Unemployment Insurance and Worker Reallocation in Recessions*

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Abstract

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1 Introduction

Since at least Barlevy (2002) economists have understood that there are competing forces shaping the allocation of workers across jobs over the business cycle. Recessions are typically times when lower productivity jobs are "cleansed" out of the market, promoting a more efficient allocation of workers across jobs. At the same time the decline in job creation during recessions slows down the speed at which workers move into jobs they are better suited for - a "sullying" effect. Available empirical evidence suggests both these channels are at play during recessions, though on balance the cleansing effect tends to dominate such that overall the 'sorting' of workers mildly improves during downturns.[1]

This paper studies a previously unexplored channel which is potentially important for both the cleansing and sullying effects of recessions in the labour market: the design of unemployment insurance policy (hereafter: UI). In the United States, UI is the main social security programme for supporting the incomes of workers who involuntarily lose their jobs, and becomes *more generous* during recessions. This is both by design as well as through discretionary interventions made by successive governments.[2] Evidence suggests that increasing UI generosity increases unenployment duration as it incentivises recipients to wait for better quality job offers.[3] In equilibrium, changes in the job search behaviour of workers can have implications for job creation incentives, both in terms of the aggregate number of jobs but also the *type* of new jobs created.[4] Overall it is not obvious *ex ante* whether countercycically generous UI policy strengthens or weakens either the cleansing or sullying effects we observe in the data, or whether any effects are quantitatively significant.

In this paper we explore the interaction between cyclical UI design and the forces shaping worker sorting over the business cycle. We seek to address the following questions: How do changes in UI generosity affect the cleansing and sullying effects of recessions? Are these effects quantitatively important for the sorting patterns we observe in the data? Shedding light on these questions is important for assessing the design of UI policy, which has become the subject of an active policy debate in the US recent years in response to large extensions during the Great Recession and the Covid-19 recession.

[1] For example, see Haltiwanger et al. (2022), Crane et al. (2023) and Baley et al. (2023).

[2] Since at least 1970 with the introduction of the Extended Benefits (EB) programme UI duration within a given state is automatically extended when the state-level unemployment rate exceed a certain threshold. Additionally, in the majority of recessions during the post-war period UI extensions have been legislated at the Federal level by the national government. This was most recently seen during the Great Recession in 2008 with the Emergency Unemployment Compensation (EUC) programme (which increased maximum UI duration to 99 weeks across all states), as well as during the Covid-19 recession in 2020 where the CARES act provided increased insurance to workers losing jobs.

[3] For example, Marinescu and Skaldalis (2020) provide strong evidence that job search behaviour of the unemployed in the US is generally consistent with the predictions of standard models of job search.

[4] Hagedorn et al. (2019) in particular provide quasi-experimental evidence that changes in UI policy have adverse general equilibrium effects on firm job creation.

Firstly, using panel data on workers we document how labour market risk varies across workers based on their rank and provide new evidence on the effects of UI policy changes on workers. Secondly, we use this micro-level evidence to discipline the model of cyclical labour market sorting proposed by Lise and Robin (2017), modified to allow for cyclicality in UI policy consistent as in the data, to study the implications of the cyclical design of UI policy for patterns of labour market sorting.

The first contribution of the paper is empirical. We start the analysis by using microdata from the Survey of Income and Programme Participation (SIPP). Firstly, we rank workers into 'types' using standard methods proposed in the literature and analyse differences in characteristics and unemployment risk across worker types. We find no large differences in characteristics such education or occupation by worker rank, whilst lower-type workers tend to earn lower wages and hold less liquid wealth. Moreover, we document that increased unemployment risk of low-type workers in the labour market is driven by elevated separation risk relative to the average, rather than difference in job finding rates across workers.

Additionally, we provide new estimates of the labour market effects of UI which we will use to discipline the effects of UI in the quantitative model. We use panel local projections to estimate the effects of UI on labour market flows and wages using the state-level UI shocks identified by Chodorow-Reich et al. (2019). We document that an unexpected 1 month increase in UI duration is associated with a significant fall in the state-level job finding rate on impact (which unwinds fairly quickly), whilst the response of separations is essentially flat. We also find that on average wages are insensitive to changes in UI policy, although digging deeper we find that the wages of workers who have been recently unemployed in the sample are much more sensitive. This finding provides new evidence in favour of wage bargaining processes where the sensitivity of the wage to changes in UI depends on their labour market history, as in models of on-the-job search where competing offers serve as the worker's relevant outside option (e.g. Postel-Vinay and Robin 2002).

Next, we outline a model of labour market sorting which is broadly consistent with these empirical findings. The model features heterogeneity across both workers and jobs, endogenous vacancy creation, on-the-job search, and aggregate shocks. Workers and jobs are ranked in terms of their productivity. Complementarities in production ensures positive assortative matching in equilibrium. This environment generates differences in job finding rates, separation rates, and wages across workers as we see in the data. All unemployed workers receive UI whilst searching for a job, and the generosity of UI depends on the state of the aggregate economy. Employed workers can search on-the-job and are able to use alternative job offers in the wage bargain as in Postel-Vinay and Robin (2002). We discipline the model to match standard stocks and flows, as well as the estimates for the elasticities of labour market flows to changes in UI generosity, cross-sectional dispersion in wages, the cross-sectional concentration of unemployment, and the average level and cyclicality of UI generosity. The resulting framework is also able to match several untargeted features of the data, such as the heterogeneity in unemployment risk by worker rank and cyclical sorting patterns of the worker and firm distribution.

