^{NT}_{0,1} + a' \leq \left(1+r\right)a + h\\
& c_{0,0} + a' \leq \left(1+r\right)a + h\\
& p' \sim F\left(p'\,|\,p\right), \quad y' \sim Q\left(y'\,|\,y\right),
\end{aligned}
$$

where we use the result from above that market tightness does not depend on Γ, and $c_{1,0}$, $c^T_{0,1}$, $c^{NT}_{0,1}$, and $c_{0,0}$ represent consumption of the employed, unemployed eligible who take up UI, unemployed eligible who do not take up UI, and unemployed ineligible, respectively. In the above equation, the first two lines on the right-hand side represent the problem of an employed individual; the last three lines represent the problem of an ineligible unemployed; and the lines in between represent the problem of an eligible unemployed with a choice of UI take-up effort.

Assuming the utility function is bounded and continuous, $\mathcal{R}$ is the set of continuous and bounded functions. Then, we can show that the operator T_R maps a function from $\mathcal{R}$ into $\mathcal{R}$ (i.e., $T_R : \mathcal{R} \to \mathcal{R}$). Then, using Blackwell's sufficiency conditions for a contraction and the assumptions of the boundedness of the sets of exogenous processes $\mathcal{P}$ and $\mathcal{Y}$ and the choice sets $\mathcal{W}$ and $\mathcal{A}$, and given that choice sets on UI take-up effort $d \in [0, 1]$ and job-search effort $s \in [0, 1]$ are bounded, we can show that T_R is a contraction and has a unique fixed point $R^* \in \mathcal{R}$. Thus, the solution to the individual's problem does not depend on Γ. This result, together with the solution to the firm's problem and implied labor market tightness (both of which do not depend on Γ), constitutes a BRE given that UI policy is a function of p only.

Uniqueness: Now, we prove the uniqueness of the policy functions for assets and wages, as well as UI take-up and job-search effort.

Wage policy function: Under the assumptions on $u(\cdot)$, $\nu(\cdot)$, and $\phi(\cdot)$ together with the assumptions of the boundedness of the sets of exogenous processes $\mathcal{P}$ and $\mathcal{Y}$ and the choice sets $\mathcal{W}$ and $\mathcal{A}$, value functions V^l are strictly concave in w for $l = \{W, B\}$, and $l = NB$ is constant in w. For simplicity, assume that p and y are non-stochastic and $\delta(y, p) = \delta$.[9] We then obtain the equilibrium value of a matched firm using Equation (4) as follows:

$$J^*(w, y; p) = \frac{py - w}{r + \delta + \omega(1 - \delta)}(1 + r).$$

Then, we can write the job-finding rate in a submarket as

$$f(\theta^*(w, y; p)) = \theta^*(w, y; p) = \frac{J^*(w, y; p)}{\kappa},$$

where we assume that $M = \min\{v, S\}$ in the first equality, and the second equality uses the free-entry condition.[10] Using the expression for $J^*(w, y; p)$ gives

$$f(\theta^*(w, y; p)) = \frac{1 + r}{\kappa[r + \delta + \omega(1 - \delta)]}[py - w] > 0.$$

[9] The following results can be obtained under an N state Markov process assumption for p and no restrictions on the job destruction rate.

[10] We choose this functional form for the matching function for clarity of demonstration. This result follows also for the CES matching function we use in Section III.

Thus, the job-finding rate $f(\cdot)$ is linear and decreasing in w. Then, rewriting the objective function for the wage choice of eligible unemployed, we have

$$\max_{\tilde{w}} sf(\theta(\tilde{w},y;p))V^W(a',\tilde{w},y;p)+(1-sf(\theta(\tilde{w},y;p)))$$
$$\times\left[(1-e(p))V^B(a',w,y;p)+e(p)V^{NB}(a',y;p)\right].$$

Using the result that V^W and V^B are strictly concave in w, V^{NB} is constant in w, and $f(\cdot)$ is linear and decreasing in w, it is easy to show that the objective function above is strictly concave in w. This implies that the wage policy function of the eligible is unique.

Similarly, rewriting the objective function for the wage choice of the ineligible yields

$$\max_{\tilde{w}} sf(\theta(\tilde{w},y;p))V^W(a',\tilde{w},y;p)+(1-sf(\theta(\tilde{w},y;p)))V^{NB}(a',y;p).$$

Using the same reasoning implies that the wage policy function of the ineligible is also unique.

