ECONOMIC RESEARCH
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WORKING PAPER SERIES

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Working Paper Number	2019-022F
Revision Date	November 2021
Citable Link	https://doi.org/10.20955/wp.2019.022
Suggested Citation	Birinci, S., See, K., 2021; Labor Market Responses to Unemployment Insurance: The Role of Heterogeneity, Federal Reserve Bank of St. Louis Working Paper 2019-022. URL https://doi.org/10.20955/wp.2019.022

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

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November 2021

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 study the implications of this heterogeneity on UI's insurance-incentive trade-off using a heterogeneous-agent job-search model capable of matching the wealth and income differences that distinguish UI recipients from non-recipients. Insurance benefits are larger for UI recipients who are predominantly wealth-poor. Meanwhile, incentive costs are non-monotonic in wealth because the poorest individuals, who value employment, exhibit weak responses. Differential elasticities imply that accounting for the composition of recipients is material to aligning model predictions with empirical estimates.

Keywords: Unemployment Insurance, Fiscal Policy and Household Behavior, Job Search
JEL Classification: E24, H31, J64, J65

*This paper was previously titled as "How Should Unemployment Insurance Vary over the Business Cycle?". We are grateful to Anmol Bhandari, Kyle Herkenhoff, Loukas Karabarbounis, Ellen McGrattan, our editor Ayşegül Şahin, and two anonymous referees for their guidance. We also thank Naoki Aizawa, Jonathan Heathcote, Fatih Karahan, Jeremy Lise, Guido Menzio, Kurt Mitman, Simon Mongey, Christian Moser, Fabrizio Perri, and seminar participants at many conferences for comments and suggestions. We thank Aaron Amburgey for excellent research assistance and Jennifer Ives and Lydia Johnson for excellent editorial assistance. This research was supported in part through computational resources provided by the University of Minnesota Supercomputing Institute and the BigTex High Performance Computing Group at the Federal Reserve Bank of Dallas. We thank Andrew Gustafson and Christopher Simmons for their help in accessing resources. The views expressed in this paper do not necessarily reflect the positions of the Federal Reserve Bank of St. Louis or the Bank of Canada.
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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 and how these distortions should be weighed against the insurance benefits transfers provide. The answer to this question is 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 analyze the insurance-incentive trade-off of UI policy reform must account for the rich heterogeneity that the unemployed exhibit. Capturing this heterogeneity is especially important when job seekers differ greatly in their valuation of transfers and their labor market responses to policy changes.

We make two key contributions to understanding this fundamental trade-off. First, we provide empirical evidence on the scope of heterogeneity *within* the unemployed. Importantly, we not only emphasize heterogeneity in income and wealth but also emphasize how these relate with heterogeneity in both labor market prospects and UI status. We use 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 not only of matching the heterogeneity we document but also of assessing the extent to which different dimensions of heterogeneity affect the sizes of the predicted insurance benefits and labor market responses that arise from UI reform. We show that abstracting from heterogeneity implies that model-predicted insurance benefits would be understated, while incentive costs would be overstated. Importantly, we also bridge the model with the broader empirical literature by juxtaposing model-predicted elasticities that are comparable with those arising from estimates based on microdata and natural experiments.

Our empirical analysis addresses several questions: How do income and wealth affect employment transitions? What distinguishes the UI-eligible unemployed who take up benefits from those who do not? How do eligibility and take-up rates move with the business cycle?[1] 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

[1] The 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.

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 remain 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 UI 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 eligibility and take-up rates are both countercyclical, implying that the composition of UI recipients can also vary over the business cycle.

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 business 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.

We contrast the fully featured model with an alternative (nested) model that misses the connection between the heterogeneity in income and wealth and the heterogeneity in unemployment

[2] Shimer (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.

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, eligibility rates, 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, and 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 among high earners.

What tangible implications does this divergence have for the insurance-incentive trade-off? We show that the baseline and alternative models also disagree on their predictions about the magnitude of the consumption losses of job losers and behavioral responses in the labor market to a change in UI generosity. For insurance benefits, consumption losses among UI recipients are much larger in the baseline model, which features heterogeneous unemployment risk and endogenous take-up where agents self-select to become UI recipients. The alternative model, which fails to match the empirical observation that the unemployed are predominantly wealth-poor, understates these losses and thus underestimates the insurance benefits of additional UI payments. For incentive costs, the baseline model predicts that 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, their expected surplus from match formation is large. This large surplus induces them to exert effort 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: individuals in these quintiles have little stake in UI changes because they are sufficiently self-insured, enjoy low separation risk and high job-finding rates, and receive low replacement rates. For these reasons, the match surplus of wealthy individuals is invariant to changes in UI. Individuals in the middle of the two groups exhibit higher elasticities: for those with some degree of self-insurance, additional UI generosity affords them the ability reduce search effort and look for high-wage jobs that are difficult to find. The resulting inverse-U-shaped pattern implies that the position of UI recipients in the wealth distribution ultimately determines the sizes of the 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 response to changes in UI generosity. The alternative model, which homogenizes unemployment risk and UI outcomes, drastically changes the demographics of UI recipients. They now include wealthier individuals who have much less to gain from UI and are even more elastic to UI in this model because take-up is costless.

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 the empirical estimates, predictions from the alternative model either approach or exceed the largest magnitude of the range of the 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 the empirical estimates.

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, of eligibility and take-up of UI. We then construct a framework that is capable of capturing this heterogeneity and show that accounting for cross-sectional heterogeneity within the unemployed crucially affects the insurance-incentive trade-off of UI policy changes.

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). 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 the 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 Imrohoroğlu 1992; Shimer and Werning 2008; Koehne and Kuhn 2015; Kroft and Notowidigdo 2016; Kekre 2019; Braxton, Herkenhoff, and Phillips 2020; and Birinci, Karahan, Mercan, and See 2021) or with aggregate risk (Jung and Kuester 2015; Mitman and Rabinovich 2015; McKay and Reis 2016; Landais, Michaillat, and Saez 2018; McKay and Reis 2020; Pei and Xie 2020; and Birinci 2021). Relative to these papers, 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. Section 5 discusses model validation, and Section 6 presents the results. Section 7 provides robustness checks, and Section 8 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. The findings highlight the need to model the interaction of both dimensions of heterogeneity and 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 quintiles 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 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).[3]

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. Without it, one cannot separately identify the unemployed who are ineligible and the unemployed who are eligible but

[3]The 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.

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.[4]

Monetary eligibility dictates that applicants meet certain earnings and employment requirements during a base period – typically the first four of the last five completed calendar quarters preceding the applicant's UI claim. 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, claimants 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.[5] 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 greater 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 the eligibility status of individuals.

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 eligible for UI. This rule is typically enforced 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 present novel facts on the heterogeneity

[4] Detailed information on state UI eligibility rules and weekly benefit amounts is obtained from the Department of Labor Employment and Training Administration.

[5] Between 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.

of the FEU and TUR across the previous income, asset, and asset-to-income ratio distributions.

Heterogeneity in UI replacement rates Finally, we calculate individual-specific replacement rates by combining a respondents' 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.[6] This step 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 relative to the overall average transition rates, similar to what Krusell, Mukoyama, Rogerson, and Şahin (2017) report.[7] We highlight several important results.[8] 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. 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

[6]This 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 the 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.

[7]Fujita, Nekarda, and Ramey (2007) discuss that flow rates measured from the Current Population Survey (CPS) and the SIPP differ. We find the same result: the average UE and EU rates in our SIPP sample are 22 percent and 0.65 percent, which are close to their estimates in the SIPP and lower than CPS values. For this reason, we report SIPP flow rates relative to the average. In Section 4, we calibrate our model to match average flow rates in the CPS and the heterogeneity of flow rates in the SIPP.

[8]Unless 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.

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	0.90	1.01	0.98	0.98	1.14	1.13	0.80	0.96	1.05	1.06	1.08	0.86	0.98	0.98	1.10
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.

the asset and asset-to-income ratio distributions, their EU rates are relatively lower, as they work at relatively higher-paying jobs. Third, the UE rate is higher for unemployed individuals with the highest 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. Taken together, they motivate a model where labor market transition rates depend on an individual's relative position within the income and wealth distributions.

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.[9]

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. Further, the FEU is non-monotonic and exhibits a U-shaped pattern with respect to wealth. 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 greater than the heterogeneity of the FEU in assets, 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

[9]Blank 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 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.

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 greater ability to self-insure. We find that the average asset-to-income ratio is 1.25 for the take-up group and 5.03 for the non-take-up group, which implies that on average, those who do not take up benefits have enough liquid wealth to cover 5 months of lost earnings, whereas UI recipients can only cover 1.25 months. The stark difference in the wealth distributions of UI recipients and the eligible unemployed provides compelling evidence of the importance of *self-selection* into the take-up group.[10]

Third, replacement rates decline considerably with previous income – mostly due to maximum UI payment thresholds – and exhibit a non-monotonic pattern in assets and the asset-to-income ratio. This declining pattern of replacement rates in previous earnings is at odds with a common modeling choice that assumes a uniform replacement rate across all unemployed individuals. Finally, these differences in UI status also affect the labor market prospects of individuals. Table A2 shows that, among the UI-eligible, the unemployed who do not take up benefits have significantly shorter unemployment durations than those who do. This is partly attributable to the former group being composed of workers with higher previous earnings and job-finding rates.