We use the model to simulate a policy counterfactual where UI generosity is acyclical, and study the implications for worker-firm sorting patterns in the model. Our first main result is that UI extensions in the model strengthen *both* the cleansing and sullying effects of recessions. Increasing UI in a downturn leads to a greater reduction in the number of feasible employment opportunities for low-type workers, as well as incentivising workers to create more high-type jobs. This leads to a greater reduction in the share of low-type workers (i.e. a greater cleansing of the worker distribution). At the same time the incentives to create *all* jobs are adversely affected, which leads to a greater shutdown in the job ladder and larger decline in poaching hires, such that a greater share of low-type firms survive (i.e. a sullying of the firm distribution). Overall we find that under our baseline calibration the strengthening of the cleansing effect dominates the amplified sullying effect, such that countercyclical UI policy promotes better sorting in downturns.

Our second main result is that the effect of cyclical UI policy on worker-firm sorting over the business cycle is quantitatively significant. We find that countercyclcial UI policy significantly strengthens the degree of worker-firm agreement during a recession, though at the cost of significantly raising unemployment. Overall these two channels almost exactly offset each other quantitatively in terms of their effect on aggregate output: countercyclical UI worsens the increase in unemployment, but generates an overshooting effect during the recovery due to the fact that it encourages the formation of higher productivity matches during the recession.

Finally, we also use the model to explore the welfare implications of cyclicality in the design of UI policy. Relative to an acyclical UI policy, we find that the model can generate welfare gains from procyclical UI policy by stabilising fluctuations in unemployment, as in standard models with representative workers and firms (e.g. Mitman and Rabinovich 2015). However the model also generates welfare gains from *countercyclical* UI policy by improving the sorting of workers and firms in recessions. This is a novel result. Decomposing these welfare gains reveals that workers benefit in the first instance from increased employment opportunities and in the second case from improved wages, whilst firms are only better off under a procyclical UI policy. Overall, whilst countercyclical UI policy can generate welfare gains in this environment, these gains are relatively small in output terms (less than 0.1% annual GDP).

Related literature. (to be added) This paper brings together two different strands of the literature: (i) the extensive literature studying UI policy and its effects on the labour market, and (ii) a more recent literature studying the cyclical patterns of worker-firm sorting.

The remainder of the paper proceeds as follows. Section 2 presents a discussion of the data sources and the key empirical findings of the paper. Section 3 outlines a random search model with heterogeneous workers and jobs. Section 4 details how we bring the model to the data. Section 5 explores the patterns of worker-firm sorting in the model to the data, as well as the counterfactual where UI is acyclical. Section 6 explores the macroeconomic implications of the interaction between UI and worker-firm sorting. Section 7 quantifies the welfare gains from different UI policies. Section 8 concludes.

2 Empirical Facts

In this section we first document some facts about the characteristics of different worker ranks and the relative differences in their unemployment risk. Secondly, we provide new estimates of the effects of changes in UI on labour market flows and wages. We later use some of these micro-level facts to discipline the model of labour market sorting.

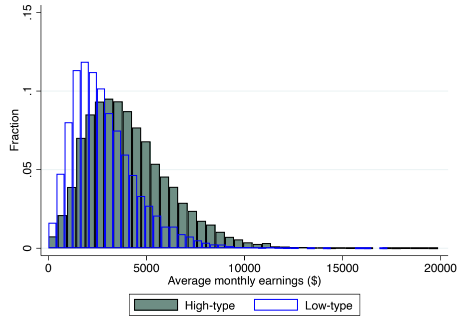
2.1 Data sources

SIPP. We use data from the 1996-2008 panels of the Survey of Income and Programme Participation (SIPP). This monthly dataset follows a large number of workers for up to four years, and contains detailed information on individual worker earnings from employment, government programs, and assets, as well as supplemental data on assets and liabilities of workers.[5] The overall sample covers the years 1996-2013. We use the PCE price index to convert the reported market values of wages, assets, and other earnings sources into real values.

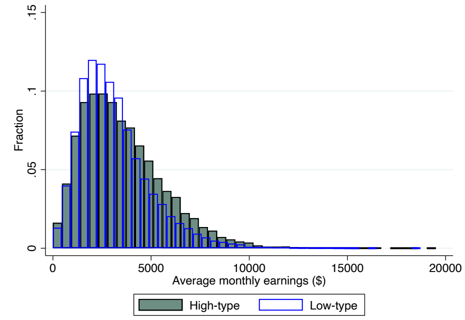
Sample construction. Following standard practice, we restrict our attention to workers between the ages 25-65 (i.e. prime age workers) who are not in the armed forces, who do not own businesses and are not self-employed. The resulting sample consists of 67,561 individuals observed for 30 months (2.5 years) on average, covering the sample period 1996-2013. Further details about the data sources, as well as the definitions and construction of key variables in our analysis, can be found in the Data Appendix A.

UI shocks. For a measure of exogenous variation in UI duration we adopt the shock series identified in Chodorow-Reich et al. (2019). Their methodology exploits the design of UI in the United States, where UI is administered at the state-level and responds endogenously to changes in real-time estimates of the state unemployment rate, which is then subject to revision *ex post*. The result is a state-monthly series of UI innovations covering the 1996-2013 sample period.

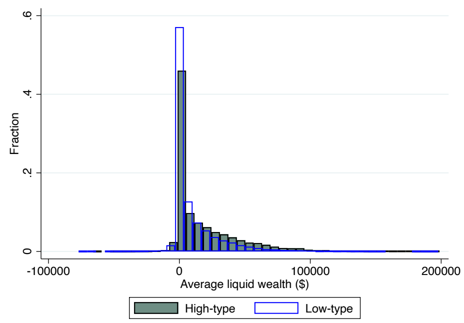
[5] Information regarding assets and liabilities is provided at a less than monthly frequency.



