

Labor Market Responses to Unemployment Insurance: The Role of Heterogeneity*

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Abstract

We document considerable scope of heterogeneity within the unemployed, especially when the unemployed are divided along eligibility and receipt of unemployment insurance (UI). We develop a heterogeneous-agent job-search model capable of matching the wealth and income differences that distinguish UI recipients from non-recipients. Labor market responses to UI changes are non-monotonic in wealth because the poorest individuals exhibit weak responses due to the high value they attribute to employment. Differential elasticities imply that the extent to which structural models account for the composition of UI recipients is material to aligning predicted responses with empirical estimates and to policy evaluation.

Keywords: Unemployment Insurance, Business Cycles, Job Search

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1 Introduction

A recurrent question in the study of labor market policies is the extent to which fiscal transfers distort job-search activities and employment outcomes. The answer to this question is particularly important for both researchers and policymakers concerned with the effects of unemployment insurance (UI) program design. In this paper, we argue that structural models used to predict behavioral responses to UI policy changes must account for the rich heterogeneity that the unemployed exhibit, since individual responses differ greatly across types of job seekers.

We make two key contributions to understanding this fundamental issue. First, we provide empirical evidence on the scope of heterogeneity *within* the unemployed. Importantly, we emphasize not only heterogeneity in income and wealth but also how these relate with heterogeneity in both labor market prospects and UI status. We utilize microdata on employment, income, and wealth combined with state-specific and time-varying laws that govern UI eligibility and generosity to document how labor market flows, as well as UI-eligibility, take-up, and replacement rates vary with the wealth and income of the unemployed. Second, we develop a structural framework capable of not only matching this heterogeneity but also of assessing the extent to which different dimensions of heterogeneity affect the sizes of predicted labor market responses to UI changes. We compare model-predicted elasticities with those of existing estimates and show that abstracting from heterogeneity implies model elasticities that either approach or exceed the upper range of empirical estimates. Beyond bridging the gap between empirical studies and structural models, we also provide an illustration of how different modeling choices, insofar as heterogeneity within the unemployed is concerned, affect the evaluation of UI policy reform.

Our empirical analysis addresses several questions: How do income and wealth affect employment transitions? What distinguishes UI-eligible unemployed who take up benefits from those who do not? How does eligibility and take-up behavior change over the business cycle? A necessary ingredient to address these questions is information on individual UI eligibility. While existing microdata such as the Survey of Income and Program Participation (SIPP) collect information on employment, income, wealth, and UI benefit amounts, none provide information on eligibility. For this reason, one cannot separately identify the unemployed who are ineligible from those who are eligible for UI but choose not to collect benefits. We construct a program that overcomes this deficiency by combining labor market histories from the SIPP with state-level UI laws on monetary and non-monetary eligibility rules over a period of 20 years to predict the respondents' UI-eligibility and replacement rates. This critical step allows us to analyze the distributional properties of the unemployed when subdivided along relevant margins that are first-order to UI policy, such as the eligibility, take-up, and expected replacement rates.

Our empirical findings underscore key dimensions of heterogeneity within the unemployed that remains understudied in the sphere of quantitative studies on UI. We find that while low-

income workers face greater job loss risk and lower job-finding probabilities, they are also less likely to be eligible upon unemployment. Conditional on eligibility, low-income workers receive higher replacement rates should they take up benefits. In terms of wealth, the concentration of unemployment risk among poorer workers implies that the unemployed possess less self-insurance than the employed. Importantly, UI recipients have substantially lower wealth holdings and capacity to self-insure than their counterparts who are eligible but do not take up benefits. Finally, we document that the eligibility and take-up rates are both countercyclical.¹ The former is driven by the changing earnings composition of job losers and UI extensions during recessions, while the latter is driven by the take-up decisions of individuals with some degree of wealth to insure against unemployment during normal times but not enough during sharp downturns.

These empirical findings motivate a framework that connects the heterogeneity in income and wealth to the heterogeneity in labor market transitions as well as UI eligibility, take-up, and replacement rates over the business cycle. We develop a heterogeneous-agent directed-search model with aggregate fluctuations and incomplete markets, where individuals can save or borrow at an exogenous interest rate. Individuals are heterogeneous in terms of their labor productivity, which affects job-finding rates, job-separation rates, and labor income. Moreover, aggregate risk causes exogenous variations in job-separation risk and matching efficiency, which then lead to fluctuations in job-separation and job-finding rates over time.² Unemployed individuals direct their job-search effort toward submarkets that are characterized by wages. Eligibility for UI depends on their previous earnings, and the decision to take up benefits is endogenous. UI benefits are funded through a proportional tax that balances the government's budget in the long run. We calibrate the model to match not only the level and volatility of labor market transitions and UI-related outcomes but also their heterogeneity across the income distribution.

We validate the model against untargeted moments both in the cross-section and over the cycle. First, the unemployed possess much less self-insurance than the employed. However, analyzing the pool of unemployed as a single group hides key differences across UI subgroups. Among the eligible, individuals with sufficiently high self-insurance and shorter unemployment spells do not take up benefits, consistent with the data. Second, the model captures salient features of the joint distribution of income and wealth. In particular, the low unemployment risk among higher earners generates a considerable mass of individuals with high income but weak precautionary saving motives and thus low liquid wealth. Finally, the model also generates countercyclical eligibility and take-up rates as well as a rightward shift in the wealth distributions of both the take-up and non-take-up groups during recessions. This is because relatively wealthier

¹The eligibility rate is the fraction of unemployed individuals who are UI eligible. The take-up rate is the fraction of UI-eligible individuals who receive benefits.

²Shimer (2005) shows that the standard search model fails to endogenously generate the observed magnitude of unemployment volatility. Exogenous variations in job-separation risk and matching efficiency over time allows our model to overcome this.

individuals opt in to the UI program due to elevated unemployment risk during recessions. Equivalently, the required level of wealth to justify non-take-up also becomes higher in recessions.

We contrast the fully featured baseline model with an alternative (nested) model that misses the connection between the heterogeneity in income and wealth and the heterogeneity in unemployment risk and eligibility, take-up, and replacement rates. The alternative model features exogenous take-up and is calibrated to match the same heterogeneity in income and wealth, but only the average labor market flows and eligibility and replacement rates. A natural consequence of this model is the dilution of the empirically observed differences in wealth, income, and UI prospects between the employed and unemployed and among the latter's UI subgroups. Uniform unemployment risk eliminates the wealth and income gaps between the employed and unemployed, uniform eligibility eliminates the income gap between the eligible and ineligible, while exogenous take-up eliminates the large wealth gap between the take-up and non-take-up groups. Thus, this model fails to match the sizable presence of high-income workers with low liquid wealth, as uniform labor market risk strengthens precautionary saving amongst high earners. The alternative model's shortcomings is also apparent in its cyclical predictions. As opposed to the rightward shift in the data and the baseline model, the wealth distribution of UI recipients exhibits a large leftward shift during recessions because exogenous take-up prevents relatively wealthier eligible workers from claiming UI during recessions.

What are the tangible implications of this divergence? We show that the baseline and the alternative model also disagree on their predicted magnitudes of behavioral responses in the labor market to a change in UI generosity. In the baseline model, the job-search activities, i.e., job-search effort and reemployment wage choices, of individuals in the lowest quintile of wealth are less elastic to changes in UI. Being close to the borrowing constraint with no self-insurance, they attribute a high value to employment and exert efforts to secure reemployment even in the face of more generous UI. In this sense, the presence of borrowing constraints self-disciplines the job-search behavior of the wealth-poor unemployed. The top quintiles are also less elastic, albeit for a different reason: they have little stake in UI changes because they are sufficiently self-insured, enjoy high job-finding rates, and face low replacement rates. Individuals in the middle of the two groups exhibit higher elasticities: for those with some degree of self-insurance, additional benefit generosity affords them the ability to look for high-wage jobs that are difficult to find. The resulting inverse-U-shaped pattern implies that the relative position of UI recipients in the wealth distribution ultimately determine the sizes of behavioral responses. Given that primarily individuals with low income and wealth become unemployed and eventually take up UI, the baseline model predicts a limited overall responses to changes in UI generosity. An alternative model that homogenizes unemployment risk and UI outcomes drastically changes the demographics of UI recipients. They now include wealthier individuals who are even more elastic to UI in this model because take-up is costless and they enjoy generous replacement rates.

We then benchmark the model-implied behavioral responses of individuals to a change in UI generosity against the available empirical estimates on the elasticity of nonemployment duration, reemployment wages, wealth holdings, and heterogeneous unemployment hazard rates with respect to changes in UI generosity. While the baseline model generates magnitudes of these elasticities that are within the range of empirical estimates, predictions from the alternative model either approach or exceed the largest magnitude of the range of empirical estimates. Hence, we conclude that the model’s ability to connect the heterogeneity in income and wealth holdings with the heterogeneity in labor market prospects and UI-related outcomes enables it to generate the magnitudes of elasticities within the range of empirical estimates. As a result, our findings have important implications for UI policy design over the business cycle. We conclude the paper with an exercise to illustrate how modeling heterogeneity within the unemployed is pivotal to the predicted insurance benefits and incentive costs associated with UI policy reform.

Related literature There is a growing literature on heterogeneous-agent labor-search frameworks with incomplete markets and business cycles (Krusell, Mukoyama, and Şahin 2010; Nakajima 2012; and Herkenhoff 2019). Our contribution is to bridge the heterogeneity in income and wealth with how they relate with labor market transitions as well as UI-eligibility status and UI take-up decisions. We accomplish this by first providing empirical evidence on the extent of heterogeneity within the unemployed, both in terms of income and wealth and, crucially, eligibility and take-up of UI. We then construct a framework that is capable of capturing this heterogeneity and analyzing to what extent it affects predicted labor market elasticities and policy evaluation. We show that accounting for cross-sectional heterogeneity within the unemployed crucially affects the magnitudes of labor market responses to a change in UI generosity.

This paper also contributes to the empirical literature that estimates the effect of changes in UI policy on nonemployment duration and reemployment wages (among others, Card, Chetty, and Weber 2007; Schmieder, von Wachter, and Bender 2016; Nekoei and Weber 2017; and Johnston and Mas 2018), wealth holdings (Engen and Gruber 2001), and heterogeneous unemployment hazard rates (Chetty 2008). Within this literature, our contribution is to enhance the link between quantitative frameworks and the existing body of empirical evidence by developing a model that can generate direct comparisons to the micro elasticities estimated in this literature, especially with respect to the key demographics and labor market outcomes studied. We show that it is the model’s ability to reproduce the observed heterogeneity within the unemployed in the data that enables it to generate the magnitudes of elasticities within the ranges of empirical estimates. Equivalently, an alternative model that fails to capture the empirical cross-sectional heterogeneity in labor market prospects and UI status produces elasticities that either approach or exceed the upper ranges of empirical estimates.

Finally, our work has implications for the large strand of literature that studies positive and normative questions pertaining to UI under the presence of incomplete markets without

aggregate risk (Hansen and Imrohoroglu 1992; Shimer and Werning 2008; Koehne and Kuhn 2015; Kroft and Notowidigdo 2016; Kekre 2019; Braxton, Herkenhoff, and Phillips 2020; Birinci, Karahan, Mercan, and See 2021) or with aggregate risk (Jung and Kuester 2015; Mitman and Rabinovich 2015; McKay and Reis 2016; Landais, Michailat, and Saez 2018; Birinci 2019; McKay and Reis 2020; Pei and Xie 2020).³ Relative to these papers, our model focuses on the role of cross-sectional heterogeneity in determining the magnitudes of labor market responses to UI changes. Further, we show that underlying heterogeneity in the model affects the trade-off between insurance benefits and incentive costs from UI reform. Hence, we conclude that a quantitative analysis of labor market effects of UI changes requires careful modeling of the cross-sectional heterogeneity within the unemployed.

This paper is organized as follows. Section 2 discusses our empirical findings, and Section 3 presents our model. Section 4 provides calibration details, and Section 5 discusses the main results. Section 6 provides a discussion on the implications of our results on UI policy design over the business cycle as well as several robustness checks, and Section 7 concludes.

2 Empirical Findings

In this section, we document empirical evidence that links the heterogeneity in wealth and income with the heterogeneity in labor market prospects as well as in UI-eligibility status, take-up decisions, and replacement rates, both in the cross-section and over time. The findings highlight the need to model the interaction of both dimensions of heterogeneity and thus motivates our modeling choices in Section 3.

We use SIPP data between 1996 and 2016, which provide monthly information on respondents' demographics, earnings, employment status, and amount of UI receipt. Importantly, the SIPP also contains data on wealth holdings, but they are reported on a less-frequent basis. We restrict our sample to individuals aged 25 to 65 who do not own a business. Appendix A provides more details on the SIPP data, variable construction, and additional results.

2.1 Measurement

Heterogeneity in labor market flows We start with explaining how we measure heterogeneity in the employment-to-unemployment (EU) and unemployment-to-employment (UE) rate across the income, asset, and asset-to-income ratio distributions. We construct EU and UE transition probabilities using longitudinally matched individual-level data. For any given month, we measure the heterogeneity in EU rates across the income distribution by assigning the employed into quintile groups based on their current labor earnings. For each quintile, we calculate the EU rate as the fraction of employed who report being unemployed in the next month. A similar

³While some of these papers use models with full general equilibrium and ours does not, our paper studies the effects of UI policy changes over the business cycle in an incomplete markets framework with a non-degenerate wealth distribution.

procedure is applied to calculate UE rates, except that the unemployed are grouped based on previous income, which is measured as the average labor earnings three months prior to job loss.

We also calculate EU and UE rates across asset and asset-to-income ratio quintiles. Since SIPP wealth information is usually reported in one-year intervals, we approximate the respondent's assets in each month using the SIPP wave with asset information closest to that month. We measure the assets of an individual as net liquid assets, which are defined as the summation of liquid assets net of revolving debt. The asset-to-income ratio is simply assets divided by income, where we use current (previous) monthly labor earnings for the employed (unemployed).⁴

Heterogeneity in UI eligibility and take-up rates While the SIPP provides information on the amount of UI receipt, it does not collect information on eligibility. Thus, without information on eligibility, one cannot separately identify the unemployed who are ineligible and the unemployed who are eligible but do not collect benefits. To overcome this, we construct a program that combines SIPP data with state-level and time-varying UI laws on monetary and non-monetary eligibility rules between 1996 and 2016 to predict a respondent's eligibility.⁵

Monetary eligibility dictates that applicants meet certain labor earnings and employment requirements during a base period – typically the first four of the last five completed calendar quarters preceding the applicant's claim for benefits. Importantly, these requirements vary across states and over time. While almost all states require a certain number of quarters with positive earnings, some states impose a threshold for base period earnings, and others impose a combination of requirements based on quarter-specific earnings and the expected weekly UI benefit amount (WBA). For example, in 2008 and 2009, unemployed individuals in Indiana were required to have i) a total of \$2,750 base period earnings, ii) base period earnings sans the highest quarter that is at least 25 percent higher than the highest-quarter earnings, and iii) at least \$1,650 of earnings in the last two quarters of the base period. However, these rules became more stringent from 2010 to 2013.⁶ In contrast, the monetary eligibility rules in California did not change during the 2008 to 2013 period and required claimants to have either i) at least \$1,300 in the highest quarter of the base period or ii) at least \$900 in the highest quarter and total base period earnings more than 1.25 times the highest quarter's earnings. These examples demonstrate that one cannot simply take a common rule for all states and over time to determine eligibility status of individuals given that states have different rules that may change over time.

Non-monetary eligibility is based on the reason for unemployment. If individuals become unemployed as a result of quitting or being fired due to misconduct, then they would not be

⁴The asset-to-income ratio is often used in the literature, as it provides a useful metric of self-insurance in that it measures how many months of labor earnings net liquid assets can replace.

⁵Detailed information on state UI eligibility rules and weekly benefit amounts are obtained from the [Department of Labor Employment and Training Administration](#).

⁶Between 2010 and 2013, these rules changed to i) a total of \$4,200 base period earnings, ii) earnings outside the highest quarter that are at least 50 percent higher than the earnings in the highest quarter in the base period, and iii) at least \$2,500 of earnings in the last two quarters of the base period.

eligible for UI. This rule is typically applied and invariant over time. UI eligibility also expires once an individual claims benefits beyond a certain number of weeks, which varies over time.

Given these rules, we construct each respondent’s WBA (discussed below) and use SIPP data between 1996 and 2016 on employment, earnings, reason for unemployment, UI receipt duration, and state of residence to predict UI eligibility status. This requires combining SIPP labor market histories with state-level UI laws for around 20 years. Together with information on self-reported UI receipt, this allows us to separately identify the unemployed who are ineligible from the unemployed who are eligible but do not take up benefits.

Now that we have the eligibility status of individuals, we construct monthly measures of the fraction of UI-eligible unemployed (FEU), i.e., $\frac{\text{Eligible Unemployed}}{\text{Unemployed}}$, and the fraction of unemployed receiving UI among UI-eligible unemployed, i.e. the take-up rate (TUR) $\frac{\text{UI recipients}}{\text{Eligible Unemployed}}$ between 1996 and 2016. Importantly, combining the eligibility and take-up information with the income, asset, and asset-to-income ratio information allows us to provide novel facts on the heterogeneity of the FEU and TUR across previous income, asset, and asset-to-income ratio distributions.

Heterogeneity in UI replacement rates Finally, we calculate individual-specific replacement rates by combining a respondent’s earnings histories with state-specific WBA formulas. Going through these formulas across states for 1996 to 2016, we find that they vary across states but rarely change over time. Some states use a formula based on a fraction of average wages in the highest quarter, while others use a combination of various thresholds based on the average weekly wages (AWW) during the base period, the AWW in the highest quarter of the base period, or state-level AWW. For example, between 2008 and 2013, the WBA formula in Minnesota was the higher of i) 50 percent of the worker’s AWW in the base period up to a maximum of 67 percent of the state AWW or ii) 50 percent of the worker’s AWW during the highest quarter in the base period up to a maximum of 43 percent of the state’s AWW. Further, states implement a minimum and maximum WBA amount, with the latter implying a cap to the replacement rate high-income individuals could receive. Once we collect WBA formulas for all states over time, we obtain the predicted replacement rate for an eligible unemployed worker as the ratio of their predicted WBA and their AWW during months in the base period where they have positive earnings.⁷ This step also allows us to document replacement rates across the previous income, asset, and asset-to-income ratio distributions.

2.2 Heterogeneity within the unemployed

Heterogeneity in labor market flows Table 1 summarizes the results for the heterogeneity in EU and UE rates across distributions, where we report EU and UE rates for each quintile

⁷This implies that the average replacement rate we produce is a measure of the generosity of the UI replacement rate offered by the government and not actual average replacement rate among claimants, as the latter is influenced by selection and depends on the distribution of individuals who take up benefits. Replacement rates are also important to correctly predicting eligibility given that some states have WBA requirements.