When considered jointly, these results signal potential explanations as to why some eligible individuals do not collect benefits: they hold much higher liquid wealth, receive lower replacement rates, and experience shorter unemployment spells, all of which diminish UI's insurance value.

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 net liquid asset holdings. Second, there is

[10] In Appendix A (Table A1), we estimate an empirical model and find that eligible unemployed with lower self-insurance are more likely to take up UI, even after controlling for demographic and economic characteristics.

[11] The 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.

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

	All					Less than high school degree					More than master's degree				
	Assets														
Income	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 labor earnings of the respondent from their current job (for employed) or the average labor earnings in their previous job (for unemployed). Assets are measured as net liquid wealth holdings.

a sizable fraction of individuals in the upper quintiles of the income distribution who are located in the bottom two quintiles of the net liquid asset holdings distribution.[12] Next, the comparison of the results across education groups reveals that 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.

2.3 Cyclicality of eligibility and take-up rates

Moving from cross-sectional heterogeneity, we now analyze how labor market flows, and eligibility and take-up rates 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.[13] We align the CPS with the sample period of the SIPP and use data from 1996 to 2016.[14]

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. 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. The FEU is also positively correlated with the unemployment rate, implying that a larger fraction

[12] In Table A3, we present the joint distribution of hourly income (wages) and assets. We find that these findings remain mostly unchanged when we use hourly income instead of monthly income, indicating that the results presented here are driven by the correlation between wages and assets.

[13] An 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.

[14] In 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.

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
$\text{cor}\left(UR_t, X_t\right)$	1.00	-0.935	0.828	0.583	0.481
$\text{cov}\left(UR_t, X_t\right)/\sigma_{UR}$	1.01	-0.752	0.540	0.318	0.171
$\text{cor}\left(X_t, X_{t-1}\right)$	0.947	0.828	0.716	0.746	0.694

Note: σ_X: standard deviation of the variable X; $\text{cor}\left(UR_t, X_t\right)$: correlation between unemployment rate UR_t and X_t; $\text{cov}\left(UR_t, X_t\right)/\sigma_{UR}$: elasticity of X_t with respect to UR_t; $\text{cor}\left(X_t, X_{t-1}\right)$: 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.

of the unemployed are eligible for UI during recessions. 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.[15] This means that the rise in eligibility rates during recessions is accompanied by a rise in the fraction of eligible workers who claim UI. Thus, some eligible individuals who would otherwise opt out of UI opt in during recessions.

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, among the UI-eligible unemployed, those who do not take up benefits have much greater 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.

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 insurance benefits and incentive costs of UI payments.

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.

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

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.[16]

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 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.[17] Individuals then make saving or borrowing decisions. Finally,

[16] UI policy changes are typically triggered by changes in the aggregate unemployment rate. Ideally, the UI policy instruments should depend on the unemployment rate. However, 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.

[17] The 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.

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 $\Gamma: \{W, B, NB\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{Y} \to [0,1]$ denotes the distribution of agents across states. The laws of motions for the aggregate states are given by $\Gamma' = H(\mu, p')$ and $p' \sim F(p' \mid p)$, respectively, and the law of motion for idiosyncratic productivity is given by $y' \sim Q(y' \mid y)$.

The recursive problem of the worker is given by

$$\begin{aligned} V^W(a, w, y; \mu) \; = \; \max_{c,\, a' \geq a_l} \quad & u(c) + \beta(1-\omega)\mathbb{E}\Big[(1-\delta(y', p'))V^W(a', w, y'; \mu') \\ & + \delta(y', p')\Big[(1-g(w, p'))V^B(a', w, y'; \mu') + g(w, p')V^{NB}(a', y'; \mu')\Big]\Big| y, \mu\Big] \end{aligned} \tag{1}$$

subject to

$$\begin{aligned} & c + a' \leq (1+r)a + w(1-\tau) \\ & \Gamma' = H(\mu, p'), \quad p' \sim F(p' \mid p), \quad y' \sim Q(y' \mid y). \end{aligned}$$

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 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.[18] 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.[19] 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)

[18] Modeling 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 7.

[19] The 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.

when the aggregate state is μ. Then, the take-up decision of an eligible unemployed is given by

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

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

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

subject to

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

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.[20] The choice of wage submarket $\widetilde{w}$ 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 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

[20]The 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.

be the vacancy-filling rate and $f\left(w,y;\mu\right)=\frac{M\left(v\left(w,y;\mu\right),S\left(w,y;\mu\right)\right)}{S\left(w,y;\mu\right)}$ to be the job-finding rate.[21]

First, consider a firm that is matched with a worker in submarket (w,y) when the aggregate state is μ. The value of this firm is given by

$$J\left(w,y;\mu\right) = py - w + \frac{1}{1+r}\left(1-\omega\right)\mathbb{E}\left[\left(1-\delta\left(y',p'\right)\right)J\left(w,y';\mu'\right)\Big|y,\mu\right]$$
$$\text{subject to} \tag{4}$$
$$\Gamma' = H\left(\mu,p'\right), \quad p' \sim F\left(p'\,|\,p\right), \quad y' \sim Q\left(y'\,|\,y\right).$$

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

$$V\left(w,y;\mu\right) = -\kappa + q\left(\theta\left(w,y;\mu\right)\right)J\left(w,y;\mu\right), \tag{5}$$

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, $V\left(w,y;\mu\right)=0$ for any submarket such that $\theta\left(w,y;\mu\right)>0$. By imposing the free-entry condition on Equation (5), we obtain equilibrium market tightness:

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

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 $\{b\left(w,p\right), e\left(p\right), g\left(w,p\right), \tau\}$. The government balances the following budget constraint in expectation[22]:

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

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

[22] This 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.

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.

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.[23] Importantly, we choose the curvature parameter of the search cost function χ_s to match the elasticity of nonemployment duration with respect to changes

[23]This 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.

in maximum UI duration. Several papers estimate this elasticity using variation in UI duration across states and over time.[24] 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.[25] Section 6.3 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 $\sigma^p = 0.0042$.

Similarly, the logarithm of the idiosyncratic labor productivity y_t follows an AR(1) process: $\ln y_{t+1} = \rho^y \ln y_t + \sigma^y \upsilon_{t+1}$. 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: $\delta(y, p) = \bar{\delta} \times \exp\left(\eta_p^\delta (p - \bar{p})\right) \times \exp\left(\eta_y^\delta (y - \bar{y})\right)$, 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

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

[25] Notice 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 labor market tightness and job-finding rates.

calculate the level and cyclicality of the transition probabilities, but use SIPP data to calculate moments that pertain to their cross-sectional heterogeneity.[26] The heterogeneity of the EU rate across income groups is measured as the ratio of the EU rate of workers in the first quintile to that of those in the fifth quintile of the labor earnings distribution, as shown in Table 1.

The labor market matching function is specified to be

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

where $\lambda\left(y,p\right)=\bar{\lambda}\times\exp\left(\eta_p^{\lambda}\left(p-\bar{p}\right)\right)\times\exp\left(\eta_y^{\lambda}\left(y-\bar{y}\right)\right)$. This incorporates time variation and cross-sectional heterogeneity in matching efficiency $\lambda\left(\cdot\right)$ 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 in the first quintile to that of those in the fifth quintile of the previous 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. In Section 6.1, we discuss how we measure the average consumption drop in the year of job loss and compare the consumption dynamics around the job loss between the model and the data.

[26] The 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 cyclicality of EU and UE rates are obtained from the CPS between 1996 and 2016, as shown in Table 3.

[27] Time-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.

[28] This 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 7, we explore the sensitivity of our results to this parameter.

[29] In Section 7, 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.

Savings We choose the discount factor β to match the fraction of the population with non-positive 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:

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

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

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

The slope parameter m_p^j captures the cyclicality of 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. 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., $p_t \geq \bar{p}$. 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 elect to take up these benefits; and iii) UI replacement rates vary across those who take up benefits.

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 bottom-to-top quintile ratio of the replacement rate is 2.02. 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.

Table 4: Internally calibrated parameters

Parameter	Explanation	Value	Target	Data	Model
			Preferences and borrowing limit		
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
			Labor market		
$\bar{\delta}$	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	0.79	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	0.093	0.109
			UI policy		
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.

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. 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.[30]

[30] This 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 7, we incorporate a higher level of government expenditure to account for other forms of government spending and transfers.

5 Model Validation

We present the predictions of the model and validate them against 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 across individuals. However, EU, UE, eligibility, and replacement rates are homogeneous across individuals. In addition, the alternative model features full UI take-up, as the take-up cost is set to zero. Thus, the alternative model misses the *link* between the heterogeneity in income and wealth and the heterogeneity in job-separation risk, UI-eligibility status, take-up decisions, and replacement rates.