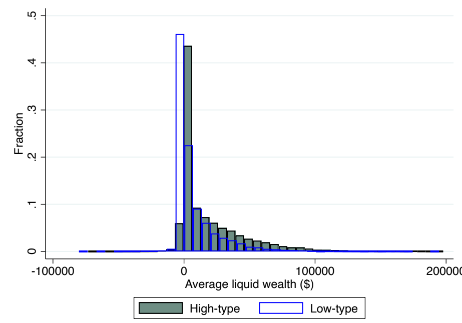
(a) Earnings (Ranking #1)



(b) Earnings (Ranking #2)



(c) Wealth (Ranking #1)



(d) Wealth (Ranking #2)

Figure 1. Earnings & wealth by worker rank

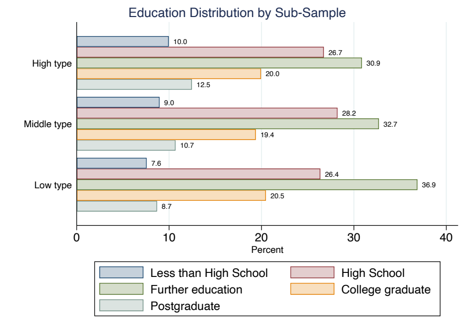
2.2 Ranking workers

To rank workers, we adopt two common approaches in the recent literature (e.g. Crane et al. 2020). The first approach we use is to rank workers by the fraction of time spent in employment vs unemployment. The idea here is that workers who have less to gain from being employed will spend less time in employment, so time spent in employment is a rough proxy for productivity. Specifically, we regress time spent in non-employment on worker demographic characteristics and then rank workers based on average residuals from the regression. The second approach we use is to rank workers by their average earnings. More specifically, we regress real earnings on demographic characteristics and then rank workers by the average residuals of this regression.

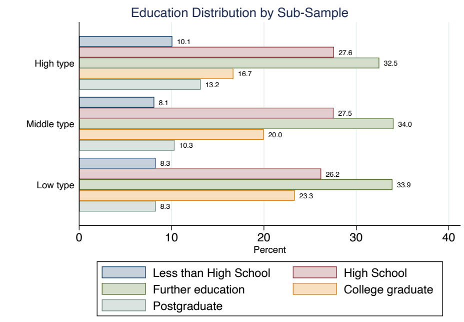
2.3 Descriptive statistics

Characteristics. How do worker characteristics differ by rank? Figure 1 plots the earnings and liquid wealth distributions by worker rank, whilst Figure 2 plots the distribution across educational attainment and occupation by worker rank group. Overall lower rank workers on average have lower wages and accumulate lower liquid wealth, but there are not huge differences across worker ranks in terms of educational attainment or occupations.

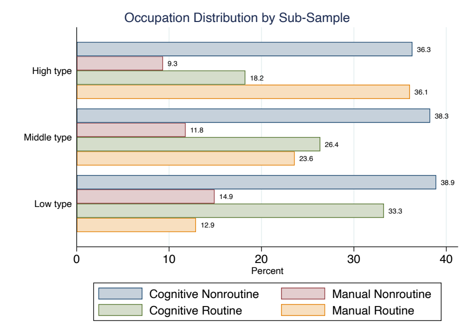
Unemployment risk. How does unemployment risk change across the ranking of workers? By



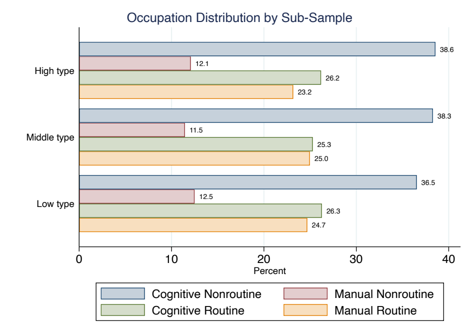
(a) Education (Ranking #1)



(b) Education (Ranking #2)



(c) Occupation (Ranking #1)



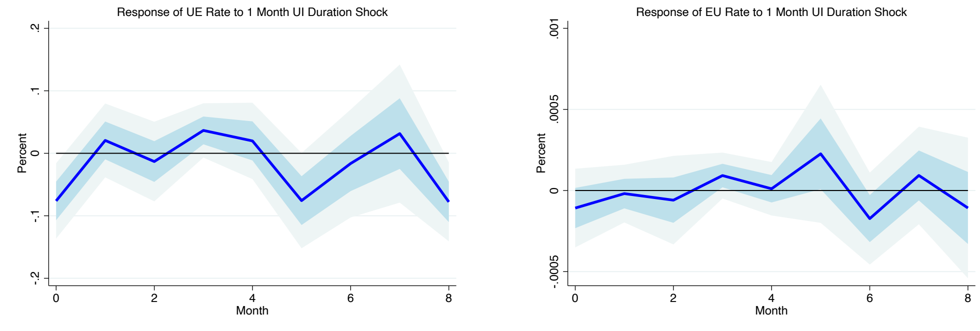
(d) Occupation (Ranking #2)