Asset policy function: Under the assumptions on the utility functions $u(\cdot)$, $\nu(\cdot)$, and $\phi(\cdot)$, choice sets $\mathcal{A}$ and $\mathcal{W}$, exogenous processes $\mathcal{Y}$ and $\mathcal{P}$, and the value functions V^l are strictly concave in assets. This implies that the objective function for the asset choice of each employment status is strictly concave in a', and thus asset policy functions are unique.

Search effort policy function: Using the same reasoning, the objective function for the search effort choices of the eligible and ineligible unemployed is strictly concave in s. This implies that the search effort policy functions are also unique.

UI take-up effort policy function: Similarly, the objective function for the take-up effort choice of the eligible unemployed is strictly concave in d. This implies that the UI take-up effort policy function is also unique.

Discussion This proposition demonstrates that the model can be solved numerically without keeping track of the aggregate distribution of agents across states Γ. One should be careful when interpreting this result. Even though we can solve for the policy functions, value functions, and labor market tightness independent of Γ, it does not mean that the distribution of agents is irrelevant for our analysis. Notice that the evolution of macroeconomic aggregates such as the unemployment rate, average spell duration, and wealth distribution of the economy are determined by individuals' policy functions. These decisions, in turn, are functions of individual states whose distribution is determined by Γ. Hence, the evolution of aggregate variables after a change in UI policy will depend on the distribution of agents at the time of the policy change.

Notice that if the UI policy instruments were to depend on the unemployment rate, then it would break the block recursivity of the model. This is because agents would need to calculate next period's unemployment rate to know the replacement rate and UI duration next period.

However, this requires calculating the flows in and out of unemployment, the latter of which depends on the distribution of agents across states Γ. Although the changes in UI policy are triggered by the changes in the unemployment rate according to the UI program in the U.S., the assumption that UI policy depends on aggregate productivity is not restrictive because of the strong correlation between the unemployment rate and aggregate productivity in our model.

B.3 Computational algorithm

The model is solved using the following steps:

1. Solve for the value function of the firm $J(w, y; p)$.

2. Using the free-entry condition $0 = -\kappa + q(\theta(w, y; p)) J(w, y; p)$ and the functional form of $q(\theta)$, we can solve for market tightness for any given wage submarket (w, y) and aggregate productivity p:
$$\theta(w, y; p) = q^{-1}\left(\frac{\kappa}{J(w, y; p)}\right),$$
where we set $\theta(w, y; p) = 0$ when the market is inactive.

3. Given the function θ, we can then solve for the individuals' value functions V^W, V^B, and V^{NB} using standard value function iteration.

4. Once policy functions are obtained, we simulate the aggregate dynamics of the model.

C Calibration

In this section, we present additional tables and figures to supplement our discussion in Section III of the main text. Table A4 provides a list of externally calibrated parameters.

Elasticity of nonemployment duration with respect to UI duration In our calibration exercise, we choose the curvature of the utility cost of job-search effort to match the magnitude of the elasticity of nonemployment duration to UI duration. Table A5 provides a summary of available empirical estimates for this elasticity together with their methodology. These papers exploit cross-sectional or time variation in UI duration to measure the response of nonemployment duration to a change in UI duration by comparing the nonemployment duration of those who are subject to the policy change (treatment group) vs. those who are not (control group).

Heterogeneity in UI replacement rates In our calibration exercise, we choose the parameters m_0^b and m_w^b of the replacement-rate function to match the average replacement rate and its bottom-to-top quintile ratio when the unemployed are ranked by their base period AWW. Figure A1 shows that our calibrated replacement-rate function closely tracks the declining profile of the replacement rate in AWW observed in the SIPP data combined with UI state regulations.

Table A4: Externally calibrated parameters

Parameter	Explanation	Value	Parameter	Explanation	Value
ω	Probability of death	0.0021	ρ^p	Persistence of aggregate labor productivity	0.9183
σ	Risk aversion	2	σ^p	Dispersion of aggregate labor productivity	0.0042
α_s	Level of utility cost of search	1	m_0^e	Level of UI expiration rate	328.48
r	Interest rate	0.0033	m_p^e	Cyclicality of UI expiration rate	-321.98
κ	Vacancy posting cost	0.58	e_{cap}	Maximum UI expiration rate during non-recessions	4/26
γ	Matching function parameter	0.5	m_p^b	Cyclicality of UI replacement rate	0
ρ^y	Persistence of idiosyncratic productivity	0.9867	m_p^g	Cyclicality of fraction of UI-eligible job losers	0

Note: This table provides a list of externally calibrated parameters. Please refer to the main text for a detailed discussion.