5.1 Baseline model

We begin by comparing how well the baseline model captures the heterogeneous UE, EU, FEU, TUR, and replacement rates documented 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, affecting the aggregate insurance benefits of UI payments. 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 that arise endogenously in the model.

Heterogeneity in labor market flows 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. The model also features an inverse-U-shaped pattern of EU rates in wealth. 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.[31] Finally, in both the model and the data, the heterogeneity in UE rates across the income, asset,

[31] This difference manifests through a gap between the asset-to-income ratio distributions of the unemployed and the employed, as shown in Table A6 in Appendix D.

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	0.90	1.01	0.98	0.98	1.14	1.13	0.80	0.96	1.05	1.06	1.08	0.86	0.98	0.98	1.10
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 respondent's monthly labor earnings in 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.

and asset-to-income ratio distributions is much lower than the heterogeneity in EU rates.

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 replacement rates are more correlated with income and less so with measures of wealth and self-insurance.

We emphasize that 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. An important feature of the model that enables it to capture this pattern is that agents with low wealth *self-select* into the UI-recipient pool. The group of eligible individuals who 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. Comparing the mean asset-to-income ratios

Table 6: Joint distribution of income and asset holdings

	Data					Model					Alternative model				
	Assets														
Income	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 across individuals. 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.

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.[32]

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, 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 and heterogeneity of behavioral responses to changes in UI. Hence, it is important that the model generates a relationship between income and wealth that reflects its empirical counterpart.

Table 6 presents the results.[33] 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

[32]Our model generates a slightly declining pattern of the TUR in previous income, while the data does not have such a pattern. In the model, we do not incorporate ex-ante differences in risk aversion across individuals. Some high-income individuals may be more risk averse than others, leading to higher take-up rates at the top quintiles. In that case, our model's performance in this dimension could improve with ex-ante heterogeneity in risk aversion.

[33]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. Similar to the data, the positive correlation between income and assets is increasing in productivity in the model.

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
$\text{cor}\left(UR_t, X_t\right)$	1.00	-0.935	0.828	0.583	0.481	1.000	-0.790	0.712	0.349	0.872
$\text{cov}\left(UR_t, X_t\right)/\sigma_{UR}$	1.01	-0.752	0.540	0.318	0.171	1.003	-0.597	0.413	0.097	0.368
$\text{cor}\left(X_t, X_{t-1}\right)$	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.

super-diagonals. For example, in the data, 61 percent of individuals in the third quintile of the income distribution are found between the second and fourth quintiles of the asset distribution. In the model, this is 51 percent. Second, the model and the data feature a considerable mass of individuals with high-income but low liquid assets. In the data (model): 15 percent (18 percent) of individuals in the top quintile of the income distribution are in the bottom quintile of the asset distribution. 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 job loss and, among those who lose a job, experience shorter unemployment durations. This weakens their precautionary saving motives and incentives to hold liquid assets.

Cyclical properties Finally, we describe the model's cyclical predictions and compare them with the data. As will be argued in Section 6.3, the extent to which unemployed demographics vary with the cycle translates to differential responses to changes in UI generosity depending on aggregate conditions. Table 7 presents the cyclical properties of the model. 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 co-movement 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 now find it beneficial to apply for UI because of prolonged unemployment spells.

5.2 Alternative model

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 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.[34] 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 the aforementioned 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 job-finding probability, 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 with longer durations are also engaged in accumulating a buffer stock of wealth, which strengthens the correlation between income and assets. As such, the alternative model is no longer able to generate a considerable fraction of high-income workers with low liquid wealth.

Heterogeneity within the unemployed Table A6 shows that the asset-to-income ratio distribution of the take-up group is now very close to that of the employed, inconsistent with the observed large gap 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 predominantly poorer agents. However, since the alternative model also features full take-up, UI recipients become drastically wealthier.[35] This is a critical difference, as it significantly alters the distribution of the demographic of those who take up UI.

Table A6 also presents the comparison of the distributions of completed unemployment spells. Since the average EU and UE rates of the alternative model are re-calibrated, the alternative model gets close to 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.

[34] Given 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.

[35] In 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.

Taking stock In this section, we show that the baseline model well-approximates several untargeted data moments. However, the alternative model that misses the link between the heterogeneity in income and wealth and the heterogeneity in job-separation risk, UI-eligibility status, take-up decisions, and replacement rates fails to capture them.

6 Heterogeneity and the Insurance-Incentive Trade-off

In this section, we argue that the distinction between the baseline and the alternative models has important ramifications for their predicted insurance benefits of UI payments and labor market elasticities 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.

6.1 Implications of heterogeneity on insurance benefits

The previous section showed that the baseline model is successful in generating the important dimensions of heterogeneity within the unemployed, while the alternative model is not. We now study the role of accounting for the heterogeneity within the unemployed in determining the magnitude of the insurance benefits of UI payments.

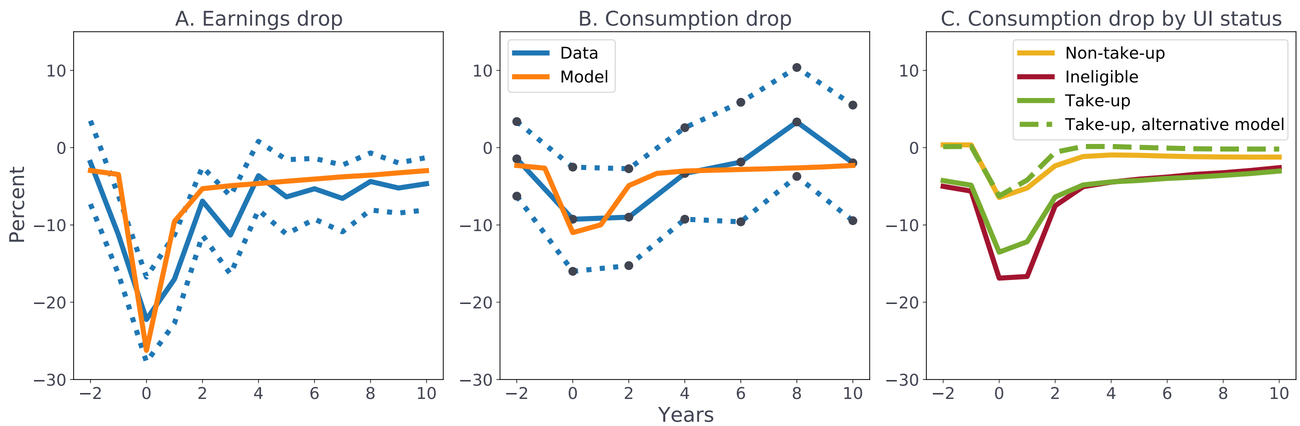
In order to understand the insurance benefits of UI in the model, we start with comparing the dynamics of earnings and consumption around an unemployment spell in the model with those in the data. Specifically, we estimate the following distributed lag regression specification using data from the Panel Study of Income Dynamics (PSID) between 1999 and 2019:

$$\log(c_{it}) = \beta X_{it} + \sum_{k=-2}^{10} \psi_k D_{it}^k + \iota_i + \xi_t + \epsilon_{it}, \tag{9}$$

where the outcome variable is the logarithm of real annual consumption expenditures c_{it} of household i in year t; the variable X_{it} is a vector of time-varying household characteristics, including a quadratic term of the head's age and the head's marital status; the variable ι_i captures a time-invariant unobserved error component associated with household i; and ξ_t is an error component common to all individuals in the sample at year t. The indicator variables D_{it}^k identify all household heads k periods prior to or after a job loss, where $k = 0$ is the period in which the job loss occurs. For instance, $D_{it}^2 = 1$ for a household head i who experiences job loss in year $t-2$, and it equals zero otherwise. Thus, ψ_k captures the effect of job loss on the outcome variable k years prior to or after household heads separate from a job (treatment group) relative to household heads with no job separation (control group). We estimate a similar specification for the household head's labor earnings to measure the dynamics of earnings around the job loss event. Appendix E provides details about our data, sample, and estimation.

To facilitate comparison with the empirical estimates, we estimate Equation (9) for earnings

Figure 1: Heterogeneous consumption losses upon unemployment



Note: This figure compares earnings and consumption dynamics upon job loss in the model and the data. Empirical results are obtained by estimating a distributed lag regression on annual/biennial earnings data from the 1968-2019 PSID panels and biennial total expenditure data that are only available for the 1999-2019 PSID panels. Estimates of the consumption drop upon job loss are only available in two-year intervals (represented by gray markers). Dotted-blue lines show the 90 percent confidence intervals. To facilitate comparison with the empirical estimates, we estimate the same regression on the model-generated data, separately for earnings and consumption, where we aggregate monthly simulations to annual frequency.

and consumption on model data, where we aggregate monthly simulations to annual frequency.[36]

Panel A of Figure 1 presents the dynamics of the head's labor earnings around job loss in the data and the model. Despite being untargeted, the model is able to generate the observed magnitude of the decline in labor earnings in the year of job loss as well as its recovery after the job loss.[37] Panel B shows that the model also generates the dynamics of consumption around job loss.[38] When considered jointly, these results imply that the model not only generates the observed income loss upon a job separation but also generates the observed pass-through of income loss to consumption. This finding is important because if, for example, the drop in consumption were to be much smaller in the model than in the data, then the model would underestimate the insurance benefits of additional UI benefits.