Figure 2. Education & occupation by worker rank

Table 1. Unemployment risk by worker rank

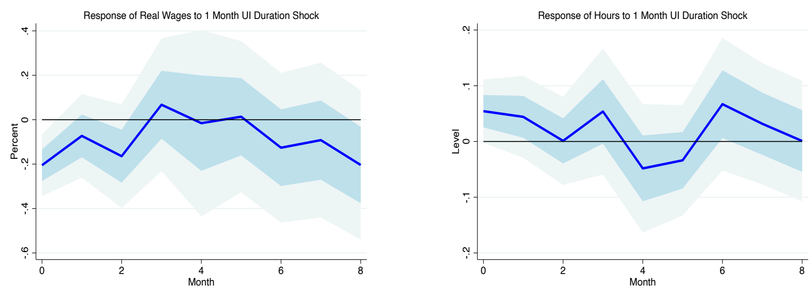
	Average (%)	Ranking #1			Ranking #2		
		Low	Mid	High	Low	Mid	High
EU	0.10	1.32	0.91	0.72	1.48	0.77	0.97
UE	27.10	1.08	1.01	0.93	0.94	0.93	0.71

unemployment risk we mean the combination of the likelihood of being separated conditional on having a job (i.e. the EU rate) and the speed at which a worker can be expected to find a new job conditional on being unemployed (i.e. the UE rate). Table 1 displays how unemployment risk varies across worker ranks. Across both ranking methods we find that the main driver of differences in unemployment risk is in the separation rate, where low-rank workers face a separation rate that is more 30% higher than the sample average. This is consistent with results in Birinci and See (2023) who using the same sample document differences in unemployment risk by earnings and wealth only. We also find that the the fraction of workers within each rank who experience unemployment or UI claims decreases monotonically in worker rank.



(a) UE Rate (b) EU Rate

Figure 3. Estimated responses of job finding and separation rates



(a) Real Wages (b) Hours

Figure 4. Impulse Responses of (Log) Real Wages and Hours

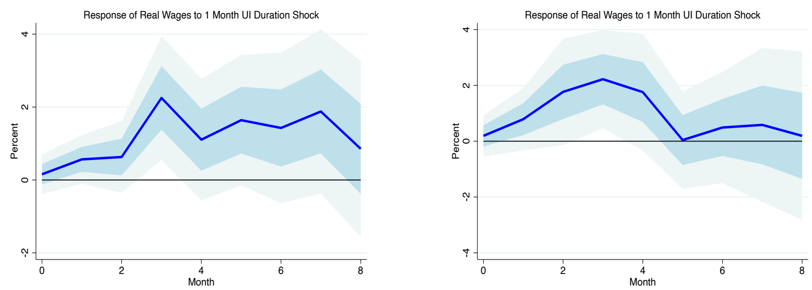
2.4 Estimating the effects of UI changes

How do changes in UI policy affect labour market outcomes? Do these effects differ across workers? To address these questions we estimate impulse responses to Chodorow-Reich et al. (2019) UI shocks using a panel version of Jordà's (2005) local projections. We first estimate average effects of the shocks using the whole sample, before estimating effects of the shocks across different worker sub-samples.

General empirical specification: We estimate the following regression for each time horizon $h \geq 0$:

$$(\Delta_h) y_{i,s,t+h} = \left(\sum_{k=-\kappa}^{h} \gamma_h \varepsilon^{UI}_{s,t+k} \right) \times \mathbb{1}_{i \in \mathcal{I}^x} + \sum_{j=1}^{L} \delta_h' \mathbf{X_{i,s,t-j}} + \phi_{i,h} + \phi_{s,h} + \phi_{t,h} + \nu_{i,t+h}$$

where $(\Delta_h) y_{i,s,t+h}$ is the (cumulative change in) worker-level variable of interest, $\varepsilon^{UI}_{s,t}$ is the UI shock in state s and time t, $\mathcal{I}^x$ is a sub-sample based on worker characteristic x (for example, $\mathcal{I}^x :=<$ 10th earnings percentile), $\mathbf{X_{i,s,t}}$ is a vector of individual and state-level controls, and $\phi_{i,h}$ and $\phi_{t,h}$ are individual and time fixed effects respectively, and $\{\gamma_h\}_{h=0}^{H}$ are the coefficients of interest which trace out the estimated impulse response function.



(a) UI Recipients

(b) Unemployed

Figure 5. Wage elasticities by labour market experience in sample

Aggregate effects. Figure 3 plots the esimtated impulse responses of state-level job finding and separation rates to an unanticipated increase in UI duration. Figure 4 plots the responses of wages and hours worked.[6] We find that a significant fall in the UE rate on impact, as well as 5 months after the shock. In contrast, we find the response of the average separation rate to a UI shock is essentially flat.[7] For wages, we see that if anything the response on impact is very small and actually slightly *negative*, and is statistically insignificant thereafter. Hours worked are also insensitive to the UI shock.

Effects by worker characteristics. How do the estimated responses change when we look at different sub-samples of workers? We re-estimate the wage responses changing the composition of workers in $\mathbb{1}^x$ by characteristics such as worker rank, education, occupation, wealth, and labour market experience.[8] In the majority of instances we do not find significantly different estimates relative to the full sample. Figure 5 instead plots the estimated wage responses for the sub-samples of workers who report claiming UI or being unemployed in the sample. Only for these sub-groups do we find that the wage sensitivity to changes in UI policy is much larger and statistically significant. For both these groups we estimate that in response to an unanticipated 1 month increase in UI duration, wages increase on average for workers in these groups by around 2%. This contrasts sharply with the average estimates, where wages appear to be highly insensitive to the stance of UI policy. Overall this evidence supports theories of wage determination where bargaining power is linked to the time an individual worker spends in employment, e.g.the wage auction approach in Postel-Vinay and Robin (2002)

[6]We use the same baseline specification but instead estimate the cumulative changes in the variables. Again the results are robust to estimating responses in terms of levels, adding a large number of individual-level controls, allowing for lagged/future shocks, and controlling for seasonality.