Table A5: Empirical estimates on the effects of UI duration on nonemployment duration

Δ in UI duration $\to$ Δ in nonemp. duration	Source	Methodology
1 week $\to$ 0.16 weeks	Moffitt (1985)	Differences in UI duration across states and time
1 week $\to$ 0.16 weeks	Katz and Meyer (1990)	Differences in UI recipients and non-recipients
13 weeks $\to$ 1 weeks	Card and Levine (2000)	13 weeks extension of UI benefits in New Jersey
10 weeks $\to$ 1.5 weeks	Valletta (2014)	Differences in UI duration across states and time
1 month $\to$ 0.15 months	Schmieder et al. (2016)	Longer UI duration for workers above age 42 in Germany
9 weeks $\to$ 0.29 weeks	Nekoei and Weber (2017)	Longer UI duration for workers above age 40 in Austria
1 month $\to$ 0.25 months	Johnston and Mas (2018)	16 weeks cut in UI duration in Missouri

Note: This table provides a summary of available empirical estimates on the effects of maximum UI duration on unemployment duration of individuals who collect UI benefits.

D Model Validation

In this section, we present additional results to supplement our discussion in Section IV.

Joint distribution of income and assets conditional on productivity In Section IV.A, we compare the joint distribution of wealth holdings and income in the model with the equivalent distribution observed in the data. Table A6 compares the empirical joint distribution of income and wealth holdings when conditioned on educational attainment with its counterpart in the model for agents with different levels of idiosyncratic productivities. As discussed in the main text, both in the data and the model, the correlation between income and assets increases in

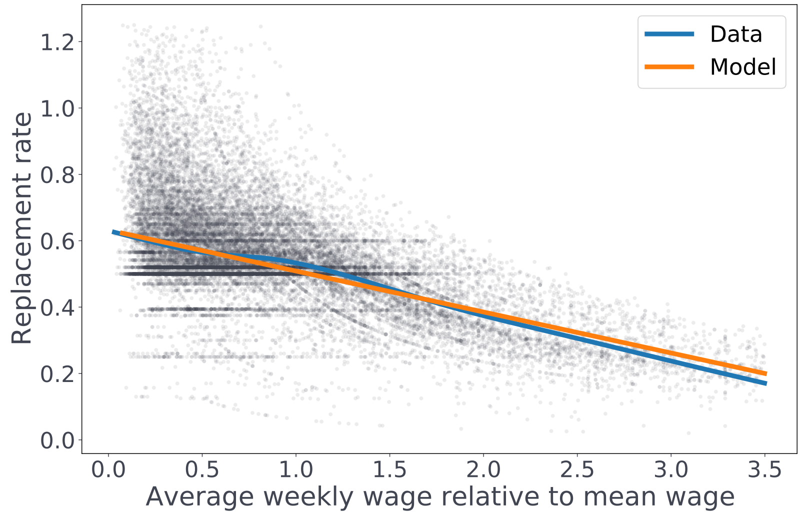

Figure A1: UI replacement rates in the data vs. model

Note: This figure compares UI replacement rates in the model and the data across the average weekly wage relative to the mean wage. We calculate the replacement rates of UI-eligible unemployed across average weekly wages by creating a program that combines information from SIPP data and eligibility rules based on state-level UI laws. Each gray dot represents an individual replacement rate in the data. Replacement rates in the model represent the calibrated $b(w, p)$ function, where we plot each value under the mean level of aggregate labor productivity; i.e., $p = \bar{p}$.

productivity, although the model overstates the difference.

E Results

In this section, we provide additional results and discussions to supplement our main results presented in Section V.

Earnings and consumption drop upon job loss In Section V.A, we use data from the PSID to estimate the dynamics of earnings and consumption around a job separation. In this section, we provide more details about the data, sample, and estimation.

The PSID is available annually between 1968 and 1997 and biannually since 1997. It contains information on labor earnings, consumption expenditures, and demographics. Labor earnings include wages and salaries, bonuses, overtime, tips, commissions, professional practice or trade, market gardening, miscellaneous labor income, and income from extra jobs. Labor earnings are available at the individual level in every survey in which an individual participates. Our measure of consumption expenditures includes expenditures on food consumed inside and outside the home, health expenditures, housing expenditures (utilities, taxes, maintenance, etc.), transportation, education, and childcare.[11] Prior to 1999, expenditure information was limited to the food category, while the other categories became available after 1999. Because of this, we use biannual data between 1999 and 2019 when estimating the dynamics of consumption

[11] As of 2005, additional categories (clothing, recreation, alcohol, and tobacco) are included in the data. To keep the consumption expenditure measure consistent over time, we do not include these categories.