The model is also capable of making predictions about the heterogeneity in consumption dynamics upon job loss across various groups within the unemployed. Panel C reveals substantial differences in the dynamics of consumption around job loss across groups. Upon unemployment, average consumption drops by 6 percent for the unemployed who are eligible but do not take up UI. In contrast, even prior to job loss, the unemployed ineligible and the unemployed eligible

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

[37]Importantly, our definition of a job loss in the data incorporates unemployment due to any reason (i.e., both voluntary and involuntary separations), given that our model does not differentiate between reasons for job loss. A large literature shows that earnings loss is much larger following an involuntary separation (see Jacobson, LaLonde, and Sullivan 1993 and Stevens 1997, for example). In our data, we confirm this result: the magnitude of the earnings loss upon an involuntary job separation is much larger (33 percent) compared to the magnitude of the earnings loss upon a job separation due to any reason (22 percent).

[38]While the magnitude of the average consumption drop in the year of job loss is targeted in our calibration exercise in Section 4, the consumption dynamics around job loss are untargeted. Moreover, in Appendix E, we provide further comparisons between the model predictions and empirical estimates in various frequencies.

who take up UI already consume around 5 percent less than agents with no job separation – because the ineligible and take-up groups consist of individuals with much lower earnings and wealth. Upon job separation, consumption drops much further from around -5 percent to -17 percent for the ineligible group and to -13.5 percent for the take-up group. Importantly, this heterogeneity in consumption losses implies that the insurance benefits of *additional* UI payments are largely different across groups within the unemployed. Since agents in the non-take-up group experience a lower consumption loss even in the absence of UI receipt, the insurance benefits of UI is much lower for them, which justifies why they do not take up UI despite being eligible for it. Meanwhile, insurance benefits are much larger for the take-up group, who experience a larger consumption loss even with UI receipt, due to their inability to self-insure.[39]

Finally, the dashed-green line in Panel C shows the drop in consumption for the take-up group in the alternative model. Recall that in the alternative model, uniform unemployment risk and full UI take-up imply that eligible unemployed individuals with high wealth also take up UI. The higher average wealth holdings of the take-up group alters their consumption dynamics in the alternative model in two important ways. First, the take-up group no longer exhibits a negative pre-trend in consumption prior to job loss. Second, the drop in consumption for the take-up group is also much smaller. These findings imply that the insurance benefit of additional UI payments is understated in the alternative model relative to the baseline model.

Taking stock This section shows that the magnitude of consumption loss upon job separation is largely different across groups within the unemployed, implying that the insurance benefits of additional UI payments are going to differ across these groups. While the insurance benefits are smaller for the eligible who do not take up UI, they are much larger for those who take up benefits due to their lower ability to self-insure. Importantly, the alternative model which ignores key dimensions of heterogeneity within the unemployed underestimates the insurance benefits of UI.

6.2 Implications of heterogeneity on incentive costs

The goal of this section is to understand the role of accounting for the heterogeneity within the unemployed in determining the magnitudes of incentive costs to changes in UI generosity. To do so, we compare model-implied behavioral responses to a 10-percentage-point increase in UI replacement rates for all eligible unemployed in the model. We initialize the experiment from its stochastic steady state and simulate two counterfactual economies: one where there is no policy change and another where a more generous UI policy is introduced. The reported labor market

[39] A comparison of the consumption dynamics between the take-up and the ineligible groups approximates the magnitude of consumption insurance provided by the existing UI policy. For example, by comparing the consumption drop in the year of job loss for the ineligible group (17 percent) with that for the take-up group (13.5 percent), we find that UI payments mitigate the annual consumption drop by around 3.5 percentage points. We verify that this result is not driven by differential wealth holdings between the take-up and ineligible groups.

responses represent the differences in labor market outcomes of agents who were unemployed at the moment of the policy change.[40]

We find that the aggregate job-finding rate decreases by only around 0.5 percent when the replacement rate increases by 10 percentage point. The baseline model predicts a limited response because primarily wealth-poor individuals become unemployed and take up UI. As we will discuss below, within the entire pool of unemployed, those in the bottom quintile of the wealth distribution are 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 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 UI benefits.

Below, we elaborate on this main result in two steps. First, we discuss the reasons behind this non-monotonic pattern in the response of the job-finding rate across the wealth distribution. Second, we show how this heterogeneity in elasticities determines the magnitude of aggregate labor market responses to UI reform.

Understanding non-monotonicity of elasticities across the wealth distribution To understand this non-monotonic pattern in the response of the job-finding rate across the wealth distribution, we examine the first-order condition (FOC) governing search effort choice s:

$$\nu'(s) \leq \beta(1-\omega)\,\mathbb{E}\left[f\left(\theta\left(\widetilde{w}^{*}, y'; p'\right)\right)\left(V^{W}\left(a', \widetilde{w}^{*}, y'; p'\right) - V^{U}\left(a', w, y'; p'\right)\right)\right], \tag{10}$$

where the value of unemployment is given by

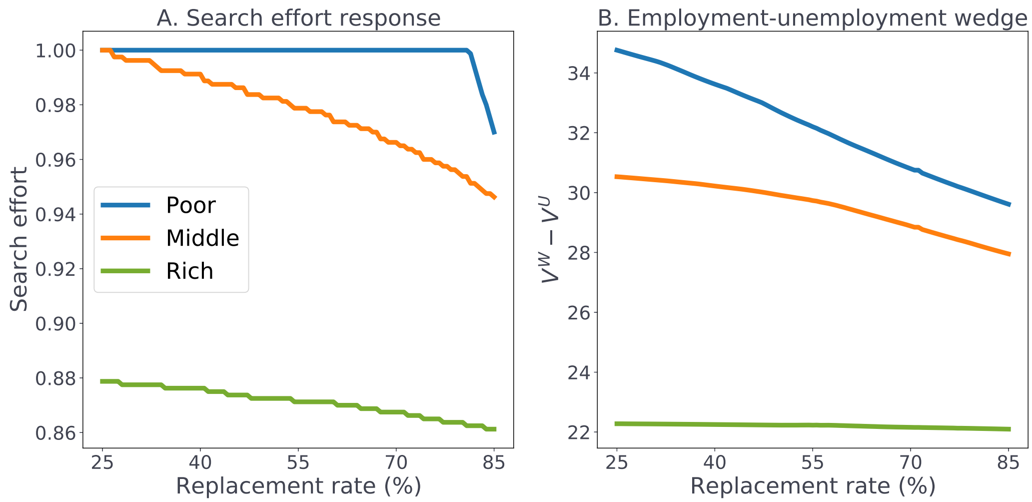
$$V^{U}\left(a', w, y'; p'\right) = \left(1 - e(p')\right)V^{B}\left(a', w, y'; p'\right) + e(p')V^{NB}\left(a', w, y'; p'\right),$$

and $\widetilde{w}^{*}$ is the optimal wage submarket choice.

The FOC shown in Equation (10) has an intuitive interpretation: the optimal search effort equates the marginal disutility of exerting additional search effort to raise the probability of finding a job to its marginal benefit which is governed by the worker's expected surplus of match formation $V^W - V^U$. Importantly, both the level of $V^W - V^U$ and how it changes when UI generosity varies determine the elasticity of search effort with respect to UI. We emphasize that this relationship between $V^W - V^U$ and UI generosity depends heavily on the choice of explicitly

[40] This is the closest approximation to the quasi-experimental designs used to estimate labor market responses to changes in UI as discussed in Section 6.3. Comparing labor market outcomes across steady states yields similar results.

Figure 2: Heterogeneous labor market elasticities



Note: This figure shows the heterogeneity in the responses of workers' search effort and underlying surplus value $V^W - V^U$ to changes in UI generosity. The plotted outcomes are obtained by re-computing the baseline model's value functions and policy functions under various replacement rates ranging from 25% to 85%. "Poor," "Middle," "Rich" refer to a worker in the 10th, 50th, and 90th percentile of the asset distribution, holding wages w and idiosyncratic productivity level y fixed to their average value.

modeling heterogeneity in unemployment risk, private insurance, and UI take-up.