[7]Our baseline estimates include no lagged/future shocks, and only include 12 lags of state-level unemployment as a single aggregate control, following the specification of Chodorow-Reich et al. (2019). Our results are robust to adding a large number of individual-level controls, allowing for lagged/future shocks, and controlling for seasonality.

[8]We cannot look at transition rates by worker rank at the state level, as we quickly run into a low count problem when we disaggregate flows between employment and unemployment.

2.5 Summary

This section documents some new facts which we use to motivate and discipline the model. Firstly, ranking workers using standard methods in the literature reveals that separation risk is the key driver of heterogeneity in unemployment risk across different types of workers in the labour market. Secondly, we estimate the effects of unanticipated UI duration shocks, finding a significant response on the job finding rate but a flat response on separations. We also document insensitivity of the wage on average to UI policy changes, but much stronger response of wages for workers who experience unemployment or claim UI in the sample. Overall these results motivate a framework where workers face different unemployment risks due to *ex ante* heterogeneity in their market productivity, and where there is a close relationship between the sensitivity of wages to changes in the generosity of UI policy and time spent in employment.

3 Model

In this section we briefly outline a model of worker reallocation over heterogeneous jobs proposed in Lise and Robin (2017), which we then discipline using the empirical evidence presented above. We make two slight modifications to their baseline sorting model: (i) we propose a more parsimonious production function, in order to reduce the number of parameters we need to identify, and (ii) we specify a more general functional form for the workers flow value of unemployment that can capture the countercyclicality of UI generosity. In the following section we discipline the model to match the properties of the UI system in the US, as well as the estimated elasticities of key labour market variables to changes in UI policy. For more details of the model see the Model Description in Appendix B and also Lise and Robin (2017).

3.1 Environment

Primitives. Time is discrete and runs forever. All agents in the economy are risk-neutral and share the same discount factor $\frac{1}{1+r}$. There is a fixed-mass of workers who are indexed by $x \in \mathcal{X}$. Firm are indexed by $y \in \mathcal{Y}$. Jobs (firms) may be either vacant or filled, where maintaining a vacancy costs a firm $c(v(y))$ per period. Firms post vacancies of type y until the value of doing so is driven to zero (i.e. free entry). Workers search full-time when unemployed, and also when employed with relative search intensity $s \in (0,1)$. Search in the labour market is random and determined by a constant returns to scale matching function. Matches dissolve endogenously for one of two reasons: (i) a fall in the aggregate productivity z makes an existing match unprofitable, or (ii) the worker is poached away from their current match by another firm. Matches also dissolve exogenously with probability $\delta \in (0,1)$.

Value-added. A worker-firm match produce value-added $p(x,y,z)$, where z is the aggregate productivity shock.[9] To generate positive assortative matching in equilibrium we require that $p(x,y,z)$ is *supermodular* in x and y, i.e. that there are complementarities in production between worker- and firm-types. For simplicity we assume a production function of the following form:

$$p(x,y,z) = z \cdot (p_1 x + p_2 y - p_3 \min\{x-y,0\}^2]$$

where p_1 captures the returns to worker-type, p_2 the returns to firm-type, and p_3 captures the cost of *mismatch* between workers and firms and therefore controls the strength of complementarities.[10]

UI policy. All unemployed workers receive UI income $b(x,z)$, which given by[11]:

$$b(x,z) = \Psi(z) \cdot p(x, y^*(x,1), 1)$$

where $y^*(x,1)$ indicates the optimal firm-type for worker x when the aggregate state $z=1$ (i.e. at the ergodic steady state).[12] The function $\Psi(z)$ determines the generosity and cyclicality of UI in the model. We propose a very parsimonious functional form with minimal parameters needed to target the cyclical design UI in the data. Specifically, we propose:

$$\Psi(z) = b_0 \cdot z^{b_1}$$

where b_0 captures the average generosity of UI income (i.e. the replacement rate), whilst b_1 captures the cyclicality of UI generosity with respect to the aggregate state.

Wages. Wage setting in this environment follows the protocol in Postel-Vinay and Robin (2002). Workers who are employed earn a wage $w(\sigma,x,y,z)$, where $\sigma \in (0,1)$ is the workers fraction of the match surplus (i.e. the wage contract). We assume that workers hired from unemployment have no bargaining power and that the firm can extract all the surplus, i.e. $\sigma = 0$. However once in employment workers can solicit job offers from other firms. If a worker receives a credible job offer they can use this to force a renegotiation, which triggers Bertrand competition between firms. The overall outcome is that the worker will go to the firm with the highest match value,

[9]For brevity we will suppress explicit dependence on z, which will instead be indicated by the presence of a time subscript t.

[10]This functional form differs from that used in Lise and Robin (2017) and Crane et al. (2020), who assume a second-order Taylor approximation to $p(x,y,z) = p_1 + p_2 x + p_3 y + p_4 x^2 + p_5 y^2 + p_6 xy$, where p_6 captures the strength of complementarities. Our functional form allows for non-linearities and complementarities in production whilst reducing the number of parameters to identify in estimation.

[11]For simplicity we abstract from heterogeneity in UI eligibility across workers and UI expiration, which are two key features of UI policy in the US.

[12]Specifying UI income as a markdown on flow value-added $p(x,y,z)$, as opposed to a markdown on earnings as in the data, makes the model much easier to solve and captures the same idea given that wages will ultimately depend on match productivity. Also allowing dependence on x captures the fact that in the US the amount of UI income a worker receives is determined by most recent earnings so naturally differs across workers rather than being equal.

and the wage contract σ will deliver the same value as if the worker earned the full surplus with the losing firm. Lentz et al. (2016) show that under these assumptions the wage $w(\sigma, x, y, z)$ can be written as:

$$w(\sigma, x, y, z) = \sigma p(x, y, z) + (1 - \sigma) b(x, z) - \Delta \tag{1}$$

where Δ captures expected future renegotiation opportunities.