Table A6: Joint distribution of income and asset holdings across productivity

	Less than high school degree / Low y					More than master's degree / High y				
	Data									
	Assets									
Income	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1	0.17	0.27	0.22	0.18	0.16	0.38	0.28	0.09	0.17	0.07
Q2	0.18	0.25	0.26	0.18	0.12	0.19	0.31	0.21	0.19	0.09
Q3	0.19	0.20	0.22	0.22	0.17	0.19	0.19	0.27	0.18	0.17
Q4	0.22	0.14	0.18	0.25	0.22	0.14	0.18	0.22	0.21	0.25
Q5	0.25	0.11	0.13	0.17	0.33	0.08	0.11	0.18	0.23	0.40
	Model									
	Assets									
Income	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1	0.45	0.28	0.08	0.07	0.12	0.81	0.09	0.01	0.00	0.09
Q2	0.16	0.36	0.21	0.11	0.17	0.10	0.75	0.11	0.01	0.03
Q3	0.15	0.17	0.36	0.16	0.17	0.04	0.04	0.80	0.09	0.02
Q4	0.13	0.12	0.26	0.32	0.17	0.03	0.06	0.05	0.77	0.09
Q5	0.11	0.08	0.10	0.34	0.38	0.02	0.05	0.03	0.13	0.77

Note: This table compares the joint distribution of assets and income implied by the baseline model with those empirically observed in the data. The joint distribution for respondents with less than a high school degree and with more than a master's degree in the data are compared with the joint distribution for agents with the lowest and highest productivity, $y_{\min}$ and $y_{\max}$, respectively. Rows represent quintiles of income, and columns represent quintiles of assets. Income corresponds to the monthly labor earnings of the respondent from their current job (for employed) or the average monthly labor earnings in their previous job (for unemployed). Assets in the data are measured as net liquid wealth holdings.

upon job loss. While consumption expenditures are provided at the household level, earnings are observed for individuals. We focus on the dynamics of the household head's earnings and household consumption following the head's job loss. This approach ensures that comparable events are used when studying the responses of earnings and consumption.

We construct variables for job loss using a question that asks individuals who are either jobless or have been employed in their current job for less than a year about the reason for the loss of their previous job. Since our model does not differentiate between reasons for unemployment, our definition of a job loss in the data incorporates unemployment due to any reason (i.e., voluntary/expected separations such as quits, firings, and the end of temporary/seasonal jobs as well as involuntary/unexpected separations such as layoffs and business closures). Moreover, since the 1968 survey only identifies workers who have been separated within the past 10 years, we cannot determine the exact year of displacement. Therefore, we exclude separations that occur in 1968 from our analysis.

Our sample consists of household heads between the ages of 25 and 64. We drop families observed for only one year and those with labor earnings or consumption expenditures that exceed the 99th percentile. Using this sample, we estimate Equation (8) for consumption expenditures and for the household heads' labor earnings. To facilitate comparison with the empirical results, we estimate the same specification on model-generated data, separately for earnings and consumption, where we aggregate monthly simulations to annual frequency.[12]

The estimated earnings dynamics around job loss in the data (see Figure 1) are reasonable when compared to the existing estimates in the literature. A large literature shows that involuntary job separations have large negative and persistent effects on labor earnings (see Jacobson, LaLonde, and Sullivan 1993 and Stevens 1997, for example). Because our job-loss variable incorporates both involuntary and voluntary separations, the initial estimated earnings loss in our specification is unsurprisingly lower and less persistent. Once we restrict separations to only those that are involuntary, our estimates become similar to the existing estimates.

Our empirical results on consumption dynamics around job loss are also in line with the existing estimates in the literature. For example, Saporta-Eksten (2014) estimates a similar regression specification using the PSID between 1999 and 2009 and finds that the average consumption drop in the year of job loss is 8 percent, which is close to our estimate of 9.3 percent.

Finally, we make further comparisons of consumption dynamics between the model and the data for higher frequencies. First, Burgess et al. (1981) use data from the Arizona Benefit Adequacy Study completed between 1975 and 1978. The data incorporate information on various expenditure components before and after job loss.[13] Analyzing a sample of *continuously* unemployed individuals who receive UI, they find an average consumption drop of 15.2 percent from the month prior to job loss to the 13th week of unemployment. For comparison, we use model-generated monthly data and compute the percent change in consumption between the third month of unemployment and the month prior to job loss for the same group of agents. We find that the average consumption loss is 10.2 percent in the model.