For wealth-poor individuals who are close to the borrowing constraint, the surplus value $V^W - V^U$ is large given that borrowing constraints severely curtail consumption during unemployment, while higher income from employment allows them to begin reaccumulating wealth to insure against future shocks. When employment is highly valuable, i.e., the surplus is large enough, exerting maximal search effort $s = 1$ may not be enough to satisfy Equation (10) with equality. In other words, the unconstrained optimal search effort exceeds the agent's available time endowment. The reason why borrowing-constrained individuals are inelastic to changes in UI is that $V^W - V^U$ remains sufficiently large for a wide range of UI generosity such that maximal search effort is expended. This occurs despite $V^W - V^U$ being very elastic, because UI substantially relaxes wealth-poor workers' liquidity constraints and these workers have high exposure to UI changes because of their high job-loss risk and take-up rates.[41] Figure 2 Panel A shows that the response of search effort for wealth-poor individuals remains inelastic for the relevant range of replacement rates. Once UI is sufficiently generous (above 80 percent), the elasticity of $V^W - V^U$ seen in Panel B now translates to decreasing search effort. Hence, for changes in replacement rates around empirically plausible values of UI replacement rates (around 50 percent for the bottom quintile of the asset distribution, as shown in Table 2), the search efforts of wealth-poor individuals are less elastic to changes in UI.[42]

[41]Indeed, in the setup of a related work by Chetty (2008), $V^W - V^U$ is also the most elastic for wealth-poor individuals. The key difference is that the size of $V^W - V^U$ is small due to the fact that in his model, agents no longer face unemployment risk after securing employment after an initial spell.

[42]Note that our example involves the case of the unemployed eligible who take up benefits. In the case of

In contrast, wealth-rich workers are capable of insuring against job loss, implying that the surplus $V^W - V^U$ would be small and search effort would be low. Importantly, since these workers have negligible unemployment risk, are less likely to take up benefits, and do not face liquidity constraints, their employment surplus remains small regardless of UI generosity. Low exposure to changes in UI policy is what drives their small responses. Figure 2 shows that rich workers indeed exert lower search effort and are also less responsive to rising replacement rates. It is important to note that the source of inelastic labor supply responses are very different between the rich and the poor. For wealth-poor individuals, it is driven by the *size* of the employment surplus, whereas for wealth-rich individuals, it is driven by the *inelasticity* of the surplus.

Finally, for workers in between, i.e., those who possess some degree of self-insurance, search effort is high but not binding. This implies that any change in $V^W - V^U$ translates into a substantial change in search effort for these individuals, as demonstrated in Figure 2. As replacement rates increase, $V^W - V^U$ is still elastic for these workers (though not as much as for wealth-poor agents) because they still have exposure to UI – job-loss risk and take-up rates are higher than wealth-rich agents and the marginal benefit of UI plays a role in narrowing the gap between employment and unemployment. Note that both elements are key here: search effort is not binding for the relevant range of UI generosity and $V^W - V^U$ is sufficiently elastic to changes in UI generosity. Thus, these workers exhibit the largest elasticities with respect to UI changes.

Similarly, the elasticity of wage choices to UI is also non-monotonic in wealth, albeit to a lesser degree than search effort. Consider the FOC with respect to wages:

$$-f'\left(\theta\left(\widetilde{w}, y'; p'\right)\right)\left[V^W\left(a', \widetilde{w}, y'; p'\right) - V^U\left(a', w, y'; p'\right)\right] = f\left(\theta\left(\widetilde{w}, y'; p'\right)\right) V^W_{\widetilde{w}}\left(a', \widetilde{w}, y'; p'\right).$$

The marginal cost of raising the wage choice is the decline in the job-finding probability $f(\cdot)$ and the forgone surplus associated with employment $V^W - V^U$. The marginal benefit is securing a higher-paying job. For wealth-poor individuals, when UI generosity increases, $V^W - V^U$ declines fast, encouraging a rise in their wage choice. However, this rise is dominated by a larger decline in their job-finding probability. This occurs because, for the wealth-poor individuals with low productivity y, small changes in asking wages results in a large percentage decline in firm profits (implying that $f'(\cdot)$ is negative and large).[43] As such, the range of active submarkets available to these agents are limited and, concomitantly, their job-finding rates rapidly drop to zero. For workers with moderate wealth, $V^W - V^U$ declines more slowly, but the decline in their job-finding rate is also more modest. The presence of a wider range of available submarkets with

the unemployed ineligible who are borrowing constrained, labor market responses are even smaller. For this group, the surplus value $V^W - V^{UI}$ is both large and inelastic given that the value of remaining unemployed and ineligible for benefits V^{NB} does not rise substantially with changes in UI generosity, because ineligibility is an absorbing state and increasingly generous benefits are not readily enjoyed by the agents in this group.

[43]Alternatively, one could consider a Nash bargaining setup where the firm's surplus only remains positive for a limited range of wages when the prospective worker is not productive.

Table 8: Heterogeneity in job-finding rate $sf(w)$ responses

	Baseline model					Alternative model				
Asset-to-income ratio	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
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
Non-take-up	-2.57	-1.92	-0.54	-0.18	-0.10					
Ineligible	0.03	0.37	0.73	0.02	0.00	0.00	0.00	-0.01	-0.03	-0.14

Note: This table compares the changes in the average job-finding rate of the unemployed across asset-to-income ratio quintiles when the replacement rate is raised by 10 percentage points in the baseline model and the alternative model. Values in the table are percent changes of the job-finding rates relative to their values under the calibrated policy. Quintiles are based on the overall asset-to-income ratio distribution. "Take-up" refers to unemployed workers who are observed to receive UI within a month after job loss.

positive job-finding probability enables a larger change in their wage choices. For wealth-rich individuals, the change in surplus $V^W - V^U$ is negligible as UI generosity increases because of their sufficiently high self-insurance levels.

Taken together, the heterogeneity in search effort and wage choice responses ultimately result in magnitudes of elasticities of the job-finding rate $sf(w)$ that are inverse-U-shaped in wealth. This finding is summarized by Table 8, which shows the percent declines in the average job-finding rates across the 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 top quintile is also less elastic.

Heterogeneity in elasticities are also observed across groups within the unemployed.[44] The responses among the UI 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. Within this group, the take-up unemployed feature the largest responses but still maintain the inverse-U-shaped pattern.[45] In contrast, the non-take-up unemployed, who are typically in the upper quintiles of the wealth distribution, have small responses. A small fraction of the non-take-up group, who is in the lower quintiles, has limited private insurance but uses the option value of claiming more generous UI to search for higher-paying jobs that are difficult to find. Thus, for the non-take-up group, the magnitude of the change in the job-finding rate is decreasing in wealth. Finally, ineligible workers respond by *increasing* their job-finding rates to secure employment that will allow them to regain eligibility for UI, which would be valuable in the event of future unemployment. The inverse-U-shaped pattern is also observed

[44] Table A8 shows that when the changes in the job-finding rate are decomposed into responses coming from the decrease in search effort s and increase in wage choices w – the latter of which is represented as the decline in job-finding probability $f(w)$ in the submarket w conditional on s – the same patterns are observed.

[45] Here, the subgroup labeled "Take-up" refers to the response of those already taking up benefits under the existing policy, and thus excludes the job-search responses coming from agents who take up UI under the new policy but did not under the old policy. Appendix E elaborates further on this distinction through Table A9.

Table 9: Effect of UI benefits on the job-finding rate in different models

	Baseline	$\alpha_d = 0$	$\alpha_d = 0$ $\eta_y^\delta = 0$	$\alpha_d = 0$ $\eta_y^\delta = 0$ $g = 0.41$	$\alpha_d = 0$ $\eta_y^\delta = 0$ $g = 0.41$ $b = 0.51$
Percent change in job-finding rate	-0.47	-1.35	-2.70	-1.80	-2.46

Note: This table compares the percent change 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 and imperfect take-up, ii) heterogeneous job separation rates, iii) heterogeneous UI eligibility rates, and iv) heterogeneous UI replacement rates.

for this group, for reasons similar to those discussed above.

These results emphasize that the heterogeneity in elasticities is a critical feature of the baseline model, where the response of the average job-finding rate is inextricably tied to the underlying wealth distribution of the unemployed. Given that individuals in the bottom quintile are more likely to become unemployed and take up UI, their limited behavioral response translates into a small change in the average job-finding rate.

The role of heterogeneity on incentive costs Next, we show how abstracting from the important dimensions of heterogeneity across workers leads to largely different estimates on the incentive costs of UI benefits. In doing so, we start from the baseline model and sequentially remove the following features: i) endogenous and imperfect take-up, ii) heterogeneous job-separation rates, iii) heterogeneous UI eligibility rates, and iv) heterogeneous UI replacement rates. This way, we are able to pin down how features of the baseline model separately affect the model's predictions.

The first column of Table 9 shows that the aggregate job-finding rate decreases by 0.47 percent when the replacement rate increases by 10 percentage points in the baseline model. The second column shows the resulting change in the job-finding rate when we remove both endogenous and imperfect take-up. Formally, this is achieved by setting the utility cost of take-up to zero; i.e., $\alpha_d = 0$. Two major changes occur here. First, UI coverage expands to relatively wealthier agents who, if given the choice, would have otherwise refused to claim UI. Since the search effort and wage choices of this group are more responsive to UI changes compared with borrowing-constrained individuals, as shown in Table 8, a model with exogenous take-up raises the response of the job-finding rate. Second, all eligible workers now optimally choose to take up UI. This raises the economy's exposure to UI, as UI becomes a guaranteed payment 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.[46] Overall, this exercise highlights the importance of the endogenous and imperfect take-up features of the model, where the wealth-poor unemployed self-select into the pool of UI recipients.