Table 1: Heterogeneity in labor market flows and eligibility, take-up, and replacement rates

	Income					Assets					Asset-to-income ratio				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
EU	2.39	1.03	0.63	0.52	0.43	0.97	1.64	1.11	0.76	0.61	1.08	1.22	0.95	0.80	0.94
UE	0.78	0.93	1.05	1.08	1.16	1.14	0.80	0.96	1.05	1.04	1.06	0.93	1.00	1.01	0.98
FEU	0.63	0.95	1.09	1.17	1.16	1.17	0.77	0.97	1.07	1.03	1.08	0.97	1.05	1.04	0.88
TUR	0.89	1.13	1.02	0.95	1.02	1.10	1.08	1.07	0.85	0.90	1.18	1.01	1.10	0.94	0.76
RR	1.35	1.16	1.07	0.97	0.67	0.96	1.15	1.15	1.03	0.86	0.99	1.07	1.00	0.97	0.97

Note: This table documents the heterogeneity in employment-to-unemployment (EU) and unemployment-to-employment (UE) worker flow rates, as well as the fraction of UI-eligible unemployed (FEU), the fraction of unemployed receiving UI among UI-eligible unemployed, i.e., the take-up rate (TUR) and UI replacement rate (RR) across income, asset, and asset-to-income ratio quintiles using the SIPP 2004 panel. In each row, we report values for each quintile relative to the overall average. Income corresponds to the monthly labor earnings of the respondent from their current job (for EU) or the average monthly labor earnings in their previous job (for UE, FEU, TUR, and RR). Assets are measured as net liquid wealth holdings.

relative to the overall average transition rates, similar to what [Krusell, Mukoyama, Rogerson, and Şahin \(2017\)](#) report.⁸ We highlight several important results.⁹ First, the EU rate declines significantly in income, implying that the job-separation probability is much larger for workers in lower-paying jobs. For example, a worker in the bottom income quintile is around 2.4 times more likely to experience job loss relative to a worker who earns the average income. Thus, the unemployed have markedly lower (previous) earnings than the employed, as shown in [Table A1](#). Second, the EU rate is non-monotonic and exhibits an inverse-U-shaped pattern with respect to assets and the asset-to-income ratio. As we will show in [Table 2](#), this is explained by the presence of relatively high-paid workers with low liquid wealth. While these individuals are at the bottom quintile of the asset and asset-to-income ratio distributions, their EU rates are relatively lower, as they work at relatively higher-paying jobs. Despite the non-monotonicity, overall, workers in the lower wealth quintiles exhibit higher separation risk. As a result, the unemployed hold lower self-insurance than the employed, as shown in [Table A1](#). Third, the UE rate is higher for unemployed individuals with higher previous earnings. Finally, heterogeneity in UE rates across income, asset, and asset-to-income ratio quintiles is much lower than the heterogeneity in EU rates. Overall, these findings emphasize that labor market prospects vary substantially with individual characteristics. Thus, they motivate a model where labor market transition rates depend on an individual’s relative position within the wealth and income distributions.

⁸[Fujita, Nekarda, and Ramey \(2007\)](#) discuss that flow rates measured from the Current Population Survey (CPS) and the SIPP differ. For this reason, in [Section 4](#), we calibrate our model to match average flow rates in the CPS and the heterogeneity of flow rates in the SIPP. Hence, we report here flow rates relative to the average.

⁹Unless otherwise noted, empirical results in this section are obtained from the 2004 panel of the SIPP, which covers the period 2004 to 2007. Use of this panel is to ensure consistency, as these results are used to inform our model, which is calibrated to match moments from the same time period. Results remain similar when we use all SIPP panels between 1996 and 2014, which cover the period 1996 to 2016.

Heterogeneity in UI eligibility, take-up, and replacement rates Turning to UI outcomes, we find an average FEU of 57 percent, TUR of 61 percent, and replacement rate of 52 percent using the SIPP 2004 panel, implying that around one-third of the unemployed receive UI benefits that cover around half of their previous labor earnings. While these estimates are close to the previous estimates in the literature, we go beyond looking at average levels and explore the underlying heterogeneity in the FEU, TUR, and replacement rates across distributions.¹⁰

Table 1 presents the results for the heterogeneity in the FEU, TUR, and replacement rates across distributions. We emphasize some key patterns. First, the FEU is increasing in income because monetary eligibility rules require sufficient labor earnings prior to job loss. This is further supported by the results presented in Table A1, which shows that the previous earnings of UI-eligible unemployed are higher than for the average unemployed worker, especially at the bottom percentiles, as some individuals with very low previous earnings do not meet monetary eligibility rules. Further, the FEU is non-monotonic and exhibits a U-shaped pattern with respect to assets and the asset-to-income ratio. Again, this is due to the presence of high-income workers with low liquid wealth but higher eligibility rates. However, the heterogeneity of the FEU in income is much higher than the heterogeneity of the FEU in asset and asset-to-income ratio, given that UI eligibility rules are based on previous earnings.

Second, we document that the UI take-up decision depends critically on the level of available self-insurance. The take-up rate of an unemployed individual at the bottom quintile of the asset-to-income ratio distribution is 18 percent higher than the average, while the take-up rate of the top quintile is 24 percent lower. This demonstrates that the group of individuals who are eligible but do not claim UI is composed of those with high levels of available self-insurance. As Table A1 documents, the average asset-to-income ratio of the take-up group is 1.25 and for the non-take-up group is 5.03, which implies that on average, those who do not take-up benefits have liquid wealth to cover 5 months of lost earnings, whereas UI recipients have only enough to cover 1.25 months. In Appendix A, we also estimate an empirical model and find that, among the eligible unemployed, those who have lower self-insurance are more likely to take up UI, even after controlling for various demographic and economic characteristics.

Third, replacement rates significantly decline in previous income – mostly because of maximum UI benefit amount thresholds – and exhibit a non-monotonic pattern in assets and the asset-to-income ratio. Importantly, the declining pattern of replacement rates in previous labor earnings is at odds with a common modeling choice in the literature that assumes uniform replacement rate across all unemployed individuals. Finally, these differences in UI status also

¹⁰Blank and Card (1991) estimate the average FEU and TUR between 1977 and 1987 to be 43 percent and 71 percent, respectively, using the CPS. Auray, Fuller, and Lkhagvasuren (2019) use the same methodology and provide more recent estimates from the CPS. They find the average FEU and TUR between 1989 and 2012 to be 46 percent and 77 percent, respectively. Hence, both papers also conclude that around one-third of unemployed individuals receive UI.

Table 2: Joint distribution of income and asset holdings across education groups

Income	All					Less than high school degree					More than master's degree				
	Assets														
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1	0.17	0.34	0.23	0.14	0.12	0.17	0.27	0.22	0.18	0.16	0.38	0.28	0.09	0.17	0.07
Q2	0.21	0.27	0.25	0.17	0.10	0.18	0.25	0.26	0.18	0.12	0.19	0.31	0.21	0.19	0.09
Q3	0.23	0.18	0.22	0.21	0.15	0.19	0.20	0.22	0.22	0.17	0.19	0.19	0.27	0.18	0.17
Q4	0.22	0.12	0.18	0.24	0.23	0.22	0.14	0.18	0.25	0.22	0.14	0.18	0.22	0.21	0.25
Q5	0.15	0.08	0.13	0.23	0.42	0.25	0.11	0.13	0.17	0.33	0.08	0.11	0.18	0.23	0.40

Note: This table documents the joint distribution of income and asset holdings for all individuals, individuals with less than a high school degree, and individuals with more than a master's degree, using the SIPP 2004 panel. 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 are measured as net liquid wealth holdings.

affect the labor market prospects of unemployed individuals. Table A1 compares the distributions of completed unemployment spell durations across groups. Among the UI-eligible, the unemployed who do not take up benefits have significantly lower spell durations than those who take up benefits. This is partly attributable to the former group being composed of workers with higher previous earnings and higher job-finding rates.

When considered jointly, these results signal potential explanations as to why some unemployed individuals do not collect UI benefits despite being eligible: they hold much higher liquid wealth and experience shorter unemployment spells, both of which diminish the insurance value of public transfers such as UI.

Joint distribution of income and assets The previous discussion revealed that while labor market flows, the FEU, and replacement rates are monotonic in income, they are non-monotonic in wealth. This suggests the possibility of interesting patterns in the data, such as the presence of high-earnings individuals who enjoy low labor market risk but who are also incapable of self-insuring against job loss. Having shown that labor market outcomes and UI status depend on wealth and income differently, we now describe the joint distribution of income and assets both in aggregate and across education groups. In this exercise, we partition respondents into five education groups based on their highest degree received or grade completed.¹¹

Table 2 presents the results for all individuals, as well as for groups with the lowest and highest education levels. The results for all individuals show that income and asset holdings are positively correlated, evidenced by the large masses around the diagonal values. However, there are two important exceptions. First, at the bottom quintile of the income distribution, there is a sizable fraction of individuals at the second quintile of liquid asset holdings. Second, there is a

¹¹The five groups are: less than a high school degree, a high school degree, some college education but no college degree, a college or master's degree, and more than a master's degree. The final group includes individuals with a professional school degree such as doctors and lawyers and those with a doctorate degree.

sizable fraction of individuals in the upper quintiles of the income distribution who are located in the bottom two quintiles of the liquid asset holdings distribution.

The comparison of the joint distribution of income and assets conditioned on education groups uncovers two results. First, there is typically more mass along the diagonal of the joint distribution matrix for more-educated individuals than for less-educated individuals, implying that the positive correlation between income and assets rises with education. Second, while the bottom income quintile of less-educated respondents features a lower fraction of individuals in the bottom asset quintile (17 percent) when compared with more-educated individuals (38 percent), at the top income quintile, the two groups have a closer mass at the top asset quintile (33 percent vs. 40 percent).

2.3 Cyclicalities of eligibility, take-up, and heterogeneity

Moving from cross-sectional heterogeneity, we now analyze how labor market flows and eligibility and take-up rates, as well as the heterogeneity within the unemployed vary over the cycle. Since our goal is to measure long-run volatilities, we use the CPS to generate the second moment properties of the EU and UE rates, as the SIPP suffers from missing periods between panels. We construct employment transition probabilities from the CPS longitudinally matched individual-level data, similar to the way we calculate the EU and UE rates from the SIPP.¹² We align the CPS with the sample period of the SIPP and use data from 1996 and 2016.¹³

Table 3 summarizes our findings. The second moment properties of the unemployment rate as well as EU and UE rates have been studied previously, and our results are similar to existing findings in the literature. A novel contribution of our analysis is to document the second moment properties of the eligibility (FEU) and take-up (TUR) rates in the data. We find that the standard deviation of the eligibility rate is 7.6 percent, similar in magnitude to the standard deviation of the EU rate for this time period. The FEU is also positively correlated with the unemployment rate, implying that a larger fraction of the unemployed are eligible for UI during recessions. The countercyclicalities of the eligibility rate could arise from both the higher incidence of job loss among higher-earning workers during recessions as well as from UI benefit extensions that occur during downturns. Moving to the take-up rate, we find that the standard deviation of the TUR is 5.2 percent. The TUR also exhibits a sizable positive correlation with the unemployment rate, implying that the fraction of the eligible unemployed who take up UI rises during recessions.¹⁴ This means that the rise in eligibility rates during recessions is accompanied

¹²An alternative method uses data on the number of unemployed workers and short-term unemployed (less than five weeks), as in Shimer (2012). While this leads to level differences in labor market flows, we find that the second moment properties of the EU and UE rates are mostly similar under both methodologies.

¹³In Appendix A, we discuss a survey redesign in the 2014 panel of the SIPP that caused an underestimation of UI take-up rates. Hence, we exclude this panel when calculating the second moment properties of the TUR.

¹⁴For example, while the average TUR between 2004 and 2006 was 61 percent, it increased to 74 percent during the Great Recession.

Table 3: Second moment properties

	UR_t	UE_t	EU_t	FEU_t	TUR_t
σ_X	0.119	0.094	0.076	0.076	0.052
$\text{cor}(UR_t, X_t)$	1.00	-0.935	0.828	0.583	0.481
$\text{cov}(UR_t, X_t) / \sigma_{UR}$	1.01	-0.752	0.540	0.318	0.171
$\text{cor}(X_t, X_{t-1})$	0.947	0.828	0.716	0.746	0.694

Note: σ_X : standard deviation of the variable X ; $\text{cor}(UR_t, X_t)$: correlation between unemployment rate UR_t and X_t ; $\text{cov}(UR_t, X_t) / \sigma_{UR}$: elasticity of X_t with respect to UR_t ; $\text{cor}(X_t, X_{t-1})$: correlation between X_t and X_{t-1} . Data sources: UR_t : quarterly average of the monthly unemployment rate from the BLS; UE_t : quarterly average of the monthly unemployment-to-employment (UE) rate from the CPS; EU_t : quarterly average of the monthly employment-to-unemployment (EU) rate from the CPS; FEU_t : quarterly average of the monthly fraction of UI-eligible unemployed from the SIPP; TUR_t : quarterly average of the monthly fraction of unemployed receiving UI among the UI-eligible unemployed from the SIPP. Sample period: 1996:III-2016:IV for all series except TUR_t , for which we use 1996:III-2013:IV. All series are logged and HP filtered, with smoothing parameter 1600.

by a rise in the fraction of UI-eligible workers who claim UI. Thus, some eligible individuals who would otherwise opt out of UI opt in during recessions.

Finally, we analyze how these cyclical movements in employment flows, UI eligibility, and UI take-up affect how the heterogeneity within the unemployed evolve over the cycle. We compare our results from the SIPP 2004 panel, which covers the 2004 to 2007 period, to results from the SIPP 2008 panel, which largely overlaps with the Great Recession period. Table A3 documents a drastic rightward shift in the asset-to-income ratio distribution of the take-up group, especially at the top percentiles during the Great Recession. This implies that even some eligible unemployed with relatively high amounts of self-insurance decided to collect benefits during the downturn. This also suggests that the rise in the average TUR during the Great Recession is partly driven by increased take-up among the unemployed with higher levels of self-insurance. Likewise, the average asset-to-income ratio of the non-take-up group increased from 5 to around 6.5, which reflects that the required level of self-insurance to justify non-take-up of UI rises too during recessions. The bottom panel of Table A3 shows that the duration of unemployment increased significantly during the Great Recession for all types of unemployed workers. However, the size of these increases differed. For example, the average duration increased by around 75 percent for the take-up group, while it only increased by around 20 percent for the non-take-up group. We note that the larger rise in durations among UI recipients is a joint outcome of UI policy extensions, the decision to claim UI after longer spells, and compositional properties of the take-up demographic (e.g., low-income workers with lower job-finding rates).

Taking stock This section documents novel empirical findings on various dimensions of heterogeneity within the unemployed. First, low-income workers experience much higher job-separation risk, are less likely to be eligible for UI upon job loss, and take longer to find a new job compared with high-income workers. However, if eligible for UI, they have larger replacement rates. Second, income and asset holdings are positively correlated, especially for highly-educated in-

dividuals, and there is a sizable fraction of individuals with high-income but low liquid wealth. Third, among the UI-eligible unemployed, those who do not take up benefits have much larger self-insurance and shorter unemployment spells than those who take up benefits. Finally, both the fraction of eligible unemployed and the take-up rate rise during recessions, with the latter mostly driven by changes in the take-up decisions of the unemployed with relatively high self-insurance. The eligible unemployed who have very large amounts of self-insurance and short unemployment spells typically do not take up UI even during a severe downturn.

Next, we develop a model that is designed to capture these dimensions of heterogeneity. We will argue that the extent to which the model can replicate these empirical patterns determines the magnitude of the model-implied behavioral responses to changes in UI generosity.

3 Model

In this section, we first describe the model environment and lay out the individual and firm problems. We then discuss details of the government-run UI program.

3.1 Environment

Time is discrete and denoted by t . The preferences of ex-ante identical agents are given by

$$U(c_t, s_t, d_t) = u(c_t) - \nu(s_t) - \phi(d_t),$$

where $u(\cdot)$ is a strictly increasing and strictly concave utility function over consumption c , and $\nu(\cdot)$ and $\phi(\cdot)$ are strictly increasing and strictly convex functions that represent the disutility associated with job-search effort $s \in [0, 1]$ and UI take-up effort $d \in [0, 1]$, respectively. Individuals discount the future at rate β and die with probability ω .

The labor market features directed search. An individual can be a worker W , unemployed and eligible for UI B , or unemployed and not eligible for UI NB . The unemployed direct search effort toward submarkets indexed by idiosyncratic labor productivity y and firms' wage offer w . Once matched with a firm in submarket (w, y) , the worker is paid a fixed wage w until the match exogenously dissolves at rate $\delta(y, p)$, where p is aggregate labor productivity. A fraction $g(w, p)$ of job losers who used to earn w become ineligible for UI. An eligible unemployed individual who takes up UI receives a fraction $b(w, p)$ of the previous wage w . Eligibility expires stochastically at rate $e(p)$. Functions $g(\cdot)$, $b(\cdot)$, and $e(\cdot)$ are the government's UI policy instruments.¹⁵

Agents pay a fraction τ of their wages or benefits to balance the government budget in expectation. They have access to incomplete asset markets where they can save or borrow at an

¹⁵UI policy changes are typically triggered by changes in the aggregate unemployment rate. Ideally, the UI policy instruments should depend on the unemployment rate. However, as we explain in Appendix B.2, this would make the model intractable. Instead, we define policy instruments to be a function of aggregate productivity – a good approximation since the unemployment rate is driven by aggregate productivity in our model.

exogenous rate r . On the other side of the labor market, there is free entry of firms that decide the submarket in which to post a vacancy. Once matched, the firm-worker pair produces output, the amount of which is determined by the worker's productivity y and aggregate productivity p .

The timing of the model is as follows. Each period begins with the realization of idiosyncratic productivity y and aggregate productivity p . These determine the prevailing UI policy $b(w, p)$, $e(p)$, and $g(w, p)$ as well as the job-separation rate $\delta(y, p)$ for the period. After the realization of exogenous shocks, individuals and firms make a series of decisions. First, the labor market opens and firms select the submarket in which to post a vacancy, while the unemployed choose a wage submarket w for their own productivity y within which to look for a job. Once the labor market closes, the UI-eligible decide on their take-up effort. This is followed by production and consumption, where each firm-worker pair produces, wages are paid to workers, UI benefits are paid to the eligible depending on their take-up effort, and all unemployed receive the monetized value of non-market activities h .¹⁶ Individuals then make saving or borrowing decisions. Finally, prior to time $t + 1$, the unemployed choose the search effort s they will exert in the labor market stage of time $t + 1$, where the utility cost of that search effort is incurred at time t .

3.2 Individual's problem

An individual's state vector consists of employment status $l \in \{W, B, NB\}$, asset $a \in \mathcal{A} \equiv [a_l, a_h] \subseteq \mathbb{R}$, wage $w \in \mathcal{W} \equiv [w_l, w_h] \subseteq \mathbb{R}_+$, and idiosyncratic productivity $y \in \mathcal{Y} \equiv [y_l, y_h] \subseteq \mathbb{R}_+$.

The aggregate state is denoted by $\mu = (p, \Gamma)$, where $p \in \mathcal{P} \subseteq \mathbb{R}_+$ denotes the aggregate productivity and $\Gamma : \{W, B, NB\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{Y} \rightarrow [0, 1]$ denotes the distribution of agents across states. The laws of motions for the aggregate states are given by $\Gamma' = H(\mu, p')$ and $p' \sim F(p' | p)$, respectively, and the law of motion for idiosyncratic productivity is given by $y' \sim Q(y' | y)$.

The recursive problem of the worker is given by

$$V^W(a, w, y; \mu) = \max_{c, a' \geq a_l} u(c) + \beta(1 - \omega) \mathbb{E} \left[(1 - \delta(y', p')) V^W(a', w, y'; \mu') \right. \\ \left. + \delta(y', p') \left[(1 - g(w, p')) V^B(a', w, y'; \mu') + g(w, p') V^{NB}(a', y'; \mu') \right] \middle| y, \mu \right] \quad (1)$$

subject to

$$c + a' \leq (1 + r)a + w(1 - \tau) \\ \Gamma' = H(\mu, p'), \quad p' \sim F(p' | p), \quad y' \sim Q(y' | y).$$

Notice that the worker may not qualify for UI with probability g upon job loss. This captures the fact that not all workers who transition into unemployment are eligible, as discussed in

¹⁶The variable h encompasses both the value of leisure or home production and other transfers. Our results would be similar if h were a utility value instead of a monetary value.