Second, Browning and Crossley (2001) analyze panel data on individuals who experienced a job loss between February and May of 1993 in Canada. The data incorporate expenditure information on housing, food at home, food outside the home, clothing, and other expenses before and after job loss. They use a sample of individuals who are continuously unemployed for around six months to measure the change in expenditures from before the job loss to six months after the job loss, and find an average consumption fall of 14 percent. Similarly, we use

[12] Both in the model and the data, there are observations with zero annual labor earnings following a job loss. So as not to underestimate the magnitude of the earnings loss upon a job separation, we estimate the regression specification in Equation (8) for labor earnings with the dependent variable set to real labor earnings of the family head and obtain the coefficients ψ_k in real dollar units. We then report them in Figure 1 as a percent of the mean of the real labor earnings one year prior to job separation.

[13] The total expense measure incorporates spending on housing (including utilities and maintenance), food, medical care, credit and loan payments, clothing, transportation, insurance, services and other regular payments, taxes, support of persons outside the household, education, charity and gifts, and travel and entertainment.

Table A7: Decomposition of heterogeneity in labor market responses

		Baseline model					Alternative model				
Asset-to-income ratio		Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Search s	Unemployed	-0.03	-0.65	-0.46	-0.24	-0.15	-0.08	-1.44	-3.31	-3.65	-3.36
	Eligible	-0.07	-0.85	-0.60	-0.31	-0.23	-0.19	-3.24	-5.14	-5.89	-6.61
	Take-up	-0.06	-0.85	-2.25	-3.33	-0.63	-0.19	-3.24	-5.14	-5.89	-6.61
	Non-take-up	-0.09	-0.87	-0.07	-0.10	-0.11					
	Ineligible	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
Submarket $f(w)$	Unemployed	-0.46	-0.66	-0.51	-0.18	-0.03	-0.80	-0.68	-0.59	-0.26	-2.37
	Eligible	-0.99	-0.88	-0.67	-0.23	-0.05	-1.90	-1.82	-0.97	-0.43	-4.43
	Take-up	-0.34	-0.47	-1.50	-2.36	-0.36	-1.90	-1.82	-0.97	-0.43	-4.43
	Non-take-up	-2.56	-1.71	-0.51	-0.16	0.00					
	Ineligible	0.03	0.04	0.07	0.01	0.01	0.00	0.00	-0.01	-0.03	-0.13

Note: This table compares the changes in the average search effort s and average reemployment wage choice of the unemployed — the latter of which is represented as the average submarket-specific job-finding probability $f(w)$ in submarket w conditional on search effort — across asset-to-income ratio quintiles when the replacement rate is increased by 10 percentage points in the baseline model and the alternative model. Values in the table are percent changes of average search effort s and average submarket job-finding probability $f(w)$ relative to their values under the calibrated policy. Quintiles are based on the asset-to-income ratio distribution.

Table A8: Effect of additional take-up on labor market responses

	Unemployment duration response				
Asset-to-income ratio	Q1	Q2	Q3	Q4	Q5
Unemployed (take-up group fixed)	0.28	1.20	1.44	1.02	0.37
Unemployed	0.37	2.05	1.48	1.36	0.48

Note: This table compares the changes in the average completed spell duration across asset-to-income ratio quintiles when the replacement rate is increased by 10 percentage points in the baseline model and the alternative model. The first row presents the change in durations when we eliminate the response of individuals who changed their take-up decision in response to the increase in UI generosity – and thus shows the effects coming purely from changes in job-search behavior. The second row presents the full change in unemployment durations, accounting for both changes in take-up and changes in job-search behavior.

our model-generated data and construct the same measure for the same group. We find that the average consumption loss is 14 percent in the model. Hence, our model-implied estimates on the decline of consumption upon job loss are close to empirical estimates that use different samples or frequencies.

Labor market responses: Decomposing job-finding rate responses In Section V.B, we show that the elasticity of the job-finding rate is heterogeneous across agents with different wealth positions and UI status. Table A7 shows that when the changes in job-finding rate are decomposed into responses coming from the average decrease in search effort s and increase in wage choices w – the latter of which is represented as the average decline in job-finding probability $f(w)$ in the submarket w conditional on s – the same patterns are observed.