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 effort and 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., $m_w^g = 0$. We 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 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 the 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, richer agents 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 8 shows that, in the alternative model with full take-up and uniform job-separation risk, UI eligibility, and replacement rates, the magnitude of the job-finding rate elasticity is increasing in wealth, as opposed to the inverse-U-shaped pattern in the baseline model. 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.

Taking stock We emphasize two key points. *Modeling* key dimensions of heterogeneity that differentiate workers along the risk and severity of unemployment as well as their propensity to take up UI is important. These factors shape both the level and elasticity of the surplus of employment, which plays a critical role in the optimal search and wage choices. An implication of this is that agents of varying wealth and UI status exhibit heterogeneous behavioral responses to changes in UI. A consequence of these varying responses is that *matching* the observed composition of the unemployed becomes equally important in shaping the model's predicted aggregate

[46] This effect can be further decomposed into that which results from endogenous take-up and that which results from imperfect take-up. The former is achieved by exogenously setting $d = 0.55$, the average take-up rate in the baseline model. We find that endogenous take-up explains close to 20 percent of the total effect.

elasticity. When borrowing-constrained individuals among UI recipients are underrepresented, there are much larger incentive costs associated with an increase in UI generosity.

6.3 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 unemployment. Given that our model is capable of replicating the experiments used to measure these empirical elasticities, the model-implied elasticities are comparable to their empirical counterparts. Table 10 summarizes 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.[47] We simulate a large number of agents and extend the maximum UI duration of a randomly selected group of agents. We then compute for differences in outcomes 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.

[47] The 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
		Average responses	
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
		Heterogeneous responses	
Unemployment hazard rate (percent)			
Q1	-0.67	-3.21	-2.40
Q2	-0.70	-4.96	-3.04
Q3	-1.67	-4.93	-3.20
Q4	-5.14	-8.53	-3.16
Q5	-1.66	-12.51	-2.61
		Cyclical responses	
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.

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 $\ln(w_i^{\text{post}}) - \ln(w_i^{\text{pre}})$. 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 endogenously affects the job-search behavior of the unemployed. First, UI recipients are predominantly low-wealth individuals, 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 deccumulation 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 UI while 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:

$$\log h_{itj} = \iota_{tj} + \sum_{j=1}^{5} \zeta_1^j Q_{ij} \log WBA_i + \zeta_2 X_{itj}, \tag{11}$$

where Q_{ij} is an indicator that takes a value of 1 if respondent i is in the jth quintile of the asset-to-income ratio distribution, 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, martial 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 within one month after job loss, where we use predicted WBA values that we obtain from the UI-program discussed in Section 2.[48]

Using the coefficients-of-interest $\left\{\zeta_1^j\right\}_{j=1}^5$, Table 10 reports the heterogeneous responses of the hazard rate to a 10 percent rise in UI benefits.[49] The hazard rate of the bottom quintile responds the least (2.4 percent) while the third and fourth quintiles exhibit the largest responses of close to 3.2 percent. The top quintile exhibits a smaller response of roughly 2.6 percent.

We run a comparable regression using model-generated data from both the baseline and alternative models, controlling for model observables such as previous wages and assets, focusing on a sample of UI recipients who claim UI within one month after job loss. As seen in Table 10, similar to the data, the baseline model predicts hazard elasticities whose magnitudes have an inverse-U-shaped pattern in the asset-to-income ratio. In contrast, the alternative model not only predicts much larger elasticities across all quintiles, it also predicts monotonically increasing elasticities – a result that is at odds with our empirical estimates and the findings in Chetty (2008).[50] Finally, we note that the non-monotonic and smaller responses of the unemployment

[48]The restriction of the sample to workers who took up benefits within one month after job loss follows Chetty (2008). Estimating the same regression for a sample of workers who took up benefits at any point in their spell yields similar results.

[49]Table A10 in Appendix E reports the full results of this exercise. We note that our estimation 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, Chetty (2008) restricts his sample to prime-aged males. 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.

[50]Across various specifications, Chetty (2008) finds that the magnitudes of unemployment hazard elasticities

hazard rate obtained from the baseline model and the monotonic and larger responses obtained from the alternative model are consistent with patterns in the response of the job-finding rate as shown in Table 8.

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. Studies have arrived at mixed conclusions ranging from 0.1 percentage points (Rothstein 2011 and Chodorow-Reich, Coglianese, and Karabarbounis 2019) to 2.15 percentage points (Hagedorn, Karahan, Manovskii, and Mitman 2019), as detailed in Table A11 in Appendix E.

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 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 E. 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. 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 a larger effect, i.e., it would have been 4.75 percentage points lower.

Taking stock Overall, we 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

are either declining in wealth or exhibit an inverse-U-shaped pattern in wealth. Among these specifications, the specification that uses individual level WBA as a measure of UI generosity is closest to ours.

model's predicted elasticities would lie within the range of available empirical estimates.

7 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 (2021), 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 A12 shows that our main results remain similar under different values of both parameters. In particular, the alternative model still underestimates the insurance benefits of UI and arrives at significantly larger labor market behavioral responses.

Different model assumptions Next, we conduct a series of robustness checks to understand the implications of certain model assumptions. 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. 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 UI. 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, 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 in Hagedorn and Manovskii (2008). Finally, we consider the effects of introducing a higher level of government expenditure to account for other forms of fiscal spending. The intention of this exercise is to understand whether a marginal change in taxes to fund UI will have different effects depending on the level of taxes. Here, we also relax the assumption of a constant labor income tax and introduce progressive taxation. As summarized in Table A12, we find that under all modifications, the divergence between the baseline and alternative model's predictions on insurance benefits and incentive costs remains.

8 Conclusion

We document novel facts about the interaction between heterogeneity in income and wealth and heterogeneity in labor market and UI outcomes. 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 insurance-incentive trade-off of UI policy changes over the 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 and longer unemployment spells of the UI take-up group relative to the non-take-up group, the joint distribution of income and wealth, and the countercyclicality of eligibility and take-up rates. 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 assign differential value to the insurance benefits of UI payments and have differential responses to changes in UI generosity. We show that the alternative model underestimates the insurance benefits of UI and 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 insurance benefits and incentive costs of UI changes.

Our findings have important implications for UI policy design over the business cycle. 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 moments described in Section 2. We also present additional results to supplement our discussion.

A.1 SIPP data

We use the SIPP data to discipline labor market flows, the distributions of income, assets, the asset-to-income ratio, and the unemployment spell duration, as well as UI eligibility, take-up, and replacement rates. The SIPP is a longitudinal survey that follows individuals for a duration of up to five years. Until the 2014 panel, interviews were held in four-month intervals called waves. Each respondent was then assigned to one of four rotation groups. The rotation group determined which month within a wave a respondent was interviewed. Each interview covered information about the four months (reference months) preceding the interview month. For example, when a new SIPP panel started and Wave 1 (the first four months of the new panel) commenced, the first rotation group was interviewed in the first month of Wave 1, the second rotation group was interviewed in the second month of Wave 1, and so on. Once all four rotation groups 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

[1]This 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

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

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

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

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

Effect of wealth on UI take-up decision In light of the results presented in Section 2.2, we conclude that eligible individuals who take up UI possess less self-insurance than those who do not. In this section, we estimate an empirical model to provide further evidence on this

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

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

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

Dependent variable: UI take-up indicator		
	Coefficient estimate	Std. error
Asset-to-income ratio	-0.012	(0.004)
College	-0.199	(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.

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.[7] To understand the effect of wealth holdings on the UI take-up decision, we estimate the following regression for the unemployed in our sample:

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

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

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

Heterogeneity in unemployment spell durations Section 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. Here, we provide results on the distributions of the completed

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

Table A2: Heterogeneity in unemployment spell duration

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

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

unemployment spell durations across different groups within the unemployed, using the SIPP 2004 panel. Table A2 shows that the eligible unemployed who do not take up UI have significantly shorter unemployment spell durations than those who take up. This is an important empirical finding because it allows us to further understand the characteristics of those who do not claim UI despite being eligible: in addition to holding much higher liquid wealth, they also experience much shorter unemployment spells, both of which diminish the insurance benefits of UI transfers.

Joint distribution of hourly income and assets Table 2 in Section 2.2 documents features of the joint distribution of monthly income and asset holdings. In order to understand whether these results are driven by the correlation between wages and assets or between hours worked and assets, we now provide results for the joint distribution of hourly income (wages) and assets.

The SIPP provides information on respondents' usual number of hours worked per week at each job. Using this information, we first calculate the total usual hours worked in a month in all jobs. We then calculate the hourly income (wages) of employed individuals by dividing monthly labor earnings by monthly total usual hours worked. For unemployed individuals, we use their previous labor earnings and hours worked three months prior to job loss to obtain hourly income. We then calculate the joint distribution of hourly income and assets for our entire sample.