Section 2. Notice also that we keep track of previous wages w only for the UI-eligible unemployed, because a $b(w, p)$ fraction of that wage is paid to them as UI in case they take up benefits.

Eligible unemployed can raise the probability of receiving benefits by exerting more take-up effort d but incur utility cost $\phi(d)$ in doing so.¹⁷ We interpret this as time and effort devoted to filing a UI claim and providing proof of initial or on-going eligibility. Increased compliance with regulatory requirements raises the chances of approval.¹⁸ In addition, the unemployed decide on how much search effort s to exert and they direct their search toward a wage submarket w based on their productivity y , with an associated tightness $\theta(w, y; \mu)$, which is defined below. Let $f(\theta(w, y; \mu))$ denote the job-finding probability for the unemployed who visit submarket (w, y) when the aggregate state is μ . Then, the take-up decision of an eligible unemployed is given by

$$V^B(a, w, y; \mu) = \max_d dV_T^B(a, w, y; \mu) + (1 - d)V_{NT}^B(a, w, y; \mu) - \phi(d), \quad (2)$$

where the recursive problem of an eligible unemployed who takes up UI benefits V_T^B is given by

$$V_T^B(a, w, y; \mu) = \max_{c, a' \geq a_l, s} u(c) - \nu(s) + \beta(1 - \omega) \mathbb{E} \left[\max_{\tilde{w}} \left\{ sf(\theta(\tilde{w}, y'; \mu')) V^W(a', \tilde{w}, y'; \mu') \right. \right. \\ \left. \left. + (1 - sf(\cdot)) \left[(1 - e(p')) V^B(a', w, y'; \mu') + e(p') V^{NB}(a', y'; \mu') \right] \right\} \middle| y, \mu \right]$$

subject to

$$c + a' \leq (1 + r)a + h + b(w, p)w(1 - \tau) \quad (3) \\ \Gamma' = H(\mu, p'), \quad p' \sim F(p' | p), \quad y' \sim Q(y' | y).$$

The static UI take-up decision given in Equation (2) implies that an unemployed individual can take up benefits as long as eligibility is maintained, which is consistent with the current UI policy. As seen in Equation (3), UI-eligibility expires with probability e .¹⁹ The choice of wage submarket \tilde{w} is influenced by a trade-off between the level of surplus (determined by the wage) and the fact that there are fewer vacancies posted for higher-paying jobs, resulting in lower job-finding probabilities. The value of an eligible unemployed individual who does not take up benefits V_{NT}^B is the same except UI benefits do not enter the budget constraint.

The problem of the ineligible unemployed is similar except for the absence of a take-up effort

¹⁷Modeling take-up as a continuous choice allows us to discipline the volatility of the average take-up rate over time, as discussed in Section 4. Alternatively, take-up can be modeled as a binary choice subject to a fixed utility cost. We explore this nested version in a robustness exercise in Section 6.2.

¹⁸The UI system has an experience rating system that penalizes firms for additional layoffs by increasing tax rates. This gives firms an incentive to challenge worker UI claims (Auray and Fuller, 2020). Hence, a claim's success of approval sometimes depends on how much effort the worker puts into overturning the firm's challenge.

¹⁹The benefit expiration rate e is stochastic, as in Mitman and Rabinovich (2015). This assumption simplifies the solution of the model because we do not need to carry the unemployment duration as another state variable.

choice and benefits. Ineligible agents are also unable to regain eligibility if job search fails. This is in accordance with current UI policy in the U.S. where the unemployed receive UI benefits only for a certain number of weeks and once that threshold is reached, eligibility is terminated. We lay out the recursive problem of this agent in Appendix B.1.

3.3 Firm's problem

Firms post vacancies that offer fixed wage contracts in different submarkets. The labor market tightness of submarket (w, y) is defined as the ratio of vacancies v posted in the submarket to the aggregate search effort S exerted by all of the unemployed searching for a job within that submarket. Market tightness is denoted as $\theta(w, y; \mu) = \frac{v(w, y; \mu)}{S(w, y; \mu)}$. Let $M(v, S)$ be a constant-returns-to-scale matching function that determines the number of matches in a submarket with aggregate search effort S and vacancies v . We can then define $q(w, y; \mu) = \frac{M(v(w, y; \mu), S(w, y; \mu))}{v(w, y; \mu)}$ to be the vacancy-filling rate and $f(w, y; \mu) = \frac{M(v(w, y; \mu), S(w, y; \mu))}{S(w, y; \mu)}$ to be the job-finding rate.²⁰

First, consider a firm that is matched with a worker in submarket (w, y) when the aggregate state is μ . The pair produces py units of output until the match dissolves with probability $\delta(y, p)$. The value of this firm is given by

$$J(w, y; \mu) = py - w + \frac{1}{1+r} (1 - \omega) \mathbb{E} \left[(1 - \delta(y', p')) J(w, y'; \mu') \mid y, \mu \right]$$

subject to

$$\Gamma' = H(\mu, p'), \quad p' \sim F(p' | p), \quad y' \sim Q(y' | y).$$
(4)

Meanwhile, the value of a firm that posts a vacancy in submarket (w, y) is given by

$$V(w, y; \mu) = -\kappa + q(\theta(w, y; \mu)) J(w, y; \mu),$$
(5)

where κ is a fixed cost of posting a vacancy. When profit-maximizing firms decide which wage and productivity submarket to post vacancies in, they face a trade-off between the probability of filling a vacancy and the level of surplus from a possible match. A firm that is posting a vacancy in a high-wage submarket would enjoy a higher probability of filling the job at the expense of extracting a lower surplus from the match. On the other hand, a firm that is posting a vacancy in a high-productivity submarket would enjoy a higher match surplus but face higher market tightness and thus find it more difficult to fill the vacancy.

Free entry implies that expected profits are just enough to cover the cost of filling a vacancy. Thus, $V(w, y; \mu) = 0$ for any submarket such that $\theta(w, y; \mu) > 0$. By imposing the free-entry condition on Equation (5), we obtain equilibrium market tightness:

²⁰The constant-returns-to-scale assumption guarantees that the equilibrium θ is sufficient to determine job-finding rate $f(\theta) = \frac{M(v, S)}{S} = M(\theta, 1)$ and vacancy-filling rate $q(\theta) = \frac{M(v, S)}{v} = M(1, \frac{1}{\theta})$.

$$\theta(w, y; \mu) = \begin{cases} q^{-1}(\kappa/J(w, y; \mu)) & \text{if } w \in \mathcal{W}(\mu) \text{ and } y \in \mathcal{Y}(\mu) \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

Market tightness is sufficient for agents to evaluate the job-finding rate in each submarket.

3.4 Government policy

The UI policy is characterized by $\{b(w, p), e(p), g(w, p), \tau\}$, where replacement rate b and eligibility rule g depend on previous wages to capture the heterogeneity in replacement rates and ineligibility rates in previous earnings in the data. Further, b , e , and g vary with productivity to capture policy variations in replacement rates, UI duration, and eligibility rules over time.

The government balances the following budget constraint in expectation²¹:

$$\sum_{t=0}^{\infty} \sum_i \left(\frac{1}{1+r} \right)^t [\mathbf{1}_{\{l_{it}=W\}} w_{it} \tau - \mathbf{1}_{\{l_{it}=B,T\}} b_{it} w_{it} (1-\tau)] = 0, \quad (7)$$

where the first term inside the brackets constitutes tax revenues from the labor income of workers and the second term represents net UI payments.

3.5 Equilibrium

We define the recursive equilibrium of this economy in Appendix B.2. In order to solve the recursive equilibrium, one must keep track of an infinite dimensional object Γ , making the solution of the model infeasible. To address this, we exploit the structure of the model and use the notion of a block recursive equilibrium (BRE) developed by [Menzio and Shi \(2010, 2011\)](#).

Definition of the BRE A BRE is an equilibrium in which the 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 current aggregate labor productivity, then there exists a unique BRE for this economy.*

Proof See Appendix B.2.

This proposition is useful because it allows us to solve the model numerically without keeping track of the aggregate distribution of agents across states Γ . We discuss more details about block recursivity and the computational algorithm employed to solve this model in Appendix B.3.

²¹This assumption is motivated by the fact that according to the current UI system in the U.S., states are allowed to borrow from a federal UI trust fund when they meet certain federal requirements, and thus they are allowed to run budget deficits during some periods.

4 Calibration

We calibrate our model to match historical patterns of UI policy and important labor market moments for the U.S. prior to the Great Recession. Table 4 summarizes the internally calibrated parameters, while Table A4 in Appendix C provides a list of externally calibrated parameters.

Demographics and preferences The model period is a month. We set the probability of death to $\omega = 0.21$ percent so that the expected duration of working life is 40 years.

The period utility function is

$$U(c_t, s_t, d_t) = u(c_t) - \nu(s_t) - \phi(d_t) = \frac{c_t^{1-\sigma}}{1-\sigma} - \alpha_s \frac{s_t^{1+\chi_s}}{1+\chi_s} - \alpha_d \frac{d_t^{1+\chi_d}}{1+\chi_d}.$$

The coefficient of relative risk aversion σ is set to 2. We normalize the level parameter of the search cost function α_s to 1.²² Importantly, we choose the curvature parameter of the search cost function χ_s to match the elasticity of nonemployment duration with respect to changes in maximum UI duration. Several papers estimate this elasticity using variation in UI duration across states and over time.²³ The magnitudes of the estimated elasticities range from an average change of 0.03 months (Nekoei and Weber 2017) to 0.25 months (Johnston and Mas 2018) in response to a one-month change in UI duration. We take a median value of 0.15 as the calibration target. In the model, we implement a sudden and unexpected decrease in the UI expiration rate $e(\cdot)$ so that the implied maximum UI duration becomes one month longer for any realization of aggregate labor productivity. Using model simulated data, we estimate the elasticity of nonemployment and choose χ_s to generate an elasticity of 0.15.²⁴ Section 5.4 provides a detailed discussion on how we measure the comparable elasticity in the model.

Finally, we use the level and curvature parameters of the disutility of UI take-up effort, i.e., α_d and χ_d , to match the average TUR of 61 percent in the SIPP 2004 panel, which covers 2004 to 2007, and the standard deviation of the average TUR of 5.2 percent as shown in Table 3.

Aggregate and idiosyncratic labor productivity The logarithm of the aggregate labor productivity p_t follows an AR(1) process: $\ln p_{t+1} = \rho^p \ln p_t + \sigma^p \epsilon_{t+1}$. We take p_t as the mean real output per person in the non-farm business sector, using quarterly data constructed by the Bureau of Labor Statistics (BLS) for the period 1951 to 2007. Estimation of the AR(1) process at a monthly frequency yields $\rho^p = 0.9183$ and $\sigma^p = 0.0042$.

²²This is because job-finding probability $sf(\cdot)$ is a multiplicative function of the search effort s and the matching efficiency $\lambda(\cdot)$, as discussed below. This implies that we cannot separately identify the level parameter of the search cost from parameters of $\lambda(\cdot)$. Hence, we choose to normalize the former.

²³Table A5 in Appendix C provides a summary of the available empirical estimates for this elasticity.

²⁴Notice that when agents change the wage submarkets in which they look for a job in response to a change in UI policy, they face different market tightness in the new wage submarket. For this reason, although changes in UI do not affect the menu of market tightness across wage submarkets, changes in wage choices translate to changes in aggregate labor market tightness and job-finding rates.

Similarly, the logarithm of the idiosyncratic labor productivity y_t follows an AR(1) process: $\ln y_{t+1} = \rho^y \ln y_t + \sigma^y v_{t+1}$. We choose $\rho^y = 0.9867$ so that individuals remain in the same productivity level for an expected duration of 40 years. We use the standard deviation of the error term σ^y to match earnings dispersion, specifically, the ratio of the 90th to 10th percentiles of the labor earnings distribution among the employed individuals in SIPP 2004 panel.

Labor market Following [Shimer \(2005\)](#), we use a process for the job destruction rate that depends on aggregate productivity p and modify it to incorporate heterogeneity across idiosyncratic productivity y : $\delta(y, p) = \bar{\delta} \times \exp(\eta_p^\delta (p - \bar{p})) \times \exp(\eta_y^\delta (y - \bar{y}))$, where i) $\bar{\delta}$ is the average job destruction rate over time and \bar{p} and \bar{y} are the mean aggregate and idiosyncratic productivities, respectively; ii) η_p^δ captures the volatility of the job destruction rate over time; and iii) η_y^δ captures the variation of the job destruction rate across income groups. We jointly choose these parameters to match i) the average monthly EU rate, ii) its standard deviation, and iii) its heterogeneity across the income distribution in the data. As discussed in [Fujita, Nekarda, and Ramey \(2007\)](#), the transition probabilities computed from the CPS and the SIPP differ in levels. For this reason, as in [Krusell, Mukoyama, Rogerson, and Şahin \(2017\)](#), we use CPS data to calculate the level and cyclicity of the transition probabilities, but use SIPP data to calculate moments that pertain to their cross-sectional heterogeneity.²⁵ The heterogeneity of the EU rate across income groups is measured as the ratio of the EU rate of workers below the first quintile to that of those above the fifth quintile of the labor earnings distribution, as shown in Table 1.

The labor market matching function is specified to be

$$M(v(w, y; \mu), S(w, y; \mu)) = \lambda(y, p) \frac{v(w, y; \mu) S(w, y; \mu)}{[v(w, y; \mu)^\gamma + S(w, y; \mu)^\gamma]^{1/\gamma}},$$

where $\lambda(y, p) = \bar{\lambda} \times \exp(\eta_p^\lambda (p - \bar{p})) \times \exp(\eta_y^\lambda (y - \bar{y}))$.²⁶ This incorporates time variation and cross-sectional heterogeneity in matching efficiency $\lambda(\cdot)$ into an otherwise standard CES matching function as in [Den Haan, Ramey, and Watson \(2000\)](#).²⁷ We jointly choose $\bar{\lambda}$, η_p^λ , and η_y^λ to match i) the average monthly UE rate, ii) its standard deviation, and iii) its heterogeneity across the income distribution in the data. For the last moment, we use the ratio of the UE rate of the unemployed below the first quintile to that of those above the fifth quintile of the previous

²⁵The average EU and UE rates are obtained from the CPS between 2004 and 2007. The heterogeneity in EU and UE rates across the income distribution are obtained from the SIPP 2004 panel, as shown in Table 1. Finally, the cyclicity of EU and UE rates are obtained from the CPS between 1996 and 2016, as shown in Table 3.

²⁶Based on this functional form of the matching function, the job finding rate and the vacancy-filling rate are given by $f(\theta(w, y; \mu)) = \lambda(y, p) \theta(w, y; \mu) (1 + \theta(w, y; \mu)^\gamma)^{-1/\gamma}$ and $q(\theta(w, y; \mu)) = \lambda(y, p) (1 + \theta(w, y; \mu)^\gamma)^{-1/\gamma}$, respectively. The CES matching function guarantees that job-finding and vacancy-filling rates are strictly between 0 and 1.

²⁷Time-varying matching efficiency can be interpreted as changes in the aggregate recruiting intensity over the cycle, as documented by [Mongey and Violante \(2020\)](#). We do not model the firm's recruiting decisions, but the above specification captures the cyclical variation in aggregate matching efficiency through η_p^λ in reduced form.

earnings distribution, as shown in Table 1. We set the matching function parameter γ to 0.5.²⁸

Shimer (2005) shows that the standard search model fails to endogenously generate the observed magnitude of the volatility of the unemployment rate. In our model, changes in aggregate productivity generate exogenous variations in both the job-separation rates and the matching function efficiency. We calibrate the parameters of these processes to match the observed levels and volatilities of both the EU and UE rates. This enables the model to generate the magnitude of unemployment volatility in the data, as we detail in Section 5.1.²⁹

We set the vacancy cost $\kappa = 0.58$, following Hagedorn and Manovskii (2008), who estimate the combined capital and labor costs of vacancy creation to be 58 percent of labor productivity.

When agents experience a job loss, they lose earnings but receive a monetary value of nonmarket activity h , which can be interpreted as income support from family or government transfers other than UI. Since the magnitude of h controls the magnitude of budgetary loss upon job separation, we use it to match the average consumption drop upon job loss. Several papers estimate the average consumption drop upon job loss from various data sources for different frequencies. The resulting estimates in annual frequency are between 7 and 19 percent, and we take the median estimate of 12 percent as our data target. Appendix C explains how we obtain the estimate in the model, discusses available empirical estimates based on different datasets and frequencies, and provides further comparisons with model-implied estimates in various frequencies.

Savings We choose the discount factor β to match the fraction of the population with nonpositive net liquid wealth in the SIPP 2004 panel. We set the borrowing limit a_l to match a median value of the credit-limit-to-quarterly-income ratio of 74 percent in the Survey of Consumer Finances. We choose $r = 0.33$ percent to generate an annual return of around 4 percent.

UI policy We assume the following functional forms for the UI policy instruments:

$$1/e(p) = \begin{cases} m_0^e + m_p^e p & \text{if } p < \bar{p} \\ 1/e_{cap} & \text{otherwise} \end{cases}$$

$$b(w, p) = m_0^b + m_w^b w + m_p^b p \tag{8}$$

$$g(w, p) = m_0^g + m_w^g w + m_p^g p.$$

The slope parameter m_p^j captures the cyclical policy instrument j , while m_w^b and m_w^g capture the heterogeneity in UI replacement rates and eligibility rates across the previous income distribution. Finally, e_{cap} captures the maximum duration of UI payments during non-recessions.

²⁸This value is close to those used in Hagedorn and Manovskii (2008) and Mitman and Rabinovich (2015), who also use the CES matching function. In Section 6.2, we explore the sensitivity of our results to this parameter.

²⁹In Section 6.2, we consider an alternative way of generating the observed magnitude of unemployment volatility. In particular, we eliminate the fluctuations in matching efficiency over time and calibrate a high level of average replacement rate, as in Hagedorn and Manovskii (2008). We then explore the robustness of our results.