Table A9: Unemployment hazard regression

Dependent variable: Unemployment hazard rate		
	Coefficient estimate	Std. error
Q1$\times$ log WBA	-0.257	(0.040)
Q2$\times$ log WBA	-0.337	(0.046)
Q3$\times$ log WBA	-0.324	(0.054)
Q4$\times$ log WBA	-0.317	(0.039)
Q5$\times$ log WBA	-0.279	(0.055)
Age	-0.009	(0.007)
Age^2	0.00004	(0.00009)
Married	0.090	(0.015)
College	-0.043	(0.025)
White	0.138	(0.029)

Note: This table presents the results for a stratified Cox (unemployment) hazard model when individuals are grouped by asset-to-income ratio quintiles. The sample is restricted to unemployment spells in the 1996–2008 panels of the SIPP that have at least three months of prior labor market history and for whom respondents reported receiving UI within one month after job loss. The WBA for each spell is obtained from a UI program that calculates predicted WBA based on state laws and labor market histories. Values in parenthesis denote the standard errors. Other controls include wealth level, state, year, the interaction of asset-to-income ratio quintiles with a 10-piece log-linear spline for the claimant's earnings prior to job loss, and a seam indicator to account for seam effect.

Labor market responses: Decomposing changes in take-up vs. job-search behavior In Section V.B, we demonstrated the heterogeneous responses of the job-finding rate to a 10 percentage point increase in replacement rates. The increase in unemployment duration that arises can be attributed to two margins: a change in the level of take-up and a change in the job-search behavior of the unemployed. To understand the relative importance of each channel, Table A8 reports intermediate results for the case when we remove the responses for individuals that switched to taking up UI after the increase in generosity. This removes the impact of a level change in take-up rates and isolates the responses along the search effort and reemployment wage margins. As seen in Table A8, the response along the take-up and job-search behavior margins both play a significant role, although the latter is larger. For example, among those in the bottom quintile, unemployment durations would have increased by 0.28 percent if the take-up decision were held fixed, lower than the full impact of 0.37 percent.

Unemployment hazard elasticities across the wealth distribution Here, we provide details about the estimation of heterogeneous elasticities using the hazard model in Equation (10) à la Chetty (2008) described in Section V.C. We focus on a pooled sample of unemployment spells observed from the 1996–2008 SIPP panels during which respondents reported having received UI benefits within one month after job loss. For each spell, we assign a predicted WBA based the methodology outlined in Section I. Apart from demographic, wealth, wage, state, and year variables, our controls include a seam indicator which takes a value of 1 for months that

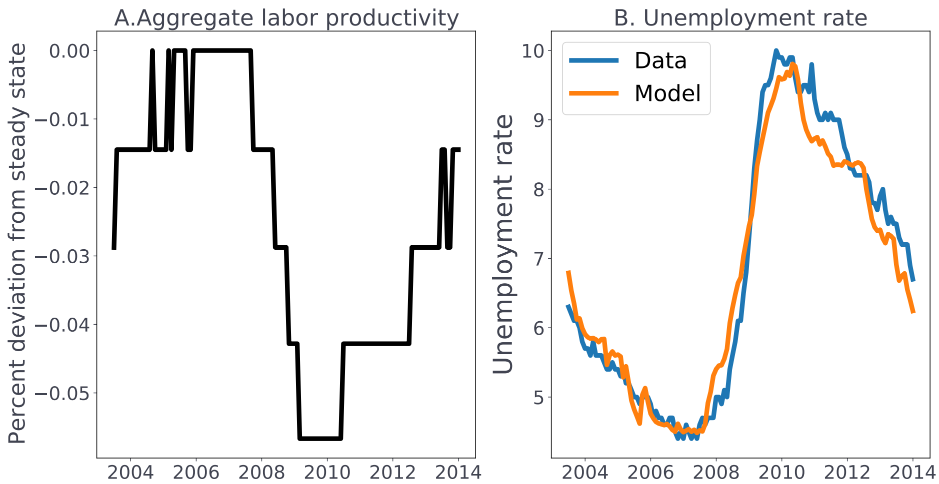

Figure A2: Great Recession simulation in the model

Note: This figure shows the series of aggregate labor productivity (Panel A) that we feed into our model to generate the observed unemployment rate (Panel B) before and after the Great Recession. We use this simulation to study the unemployment rates and LTU shares with and without UI extensions during the Great Recession in Section V.C.