Table A3 provides the results. A comparison of the results in Table 2 and the results in Table A3 reveals that the joint distribution of income and assets and the joint distribution of hourly income and assets are very close to each other. Thus, we conclude that the results presented in Section 2.2 are driven by the correlation between wages and assets. This finding is consistent with our model, given that the variation in income is completely driven by wage differences in our model.

B Model

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

Table A3: Joint distribution of hourly income and asset holdings

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

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

B.1 Problem of ineligible unemployed

The recursive problem of the ineligible unemployed is given by

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

subject to

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

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

B.2 Equilibrium

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

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

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

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

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

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

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

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

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

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

subject to

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

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

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

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

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

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

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

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

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

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

[10] We choose this functional form for the matching function for clarity of demonstration. This result follows also for the CES matching function we use in Section 4.

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

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

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

B.3 Computational algorithm

The model is solved using the following steps:

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

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

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

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

C Calibration

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

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

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

Table A4: Externally calibrated parameters

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

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

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

Δ in UI duration $\rightarrow$ Δ in nonemp. duration	Source	Methodology
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 non-recipients
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.

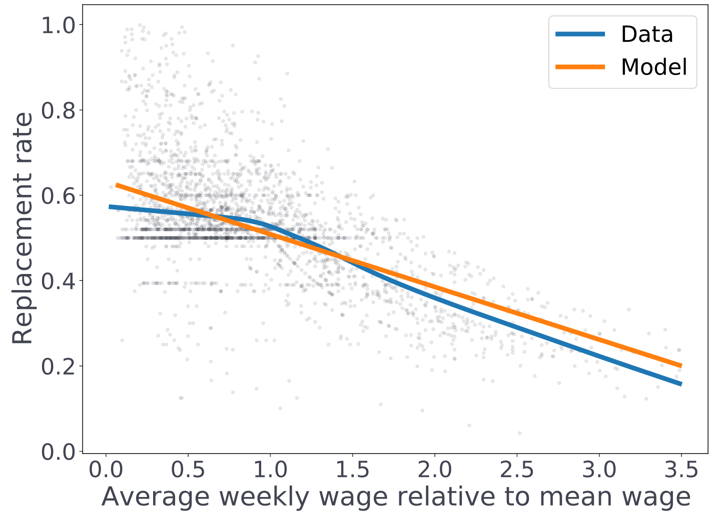
D Model Validation

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.

Here, we provide the distributions of the asset-to-income ratio and the unemployment spell duration when individuals are grouped by their employment and UI status. In Section 5.1,

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

we emphasize the following results from Table A6. 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, eligible job losers who take up UI have a substantially lower capacity to self-insure compared with those who do not to receive UI despite being eligible. Finally, UI recipients experience longer unemployment spells than eligible non-recipients. All these predictions of the model are in line with the data. Meanwhile, as we discuss in Section 5.2, the predictions of the alternative model do not align well with these empirical findings.

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 empirical joint distribution of income and wealth holdings when conditioned on educational attainment with its counterpart in the model for agents with different levels of idiosyncratic productivities. As discussed in the main text, both in the data and the model, the correlation between income and assets increases in productivity, although the model overstates the difference.

E Results

Earnings and consumption drop upon job loss In Section 6.1, we use data from the PSID to estimate the dynamics of earnings and consumption around a job separation. In this section, we provide more details about the data, sample, and estimation.

The PSID is available annually between 1968 and 1997 and biannually since 1997. It contains

Table A6: Heterogeneity within the unemployed

	Asset-to-income ratio						Unemployment spell duration					
	Data											
	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						
Unemployed	-1.66	-0.12	0.30	2.00	9.46	6.53	1	1	2	4	6	3.13
Eligible	-1.34	-0.12	0.28	1.74	7.78	2.92	1	1	2	4	7	3.31
Take-up	-2.02	-0.41	0.24	1.23	3.70	1.25	1	2	3	5	8	3.81
Non-take-up	-0.87	-0.01	0.44	2.72	12.94	5.03	1	1	2	3	5	2.42
	Model											
	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						
Unemployed	-2.94	-1.13	-0.17	1.10	4.03	0.63	1	1	2	4	7	3.42
Eligible	-1.21	-0.40	0.07	1.51	4.51	1.26	1	1	2	4	7	3.34
Take-up	-1.71	-0.62	-0.26	0.07	1.16	-0.01	1	2	3	6	9	4.32
Non-take-up	-0.46	0.27	1.32	2.52	7.44	2.83	1	1	2	3	5	2.42
	Alternative Model											
	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						
Unemployed	-3.18	-1.11	0.28	1.29	2.67	0.38	1	1	2	4	7	3.43
Eligible	-2.59	-0.41	0.75	1.44	3.00	0.90	1	1	3	5	8	3.67
Take-up	-2.59	-0.41	0.75	1.44	3.00	0.90	1	1	3	5	8	3.67
Non-take-up												

Note: This table compares model-generated distributions of the asset-to-income ratio and completed unemployment spell duration with those empirically observed in the data. The asset-to-income ratio in the data is calculated by dividing the net liquid wealth holdings by 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).

information on labor earnings, consumption expenditures, and demographics. Labor earnings include wages and salaries, bonuses, overtime, tips, commissions, professional practice or trade, market gardening, miscellaneous labor income, and income from extra jobs. Labor earnings are available at the individual level in every survey in which an individual participates. Our measure of consumption expenditures includes expenditures on food consumed inside and outside the home, health expenditures, housing expenditures (utilities, taxes, maintenance, etc.), transportation, education and childcare.[11] Prior to 1999, expenditure information was limited

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

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

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

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

to the food category, while the other categories became available after 1999. Because of this, we use biannual data between 1999 and 2019 when estimating the dynamics of consumption upon job loss. While consumption expenditures are provided at the household level, earnings are observed for individuals. We focus on the dynamics of the household head's earnings and household consumption following the head's job loss. This approach ensures that comparable events are used when studying the responses of earnings and consumption.

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

Our sample consists of household heads between the ages of 25 and 64. We drop families observed for only one year and those with labor earnings or consumption expenditures that exceed the 99th percentile. Using this sample, we estimate Equation (9) for consumption expenditures and for the household heads' labor earnings. To facilitate comparison with the empirical results, we estimate the same specification on model-generated data, separately for earnings and consumption, where we aggregate monthly simulations to annual frequency.[12]

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

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

Finally, we make further comparisons of consumption dynamics between the model and the data for higher frequencies. First, Burgess et al. (1981) 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.[13] Analyzing a sample of *continuously* unemployed individuals who receive UI, they find an average consumption drop of 15.2 percent from the month prior to job loss to the 13th week of unemployment. For comparison, we use model-generated monthly data and compute the percent change in consumption between the third month of unemployment and the month prior to job loss for 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 incorporate information on housing, food at home, food outside the home, clothing, and other expenses before and after job

[12] Both in the model and the data, there are observations with zero annual labor earnings following a job loss event. So as not to underestimate the magnitude of the earnings loss upon a job separation, we estimate the regression specification in Equation (9) for labor earnings with the dependent variable set to real labor earnings of the family head and obtain the coefficients ψ_k in real dollar units. We then report them in Figure 1 as a percent of the mean of the real labor earnings one year prior to job separation.

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

Table A8: Decomposition of heterogeneity in labor market responses

		Baseline model					Alternative model				
Asset-to-income ratio		Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Search s	Unemployed	-0.03	-0.65	-0.46	-0.24	-0.15	-0.08	-1.44	-3.31	-3.65	-3.36
	Eligible	-0.07	-0.85	-0.60	-0.31	-0.23	-0.19	-3.24	-5.14	-5.89	-6.61
	Take-up	-0.06	-0.85	-2.25	-3.33	-0.63	-0.19	-3.24	-5.14	-5.89	-6.61
	Non-take-up	-0.09	-0.87	-0.07	-0.10	-0.11					
	Ineligible	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
Submarket $f(w)$	Unemployed	-0.46	-0.66	-0.51	-0.18	-0.03	-0.80	-0.68	-0.59	-0.26	-2.37
	Eligible	-0.99	-0.88	-0.67	-0.23	-0.05	-1.90	-1.82	-0.97	-0.43	-4.43
	Take-up	-0.34	-0.47	-1.50	-2.36	-0.36	-1.90	-1.82	-0.97	-0.43	-4.43
	Non-take-up	-2.56	-1.71	-0.51	-0.16	0.00					
	Ineligible	0.03	0.37	0.73	0.02	0.01	0.00	0.00	-0.01	-0.03	-0.13

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

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 on the decline of consumption upon unemployment are close to empirical estimates that use different samples or frequencies.

Labor market responses: decomposing job-finding rate responses In Section 6.2, we show that the elasticity of the job-finding rate is heterogeneous across agents with different wealth positions and UI-status. Table A8 shows that when the changes in job-finding rate are decomposed into responses coming from the average decrease in search effort s and increase in wage choices w – the latter of which is represented as the average decline in job-finding probability $f(w)$ in the submarket w conditional on s – the same patterns are observed.