Table 4: Internally calibrated parameters

Parameter	Explanation	Value	Target	Data	Model
<i>Preferences and borrowing limit</i>					
β	Discount factor	0.9941	Frac. non-pos. net liq. wealth	0.27	0.30
χ_s	Curvature of utility cost of search	1.51	Elasticity of nonemp. duration with respect to UI duration	0.15	0.14
α_d	Level of utility cost of UI take-up	1.43	UI take-up rate among eligible	0.61	0.55
χ_d	Curvature of utility cost of take-up	0.10	Std. dev. of UI take-up rate	0.052	0.054
a_l	Borrowing limit	-2.17	Median credit limit/income	0.74	0.74
<i>Labor market</i>					
$\bar{\delta}$	Avg. job-separation rate	0.012	Monthly EU rate	0.012	0.013
η_p^δ	Cyc. job-separation rate	-7.88	Std. dev. of EU rate	0.076	0.075
η_y^δ	Heterogeneity of job-sep. rate	-1.18	EU rate ratio of low- (Q1) vs high-income (Q5) workers	5.54	6.29
$\bar{\lambda}$	Avg. of matching efficiency	1.01	Monthly UE rate	0.35	0.30
η_p^λ	Cyc. of matching efficiency	4.63	Std. dev. of UE rate	0.094	0.097
η_y^λ	Heterogeneity of matching efficiency	0.18	UE rate ratio of low- (Q1) vs high-income (Q5) workers	0.67	0.50
σ^y	Dispersion of id. labor prod.	0.08	Ratio of 90th to 10th percentiles of labor earnings dist.	6.88	7.42
h	Value of nonmarket activity	0.04	Consumption drop upon job loss	0.12	0.12
<i>UI policy</i>					
m_0^b	UI replacement rate level	0.63	UI replacement rate	0.52	0.51
m_w^b	Heterogeneity of UI rep. rate	-0.24	Ratio of rep. rate of low- (Q1) vs high-income (Q5) workers	2.02	2.19
m_0^g	Level of UI eligibility	0.42	Frac. of UI-eligible unemployed	0.57	0.59
m_w^g	Heterogeneity of UI eligibility	-0.28	Ratio of frac. of UI-eligible unemployed of low- (Q1) vs high-income (Q5) workers	0.55	0.59

Note: This table provides a list of parameters that are calibrated in our model. Please refer to main text for a detailed discussion.

Below, we explain how we discipline these parameters.

First, we calibrate the parameters of the UI expiration rate. We set $e_{cap} = 4/26$ to match the maximum duration of 26 weeks of UI payments during non-recessions, i.e., $p_t \geq 1$. Historically, the maximum UI duration has been extended during recessions, when the unemployment rate is higher. For example, during the Great Recession, this duration was extended to up to 99 weeks. We pick m_0^e and m_p^e so that the maximum UI duration ($1/e$) is linearly increasing from 26 weeks, when aggregate productivity is at its mean, to 99 weeks, when it is at its lowest value.

Second, we calibrate the parameters for replacement rate b and ineligibility rate g . Recall that in the model i) only a fraction of job losers are UI-eligible; ii) among those eligible, UI is paid only to those who take up UI; and iii) replacement rates vary across those who take up UI.

To discipline these aspects of our model, we use our findings in Section 2 from the SIPP data. We jointly choose m_0^b , m_w^b , and m_p^b to match i) the average replacement rate of the eligible-unemployed, ii) the bottom-to-top quintile ratio of the replacement rate when the unemployed are ranked according to their base period AWW, and iii) the variations in the WBA formulas over time. Using the SIPP 2004 panel, we find that the average replacement rate among UI recipients is 52 percent and that the average quintile ratio of the replacement rate is 2.02.³⁰ Given that states rarely changed their formula to calculate their UI benefit amounts, except for inflation-related adjustments of minimum and maximum benefit amounts, we set $m_p^b = 0$. Figure A1 in Appendix C compares the heterogeneity of the replacement rates across AWW in the data and the calibrated model. The linearity of the UI replacement rate in previous wages in the model well approximates the heterogeneity of replacement rates in the data.

Next, we discipline the parameters of the UI eligibility rate. We use level parameter m_0^g to match an average FEU of 57 percent; the slope parameter with respect to wage, m_w^g , to match a bottom-to-top quintile FEU ratio of 0.55 when the unemployed are ranked according to their previous earnings; and the slope parameter with respect to aggregate productivity, m_p^g , to match the variations in the eligibility rules over time.³¹ Based on state UI laws over the period 1996 to 2019, we see that earnings requirements to qualify for UI do not exhibit systematic changes over the business cycle. Hence, we also set $m_p^g = 0$. Under this joint calibration of model parameters, the income tax rate τ that satisfies Equation (7) in equilibrium is 0.34 percent.³²

5 Results

We now present the distributional and cyclical implications of the model and compare them with the empirical findings presented in Section 2. We then contrast the predictions of the baseline model to those of an alternative model that omits i) imperfect and endogenous take-up, ii) heterogeneous job-separation rates, iii) heterogeneous eligibility rates, and iv) heterogeneous replacement rates. This alternative model is designed to generate the same average EU, UE, eligibility, and replacement rates, and it still features the *same heterogeneity* in income and wealth holdings across individuals. However, EU, UE, eligibility, and replacement rates are now homogeneous across individuals. In addition, the alternative model features full UI take-up, as we eliminate the UI take-up cost. Thus, the alternative model misses the *link* between the hetero-

³⁰An average replacement rate quintile ratio of 2.02 means that the average replacement rate of UI recipients whose previous earnings are in the bottom quintile of the income distribution is more than double the average replacement rate of UI recipients whose previous earnings are in the top quintile.

³¹An average FEU quintile ratio of 0.55 means that job losers whose previous labor earnings are in the top quintile of the income distribution are around two times more likely to be eligible for UI benefits upon job loss than those whose previous labor earnings are in the bottom income quintile.

³²This income tax is much lower than U.S. income tax levels because the government in this model only needs to finance UI payments. In Section 6.2, we incorporate a higher level of government expenditure to account for other forms of government spending and transfers, which implies higher levels of income taxes. Then, we check the implications of this assumption for our main results.

geneity in income and wealth holdings and the heterogeneity in job-separation risk, UI-eligibility status, take-up decisions, and replacement rates. We show that the alternative model fails to capture important untargeted data moments. Finally, we argue that this distinction between the two models has important ramifications for the predicted labor market elasticities they generate and, importantly, where they align with empirical estimates of labor market responses to changes in UI generosity, both in the cross-section and over time.

5.1 Model validation

We begin by comparing how well the model captures heterogeneous UE, EU, FEU, TUR, and replacement rates observed in the empirical findings of Section 2. This is an important point of comparison as differences in unemployment risk affect the distribution of agents that flow into the unemployment pool. If heterogeneous agents respond differently, then the nature of this distribution ultimately alters the aggregate labor market response to changes in UI. Likewise, the probability of finding a job alters the incentives to take up UI. Self-insured workers that expect a short unemployment spell are less likely to take up UI. On the other hand, unemployed workers with lower previous earnings who typically have low liquid wealth are less likely to be eligible, but if they are, they receive larger replacement rates and are more likely to take up UI. These selection effects shape the demographics of UI recipients – the relevant subpopulation with potentially the largest response to UI changes – that arise endogenously in the model.

Heterogeneity in labor market flows Similar to our treatment of the data, we divide agents into quintiles of assets, income, and the asset-to-income ratio. Table 5 presents the comparison between the data and the model. Recall from Section 4 that we only target the bottom-to-top income quintile ratios of the EU and UE rates, while the rest of the moments are untargeted. Naturally, the model generates EU rates that are declining with income and UE rates that are increasing in income. As a consequence of higher job-separation rates in lower-paying jobs, the previous earnings of unemployed are lower than the earnings of employed. Table A6 shows that the mean previous earnings of the unemployed is 63 percent of the mean earnings of the employed in the model, which is close to 73 percent in the data. The model also matches the inverse-U-shaped pattern of EU rates in the data when agents are conditioned on assets. This is due the presence of high earners with low unemployment risk and lower precautionary saving motives. The difference between the first and second asset quintiles, however, is not as pronounced in the model. Despite the non-monotonicity, upper quintiles of the wealth distribution still exhibit lower EU rates, implying that unemployed possess less self-insurance compared with the employed. This difference manifests through a gap between the asset (or asset-to-income ratio) distributions of the unemployed and the employed, as shown in Table A6. Finally, in both the model and the data, the heterogeneity in UE rates across the income, asset, and asset-to-income ratio distributions is much lower than the heterogeneity in EU rates.

Table 5: Heterogeneity in labor market flows and eligibility, take-up, and replacement rates

	Income					Assets					Asset-to-income ratio				
	Data														
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
EU	2.39	1.03	0.63	0.52	0.43	0.97	1.64	1.11	0.76	0.61	1.08	1.22	0.95	0.80	0.94
UE	0.78	0.93	1.05	1.08	1.16	1.14	0.80	0.96	1.05	1.04	1.06	0.93	1.00	1.01	0.98
FEU	0.63	0.95	1.09	1.17	1.16	1.17	0.77	0.97	1.07	1.03	1.08	0.97	1.05	1.04	0.88
TUR	0.89	1.13	1.02	0.95	1.02	1.10	1.08	1.07	0.85	0.90	1.18	1.01	1.10	0.94	0.76
RR	1.35	1.16	1.07	0.97	0.67	0.96	1.15	1.15	1.03	0.86	0.99	1.07	1.00	0.97	0.97

	Model														
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
EU	1.82	1.39	0.95	0.55	0.29	1.00	1.15	1.11	0.74	1.00	1.17	0.93	1.00	0.76	1.13
UE	0.67	0.74	1.08	1.18	1.33	1.03	0.94	0.85	1.08	1.09	0.87	1.03	0.94	1.14	1.02
FEU	0.77	0.85	0.95	1.13	1.31	0.57	0.93	1.05	1.21	1.24	0.59	0.89	1.09	1.26	1.17
TUR	1.05	1.03	1.03	1.03	0.86	1.28	1.05	1.04	1.02	0.61	1.30	1.05	1.01	1.03	0.60
RR	1.09	1.05	1.01	0.93	0.50	0.95	1.01	1.01	1.01	0.99	1.06	0.98	0.94	1.02	1.04

Note: This table compares the heterogeneity in employment-to-unemployment (EU) and unemployment-to-employment (UE) worker flow rates, as well as the fraction of UI-eligible unemployed (FEU), the fraction of unemployed receiving UI among UI-eligible unemployed, i.e., the take-up rate (TUR) and UI replacement rate (RR) across income, asset, and asset-to-income ratio quintiles in the data and the model. In each row, we report values for each quintile relative to the overall average. Income corresponds to the monthly labor earnings of the respondent from their current job (for EU) or the average monthly labor earnings in their previous job (for UE, FEU, TUR, and RR). Assets in the data are measured as net liquid wealth holdings.

Heterogeneity in UI eligibility, take-up, and replacement rates Table 5 also compares the heterogeneity in eligibility, take-up, and replacement rates across distributions between the model and the data. Again, note that in Section 4, we only use the bottom-to-top income quintile ratio of the FEU and replacement rates as calibration targets, while the remaining moments are untargeted. Hence, the model features increasing eligibility rates and declining replacement rates in income. The model also aligns with another empirical pattern that shows that the FEU and replacement rates are more correlated with income and less so with measures of wealth and self-insurance, although the model overestimates the heterogeneity of the FEU in assets and asset-to-income ratio relative to the data. Since the FEU is increasing in income, Table A6 shows that the eligible have higher previous earnings than the unemployed because within the pool of the unemployed, individuals with lowest previous earnings are ineligible.

Importantly, the TUR declines in assets and the asset-to-income ratio, especially at the top quintile. For example, in the model (data), while an unemployed who is at the bottom quintile of the asset-to-income ratio distribution is 30 (18) percent more likely to claim UI relative to the average, an unemployed at the top quintile is 40 (24) percent less likely to take up UI. This finding demonstrates that the group of individuals who are eligible but do not claim UI is composed of those with high levels of self-insurance both in the model and the data, although the

model exhibits a stronger correlation. As a result, comparing the mean asset-to-income ratios reported in Table A6 reveals that in the model (data), the non-take-up demographic enjoys on average an additional 3 (3.75) months of self-insurance compared with those who take up UI.

Finally, labor market prospects also differ between the take-up and non-take-up groups. Table A6 shows that UI recipients experience longer unemployment spells than eligible non-recipients. In the model (data), the average spell duration of the take-up and non-take-up groups are 4.32 (3.81) and 2.42 (2.42), respectively. We flag that this is not entirely attributable to the moral hazard effects of UI and is also an artifact of endogenous selection: agents with higher job-finding rates are less likely to take up UI, as their spells are too short to justify incurring take-up costs.

Joint distribution of income and wealth Next, we benchmark the joint distribution of wealth and income generated by the model against the data. In the data, unemployment risk, eligibility rates, and replacement rates vary significantly with income, while take-up varies substantially with wealth. In the model, the interaction between income and wealth determine how relevant unemployment risk is, how valuable the insurance benefits of UI are, and ultimately the size of heterogeneous behavioral responses to the changes in UI. Hence, it is important that the model generates a relationship between income and wealth that reflects its empirical counterpart.

Table 6 focuses on the economy-wide joint distributions. We highlight two features of the empirical joint distribution that our model replicates. First, both the data and the model exhibit relatively high correlation between income and assets, with a large mass located either along the diagonal or the sub- and super-diagonals. For example, in the data, roughly 60 percent of individuals in the third quintile of the income distribution are found between the second and fourth quintiles of asset distribution. In the model, this is roughly 51 percent. Second, the model and the data feature a considerable mass of individuals with high-income but low liquid assets. For example, in the data (model): 37 percent (31 percent) of individuals in the bottom quintile of the asset distribution actually have incomes in the top two quintiles. How is the model able to generate this? It is able to do so because of the heterogeneity in job-separation and job-finding probabilities: high-income individuals face little risk of employment loss and among those who lose a job experience shorter unemployment durations. This lowers their precautionary saving motives and weakens their incentives to hold liquid assets. As discussed in Appendix D, the presence of such high-income but low-liquid-wealth individuals helps the model approach empirical estimates of the average marginal propensity to consume (MPC) out of unexpected transfers – a summary metric to assess how the model’s ability to match distributions translates to reasonable predictions on how valuable UI’s insurance benefits are to agents.

Table A7 in Appendix D shows the same joint distribution but conditions on individual productivity y . We compare the distribution of agents with the lowest and highest productivity with SIPP respondents who report having less than a high school degree or more than a master’s degree, respectively. We view this as simply illustrative, with productivity in the model serving

Table 6: Joint distribution of income and asset holdings

Income	Data					Model					Alternative model				
	Assets														
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1	0.17	0.34	0.23	0.14	0.12	0.38	0.40	0.12	0.02	0.08	0.69	0.21	0.05	0.02	0.03
Q2	0.21	0.27	0.25	0.17	0.10	0.20	0.21	0.45	0.04	0.10	0.22	0.54	0.14	0.04	0.06
Q3	0.23	0.18	0.22	0.21	0.15	0.11	0.01	0.14	0.36	0.38	0.05	0.14	0.64	0.09	0.08
Q4	0.22	0.12	0.18	0.24	0.23	0.13	0.01	0.21	0.40	0.24	0.03	0.08	0.12	0.60	0.18
Q5	0.15	0.08	0.13	0.23	0.42	0.18	0.37	0.07	0.18	0.20	0.01	0.03	0.04	0.25	0.66

Note: This table compares the joint distributions of assets and income implied by the baseline model and an alternative model with those in the data. The alternative model features full take-up as well as uniform job-separation risk, eligibility rates, and replacement rates. 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.

as a proxy for educational attainment. Similar to the data, the mass along the diagonal is increasing in productivity in the model. This difference, however, is overstated by the model. The lower correlation between income and assets seen for agents with low productivity is a result of their higher job-loss risk and lower job-finding rates. This creates strong precautionary saving motives so that low-income workers are not necessarily found in the lowest quintile of assets.

Cyclical properties In the following discussion, we describe the model’s cyclical predictions and compare them with the data. As will be argued in Section 5.4, the extent to which unemployed demographics vary with the business cycle will translate to differential responses to changes in UI generosity depending on aggregate economic conditions. For example, during a downturn that causes agents to deplete wealth and approach the borrowing constraint, a change in UI generosity may have limited effects on job-search behavior due to the relatively high value of employment. On the other hand, increased take-up during recessions may induce the opposite effect through enlarging the group of individuals who benefit directly from generous UI.

Table 7 focuses on the dynamics of labor market aggregates. In terms of labor market flows, since the model is calibrated to match the volatility of EU and UE flows, it generates sufficient volatility in the unemployment rate as well. The model also well approximates the degree of comovement between the unemployment rate and its underlying flows. Turning to the dynamics of UI status, the model predicts countercyclical eligibility and take-up rates, in line with the data. In the model, eligibility expands during recessions because of UI extensions and the inflow of high-income workers with high eligibility rates into unemployment during recessions. The take-up rate rises during recessions since individuals who were more likely to opt out during expansions may now find it beneficial to apply for UI because of prolonged unemployment spells.

We now turn to how the distributions of agents evolve over the business cycle, paying particular attention to different subgroups of unemployed workers. In Section 2, we compared the

Table 7: Second moment properties

	Data					Model				
	UR_t	UE_t	EU_t	FEU_t	TUR_t	UR_t	UE_t	EU_t	FEU_t	TUR_t
σ_X	0.119	0.094	0.076	0.076	0.052	0.129	0.097	0.075	0.036	0.054
$\text{cor}(UR_t, X_t)$	1.00	-0.935	0.828	0.583	0.481	1.000	-0.790	0.712	0.349	0.872
$\text{cov}(UR_t, X_t) / \sigma_{UR}$	1.01	-0.752	0.540	0.318	0.171	1.003	-0.597	0.413	0.097	0.368
$\text{cor}(X_t, X_{t-1})$	0.947	0.828	0.716	0.746	0.694	0.827	0.686	0.583	0.599	0.714

Note: This table compares labor market properties in the data and the model. Both for the model and the data, each series is converted to quarterly averages of their respective monthly series, logged, and HP filtered with a smoothing parameter of 1600. UR , UE , EU , FEU , and TUR denote the unemployment rate, UE rate, EU rate, UI eligibility rate, and UI take-up rate, respectively.

asset-to-income ratio and unemployment spell duration distributions for two SIPP panels that represent non-recessionary and recessionary periods: the 2004 panel, which covers October 2003 through December 2007, and the 2008 panel, which covers May 2008 through November 2013. To make a direct comparison, we use the model to simulate the roughly 10-year period that spans both SIPP panels by choosing the realizations of aggregate labor productivity to match the unemployment rate between October 2003 and November 2013. Figure A2 in Appendix D shows the resulting aggregate productivity series in this experiment and compares the unemployment rate generated by the model with that in the data for this time period.

Table A8 compares model-generated asset-to-income ratio distributions for the same time periods that each panel covers.³³ Both in the model and the data, the recession is accompanied by a rightward shift in the asset-to-income ratio distribution of the take-up group. This reveals which demographics drive countercyclical TUR. Longer unemployment spells imply that agents with relatively more self-insurance find that their wealth alone is no longer sufficient to smooth consumption and thus decide to claim UI. Equivalently, the required level of wealth to justify non-take-up becomes even higher in recessions, resulting in a rightward shift of the asset-to-income ratio distribution for the non-take-up group as well, especially at the top percentiles.

Table A9 makes the same comparison for how the distributions of unemployment durations across different types of agents vary over the cycle. For the entire pool of the unemployed, the model predicts a rise in spell duration similar to that in the data, as we calibrate our model to match the cyclicity of average job-finding rates. However, significant differences are observed when the unemployed are broken down by take-up choice. In the model (data), the average spell duration of UI recipients rises by around 50 (75) percent, while the average duration of the non-take-up group rises by 15 (20) percent. Note that the rise in durations is a combination of individual labor market decisions, aggregate conditions that depress job-finding rates, and a selection effect where agents that observe longer spells are more likely to take up UI.³⁴

³³We view these observations as illustrative given that the SIPP provides us at most a yearly snapshot of wealth information among respondents.