Table A10: Estimates on the effect of Great Recession UI extensions on the unemployment rate

Source	Δ unemp. rate (pp)		Methodology
	Min	Max	
Rothstein (2011)	0.1	0.5	State, time, and indiv. diff. in unemployment hazards
Chodorow-Reich et al. (2019)	0.1	0.3	Variation in UI extensions due to measurement error
Valletta and Kuang (2010)	0.4		Compare durations of UI eligible and UI ineligible
Farber and Valletta (2015)	0.4		State variation in UI extension size/timing
Elsby, Hobijn, and Şahin (2010)	0.7	1.8	Estimates of duration response to UI extension
Daly et al. (2012)	0.8		Compare durations of UI eligible and UI ineligible
Mazumder (2011)	0.8	1.2	Estimates of duration response to UI extension
Fujita (2011)	1.2		Hazard function 2004-2007 vs. 2009-2010
Fujita (2010)	1.5		Estimates of duration response to UI extension
Hagedorn et al. (2019)	2.15		UI policy discontinuity at state borders

Note: This table provides a summary of available empirical estimates on the effect of UI extensions during the Great Recession on the unemployment rate.

immediately precede an interview date. We then divide the sample into asset-to-income ratio quintiles and identify right-censored spells. Spells for which we do not have WBA or AWW information are dropped. The results of estimating Equation (10) are presented in Table A9, where we report the estimated percent changes in response to a 10 percent increase in benefits.

Great Recession simulation in the model In Section V.C, we study changes in the unemployment rate and LTU share with respect to UI generosity during the Great Recession in the model and the data. To make a direct comparison between the model and the data, we feed a series of aggregate shocks in the model to match the unemployment rate from October 2003 to November 2013 (the 10-year period that spans the SIPP 2004 and 2008 panels). The left panel of Figure A2 shows the path of aggregate productivity p that accomplishes this. The right panel compares the resulting unemployment rate simulated in the model with that in the data.

Table A10 summarizes the range of empirical estimates found by the literature that studies the impact of UI extensions during the Great Recession on the unemployment rate. Information from this table is used as the range and median of estimates found in Table 11.

F Robustness

In this section, we provide more details about the robustness exercises discussed in Section VI. Table A11 summarizes the results.

Different parameter values We analyze our main results that relate to insurance benefits (Section V.A) and incentive costs (Section V.B) under different parameter values. In these exercises, we leave other parameters of the model the same as the benchmark calibration.

In Table A11, we compare our main results with their counterparts under lower values of the curvature parameter χ_s of the utility cost of job-search effort. This is motivated by the recent work of Faberman, Mueller, Şahin, and Topa (2021), who use microdata on search effort and find search effort to be more elastic than what we obtain. Recall from Table 11 that a one-month increase in UI duration implies an increase in nonemployment duration of 0.14 months in the baseline model and 0.30 months in the alternative model, where the latter magnitude exceeds the upper range of available empirical estimates. As a result, the alternative model estimates an elasticity of nonemployment duration that is 0.16 months larger than the baseline model under the benchmark calibration of χ_s. As we lower χ_s, we find that the gap between the baseline model and the alternative model in their estimates of the nonemployment duration elasticity increases. This is intuitive because lowering χ_s increases the elasticity of the search effort and further amplifies the overestimation of nonemployment duration elasticity in the alternative model relative to the baseline model. In all of these cases, the alternative model generates a nonemployment duration elasticity that is greater than 0.30 months, which exceeds the upper range of empirical estimates. Table A11 also shows that our main results on other behavioral elasticities remain unchanged. Specifically, the response of the job-finding rate to a change UI generosity and the elasticity of the pre- and post-unemployment wage changes with respect to UI duration remain large in the alternative model relative to their respective empirical estimates. We also arrive to the same conclusion when we consider alternative values of the matching function parameter γ as shown in Table A11.

Recall from Section V.A that the consumption drop for the take-up group is larger in the baseline model than in the alternative model. Specifically, under the baseline model, in the year of job loss, UI recipients suffer a consumption drop that is 7.27 percentage points larger than

Table A11: Main results under different parameter values and model assumptions

	Job-finding rate response gap (%)	Nonemployment dur. elas. gap (months)	Wage change elas. gap (pp)	Cons. drop of take-up gap (pp)
Benchmark, $\chi_s = 1.51$, $\gamma = 0.5$	1.98	0.16	0.63	7.27
$\chi_s = 1.00$	1.59	0.16	0.74	7.35
$\chi_s = 0.75$	1.55	0.17	0.71	7.41
$\chi_s = 0.50$	1.66	0.17	0.68	7.55
$\chi_s = 0.25$	1.46	0.20	0.70	7.60
$\chi_s = 0.10$	0.81	0.21	0.68	7.59
$\gamma = 1.00$	4.73	0.34	1.30	10.12
$\gamma = 1.25$	3.71	0.34	0.96	10.66
$\gamma = 1.50$	4.14	0.39	1.02	10.98
Binary take-up choice $d \in \{0, 1\}$	1.72	0.16	0.63	7.27
High UI rep. rate and $\eta_p^\lambda = 0$	1.73	0.34	1.27	6.90
High gov. expenses and prog. tax	0.98	0.16	0.65	5.71