Labor market responses: decomposing changes in take-up vs. job-search behavior In Section 6.2, we demonstrated the heterogeneous responses of the job-finding rate to a 10 percentage point increase in replacement rates. 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 A9: Effect of additional take-up on labor market responses

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

Note: This table compares the changes in 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.

Table A10: Unemployment hazard regression

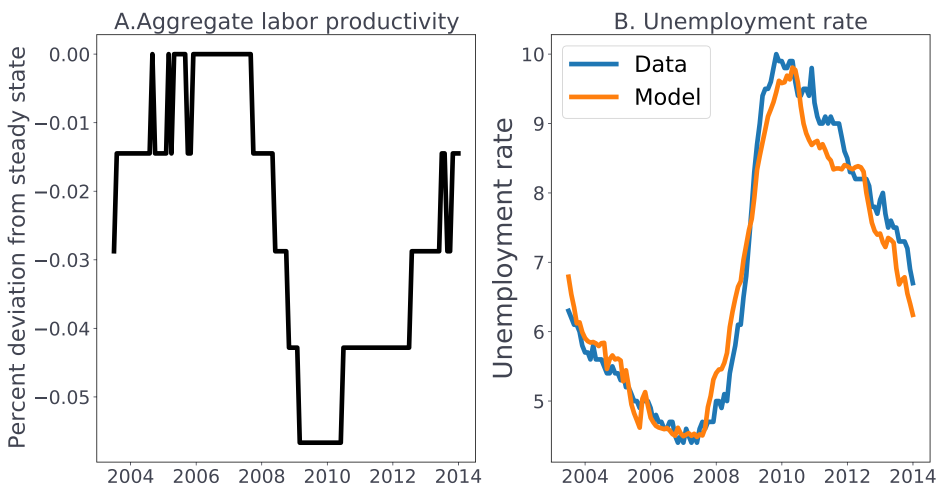
Dependent variable: Unemployment hazard rate		
	Coefficient estimate	Std. error
Q1$\times$ log WBA	-0.240	(0.041)
Q2$\times$ log WBA	-0.304	(0.046)
Q3$\times$ log WBA	-0.319	(0.058)
Q4$\times$ log WBA	-0.316	(0.038)
Q5$\times$ log WBA	-0.261	(0.057)
Age	-0.010	(0.0073)
Age^2	0.00005	(0.00009)
Married	0.092	(0.014)
College	-0.038	(0.025)
White	0.137	(0.029)

Note: This table presents the results for a stratified Cox (unemployment) hazard model when individuals are grouped by asset-to-income ratio quintiles. The sample is restricted to unemployment spells in the 1996–2008 panels of the SIPP that have at least three months of prior labor market history and for whom respondents reported receiving UI within 1 month after job loss. The WBA for each spell is obtained from a UI program that calculates predicted WBA based on state laws and labor market histories. Values in parenthesis denote the standard errors. Other controls include wealth level, state, year, the interaction of asset-to-income ratio quintiles with a 10-piece log-linear spline for the claimant's earnings prior to job loss, and a seam indicator to account for seam effect.

Table A9 reports intermediate results for the case when we remove the responses for individuals that switched to taking up UI after the increase in generosity. This removes the impact of a level change in take-up rates and isolates the responses along the search effort and reemployment wage margins. As seen in Table A9, the response along the take-up and job-search behavior margin both play a significant role, although the latter is larger. For example, among those in the bottom quintile, unemployment durations would have increased by 0.28 percent if the take-up decision were held fixed, lower than the full impact of 0.37 percent.

Unemployment hazard elasticities across the wealth distribution Here, we provide additional details about the estimation of heterogeneous elasticities using the hazard model in Equation (11) à la Chetty (2008) described in Section 6.3. We focus on a pooled sample of unemployment spells observed from the 1996–2008 SIPP panels during which respondents reported having received UI benefits within 1 month after job loss. For each spell, we assign a predicted WBA based the methodology outlined in Section 2. Apart from demographic, wealth, wage, state, and year variables, our controls include a seam indicator which takes a value of 1 for months that immediately precede an interview date. We then divide the sample into asset-to-income ratio quintiles and identify right-censored spells. Spells for which we do not have WBA or AWW information are dropped. The results of estimating Equation (11) are presented in Table A10, where we report the estimated percent changes in response to a 10 percent increase in benefits.

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 the unemployment rates and LTU shares with and without UI extensions during the Great Recession in Section 6.3.

Great Recession simulation in the model In Section 6.3, we study changes in the unemployment rate and LTU share with respect to UI generosity during the Great Recession in the model and the data. To make a direct comparison between the model and the data, we feed a series of aggregate shocks in the model to match the unemployment rate from October 2003 to November 2013 (the 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.

Table A11 summarizes the range of empirical estimates found by the literature that studies the impact of UI extensions during the Great Recession on the unemployment rate. Information from this table is used as the range and median of estimates found in Table 10.

Table A11: 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.

F Robustness

In this section, we provide more details about the robustness exercises discussed in Section 7. Table A12 summarizes the results.

Different parameter values We analyze our main results that relate to insurance benefits (Section 6.1) and incentive costs (Section 6.2) under different parameter values. In these exercises, we leave other parameters of the model the same as the benchmark calibration.

In Table A12, we compare our main results with their counterparts under lower values of the curvature parameter χ_s of the utility cost of job-search effort. This is motivated by the recent work of Faberman, Mueller, Şahin, and Topa (2021) who use microdata on search effort and find search effort to be more elastic than what we obtain. Recall from Table 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 estimates an elasticity of nonemployment duration that is 0.16 months larger than the baseline model under the benchmark calibration of χ_s. As we lower χ_s, we find that the gap between the baseline model and the alternative model in their estimates of the nonemployment duration elasticity increases. This is intuitive because lowering χ_s increases the elasticity of the search effort and further amplifies the overestimation of nonemployment duration elasticity in the alternative model relative to the baseline model. In all of these cases, the alternative model generates a nonemployment duration elasticity that is greater than 0.30 months, which exceeds the upper range of empirical estimates. Table A12 also shows that our main results on other behavioral

Table A12: Main results under different parameter values and model assumptions

	Job-finding rate response gap (%)	Nonemployment dur. elas. gap (months)	Wage change elas. gap (pp)	Cons. drop of take-up gap (pp)
Benchmark, $\chi_s = 1.51$, $\gamma = 0.5$	1.98	0.16	0.78	7.27
$\chi_s = 1.00$	1.60	0.16	0.74	7.35
$\chi_s = 0.75$	1.55	0.17	0.71	7.41
$\chi_s = 0.50$	1.66	0.17	0.68	7.55
$\chi_s = 0.25$	1.46	0.20	0.70	7.60
$\chi_s = 0.10$	0.81	0.21	0.68	7.59
$\gamma = 1.00$	4.73	0.34	1.30	10.12
$\gamma = 1.25$	3.71	0.34	0.96	10.67
$\gamma = 1.50$	4.14	0.39	1.02	10.98
Binary take-up choice $d \in \{0, 1\}$	1.72	0.16	0.63	7.27
High UI rep. rate and $\eta_p^\lambda = 0$	1.73	0.34	1.27	6.91
High gov. expenses and prog. tax	0.98	0.16	0.65	5.71

Note: This table provides a summary of main results under different parameter values and model assumptions. Job-finding rate response gap refers to the difference between the percent decline in the job-finding rate upon a 10 percentage point increase in UI replacement rates (as in Table 9) 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). Finally, consumption drop of take-up gap refers to the percentage point difference between the consumption drop in the year of job loss for the take-up group in the baseline model vs. the alternative model (as in the solid-green and dashed-green lines in Panel C of Figure 1). Our benchmark calibration incorporates the curvature of the utility cost of the job-search effort $\chi_s = 1.51$ and the matching function parameter $\gamma = 0.5$.

elasticities remain unchanged. Specifically, the response of the job-finding rate to a change UI generosity and the elasticity of the pre- and post-unemployment wage changes with respect to UI duration remain large in the alternative model, when compared with their respective empirical estimates. We also arrive to the same conclusion when we consider alternative values of the matching function parameter γ as shown in Table A12.

Recall from Section 6.1 that the consumption drop for the take-up group is larger in the baseline model than the alternative model. Specifically, under the baseline model, in the year of job loss, UI recipients suffer a consumption drop that is 7.27 percentage points larger than what the alternative model predicts (13.52 percent in the baseline model and 6.26 percent in the alternative model). Table A12 shows that this finding is preserved across a wide range of alternative values of χ_s and γ.

Binary take-up choice In our framework, we model the UI take-up decision as take-up effort $d \in [0, 1]$ such that higher take-up effort increases the chances of UI receipt. This is motivated by the fact that increased compliance with regulatory requirements to file a UI claim and providing proof of initial or 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 cyclicality 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 52 percent, which we document in the data. Under this assumption, we still find that the alternative model understates the insurance benefits associated with UI by overstating the level of self-insurance UI recipients possess. It also generates substantially larger magnitudes of key elasticities.

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