³⁴In Section 5.3, we isolate the impact of increases in UI generosity on labor market choices and unemployment

5.2 Alternative model predictions

We evaluate the predictions of a nested version of the baseline model that abstracts from i) imperfect and endogenous take-up, ii) heterogeneous separations rates, iii) heterogeneous eligibility rates, and iv) heterogeneous replacement rates. The obvious consequences of adopting this alternative model would be uniform eligibility rates and full take-up, thus limiting the differences between the average unemployed worker and those who are eligible to or those who receive benefits. Uniform replacement rates imply that the value of UI rises among high-income workers who would otherwise be subject to lower replacement rates in the baseline model, where replacement rates decline with previous income. Finally, uniform job-separation rates imply that the model is no longer able to match the declining profile of EU rates in income.³⁵ While these predictions are clearly not in line with the data, what do they imply in terms of model-generated distributions? In this section, we discuss which dimensions of the untargeted moments this model is unable to account for – beyond those that naturally arise from the removal of these features.

Joint distribution of income and wealth Table 6 shows that the alternative model exhibits a substantially higher correlation between assets and income when compared with the baseline model and the data. This arises from uniform unemployment risk and UI receipt and generosity, which result in stronger precautionary saving motives across the entire domain of the income distribution. In other words, high-income individuals who now face significant risk of unemployment are also engaged in accumulating a buffer stock of wealth from their income, which in turn strengthens the correlation between income and assets. As such, the alternative model is no longer able to generate a sizable fraction of high-income workers with low liquid wealth holdings.

Heterogeneity within the unemployed The bottom panel of Table A8 shows the asset-to-income ratio distributions of different groups. Comparing the distributions before the Great Recession, we see that the distribution of the take-up group is now very close to that of the employed, in contrast to the observed large gaps between the distributions of these two groups in the baseline model and the data. In the alternative model, uniform job-separation risk implies that unemployment inflows now include a larger fraction of high-income and wealthier individuals. While the eligible unemployed are now richer, maintaining endogenous take-up could still imply that UI recipients are pre-predominantly poorer agents. However, since the alternative model also features full take-up, the distribution of UI recipients become drastically wealthier.³⁶ This is a critical difference, as it drastically alters the distribution of the demographic of those who are directly impacted by UI and are thus more likely to respond to policy changes. To the

durations across the distribution.

³⁵Given that, by construction, the alternative model will be unable to match the heterogeneity in labor market flows and UI status, we do not present the counterpart of Table 5 for the alternative model.

³⁶In fact, UI recipients (equivalently UI eligible) have asset-to-income ratios that exceed the average unemployed worker, as those with longer spells would have become UI-ineligible already.

extent that constrained individuals react less to UI changes, a rightward shift of the distribution would translate to larger labor market responses to a change in UI generosity.³⁷

The bottom panel of Table A9 presents the comparison of the unemployment spells durations before the Great Recession. Since the average EU and UE rates of the alternative model are re-calibrated for the period before the Great Recession, the alternative model gets close to the average spell duration and the distribution of spell durations of unemployed workers observed in the baseline model and the data. However, interesting departures from the data and the baseline model emerge when the unemployed are broken down by UI status. While the baseline model exhibits a substantial difference between the spell durations of agents who take up benefits and those who do not, the alternative model is no longer able to make this distinction.

Cyclical properties After a comparison of cross-sectional moments between the baseline and alternative models, we shift our attention to the differential dynamics of the distributions implied by both models. To make these comparisons, similar to our exercise for the baseline model, we simulate the Great Recession period for the alternative model and compare distributions before and during the crisis with their counterparts in the baseline model and the data.³⁸

Table A8 presents results for the asset-to-income ratio distribution. A notable observation is that the distribution of UI recipients now experiences a leftward shift in the alternative model during the recession, as opposed to the rightward shifts in the data and the baseline model. Given that the alternative model features full take-up, we no longer observe an inflow of wealthier individuals opting to receive UI benefits during periods of longer spell durations, which is the force that drives the rightward shift in the baseline model. As a result, the leftward shift is solely driven by the depletion of assets during the recession.

Table A9 shows the same comparison for the distribution of unemployment spell durations. Since the alternative model is recalibrated and subject to the same Great Recession simulation, it observes a similar increase of average spell duration for the entire pool of the unemployed from 3.4 months to 4.6 months, when compared with the baseline model. However, in the baseline model, the demographics of the take-up and non-take-up groups imply different changes in their spell durations over the cycle. In particular, the non-take-up group is mostly composed of wealthier and high-income individuals with higher job-finding rates, while take-up group is composed of low-income individuals for whom job-finding rates are lower. The former group observes smaller changes in their spell durations during recessions. In the alternative model, these two groups are homogenized and thus do not reflect the differences in amplitude of duration fluctuations over the cycle. Since all eligible unemployed take up UI, the subgroup of non-take-up unemployed whose spell durations do not vary as much over the cycle are unaccounted for.

³⁷The implications of such distributional differences across models on elasticities are developed in Section 5.3.

³⁸See the discussion on cyclical properties in Section 5.1 for a detailed description of this exercise.

Table 8: Effect of UI benefits on the job-finding rate in different models

	Baseline	$d = 0.55$	$\alpha_d = 0$	$\alpha_d = 0$	$\alpha_d = 0$	$\alpha_d = 0$
				$\eta_y^\delta = 0$	$\eta_y^\delta = 0$	$\eta_y^\delta = 0$
					$g = 0.41$	$g = 0.41$
						$b = 0.51$
Change in	-0.077	-0.193	-0.811	-2.000	-1.558	-1.740
job-finding rate (pp)						

Note: This table compares the percentage point (pp) decrease in the average job-finding (UE) rate when the replacement rate is increased by 10 percentage points across different models: our baseline model (first column) and in models (subsequent respective columns) where we shut down the following mechanisms one by one: i) endogenous take-up, ii) imperfect take-up, iii) heterogeneous job separation rates, iv) heterogeneous UI eligibility rates, and v) heterogeneous UI replacement rates.

5.3 Elasticities and the role of heterogeneity

We discussed the distributional implications of the alternative model specification. However, these results are important only to the extent that the distribution of the unemployed has implications for the magnitudes of labor market responses to a change in UI policy.

The goal of this section is to understand the role of accounting for the heterogeneity within the unemployed in determining the magnitudes of labor market responses to changes in UI generosity. To do so, we start from the baseline model and sequentially remove the following features: i) endogenous take-up, ii) imperfect take-up, iii) heterogeneous job-separation rates, iv) heterogeneous UI eligibility rates, and v) heterogeneous UI replacement rates. We compare model-implied behavioral responses in our baseline model and in models where we shutdown these margins to a 10 percentage point increase in UI replacement rates of all eligible unemployed.

Table 8 presents the percentage point increases in the average job-finding rate (UE rate) in our baseline model and in different nested versions of our model resulting from the increase in UI generosity.³⁹ The baseline model predicts a limited response because primarily wealth-poor individuals become unemployed and take up UI. Specifically, within the entire pool of unemployed, those in the bottom quintile of the wealth distribution is less elastic to changes in UI because jobs are most valuable to them given that they are close to the borrowing limit and have almost no access to self-insurance. In this sense, the presence of borrowing constraints self-disciplines the job-search behavior of the wealth-poor unemployed. In contrast, the unemployed who are by no means wealthy but possess some degree of self-insurance are more likely to respond to changes in UI generosity because they are more capable of smoothing consumption by drawing

³⁹We acknowledge that our model abstracts from the general equilibrium (GE) effect of UI changes through asset markets. In a model where asset markets clear, an increase in UI generosity would lower savings and increase equilibrium interest rates. This would then affect the vacancy creation decisions of firms in the labor market and thus the average job-finding rate. In this comparison, however, both the baseline and nested models abstract from these GE effects, and thus any difference in the labor market responses that we highlight can be attributed to the features we successively switch off.

Table 9: Heterogeneity in labor market responses

Asset-to-income ratio		Baseline model					Alternative model				
		Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Job-finding rate $sf(w)$	Unemployed	-0.47	-0.87	-0.62	-0.24	-0.13	-0.83	-1.56	-3.66	-3.88	-4.54
	Eligible	-1.02	-1.15	-0.81	-0.31	-0.19	-1.97	-4.31	-6.26	-6.78	-9.09
	Take-up	-0.36	-0.77	-2.21	-3.83	-0.78	-1.97	-4.31	-6.26	-6.78	-9.09
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
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

Note: This table compares the changes in average job-finding rate, 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 the job-finding rate, average search effort s , and average submarket job-finding probability $f(w)$ relative to their values under the calibrated policy.

from their wealth to supplement UI receipt. Finally, the unemployed at the top quintile of the wealth distribution exhibit negligible responses since they enjoy sufficient insurance from their own savings and do not even take up benefits.

This inverse-U-shaped pattern is summarized by Table 9, which shows the percentage declines in the average job-finding rate across the asset-to-income ratio distribution following the rise in replacement rates. Within the entire pool of the unemployed, the bottom quintile is less elastic, the middle quintiles exhibit larger responses, and the richest quintile is also less elastic. When the changes in job-finding rate are decomposed into responses coming from the average decrease in search effort s and increase in reemployment 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 search effort — the same patterns are observed.⁴⁰ In addition, the responses among the eligible are larger than among the unemployed, as the option value of receiving benefits makes changes in generosity have a direct impact on the outcomes of the eligible unemployed. Unsurprisingly, the take-up demographic who already receive benefits features the largest responses but still maintains the inverse-U-shaped pattern.⁴¹ This result emphasizes that the heterogeneity in

⁴⁰To isolate labor market responses to the policy change, we take a sample of unemployed workers in the original economy and simulate their unemployment spell outcomes in a counterfactual where replacement rates are higher. We report quintile-specific percent changes of the job-finding rate, search effort s , and submarket job-finding rate $f(w)$ between the economy under the calibrated policy and the economy with higher replacement rates. The subgroup labeled “Take up” refers to the response of those already taking up benefits under the calibrated policy, and thus isolates job search responses from the effect of additional take-up. Appendix D elaborates further on this distinction through Table A10.

⁴¹The quintiles of the asset-to-income ratio distribution in Table 9 are group-specific. Given that the wealth holdings of take-up group is much lower than that of the unemployed, those who are at the second quintile of the distribution for the entire pool of unemployed turn out to be in the fourth quintile of take-up group.

elasticities is a critical feature of the baseline model, where the response of average job-finding rate is inextricably tied to the underlying wealth distribution of the unemployed. Given that individuals at the bottom quintile are more likely to become unemployed and take up UI, their limited behavioral response translates into a small change in average job-finding rate. These findings align with heterogeneous responses of unemployment hazards that we document in Section 5.4 as well as the empirical findings of Chetty (2008), who also finds a non-monotonic and inverse-U-shaped pattern response of unemployment exit hazards with respect to wealth.

The second column of Table 8 shows the resulting change in the job-finding rate when we remove endogenous take-up, i.e., impose a common $d = 0.55$, so that this model generates the same average TUR as in the baseline economy.⁴² Here, effective UI coverage expands to relatively wealthier agents who, if given the choice, would have otherwise refused to claim UI. Since the search and submarket wage choices of this group are more responsive to UI changes compared with borrowing-constrained individuals, as shown in Table 9, a model with exogenous and imperfect take-up roughly triples the response of the job-finding rate. Overall, this exercise highlights the importance of the endogenous take-up mechanism, where the wealth-poor unemployed self-select into the pool of UI recipients. In absolute terms, we still observe a small response of the average job-finding rate, as the model still features imperfect take-up and the unemployed are still predominantly wealth-poor given the presence of heterogeneous unemployment risk.

The third column of Table 8 shows that the response of job-finding rate rises substantially when we remove another source of heterogeneity within the unemployed: imperfect UI take-up. Formally, this is achieved by setting the utility cost of take-up to zero; i.e., $\alpha_d = 0$. Now, all eligible optimally choose to take up UI. This raises the economy’s exposure to UI, as UI becomes guaranteed payments conditional on eligibility. Thus, the compositional effect observed in exogenizing take-up is amplified: not only are UI recipients wealthier, but all wealthier unemployed also respond more to UI given that *all* of them now automatically receive UI.

Suppose we further assume that job-separation risk is uniform across the income distribution; i.e., $\eta_y^\delta = 0$. Given that agents with low and high incomes now face an equal probability of losing their jobs, the wealth distribution of UI recipients shifts to the right. Following the same intuition, the inclusion of a larger proportion of agents with higher self-insurance into the pool of UI recipients amplifies the elasticity of search and reemployment wage choices and thus the response of the job-finding rate to changes in UI generosity.

Next, we impose that UI eligibility upon job loss is independent of previous earnings, i.e., $m_w^g = 0$, and set $g(w, p) = 0.41$ for all agents, to target an average FEU of 59 percent as in the baseline model. Here, individuals with severely low income who used to be excluded from

However, even the individuals at the fourth quintile of take-up group are not wealthy but possess some degree of self-insurance, as shown in Table A1.

⁴²Given that this model does not incorporate UI take-up choice and agents are exogenously forced to set $d = 0.55$, we also eliminate the utility cost of take-up and set $\alpha_d = 0$.

UI due to monetary eligibility rules now enjoy a higher probability of receiving benefits. The inclusion of the lowest-earning and less elastic individuals into the pool of UI recipients dampens the overall response of job-finding rate to a change in benefit generosity.

Finally, we reduce the heterogeneity further by introducing a uniform replacement rate, i.e., $m_w^b = 0$, and set $b(w, p) = 0.51$ for all agents, to target an average replacement rate of 51 percent as in the baseline model. This version of the model corresponds to the alternative model discussed in the previous sections. Unlike in previous versions where replacement rates declined with income, the rich now enjoy higher replacement rates. Now that unemployment risk and the benefit amount are both larger for high-earners, the labor market behaviors of these individuals also become more elastic to UI changes. The right panel of Table 9 shows that, in the alternative model with full take-up and uniform job-separation risk, UI eligibility, and replacement rates, the responses of search effort, wage choice, and job-finding rate are now typically increasing in wealth, as opposed to the inverse-U-shaped pattern in the baseline model. Importantly, the large and monotonically-increasing pattern of job-finding rate responses in the asset-to-income ratio is at odds with empirical hazard elasticities documented in Chetty (2008) and our own findings outlined in Section 5.4. Overall, the homogenization of unemployment risk, UI-prospects, and take-up leads to a larger response of the job-finding rate when UI policy changes.

In conclusion, we emphasize that the preceding exercise highlights two separate but interdependent forces that amplify labor market responses. First, the *compositional effect* results in a rightward shift of the wealth distribution of UI recipients. Second, this compositional effect is amplified by an *elasticity-size effect* wherein the elasticity-wealth schedule rises in absolute terms and exhibits a monotonically increasing relationship with wealth. Uniform job-separation risk, costless take-up, and larger replacement rates imply that, in the alternative model, UI policy is more relevant for wealthier agents than it was for them in the baseline model.

5.4 Comparison to empirical elasticities

We now compare the magnitudes of model-implied elasticities with those estimated from the data. Importantly, we argue that modeling the heterogeneity within the unemployed is a key determinant of whether model elasticities align relative to the range of empirical estimates. Using quasi-experimental methods and cross-sectional or time variation in UI policy, several studies estimate the effect of UI generosity on nonemployment duration, reemployment wages, wealth holdings, and the dynamics of the unemployment rate. Given that our model is capable of replicating the same experiments used to measure these empirical elasticities, the model-implied elasticities are directly comparable to them. Table 10 summarizes the results of this comparison.

Nonemployment duration and wage outcomes The empirical estimates of the response of nonemployment duration and wage outcomes are obtained using a variety of natural and quasi-natural experiments that exploit cross-sectional or time variation in UI policy. The appeal

of these methods is that they are designed to approximate a randomized experiment design for causal inference. Under the assumption of statistically independent treatment status, these randomized experiments estimate the average treatment effect (ATE). Thus, a model-predicted elasticity that can be compared with the empirical estimates is one that arises from a randomized experiment conducted using model-generated data.⁴³ Specifically, we simulate a large number of agents in the model and extend the maximum UI duration of a randomly selected group of agents. We then compute for differences in outcomes (for completed spell duration and wages) between the treated and untreated agents. To estimate the response of an outcome variable, we report the difference-in-mean estimator α_1 obtained from the following regression:

$$y_i = \alpha_0 + \alpha_1 T_i + \epsilon_i,$$

where T_i is an indicator variable that identifies treated agents. The results of these exercises are reported in the first two rows of Table 10.

As discussed in Section 4, empirical estimates of the response of nonemployment duration to a one-month change in maximum UI duration vary from an average change of 0.03 months (Nekoei and Weber, 2017) to 0.25 months (Johnston and Mas, 2018). While the baseline model predicts an elasticity of 0.14 months, the alternative model generates a much larger elasticity of 0.30 months, greater than the upper range of existing estimates. The larger elasticity in the alternative model is a direct consequence of the inflow of relatively wealthier individuals into the pool of UI recipients for whom elasticities are larger.

We then turn to a comparison of the elasticity of wage changes between pre- and post-unemployment, i.e., $\ln(w_i^{\text{post}}) - \ln(w_i^{\text{pre}})$, with respect to benefit extensions in the model with empirical estimates. This moment is informative about the extent to which increases in benefit generosity allow workers to match with higher-paying jobs, which are, however, harder to find.

The literature presents mixed findings on this relationship. Card, Chetty, and Weber (2007) use a quasi-experimental design and conclude that the wage change effect of UI is not statistically different from zero. Schmieder, von Wachter, and Bender (2016) find that workers with longer UI duration have lower wages: a six-month (one-month) increase in UI duration leads to a 0.7 (0.12) percentage point decrease in wage changes. In contrast, Nekoei and Weber (2017) find that a nine-week (one-month) extension of UI leads to a 0.45 (0.2) percentage point increase in wage changes. They show that while increases in UI duration lead the unemployed to look for higher wages (selectivity margin), it also causes longer unemployment spells due to duration dependence in the job-finding rate, reducing subsequent wages (search margin).

Using the model, we estimate the ATE of a one-month UI extension for wage changes

⁴³The randomization implies that controlling for model-observables leads to similar conclusions. Alternatively, one could directly calculate the ATE, as we can observe counterfactual outcomes for both treated and untreated agents. Unsurprisingly, both approaches yield close to identical results.

Table 10: Empirical elasticities on labor market responses with respect to UI generosity

	Baseline model	Alternative model	Data
<i>Average responses</i>			
Nonemployment duration (months)	0.14	0.30	0.03-0.25 [0.15]
Wage change $\ln(w_i^{post}) - \ln(w_i^{pre})$ (pp)	0.05	0.68	-0.12-0.20 [0]
Asset-to-income ratio (pp)	-0.20	-0.50	-0.18
<i>Heterogeneous responses</i>			
Unemployment hazard rate (percent)			
Q1	-1.01	-4.98	-1.78
Q2	-0.69	-5.41	-2.18
Q3	-1.37	-5.48	-2.82
Q4	-4.62	-10.32	-2.62
Q5	-1.72	-13.50	-2.10
<i>Cyclical responses</i>			
Great Recession unemployment rate (pp)	0.38	0.65	0.1-2.5 [0.7]
Great Recession LTU share (pp)	3.30	4.75	0.3-7.1

Note: This table summarizes the magnitudes of labor market responses to changes in UI generosity in the model and the data. Values in square brackets represent the median value of the empirical estimates. For nonemployment duration and wage difference between pre- and post-unemployment, the values show the estimated responses to a one-month increase in UI duration. For the asset-to-income ratio, the values show the estimated average percentage point (pp) change in the asset-to-income ratio in response to a 5 percentage point increase in the replacement rate. For the heterogeneous responses, we estimate a Cox proportional hazards regression and report the percent change of the unemployment hazard to a 10 percent change in UI benefits for each asset-to-income ratio quintile as in [Chetty \(2008\)](#). Empirical estimates are obtained from spell-level information combined with weekly-benefit amounts predicted based on time-varying and state-specific laws among UI-recipients in the SIPP 1996-2008 panels. Finally, for the unemployment rate and the long-term unemployment (LTU) share, the values show the estimated percentage point increases during the Great Recession due to UI extensions implemented during this period.