Note: This table provides a summary of main results under different parameter values and model assumptions. Job-finding rate response gap refers to the difference between the percent decline in the job-finding rate upon a 10 percentage point increase in UI replacement rates (as in Table 10) in the baseline model vs. the alternative model (alternative minus baseline). Nonemployment duration elasticity gap refers to the month difference between the elasticity of nonemployment duration with respect to UI duration in the baseline model vs. the alternative model (as in Table 11). Wage change elasticity gap refers to the percentage points difference between the elasticity of pre- and post-unemployment wage changes with respect to UI duration in the baseline model vs. the alternative model (as in Table 11). Finally, consumption drop of take-up gap refers to the percentage point difference between the consumption drop in the year of job loss for the take-up group in the baseline model vs. the alternative model (the solid-green and dashed-green lines in Panel C of Figure 1, respectively). Our benchmark calibration incorporates the curvature of the utility cost of the job-search effort $\chi_s = 1.51$ and the matching function parameter $\gamma = 0.5$.

what the alternative model predicts (13.52 percent in the baseline model and 6.26 percent in the alternative model). Table A11 shows that this finding is preserved across a wide range of alternative values of χ_s and γ.

Binary take-up choice In our framework, we model the UI take-up decision as take-up effort $d \in [0, 1]$ such that higher take-up effort increases the chances of UI receipt. This is motivated by the fact that increased compliance with regulatory requirements to file a UI claim and providing proof of initial or ongoing eligibility raises the chances of approval. Modeling take-up as a continuous choice allows us to use the curvature parameter of the disutility of the take-up effort χ_d to discipline the volatility of take-up rate over time. Here, we consider a different assumption and model take-up choice as a decision on whether to file a UI claim, i.e., $d \in \{0, 1\}$ subject to a fixed utility cost. In this case, if an eligible unemployed decides to claim benefits, then he/she receives UI with full probability. In doing so, we leave the other assumptions and parameters of the model the same. Under this alternative specification, our main conclusions remain similar.

High UI replacement rate and acyclical matching function efficiency Shimer (2005) shows that the standard labor search framework fails to generate the observed magnitude of the volatility of unemployment. In this model, we get around this problem by assuming a procyclical matching efficiency process. Together with fluctuations in the job-separation rate over time, this allows our model to generate the observed volatility of the unemployment rate. Here, we consider an alternative approach suggested by Hagedorn and Manovskii (2008). Specifically, we shut down the cyclicality of the matching efficiency, i.e., $\eta_p^\lambda = 0$, and set the intercept parameter of the UI replacement rate to $m_0^b = 0.98$, which implies an average replacement rate of 83.5 percent across UI recipients with heterogeneous previous labor earnings, much higher than 52 percent, which we document in the data. Under this assumption, we still find that the alternative model understates the insurance benefits associated with UI by overstating the level of self-insurance UI recipients possess. It also generates substantially larger magnitudes of key elasticities.

High level of government expenditure and progressive taxation In the model, the income tax required to finance the UI program is 0.34 percent. Although this tax level is reasonable given the absence of any other type of government spending in our model, one concern may be whether a marginal change in taxes to fund the UI policy will have different implications depending on the level of taxes. In order to understand this, we now assume that the government has additional expenses that are 19 percent of period output, a value which is close to the average ratio of total government expenditure to GDP in the U.S. In this model, we also introduce progressive income taxation to better approach the current taxation system. Following Heathcote, Storesletten, and Violante (2014), the after-tax labor income of the individual is given by $\tilde{x} = \Phi x^{1-\Upsilon}$, where $x = w$ for a worker and $x = bw$ for a UI recipient, Φ determines the level of taxation, and $\Upsilon \geq 0$ determines the rate of progressivity built into the tax system. This implies that the government's tax revenue from an individual with labor income x is $T(x) = x - \Phi x^{1-\Upsilon}$. Then, we set $\Upsilon = 0.151$, as in Heathcote, Storesletten, and Violante (2014). In this case, we find that $\Phi = 0.834$ satisfies Equation (7). The resulting consumption drop and labor market elasticity gaps between the baseline and the alternative models in this version of the framework remain close to those under our benchmark framework. While still large, the gap in consumption drops among UI recipients in the baseline and the alternative model narrows given that the progressive tax system redistributes income more aggressively toward job losers in the baseline model who are predominantly wealth-poor.

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