Surplus. Under these assumptions Lise and Robin (2017) illustrate that the joint surplus between a worker-firm pair $S(x, y, z)$ is independent of other variables and importantly of the distributions of employed and unemployed workers:

$$S_t(x, y) = p_t(x, y) - b_t(x) + \frac{1 - \delta}{1 + r} \mathbb{E}_t \max\{S_{t+1}(x, y), 0\} \tag{2}$$

This result delivers tractability in the model whilst allowing for two-sided heterogeneity. This depends on several key assumptions: (i) transferable (linear) utility between workers and firms, (ii) firms extract all the surplus of the unemployed, such that the value of unemployment is independent of the match surplus, and (iii) the wage-setting ensures that the match surplus is preserved under a job-to-job transition. Overall for a match to be feasible it must be the case that $S_t(x, y) \geq 0$, otherwise the match will dissolve.

Timing. The within-period timing is as follows. At the beginning of each period aggregate productivity changes from z to z' according to the Markov transition probability $\pi(z, z')$. Next, separations occur. This happens exogenously due to the δ shock, or endogenously due to changes in the match surplus $S_t(x, y)$ or due to poaching. Next, firms decide how many vacancies to post and workers meet vacancies via the matching function. Upon matching bargaining takes place between firms and workers. Finally, production takes place and wages are paid.

3.2 UI and the Allocation of Workers

In this environment there are two opposing channels through which a change in UI policy $b(x, z)$ can affect the allocation of workers across jobs: (i) by changing the feasible matching set, $S_t(x, y) \geq 0$, and (ii) through the effect on job creation incentives, $v(y)$. Which effect dominates overall is a quantitative question which we address in the neext section.

Matching set. In the first instance, an increase in $b(x, z)$ leads to a contraction in the feasible matching. The maximum degree of 'mismatch' that an unemployed worker is willing to accept in order to move into employment falls. Put differently, more generous UI effectively acts as a subsidy for workers to search for longer and wait for better quality matches. This is illustrated in Figure 6, where an increase in UI generosity contracts the matching set thresholds from the solid black lines to the dashed black lines at the ergodic steady state (i.e. $z = 1$). The blue dashed

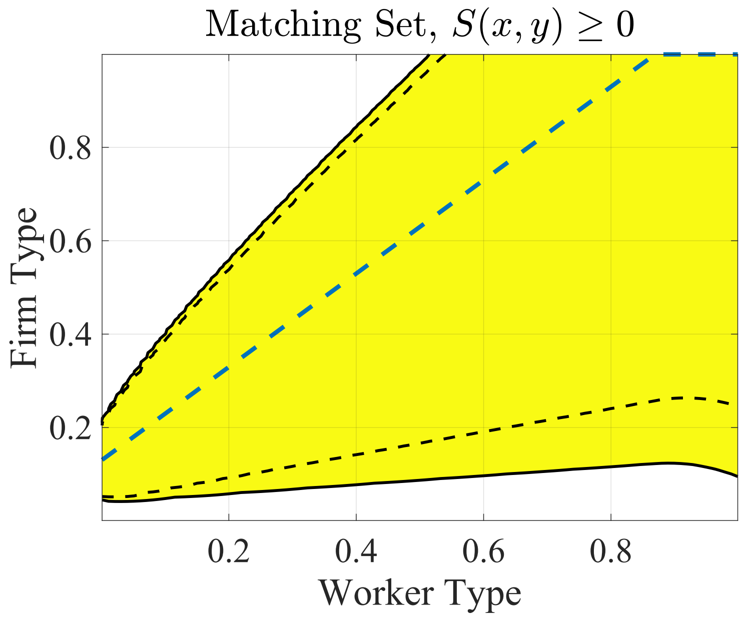


Figure 6. Changes in $b(x, z)$ and the matching set $S(x, y) \geq 0$

line plots the optimal choice of firm-type $y^*(x, 1)$.[13] The increase in UI generosity therefore leads to a contraction of the matching set towards the optimal allocation of workers across jobs. Note also that matches located between the thresholds will separate upon the change in UI policy, as these workers find it optimal to return to unemployment and search with higher intensity for a better match. Overall this channel will tend to improve worker-firm sorting by encouraging the formation of better matches from the unemployment pool whilst reducing mismatches.

Job creation. From the firm side, an increase in $b(x, z)$ firstly reduces the value of matches across the *whole* space of worker-firm matches $\mathcal{X} \times \mathcal{Y}$. This leads to a fall in aggregate job creation, which reduces the frequency at which workers come into contact with vacancies. The effect of this is to slow down both the rate at which unemployed workers find new jobs but also the rate at which employed workers reallocate toward jobs they are better suited to. Moreover, firms respond to the change in the shape of the matching set through the choice of which *type* of jobs to create. More specifically, the distribution of new jobs created $v(y)$ will shift towards *higher-type* jobs, as an increase in $b(x, z)$ has a relatively smaller effect on the match surplus associated with these jobs. Overall this effect will tend to worsen worker-firm sorting, as workers are unemployed for longer and then spend more time in worse matches.

[13] Note that the assumption of supermodularity in $p(x, y, z)$ ensures that $y^*(x, 1)$ is (weakly) monotonically increasing in worker-type x.

4 Quantification

This section outlines how we solve the model and bring the model to the data. We firstly outline the solution algorithm, before presenting the parameterization strategy and model outcomes under the baseline parameterization.