$\ln(w_i^{post}) - \ln(w_i^{pre})$. With the baseline model, we find that this leads to a negligible 0.05 percentage point increase in wages changes, a small positive estimate that lies in between the range of empirical estimates. On the other hand, the alternative model predicts a much larger response of 0.68 percentage points, which exceeds the upper range of empirical estimates.

The baseline model predicts a small elasticity of wage changes because wealth holdings endogenously affect the job-search behavior of the unemployed. First, UI recipients are predominantly low-wealth individuals with no self-insurance, so they barely increase their wage choices despite benefit extensions. For this reason, to begin with, the selectivity margin in our model is not strong. Furthermore, wealth decumulation over the unemployment spell leads job seekers to direct their search toward lower-paying jobs with higher job-finding probabilities. Hence,

even in the absence of duration dependence in the model, say due to human capital depreciation during unemployment, longer spells generate negative pressure on reemployment wages due to the wealth channel. However, in the alternative model, the search margin is weak because individuals with high self-insurance also become unemployed and collect benefits during a relatively shorter unemployment spell where they search for higher reemployment wages.

Wealth Individuals have access to both private and public insurance against unemployment risk. The degree to which individuals substitute away from private insurance when public insurance is more generous has implications for their labor market behavior given that the magnitudes of elasticities vary across the wealth distribution.

We compare the elasticity of wealth with respect to the UI generosity implied by the model with the existing empirical estimate. Engen and Gruber (2001) estimate the crowding-out effect of UI on financial assets, using SIPP data under the following regression specification:

$$WEALTH_i = \iota_i + \zeta_1 X_i + \zeta_2 RR_i + \zeta_3 \varphi_j + \zeta_4 \xi_t + \epsilon_{ijt},$$

where $WEALTH_i$ is the asset-to-income ratio of individual i ; X_i is a vector including age, sex, marital status, education, and a quartic on wages; RR_i is the replacement rate; and ι_i , φ_j , and ξ_t are individual-, state-, and year-specific dummies. They find that a 5 percentage point increase in the replacement rate decreases the asset-to-income ratio by 0.18 percentage points. Using data generated from the model, we run the same regression. The baseline model predicts that the same 5 percentage point increase in the replacement rate lowers the asset-to-income ratio by 0.20 percentage points, while the alternative model predicts a much larger response of 0.50 percentage points. The larger elasticity is explained by the alternative model's imposition of greater unemployment risk among wealthier agents who now have more representation within the unemployed. In fact, this is in line with the findings of Engen and Gruber (2001) that the substitution of private insurance with public insurance rises with unemployment risk.

Heterogeneous responses We also benchmark the baseline and alternative models' predictions on heterogeneous labor market elasticities to changes in UI. In this regard, we follow Chetty (2008) and construct unemployment spell level data from the SIPP 1996–2008 panels to estimate a stratified Cox hazard model with the following specification:

$$\log h_{itj} = \iota_{tj} + \sum_{j=1}^5 \zeta_1^j Q_{ij} \log WBA_i + \zeta_2 X_{itj}, \quad (9)$$

where Q_{ij} is an indicator that takes a value of 1 if respondent i is in the j th quintile of the asset-to-income ratio distribution of the unemployed, ι_{tj} is the quintile-specific baseline hazard function, ζ_1^j is the quintile-specific elasticity of the unemployment hazard rate with respect to

the UI weekly benefit amount (WBA) the recipient is entitled to, and X_{itj} is a vector of controls including age, sex, education, race, marital status, wealth, state, year, and a 10-piece log-linear spline for the claimant’s pre-unemployment earnings. We also control for a seam indicator to account for the seam effect. In order to estimate the hazard model, we focus a sample of UI recipients who took up benefits at any point during their unemployment spell where we use predicted WBA values that we obtain from the UI-program discussed in Section 2.

Using the coefficients-of-interest $\{\zeta_1^j\}_{j=1}^5$, Table 10 reports the heterogeneous responses of the hazard rate to a 10 percent rise in UI.⁴⁴ The hazard rate of the bottom quintile responds the least (1.8 percent) while the third and fourth quintiles exhibit the largest responses of close to 3 percent. The top quintile exhibits a smaller response of roughly 2 percent. We note that these findings align to some degree with Chetty (2008), who also finds a non-monotonic and inverse-U-shaped pattern response of unemployment exit hazards with respect to wealth holdings when using an individual level measure of benefits that is comparable to our data and model.⁴⁵

We run a comparable regression using model-generated unemployment spell level data from both the baseline and alternative models, controlling instead for productivity, previous wages, and assets. As seen in Table 10, the baseline model predicts hazard elasticities that are inverse-U-shaped pattern in the asset-to-income ratio. In contrast, the alternative model not only predicts much larger elasticity across all asset-to-income ratio quintiles, it also predicts a monotonically increasing elasticity pattern – a result that is at odds with our empirical estimates and the findings in Chetty (2008). Finally, we note that the non-monotonic and smaller responses obtained from the baseline model and the monotonic and larger responses obtained from the alternative model emerge from similar patterns in the response of job-finding rate as shown in Table 9.

Cyclical movements in the unemployment rate We now compare unemployment rate responses to changes in UI generosity over the business cycle. In particular, we focus on the large literature that estimates the impact of UI extensions on unemployment dynamics during and after the Great Recession. A common metric used is the percentage point contribution of UI extensions to the unemployment rate during the Great Recession. Overall, several studies have arrived at mixed conclusions ranging from 0.1 percentage points (Rothstein 2011 and Chodorow-Reich, Coglianesi, and Karabarbounis 2019) to 2.15 percentage points (Hagedorn, Karahan, Manovskii, and Mitman 2019), as detailed in Table A12 in Appendix D.

To understand the model’s predictions of the effect of UI extensions on the unemployment rate during the Great Recession, we simulate the model for the Great Recession period with

⁴⁴Table A11 in Appendix D reports the full results of this exercise.

⁴⁵We note that our approach differs from Chetty (2008) along certain dimensions. First, he uses the 1985–1996 SIPP panels (spanning 1985–2000) whereas we use the 1996–2008 SIPP panels (spanning 1996–2013). Second, we focus on jobless workers who took up benefits during their spell whereas he focuses on a specific sample of prime-aged males who took up benefits during the first period of job loss. Third, we align our grouping with the model’s measure of self-insurance by dividing respondents into quintiles of the asset-to-income ratio whereas Chetty (2008) groups by their actual wealth levels.

and without UI extensions and measure the time path of the unemployment rate. This is accomplished by picking the realizations of aggregate productivity to match the unemployment rate between December 2007 and November 2013 under UI extensions implemented by U.S. policy, as shown in Figure A2 in Appendix D. We find that during the depth of the recession, the baseline model-implied unemployment rate would have been around 0.38 percentage points lower in the absence of UI extensions, implying that UI extensions during the Great Recession played a limited role in exacerbating labor market conditions during that period.⁴⁶ Repeating the same exercise but with the alternative model, we find that the extensions contributed around 0.65 percentage points to the unemployment rate, which is closer to the larger estimates in the literature. This result is a direct consequence of larger nonemployment duration and wage change elasticities in the alternative model.

Finally, we compare long-term unemployment (LTU) shares during the Great Recession. Rothstein (2011) finds that UI extensions led to a 0.3 to 2.8 percentage point increase in the LTU share, while Farber and Valletta (2015) find that they led to a larger 7.1 percentage point increase. Without extensions, the baseline model predicts that the LTU share would have been 3.3 percentage points lower, while the alternative model predicts that it would have been even lower — 4.75 percentage points lower.

Overall, the preceding discussions show that accounting for heterogeneity within the unemployed, especially along dimensions that relate income and wealth differences to labor market behavior and UI-receipt differences, has demonstrable implications for the size of predicted labor market responses both in the steady state and over the cycle. This in turn determines whether the model’s predicted elasticities would lie within the range of available empirical estimates.

6 Discussion

In this section, we first summarize results about the implications of our findings on UI policy design over the business cycle. Next, we provide robustness checks on our main results.

6.1 Implications for UI policy design over the business cycle

We ask whether incorporating heterogeneity within the unemployed into our framework affects the implications of UI reform over the business cycle. We acknowledge that understanding the aggregate macroeconomic and welfare implications of UI reform or prescribing optimal UI policy over the business cycle are goals beyond the scope of this paper for at least two reasons. First, our framework does not allow for asset market clearing, implying that we abstract from the effects of changes in UI on interest rates and vacancy creation. Second, we assume in Equation

⁴⁶In a model where asset markets clear, increases in UI generosity would lower vacancy creation due to a decline in savings and a rise in interest rates. Lower vacancy creation would further amplify the increase in the unemployment rate when UI is more generous. However, comparing the mechanisms of the baseline and the alternative models, the latter would still predict a much larger response of the unemployment rate.

(7) that the government budget is balanced in expectation and that taxes do not contemporaneously respond to changes in UI, which potentially lead to an underestimation of the fiscal externality associated with changes in UI. For these reasons, we do not attempt to prescribe an optimal policy under this model and instead provide an illustrative example that compares how changes in the cyclical of UI would affect individual labor market and consumption outcomes in the baseline and alternative models.

To proceed with our exercise, we first pick welfare-improving UI policy reform, details of which are discussed in Appendix E. The resulting reform policy is countercyclical in both the replacement rate and benefit duration and features a slightly higher replacement rate for low-income workers than for high-income workers when compared with the current UI policy. In order to understand how effects of this reform policy differ between the baseline and the alternative models, we simulate a recessionary period and compare labor market dynamics and behavioral responses across two policy regimes – countercyclical reform policy and corresponding acyclical reform policy – in both models. These two policies provide the same UI generosity during normal times, but the countercyclical policy features more generous benefits for longer durations during recessions. Figure A3 demonstrates the results of this experiment.

We highlight the following results. The consumption insurance provided by the countercyclical policy is larger under the baseline model. This is because, in the baseline model, insurance benefits result from both increased benefit generosity and an endogenous rise in the fraction of UI recipients. Moving to incentive costs, the countercyclical policy induces longer unemployment durations and a larger LTU share. However, this response is muted in the baseline model because of the smaller responses of search effort and the wage choice to countercyclical UI.

While our model abstracts from general equilibrium effects, this exercise offers an illustration of how the evaluation of UI policy over the cycle depends on the extent to which a model captures the distribution of unemployed workers. The alternative model, where is no link between the heterogeneity in income and wealth and the heterogeneity in job-separation, eligibility, and take-up rates, features lower insurance benefits and larger moral hazard costs associated with expanding UI benefits during recessions relative to the baseline model.

6.2 Robustness

In this section, we present our main results under different parameter values and modeling choices. Additional discussions on these experiments are provided in Appendix F.

Different parameter values First, in our calibration exercise, we choose the curvature parameter of the utility cost of job-search effort χ_s to match the elasticity of nonemployment duration with respect to UI duration. Targeting the median value among the range of available empirical estimates of this elasticity yields a value of $\chi_s = 1.51$. We now consider different values for this parameter, motivated by the recent work of Faberman, Mueller, Şahin, and Topa (2020),

who use micro data on search effort and find search effort to be more elastic than what we obtain. Second, we consider different values for the matching function parameter γ , as we acknowledge that there is a range of values used in the literature for this parameter. Table A13 shows that our main results remain similar under different values of both parameters. In particular, the alternative model still arrives at significantly larger responses of key labor market outcomes.

Different model assumptions Next, we conduct a series of robustness checks to understand the implications of certain assumptions made in the model. First, we choose to model the UI take-up effort $d \in [0, 1]$ such that increased take-up effort raises the chances of UI claim approval. Modeling take-up as a continuous choice allows us to use the curvature parameter of the disutility of take-up effort χ_d to discipline the volatility of the take-up rate, as discussed in Section 4. Alternatively, we now consider a nested version of our model where take-up $d \in \{0, 1\}$ is a binary choice subject to a fixed utility cost. Here, eligible unemployed are guaranteed benefits if they choose to take up them. Second, in our framework, we assume that matching efficiency λ varies over the business cycle, the magnitude of which is controlled by the parameter η_p^λ . In Section 4, we choose η_p^λ so that the model generates the empirical volatility of the job-finding rate. Together with fluctuations in the job-separation rate over time, this allows our model to generate the observed volatility of the unemployment rate. An alternative assumption we implement here is to set $\eta_p^\lambda = 0$ and instead use a high average UI replacement rate to achieve the same goal, as suggested by Hagedorn and Manovskii (2008). Finally, we consider the effects of introducing a higher level of government expenditure to account for other forms of government spending. The intention of this exercise is to understand whether a marginal change in taxes to fund UI policy will have different implications depending on the level of taxes. In this model, we also relax the assumption of a constant labor income tax and introduce progressive taxation. We find that under all modifications, the alternative model overestimates the magnitudes of key elasticities, as summarized in Table A13.

7 Conclusion

We document novel facts about the interaction between heterogeneity in income and wealth and heterogeneity in labor market and UI outcomes, both in the cross-section and over the cycle. Using SIPP data combined with state-level UI laws from 1996 to 2016 to predict UI status, we find that income and wealth holdings affect not only the transitions into and out of unemployment but also UI-eligibility, take-up, and replacement rates. The key contribution of our empirical analysis is that we characterize the demographics of the unemployed and, importantly, their subgroups that have higher exposure to changes in UI policy: the UI eligible and UI recipients.

To understand the role of heterogeneity in labor market transitions, UI-eligibility, replacement rates, and UI take-up decisions on the effects of UI policy changes over the business cycle, we construct a heterogeneous-agent directed-search model with incomplete markets and aggregate

risk. The calibrated model is able to generate key untargeted empirical patterns such as the lower wealth holdings of the UI take-up group relative to the non-take-up group, the joint distribution between income and wealth, the countercyclicality of eligibility and take-up rates, and the rightward shift of the wealth distributions of the take-up and non-take-up groups during recessions. Importantly, we show that an alternative model that abstracts from the link between income and wealth holdings and job-separation, eligibility, and replacement rates, as well as UI take-up decisions, fails to capture these untargeted data moments.

The ability of the model to capture heterogeneity within the unemployed is important only insofar as heterogeneous individuals have differential responses to changes in UI generosity. We show that the baseline model predicts limited behavioral responses to a change in UI generosity, while the alternative model generates much larger behavioral responses that are close to or above the upper ranges of available empirical estimates. Taken together, these findings imply that the extent to which a model captures heterogeneity within the unemployed affects its predictions on the behavioral responses of individuals upon a change in UI policy.

Our results provide important implications for UI policy design over the business cycle. In particular, we demonstrate that the evaluation of labor market effects of reform policy will depend on the extent to which the models with which they are assessed can capture heterogeneity within the unemployed. We show that relative to the baseline model, an alternative model that homogenizes unemployment risk and the composition of the unemployed would predict larger incentive costs and lower insurance benefits from expanding UI during recessions. We do not attempt to characterize optimal policy using our framework given the absence of general equilibrium effects in the asset market. To make progress in this direction, one can extend our model to a full general equilibrium framework to study optimal design of UI policy over the business cycle. We leave this to future research.

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Appendix for Online Publication

A Data

In this section, we provide details about the SIPP data and our calculations of the empirical findings described in Section 2. Next, we 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 were interviewed at 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 at 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 age 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

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

he/she reports either having no job and actively looking for work or having a job but 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 provides 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 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

²Even 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.

³For our analysis in Section 2.3, we calculate the EU and UE transition probabilities from the CPS between 1996 and 2016 using the same methodology.

⁴The 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.

net liquid asset to monthly labor income ratio 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 rate, take-up rate, and replacement rate 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 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, Table 7-9 in an assessment by the [National Academies of Sciences and Medicine \(2018\)](#) documents 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 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 TUR.

A.3 Additional empirical results

Heterogeneity within the unemployed Section 2.2 documents results on the heterogeneity of EU, UE, FEU, TUR, and replacement rates across quintiles of income, assets, and the asset-to-income ratio. We supplement these results in the main text with a discussion on how the income,

⁵Here, 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.

⁶Moreover, 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: Heterogeneity within the unemployed

	Asset-to-income ratio						Assets					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Employed	-1.91	-0.15	0.74	2.93	8.87	16.11	-0.49	-0.04	0.19	0.89	2.90	1.00
Unemployed	-1.66	-0.12	0.30	2.00	9.46	6.53	-0.33	0.00	0.05	0.36	1.66	0.73
Eligible	-1.34	-0.12	0.28	1.74	7.78	2.92	-0.37	-0.02	0.05	0.33	1.78	0.78
Take-up	-2.02	-0.41	0.24	1.23	3.70	1.25	-0.37	-0.06	0.04	0.19	1.21	0.48
Non-take-up	-0.87	-0.01	0.44	2.72	12.94	5.03	-0.36	0.00	0.10	0.52	3.49	1.20

	Income						Unemployment spell duration					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Employed	0.27	0.48	0.79	1.23	1.84	1.00						
Unemployed	0.12	0.27	0.52	0.87	1.41	0.73	1	1	2	4	6	3.13
Eligible	0.22	0.38	0.61	0.93	1.41	0.78	1	1	2	4	7	3.31
Take-up	0.21	0.39	0.57	0.88	1.27	0.75	1	2	3	5	8	3.81
Non-take-up	0.23	0.35	0.64	0.98	1.52	0.81	1	1	2	3	5	2.42

Note: This table documents the distributions of the asset-to-income ratio, assets, income, and completed unemployment spell durations using the SIPP 2004 panel. Percentiles for asset and income distributions for each group are reported relative to the mean of employed. 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 any type of unemployed). Assets are measured as the net liquid wealth holdings.

asset, and asset-to-income ratio distributions differ between the employed, the unemployed, and various groups within the unemployed. Here, we present these results in more detail.

We separate the pool of unemployed into those who are eligible and ineligible for UI, and further subdivide the eligible into a take-up and non-take-up group. We then characterize the demographics of each UI subgroup. These comparisons are relevant since we emphasize that differences in eligibility and take-up are key determinants of an individual's level of exposure and response to changes in UI.

Table A1 summarizes the distributions of the asset-to-income ratio, assets, income, and unemployment durations when respondents are grouped by their employment and UI statuses. Values for the asset and income distributions are expressed in terms of the mean value of the employed to facilitate comparison.⁷ Table A1 shows that the unemployed have much less self-insurance compared with the employed.⁸ However, analyzing the pool of unemployed as a single

⁷Given that the SIPP collects asset information only in specific waves, we use wave 3 of the SIPP 2004 panel to report results for the asset and asset-to-income ratio distributions. Further, to remain consistent with the time frame selected, we present distribution of income from the same wave as well. Our main conclusions remain similar if we instead choose to use SIPP 2004 wave 6, the only other wave with asset information in this panel. For unemployment spell durations, we use data from all waves of SIPP 2004.

⁸Engen and Gruber (2001) also use a similar sample of individuals age 25 to 64 who are non-business owners from SIPP data between 1984 and 1990 and find that the median liquid financial assets to annual earnings ratio

Table A2: 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	-0.199	(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 the estimate on 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 age 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.

group masks important dimensions of heterogeneity across different types of unemployed. Table A1 highlights several novel empirical results that reveal the considerable heterogeneity within the unemployed. In Section 2.2, we emphasize the following results. First, the unemployed who do not take up UI possess much more self-insurance than those who take up. Second, the unemployed have markedly lower (previous) earnings than the employed, a result that is in accordance with our previous finding in Table 1 that workers in lower-paying jobs experience higher job-separation rates. Third, the previous earnings of eligible workers is higher than unemployed workers, especially at the bottom percentiles, because ineligible workers within the pool of unemployment have very low previous labor earnings. Finally, the eligible unemployed who do not take up UI have significantly shorter spell durations than those who take up.

Effect of wealth on UI take-up decision In light of the results presented in Tables 1 and A1, Section 2.2 concludes 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 age 25 to 65 who are not business owners and who are in their first month of an unemployment spell.⁹ To understand the effect of wealth holdings on the UI take-up decision, we estimate the following regression for the unemployed in our sample:

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

is 0.058. This implies a median liquid financial asset to monthly earnings ratio of 0.70. In our sample, the median net liquid assets to monthly earnings ratio in the SIPP 2004 panel is 0.73, which is very close to their estimate.

⁹To isolate the effect of wealth holdings upon unemployment, we focus on individuals at the start of their unemployment spell.

Table A3: Heterogeneity within the unemployed over the business cycle

	Asset-to-income ratio											
	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Employed	-1.91	-0.15	0.74	2.93	8.87	16.11	-1.33	0.00	1.02	3.44	11.27	10.67
Unemployed	-1.66	-0.12	0.30	2.00	9.46	6.53	-2.17	0.00	0.57	2.83	12.31	8.86
Eligible	-1.34	-0.12	0.28	1.74	7.78	2.92	-2.17	0.00	0.57	2.69	9.96	4.79
Take-up	-2.02	-0.41	0.24	1.23	3.70	1.25	-1.92	0.00	0.53	2.38	8.87	4.34
Non-take-up	-0.87	-0.01	0.44	2.72	12.94	5.03	-3.69	0.00	1.02	4.11	16.05	6.47

	Unemployment spell duration											
	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Unemployed	1	1	2	4	6	3.13	1	1	3	5	11	4.77
Eligible	1	1	2	4	7	3.31	1	2	4	7	13	5.70
Take-up	1	2	3	5	8	3.81	1	2	4	8	16	6.67
Non-take-up	1	1	2	3	5	2.42	1	1	2	4	6	2.89

Note: This table documents the distributions of asset-to-income ratio and completed unemployment spell duration prior to and during the Great Recession using SIPP 2004 and 2008 panels.

where i indexes individuals; Take-up_i is an indicator variable with a value of 1 if individual i take up UI benefits; $\text{Asset-to-income ratio}_i$ 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.

Table A2 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.

Cyclical properties Section 2.3 discusses our empirical findings on how the asset-to-income ratio and unemployment spell distributions of different groups within the unemployed change over the business cycle. In particular, we compare our results from the SIPP 2004 panel, repeated from Table A1, with results from the SIPP 2008 panel, which largely overlaps with the Great Recession period. Table A3 presents our findings that we discuss in Section 2.3.

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

$$V^{NB}(a, y; \mu) = \max_{c, a' \geq a_1, s} u(c) - \nu(s) + \beta(1 - \omega) \mathbb{E} \left[\max_{\tilde{w}} \left\{ sf(\theta(\tilde{w}, y'; \mu')) V^W(a', \tilde{w}, y'; \mu') \right. \right. \\ \left. \left. + (1 - sf(\theta(\tilde{w}, y'; \mu'))) V^{NB}(a', y'; \mu') \right\} \middle| y, \mu \right]$$

subject to

$$c + a' \leq (1 + r)a + h \\ \Gamma' = H(\mu, p'), \quad p' \sim F(p' | p), \quad y' \sim Q(y' | y).$$

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

B.2 Equilibrium

Definition of recursive equilibrium Given UI policy $\left\{ b(w, p), e(p), g(w, p), \tau \right\}_{w \in \mathcal{W}, p \in \mathcal{P}}$, 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 the 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 and show that it still admits block recursivity.

Existence: We prove the existence of the BRE in two steps. We first show that the firm value functions and the corresponding market tightness depend on the aggregate state of the economy only through aggregate productivity. Then, we show that value functions do not depend on the aggregate distribution of agents across states. As a result, the solution of the individual's problem together with the solution of the firm's problem and market tightness constitute a BRE.

Let $\mathcal{J}(\mathcal{W}, \mathcal{Y}, \mathcal{P})$ be the set of bounded and continuous functions J such that $J : \mathcal{W} \times \mathcal{Y} \times \mathcal{P} \rightarrow \mathbb{R}$, and let T_J be an operator associated with Equation (4) such that $T_J : \mathcal{J} \rightarrow \mathcal{J}$. 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

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

Hence, we also show that equilibrium market tightness does not depend on the distribution of agents across states.¹⁰ Next, we collapse the problem of individuals into one functional equation and show that it is a contraction. Then, we show that the functional equation maps the set of functions that depend on the aggregate state μ only through p .

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 $R : \{0, 1\} \times \{0, 1\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{Y} \times \Omega \rightarrow \mathbb{R}$ such that

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

¹⁰Notice 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.

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

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

subject to

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

where we use the result from above that market tightness does not depend on Γ , and $c_{1,0}$, $c_{0,1}^T$, $c_{0,1}^{NT}$, and $c_{0,0}$ represent consumption of 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., $T_R : \mathcal{R} \rightarrow \mathcal{R}$). 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 $\delta(y, p) = \delta$.¹¹ 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.¹² Using the expression for $J^*(w, y; p)$ gives

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

Thus, the job-finding rate $f(\cdot)$ is linear and decreasing in w . Then, rewriting the objective

¹¹The following results can be obtained under an N state Markov process assumption for p and no restrictions on the job destruction rate.

¹²We 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 4.

function for the wage choice of eligible unemployed, we have

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

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} , 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, 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

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	Cyclicalilty 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	Cyclicalilty of UI replacement rate	0
ρ^y	Persistence of idiosyncratic productivity	0.9867	m_p^g	Cyclicalilty 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.

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 aggregate dynamics of the model.

C Calibration

In this section, we present additional tables and figures to supplement our discussion in Section 4 of the main text. Table A4 provides a list of externally calibrated parameters.

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

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

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).

Consumption drop upon job loss Here, we first provide details on the empirical estimates of the consumption drop upon job loss, which is used as a calibration target in Section 4. We then explain how we obtain the estimate on the consumption drop upon job loss in our model. Finally, we make further comparisons between the model and the data for various frequencies.

We calibrate our model to match the average consumption drop in the year of job loss. [Gruber \(1997\)](#) uses data on food expenditures from the Panel Study of Income Dynamics (PSID) and finds that the average consumption drop upon job loss is 6.8 percent. [Saporta-Eksten \(2014\)](#) uses the PSID between 1999 and 2009 and estimates that the average consumption drop in the year of job loss is 8 percent.¹³ [Stephens \(2004\)](#) uses data from the Health and Retirement Survey (HRS) and the PSID and finds a decline in food expenditures between 12 percent (PSID) and 15 percent (HRS). Finally, [Aguilar and Hurst \(2005\)](#) uses a representative survey dataset on consumption expenditures between 1989 and 1996 collected by the U.S. Department of Agriculture. They find that total expenditure on food drops by 19 percent upon unemployment. We take the median estimate of 12 percent as our calibration target.

¹³Since 1999, the PSID started providing information on consumption beyond food expenditure. The consumption measure that [Saporta-Eksten \(2014\)](#) uses includes expenditure on non-durables and services such as food inside and outside home, health, utilities, gasoline, car maintenance, transportation, education, and childcare.

We estimate the following distributed lag regression to obtain the model-implied measure:

$$\log(c_{it}) = \iota_i + \xi_t + \sum_{k=-6}^6 \psi_k D_{it}^k + \epsilon_{it},$$

where the outcome variable $\log(c_{it})$ is the logarithm of consumption of individual i in period t , ι_i and ξ_t are individual and time-fixed effects, and ϵ_{it} represents random factors. The indicator variables D_{it}^k identify all individuals' k periods prior to or after a job loss, where $k = 0$ is the period in which job loss occurs. For instance, $D_{it}^2 = 1$ for individual i who experiences job loss at time $t - 2$, and it equals zero otherwise. The treatment group consists of individuals who experience at least one job loss during the simulation period, while the control group consists of those with no job loss during the sample period. To facilitate comparison with the available estimates on annual frequency discussed above, we estimate this regression on the model-generated data where we aggregate monthly simulation to annual frequency.¹⁴ We find that the average consumption drop in the year of job loss is 12 percent in the model.

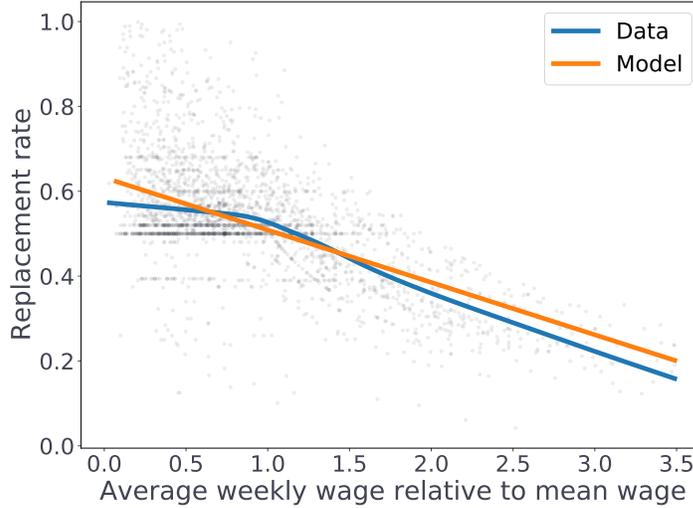
Finally, we make further comparisons between the model and the data for higher frequencies. First, [Burgess et al. \(1981\)](#) uses data from the Arizona Benefit Adequacy Study completed between 1975 and 1978. The data incorporate information on various expenditure components before and after job loss.¹⁵ 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 for the percent change in consumption between the third month of unemployment and the month prior to job loss for agents who are continuously unemployed for three months and receive UI. 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 incorporates 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. They 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 our model-generated monthly data and construct the same measure of change in consumption from before the job loss to six months after the job loss for individuals who are continuously unemployed for six months. We find that the average consumption loss is 14 percent in the model. Hence, our model-implied estimates are close to empirical estimates that use different samples or frequencies.

¹⁴The treatment group consists of individuals who experience at least one job loss in any month of the year.

¹⁵The 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.

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., $p = \bar{p}$.

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 in the data. Figure A1 shows that our calibrated replacement rate function closely tracks the declining profile of the replacement rate in AWW observed in the data.

D Validation and empirical elasticities

In this section, we present additional tables and figures to supplement our discussion in Section 5 of the main text.

Heterogeneity within the unemployed Section 5.1 compares the heterogeneity of EU, UE, FEU, TUR, and replacement rates across quintiles of income, assets, and the asset-to-income ratio in the model and the data. We supplement these results with our discussion on demographic differences in various groups within the unemployed. Here, we now present these results in detail.

Table A6 summarizes the distributions of the asset-to-income ratio, assets, income, and the unemployment spell duration when individuals are grouped by their employment and UI status. Both in the model and the data, values for the asset and income distributions are expressed in terms of the mean value of the employed to facilitate comparison. In Section 5.1, we emphasize the following results. First, unemployed individuals possess less self-insurance compared with the employed. This is not only driven by the depletion of assets during unemployment, but also the outcome of unemployment inflows being concentrated among income- and wealth-poor workers. Second, the endogenous take-up decision in the model allows it to generate an important

Table A6: Heterogeneity within the unemployed

	Data						Model					
	Asset-to-income ratio											
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Employed	-1.91	-0.15	0.74	2.93	8.87	16.11	-0.63	-0.08	0.66	2.15	3.90	1.50
Unemployed	-1.66	-0.12	0.30	2.00	9.46	6.53	-2.94	-1.13	-0.17	1.10	4.03	0.63
Eligible	-1.34	-0.12	0.28	1.74	7.78	2.92	-1.21	-0.40	0.07	1.51	4.51	1.26
Take-up	-2.02	-0.41	0.24	1.23	3.70	1.25	-1.71	-0.62	-0.26	0.07	1.16	-0.01
Non-take-up	-0.87	-0.01	0.44	2.72	12.94	5.03	-0.46	0.27	1.32	2.52	7.44	2.83

	Assets											
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
	Employed	-0.49	-0.04	0.19	0.89	2.90	1.00	-0.28	-0.05	0.39	1.31	1.99
Unemployed	-0.33	0.00	0.05	0.36	1.66	0.73	-0.75	-0.37	-0.05	0.59	1.56	0.46
Eligible	-0.37	-0.02	0.05	0.33	1.78	0.78	-0.47	-0.11	0.03	0.90	1.85	0.71
Take-up	-0.37	-0.06	0.04	0.19	1.21	0.48	-0.64	-0.18	-0.06	0.03	0.31	0.00
Non-take-up	-0.36	0.00	0.10	0.52	3.49	1.20	-0.31	0.18	0.88	1.42	4.78	1.61

	Income											
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
	Employed	0.27	0.48	0.79	1.23	1.84	1.00	0.35	0.49	0.86	1.42	2.07
Unemployed	0.12	0.27	0.52	0.87	1.41	0.73	0.21	0.33	0.47	0.82	1.34	0.63
Eligible	0.22	0.38	0.61	0.93	1.41	0.78	0.24	0.36	0.55	0.91	1.45	0.72
Take-up	0.21	0.39	0.57	0.88	1.27	0.75	0.20	0.29	0.39	0.52	0.65	0.45
Non-take-up	0.23	0.35	0.64	0.98	1.52	0.81	0.49	0.74	0.91	1.37	1.73	1.05

	Unemployment spell duration											
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
	Unemployed	1	1	2	4	6	3.13	1	1	2	4	7
Eligible	1	1	2	4	7	3.31	1	1	2	4	7	3.34
Take-up	1	2	3	5	8	3.81	1	2	3	6	9	4.32
Non-take-up	1	1	2	3	5	2.42	1	1	2	3	5	2.42

Note: This table compares model-generated distributions of the asset-to-income ratio, assets, income, and completed unemployment spell duration with those empirically observed in the data. Percentile values for asset and income distributions for each group are reported relative to the mean of employed individuals. 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 any type of unemployed). Assets in the data are measured as net liquid wealth holdings.

empirical finding: eligible job losers who take up UI benefits have a substantially lower capacity to self-insure compared with those who do not to receive benefits despite being eligible. Third,

unemployed workers earned less in their previous job relative to currently employed workers, which is a consequence of higher job-separation risk in lower-paying jobs. Further, UI-eligible unemployed workers earn more than the average unemployed worker given that, within the pool of the unemployed, some individuals with lowest previous earnings become ineligible for UI. Finally, UI recipients experience longer spell duration than eligible non-recipients. All these predictions of the model are in line with the data. This is important because insofar as labor market responses of unemployed individuals to UI policy changes depend on their self-insurance and the severity of their unemployment spells, the model’s ability to reasonably capture the demographics of the unemployed is a first-order determinant of predicted labor market elasticities.

Joint distribution of income and assets conditional on productivity In Section 5.1, we compare the joint distribution of wealth holdings and income in the model with the equivalent distribution observed from the data. Table A7 compares the conditional joint distribution of income and wealth holdings across individuals with different education levels in the data 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 productivity, although the model overstates the difference.

Marginal propensities to consume The differences in wealth, income, and employment status in the model translate to differences in agents’ marginal propensity to consume (MPC) out of transfers. This is a useful metric to assess how the model’s ability to match distributions translates to predictions on how valuable UI’s insurance benefits are to agents. In the model, we compute an agent’s MPC by calculating the fraction of an unexpected and temporary transfer – scaled to be equivalent to \$500 – spent on consumption, as in Kaplan and Violante (2014).

We find that the average quarterly MPC in the model is 14 percent, which is comparable to estimates found by Parker, Souleles, Johnson, and McClelland (2013), who document that individuals spend between 12 and 30 percent of unexpected tax rebates in the quarter that they are received. Furthermore, the model predicts that the difference in annual MPCs between the unemployed and employed is 24 percent, which is close to the results of Kekre (2019), who finds the difference to be 25 percent using the 2010 Survey of Household Income and Wealth.

The model’s success in approaching empirical MPCs lies in its ability to generate a sizable fraction of agents with high income but low liquid wealth. On one hand, unemployment risk is disproportionately high among low-income workers who are unable to save and thus consume a larger fraction out of transfers, especially when unemployed. On the other hand, high-income workers who face little to no unemployment risk have weak precautionary saving motives and thus also possess low liquid wealth and are inclined to consume more out of unexpected transfers.

Great Recession simulation in the model In Sections 5.1 and 5.2, we demonstrate how cross-sectional heterogeneity within the unemployed change between recessionary and non-recessionary

Table A7: Joint distribution of income and asset holdings across productivity

	Less than high school degree / Low y					More than masters' 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

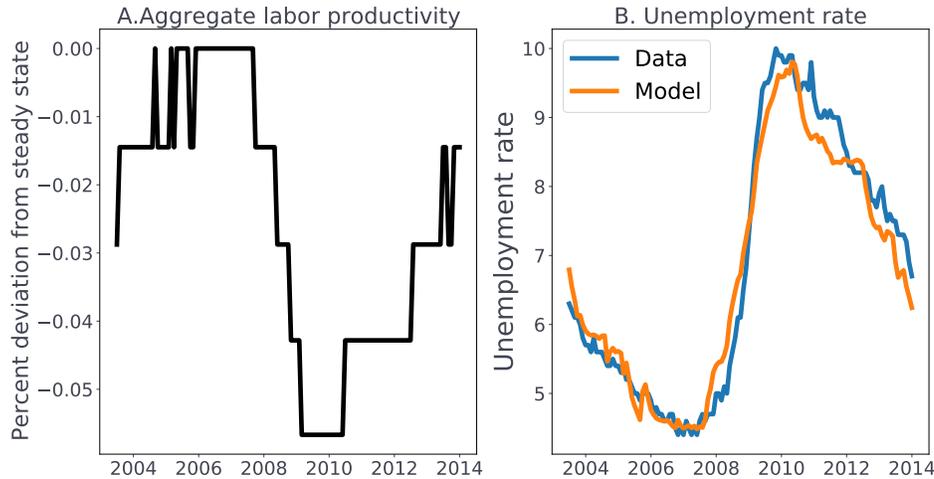
	Model									
	Assets									
Income	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1	0.45	0.28	0.08	0.07	0.12	0.81	0.09	0.01	0.00	0.09
Q2	0.16	0.36	0.21	0.11	0.17	0.10	0.75	0.11	0.01	0.03
Q3	0.15	0.17	0.36	0.16	0.17	0.04	0.04	0.80	0.09	0.02
Q4	0.13	0.12	0.26	0.32	0.17	0.03	0.06	0.05	0.77	0.09
Q5	0.11	0.08	0.10	0.34	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.

periods in the model and the data. This comparison is made for the periods prior to and during the Great Recession. 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 ten-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 from the model with that in the data.

Cyclical properties In Sections 5.1 and 5.2, we discuss how the asset-to-income ratio and unemployment spell distributions of different groups within the unemployed change over the cycle in the data, the baseline model, and the alternative model. In the data, we compare our results from the SIPP 2004 panel, repeated from Table A1, with results from the SIPP 2008 panel, which overlaps with the Great Recession period. Table A8 and Table A9 compare the asset-to-income ratio and unemployment spell distributions in the data with those in the baseline and alternative model. Discussion of results are presented in Sections 5.1 and 5.2.