4.1 Solution

As discussed above, the model has a convenient recursive structure that allows us to compute the stochastic search equilibrium in several stages. In the first stage we solve for the surplus function, $S(x,y,z)$. This is sufficient to characterise all mobility decisions in the model. In the second stage we can compute the dynamics of distributions, aggregates and wages via simulation using the surplus function.

1. For given values of the UI policy $b(x,z)$, value-added $p(x,y,z)$, the discount rate r, the exogenous separation rate δ, and a stochastic process for aggregate productivity giving transition matrix $\Pi(z,z')$, we can solve for the surplus function by iterating on the functional equation (2).

2. Given a solution to $S(x,y,z)$, a cohort of N workers can simulated alongside a process for aggregate productivity $\{z_t\}_{t=0}^{T}$ to compute the evolution of the distribution of vacancies $v_t(y)$, unemployment $u_t(x)$, worker-firm matches $e_t(x,y)$ and a distribution of wage contracts $\mathcal{W}_t(\sigma,x,y)$ with accompanying wage rates.

4.2 Parameterization

Heterogeneity. We approximate the space of worker heterogeneity x by a grid of linearly spaced points $\mathcal{X} = \{x_1,\ldots,x_{N_x}\}$ on $[0,1]$. We also approximate heterogeneity in job types via a linearly spaced grid $\mathcal{Y} = \{y_1,\ldots,y_{N_y}\}$ on $[0,1]$. Following Lise and Robin (2017) we assume that the distribution of worker types $\mathcal{L}(x)$ to be beta with shape parameters $\{\beta_1,\beta_2\}$.

Aggregate productivity. We also specify a linearly spaced grid for the aggregate productivity shock $\{a_1,\ldots,a_{N_z}\} \subset (0,1)$, where the grid for aggregate productivity is then given by $z_i = F^{-1}(a_i)$, where F is log-normal with parameters 0 and σ. The transition probability is given by $\pi(z_i,z_j) \subset C(a_i,a_j)$, where C is a Gaussian Copula density with dependence parameter ρ, and we normalize $\sum_j \pi(z_i,z_j) = 1$.

Matching. Following Schaal (2017) and Baley et al. (2023), we assume a CES matching function:

$$M(L_t,V_t) = \frac{\alpha L_t V_t}{(L_t^{\omega} + V_t^{\omega})^{1/\omega}}$$

where $\alpha > 0$ captures matching efficiency and $\omega \geq 0$ reflects the degree of substitution between vacancies and job searchers in match formation. This choice of matching function ensures that worker-firm contact rates q_t and f_t are always bounded between $(0, 1)$. Contact rates as a function of tightness θ_t are given by:

$$q(\theta_t) = (1 + \theta_t^{\omega})^{-1/\omega}, \quad f(\theta_t) = \theta_t(1 + \theta_t^{\omega})^{-1/\omega}$$

Recruiting costs. Convex recruiting costs are needed in order to guarantee a non-degenerate distribution of vacancies over job-types $v(y)$. Following Lise and Robin (2017) we assume that vacancy posting costs take the form:

$$c(v) = \frac{c_0 v^{1+c_1}}{1 + c_1}$$

where $c_0 \geq 0$ controls the level and $c_1 \geq 0$ controls the degree of convexity.

Fixed parameters. A model period is assumed to be one week and r is set such that the annual discount rate is 5%. We fix the match elasticity $\omega = 0.429$ to match an elasticity of substitution between vacancies and job searchers equal to 0.7 following Menzio and Shi (2010).[14] Finally, we set the parameters governing the aggregate productivity process $\{\rho, \sigma\}$ to generate an autocorrelation of 0.97 and a standard deviation equal to 0.77% to mimic the cyclical properties of aggregate labour productivity in the US.

Target moments. We calibrate the parameters using the method of moments with weights chosen to minimize the relative distance between the model and empirical moments. All parameters are identified jointly. In what follows we provide a heuristic mapping from the moments to the model parameters to guide intuition.

To identify matching efficiency α, the relative search intensity of the employed s, and the exogenous separation rate δ, we target the average rates at which workers flow from unemployment to employment, between jobs, and from employment to unemployment, as standard in the literature.[15]

The vacancy cost function controls how vacancies respond to changes in the profitability of producing, so we follow the strategy in Lise and Robin (2017) and target the standard deviation of vacancies and its correlation with output in the data.

Next, we use the UI policy parameters $\{b_0, b_1\}$ to ensure consistency of the model with the level and cyclicality of UI policy in the United States. Specifically, we identify b_0 by targeting a

[14] We follow Lise and Robin (2017) in fixing this parameter, as it is not possile to separately identify ω to the parameters governing the job recruitment costs $\{c_0, c_1\}$ without direct data on the latter.

[15] Specifically we target the moments reported in Lise and Robin (2017) using data from the BLS.

replacement rate of $\mathbb{E}[b/w]$ equal to the average replacement rate in the SIPP, which is 0.47. We then identify b_1 to target the correct correlation of UI generosity with GDP over the business cycle. To do this, we exploit the 'effective' replacement rate series constructed in Landais et al. (2018), which takes into account changes in eligibility and duration of UI. This series has a correlation with real GDP equal to -0.4621, indicating that UI generosity in the data is indeed countercyclical.