Figure A2: Great Recession simulation in the model



Note: This figure shows the series of aggregate labor productivity (Panel A) that we feed to our model to generate the observed unemployment rate (Panel B) before and after the Great Recession. We use this simulation to study i) the distributions of the asset-to-income ratio and unemployment spell durations before and after the Great Recession in Section 5.1 and ii) the unemployment rates with and without UI extensions during the Great Recession in Section 5.4.

Unemployment duration responses: changes in take-up vs. job-search behavior

In Section 5.3, we demonstrated the heterogeneous responses of the job-finding rate, search effort, and wage choices to a 10 percentage point increase in UI generosity. The increase in unemployment durations 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 A10 reports intermediate results for the case when we remove the unemployment duration responses for individuals that switched to taking up UI benefits 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 A10, the response along the take-up and job-search behavior margin both play a significant role, although the latter is typically larger. For example, among those in the bottom quintile of the asset-to-income distribution, 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.

Heterogeneous response of unemployment hazard rates across wealth distribution

Here, we provide additional details about how we estimate the heterogeneous elasticities using the hazard model (Equation 9) à la Chetty (2008) described in Section 5.4. Starting from our original sample, we focus on a pooled sample of unemployment spells observed from the 1996–2008 SIPP panels in which respondents' reported having received UI benefits. For each spell, we assign a predicted WBA based the methodology outlined in Section 2 that combines state-specific and time-varying UI regulations with labor market histories. Besides demographic, wealth, wage, state, and year variables, our controls include a seam indicator which takes a value

Table A8: Heterogeneity within the unemployed over the business cycle: asset-to-income ratio

Data	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Employed	-1.91	-0.15	0.74	2.93	8.87	16.11	-1.33	0.00	1.02	3.44	11.27	10.67
Unemployed	-1.66	-0.12	0.30	2.00	9.46	6.53	-2.17	0.00	0.57	2.83	12.31	8.86
Eligible	-1.34	-0.12	0.28	1.74	7.78	2.92	-2.17	0.00	0.57	2.69	9.96	4.79
Take-up	-2.02	-0.41	0.24	1.23	3.70	1.25	-1.92	0.00	0.53	2.38	8.87	4.34
Non-take-up	-0.87	-0.01	0.44	2.72	12.94	5.03	-3.69	0.00	1.02	4.11	16.05	6.47

Model	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Employed	-0.63	-0.08	0.66	2.15	3.90	1.50	-0.59	0.13	1.01	2.40	3.34	1.67
Unemployed	-2.94	-1.13	-0.17	1.10	4.03	0.63	-2.81	-0.79	0.35	1.33	4.69	0.94
Eligible	-1.21	-0.40	0.07	1.51	4.51	1.26	-1.72	-0.03	0.35	1.47	4.69	1.32
Take-up	-1.71	-0.62	-0.26	0.07	1.16	-0.01	-2.50	-0.33	0.35	0.81	2.02	0.33
Non-take-up	-0.46	0.27	1.32	2.52	7.44	2.83	-0.43	0.40	1.76	3.54	9.64	3.53

Alternative Model	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Employed	-2.00	-0.13	1.12	1.59	2.59	1.07	-2.03	0.41	1.57	1.91	2.65	1.29
Unemployed	-3.18	-1.11	0.28	1.29	2.67	0.38	-2.98	-1.28	0.29	1.45	2.63	0.28
Eligible	-2.59	-0.41	0.75	1.44	3.00	0.90	-2.98	-0.57	0.61	1.57	2.92	0.75
Take-up	-2.59	-0.41	0.75	1.44	3.00	0.90	-2.98	-0.57	0.61	1.57	2.92	0.75
Non-take-up												

Note: This table compares the asset-to-income distribution for the periods before and during the Great Recession implied by the baseline model and an alternative model with those empirically observed in the data. For the data, distributions are obtained from the SIPP 2004 and 2008 panels. For the models, distributions during the Great Recession are simulation outcomes from feeding a series of aggregate productivity shocks such that the models replicate the unemployment rate from 2008-2013, which covers the period of the 2008 SIPP panel. 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 any type of unemployed)

of 1 for months that immediately precede an interview data. 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 (9) is presented in Table A11. In Table 10, we report the implied percent changes in response to a 10 percent increase in UI benefits.

The effect of UI extensions during the Great Recession on the unemployment rate
In Section 5.4, we compare the model-predicted rise of the unemployment rate during the Great Recession attributable to UI extensions with available empirical estimates. Table A12 sum-

Table A9: Heterogeneity within the unemployed over the business cycle: spell duration

Data	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Unemployed	1	1	2	4	6	3.13	1	1	3	5	11	4.77
Eligible	1	1	2	4	7	3.31	1	2	4	7	13	5.70
Take-up	1	2	3	5	8	3.81	1	2	4	8	16	6.67
Non-take-up	1	1	2	3	5	2.42	1	1	2	4	6	2.89

Model	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Unemployed	1	1	2	4	7	3.42	1	2	3	6	10	4.64
Eligible	1	1	2	4	7	3.34	1	2	3	6	10	4.68
Take-up	1	2	3	6	9	4.32	1	2	5	9	14	6.43
Non-take-up	1	1	2	3	5	2.42	1	1	2	4	5	2.79

Alternative	Before the Great Recession						During the Great Recession					
	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90	Mean
Unemployed	1	1	2	4	7	3.43	1	2	3	6	10	4.62
Eligible	1	1	3	5	8	3.67	1	2	3	6	11	5.02
Take-up	1	1	3	5	8	3.67	1	2	3	6	11	5.02
Non-take-up												

Note: This table compares the distributions of completed unemployment spell durations for the periods before and during the Great Recession in the baseline model and an alternative model with those in the data. For the data, distributions are obtained from the SIPP 2004 and 2008 panels. For the models, distributions during the Great Recession are simulation outcomes from feeding a series of aggregate productivity shocks such that the models replicate the unemployment rate from 2008-2013, which covers the period of the 2008 SIPP panel.

Table A10: Effect of additional take-up on labor market responses

Asset-to-income ratio	Unemployment duration response				
	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 average 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.

marizes the range of estimates found by the literature that studies the impact of UI maximum duration extensions during the Great Recession. Information from this table is used as the range and median of estimates found in Table 10.

Table A11: Unemployment hazard regression

Dependent variable: Unemployment hazard rate		
	Coefficient estimate	Std. error
Q1× log WBA	-0.178	(0.037)
Q2× log WBA	-0.218	(0.044)
Q3× log WBA	-0.282	(0.058)
Q4× log WBA	-0.262	(0.037)
Q5× log WBA	-0.201	(0.053)
Age	-0.013	(0.0059)
Age ²	0.00001	(0.00007)
Married	0.105	(0.014)
College	-0.025	(0.022)
White	0.158	(0.027)

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 at any point in the spell. 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.

Table A12: 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.

E Implications for UI policy design over the business cycle

In this section, we provide details for our discussions in Section 6.1. In particular, we first explain how we determine the UI policy reform in our baseline model. Next, we provide more discussion on the effects of UI policy reform under the baseline and the alternative model.

UI policy reform To start our analysis, we first determine a welfare-improving UI policy reform in our baseline model. The government chooses UI policy instruments m_0^b , m_w^b , m_p^b , m_0^e , m_p^e and the implied tax rate τ to maximize the ex-ante lifetime utility of an individual who is born (under the veil of ignorance) into the economy under the current UI policy subject to the government budget constraint.¹⁶ Put differently, the government maximizes a utilitarian social welfare function subject to Equation (7) by choosing a set of policy instruments. The policy reform is unanticipated and permanent. Our analysis takes into account the effects of the transition path from the stochastic steady state of the economy under the current policy to that under the proposed policy. We search over policy parameters, together with the implied tax rate τ that balances the government budget in expectation, to obtain our welfare-improving UI policy reform in the baseline model. The reform policy is a policy with some m_0^b , m_w^b , m_p^b , m_0^e , m_p^e , and τ that maximizes the ex-ante welfare.

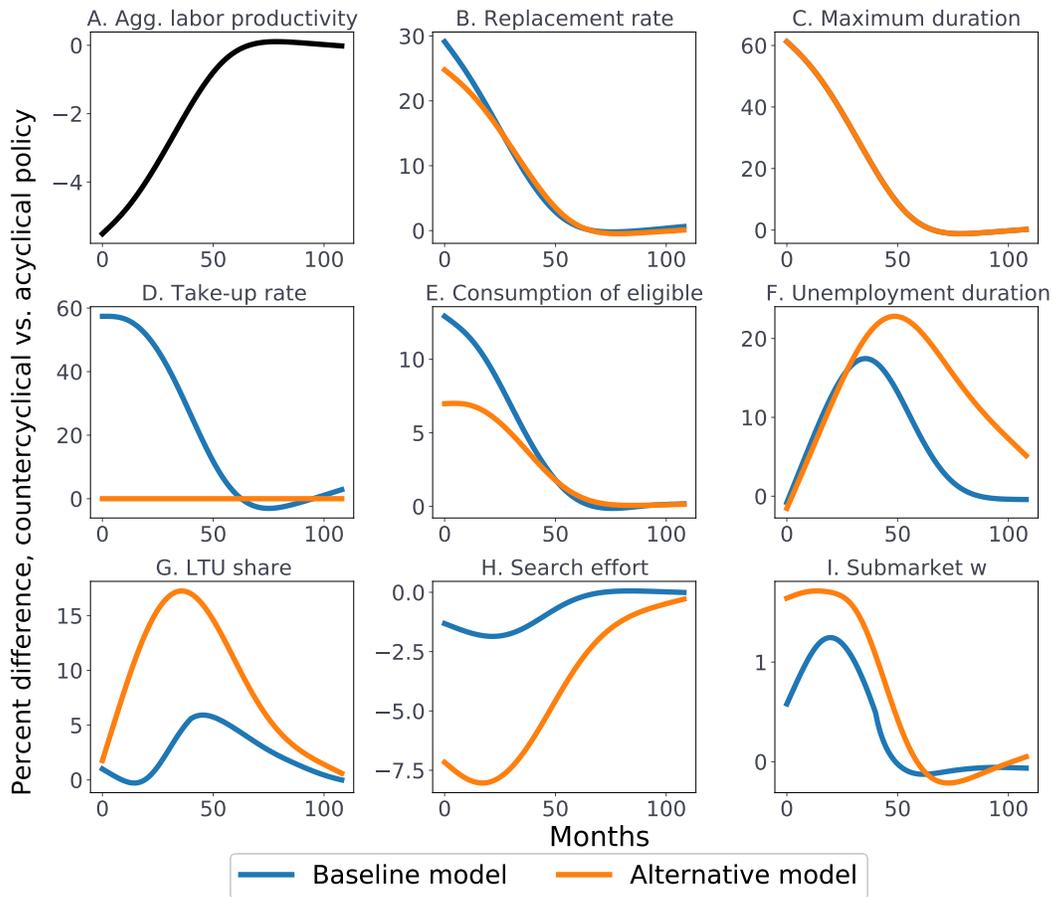
Welfare-improving countercyclical reform policy The welfare-improving policy reform is countercyclical in both replacement rate and benefit duration and features a slightly higher replacement rate for low-wage earners than high-wage earners.¹⁷ The reform policy prescribes that the replacement rate rises from 37 percent to 50 percent for the median wage earner when the aggregate productivity is depressed by around 5.5 percent from its mean, while the current policy features a 40 percent acyclical replacement rate for the median wage earner. The reform policy also offers a longer potential UI duration of 27 months during normal times and 44 months during deep recessions, compared with only 6.5 months extending to 24.8 months under the current policy. The rate at which replacement rates decline with wages is also slightly higher. At the mean productivity, the 25th percentile wage earner receives a replacement rate of 48 percent, while the 75th percentile receives only 22 percent, implying a ratio of 2.18 under the reform policy, which is slightly higher than the ratio of 2.08 under the current policy. The tax required to finance the reform policy is $\tau = 0.39$ percent, higher than the tax rate of $\tau = 0.34$ percent under the current policy. Overall, under the reform policy, replacement rates are close to the current U.S. levels, albeit countercyclical, while the UI durations are reminiscent of UI policy in many European countries. For example, Belgium, France, Spain, Denmark, and Finland prescribe up to an 80 percent replacement rate with potential UI duration longer than 24 months.

Effects of UI policy reform under baseline vs alternative model We now proceed with an illustration of how the effects of changes in UI policy during recessions differ between the baseline and alternative model. Each economy begins with its respective stationary distribution

¹⁶We focus on the level and cyclicity of the UI replacement rate and duration, but we keep the UI eligibility parameters m_0^g , m_w^g , m_p^g at their values under the current policy. This is because it is computationally burdensome to jointly evaluate welfare effects of nine parameters over a broad range. Moreover, we do not consider any cap in UI duration when testing policy reforms.

¹⁷We find that $m_0^b = 2.811$, $m_p^b = -2.202$, $m_w^b = -0.242$, $m_0^e = 326.93$, and $m_p^e = -299.93$.

Figure A3: Countercyclical policy reform, baseline vs. alternative model



Note: This figure plots the percent difference in labor market responses attributable to a countercyclical UI policy relative to an acyclical policy. The countercyclical UI policy is a welfare-improving policy that offers more generous replacement rates and UI duration during recessions than the current UI policy. The acyclical policy version makes the replacement rate and maximum duration invariant to aggregate productivity p (and is set to its value when $p = 1$). Both policies satisfy the government budget constraint in Equation (7).

and is subject to a sudden aggregate productivity drop of around 5.5 percent. Aggregate productivity returns to its mean after around 50 months. We then compare labor market dynamics and behavioral responses across two policy regimes: the welfare-improving countercyclical policy (reform policy) and a corresponding acyclical policy.

Figure A3 reports the effect of UI countercyclical policy on the evolution of labor market variables during the shock *relative* to an acyclical policy. Here, the countercyclical policy is the reform policy, while the acyclical policy is the reform policy except that the replacement rate and UI duration are not allowed to vary over the cycle and instead set to their values at the mean level of aggregate productivity. Thus, the blue lines show the net difference in baseline model responses between the acyclical policy and countercyclical reform policy. The orange lines represent the equivalent difference for the alternative model. In other words, the plotted responses are the labor market effects attributable to the countercyclical policy of the reform policy.¹⁸

¹⁸We choose to compare the implications of a countercyclical reform policy with that of the acyclical reform

In both models, the countercyclical policy results in a roughly 30 percent rise in replacement rates and a 60 percent rise in the UI duration of benefits relative to the acyclical policy. Despite similar policy responses to the negative productivity shock, there are key differences in labor market responses across the two models. In the baseline model, the countercyclical policy induces a 60 percent larger increase in take-up rates relative to the acyclical policy. Unsurprisingly, the movements of take-up rates over the cycle is absent for the alternative model as it features full take-up regardless of the cyclicity of UI policy. While replacement rates and UI durations increase in both models, the consumption insurance provided by the countercyclical policy is larger under the baseline model. This is because insurance benefits result from both increased UI generosity and an endogenous rise in the take-up rate: agents who would not claim under periods of expansion find it optimal to receive benefits when unemployment spells are longer.¹⁹

For both the baseline model and alternative model, countercyclical benefits induce both longer unemployment durations and a larger share of long-term unemployment (LTU). However, this response is muted in the baseline policy: countercyclical UI contributes at most only a 15 percent increase in unemployment durations as opposed to the higher and more persistent 25 percent increase observed for the alternative model. The differences in duration responses between the two models are, in turn, explained by the smaller response of search effort and wage choice to countercyclical UI under the baseline model.

F Robustness

In this section, we provide more details about our robustness exercises discussed in Section 6.2. Table A13 summarizes the results.

Different parameter values We analyze our main results under different parameter values. In these exercises, we leave other parameters of the model the same as the benchmark calibration. First, in Table A13, we compare our main results with their counterparts under lower values of the curvature of utility cost of the job-search effort, χ_s , motivated by the recent work of Faberman, Mueller, Şahin, and Topa (2020), who use micro data on search effort and find search effort to be more elastic than what we obtain. Recall from Table 10 that a one-month increase in UI duration implies an increase in nonemployment duration by 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 overestimates the elasticity

policy to make sure that, on average, the UI generosity across the two policies are the same. Further, we use tax rates that satisfy Equation (7) under the acyclical reform policy and countercyclical reform policy, in both the baseline model and the alternative model, separately.

¹⁹To fix ideas, consider two versions of the baseline economy that differ only in UI policy but are subject to the same shock. For example, in Panel F, the blue line represents the percent difference in the response of the baseline economy unemployment duration between a countercyclical and acyclical policy. Under the countercyclical policy, spell durations increased by 76 percent (at peak) whereas in the acyclical policy, it declined by 58 percent. This implies an extra 18 percent response attributable to the countercyclical policy relative to the acyclical policy.

Table A13: Main results under different parameter values and model assumptions

	Unemployment rate response gap (pp)	Nonemployment duration elasticity gap (months)	Wage change elasticity gap (pp)
Benchmark, $\chi_s = 1.51, \gamma = 0.5$	0.17	0.16	0.63
$\chi_s = 1.25$	0.17	0.16	0.65
$\chi_s = 1.00$	0.17	0.16	0.74
$\chi_s = 0.75$	0.18	0.17	0.71
$\chi_s = 0.50$	0.17	0.17	0.68
$\chi_s = 0.25$	0.13	0.20	0.70
$\chi_s = 0.10$	0.06	0.21	0.68
$\gamma = 0.75$	0.08	0.25	0.99
$\gamma = 1.00$	0.09	0.34	1.30
$\gamma = 1.25$	0.18	0.34	0.96
$\gamma = 1.50$	0.24	0.39	1.02
Binary take-up choice $d \in \{0, 1\}$	0.17	0.15	0.74
High UI replacement rate and $\eta_p^\lambda = 0$	0.14	0.34	1.27
High gov. expenses and progressive tax	0.15	0.16	0.65

Note: This table provides a summary of main results under different parameter values and model assumptions. Unemployment rate response gap refers to the percentage points difference between the rise in the unemployment rate upon a 10 percentage point increase in UI replacement rates (as in Table 8) 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 10). 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 10). Our benchmark calibration incorporates the curvature of the utility cost of the job-search effort $\chi_s = 1.51$ and the matching function parameter $\gamma = 0.5$.

of nonemployment duration by 0.16 months under the benchmark calibration. 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 lower 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 A13 also shows that our main results on other elasticities remain unchanged. Specifically, the response of unemployment rate to a change UI generosity and the elasticity of the pre- and post-unemployment wage changes with respect to UI duration remain overestimated in the alternative model, when compared with their respective empirical estimates. Second, we also arrive to the same conclusion when we consider alternative values of the matching function parameter γ as shown in Table A13.

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 on-going eligibility raises the chances of an 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 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 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 cyclical volatility of matching efficiency, i.e., $\eta_p^\lambda = 0$, and set the intercept parameter of the UI replacement rate $m_0^b = 0.98$, which implies an average replacement rate of 83.5 percent across UI recipients with heterogeneous previous labor earnings, much higher than 51 percent, which we document in the data. Under this alternative assumption, we still find that the alternative model 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 government has additional (thrown away) expenses of around 19 percent of period output, which is motivated by the fact that the total government expenditure to GDP ratio is around 19 percent on average 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), and search for Φ to satisfy Equation (7). In this case, we find $\Phi = 0.834$. The resulting elasticity gaps between the baseline and the alternative models in this version of the framework remain quite close to those under our benchmark framework.