The remaining parameters in the model govern the heterogeneity across worker-types and productive matches. To identify worker heterogeneity in the model $\{\beta_1, \beta_2\}$ we firstly target an average monthly unemployment rate equal to 5.8%. We also target the *concentration* of unemployment in the cross-section, i.e. the distribution of time spent in unemployment among the working population. More specifically, we target the fact reported in Morchio (2020) that the top 10% of workers by time spent unemployed account for around 66% total time spent in unemployment.[16]

Identifying the shape of the production function $p(x, y)$ is more tricky. The parameters $\{p_1, p_2, p_3\}$ determine the shape of the surplus function $S(x, y, z)$, the feasible matching set $S_t(x, y) \geq 0$, and ultimately the equilibrium distribution of worker-firm matches $e_t(x, y)$. In the first instance, the responses of the feasible matching set to changes in UI generosity will determine the response of the equilibrium flow rates. We therefore identify p_1 and p_2 by targeting the estimated elasticities of the EU and UE flow rates to a UI policy shock in the previous section. Finally, the dispersion in matches over the feasible matching space will be reflected in wage dispersion. We therefore identify the cost of mismatch p_3 by targeting a standard deviation of wages across matches equal to what we observe in the SIPP, which around 0.42..[17]

Estimation results. Table 2 shows the model fit by comparing the model-generated moments to those in the data. The overall fit of the model is satisfactory, except for a few targets: in particular, those relating to the cyclicality of job creation, the concentration of unemployment, and the replacement rate. This is related to the fact that volatility in job creation is linked to the sensitivity of the match surplus to shocks, and this is only determined by the production functon and the UI policy. Additionally, the model generates *too much* wage dispersion under this calibration.

[16] In the sample we construct from the SIPP, we find an even larger concentration of unemployment, where the top 5% account for around 66% total unemployment time, and less than 10% of our SIPP sample ever claim UI. However, we target the moment reported in Morchio (2020), as the NLSY79 data observes worker histories for a longer duration than in the SIPP. More specifically, on average in our sample an individual is observed on average for 30 months, whereas in the NLSY79 sample constructed in Morchio (2020) individuals are observed on average for 1,300 weeks, or around 325 months.

[17] Alternatively we could target the average wage elasticity in respond to a UI policy shock. However, as the wage elasticity is principally determined by worker's bargaining power, which itself depends on the rate at which workers receive feasible job offers, we cannot target both the wage elasticity and UE elasticity as these are determined by the same part of the model.

Table 2. Targeted moments

Fitted moments	Data	Model	Origin
$\mathbb{E}[UE]$	0.421	0.376	BLS
$\mathbb{E}[EE]$	0.025	0.024	BLS
$\mathbb{E}[EU]$	0.025	0.022	BLS
$\text{sd}[V]$	0.206	0.224	BLS
$\text{corr}[V, Y]$	0.721	0.568	BLS
$\mathbb{E}[U]$	0.058	0.051	BLS
$\%U$ acc. by top 10	0.660	0.444	Morchio (2020)
$\mathbb{E}[b/w]$	0.470	0.593	SIPP
$\text{corr}[b/w, Y]$	-0.462	-0.442	Landais et al. (2018)
$\epsilon_{UE,UI}$	-0.075	-0.059	SIPP
$\epsilon_{EU,UI}$	0.0003	0.0003	SIPP
$\mathbb{E}[\text{sd wages}]$	0.420	0.538	SIPP

The calibrated parameters are listed in Table 3. UI policy in the model is countercyclically generous ($b_1 = -0.984$) in order to be consistent with the data. The distribution of worker heterogeneity differs from Lise and Robin (2017) and Crane et al. (2020), with most workers being located in the middle of the range for $x \in [0, 1]$ rather than skewed. We estimate that returns to worker-type are marginally larger than to firm-type, whilst mismatch costs are a significant drag on match output.

4.3 Model outcomes

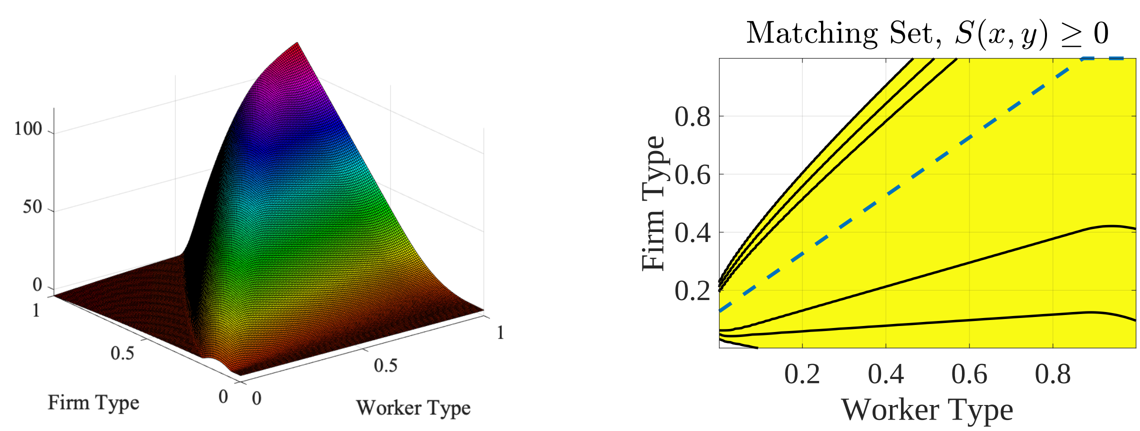
We look at additional model outcomes to inspect the properties of the calibrated model.

Surplus function. Figure 7a plots the solution for the surplus function $S(x, y)$ at the ergodic steady state, whilst Figure 7b plots the feasible matching sets for different values of the aggregate shock z. Inspecting the surplus function, it can be seen that whilst mismatch is costly in either dimension, the surplus is more steeply increasing in worker-type for a given firm-type than vice versa. This is a similar property to that estimated in Lise and Robin (2017) and Crane et al. (2020) using a different specification for $p(x, y, z)$. Inspecting the matching sets, we plot the thresholds corresponding to the aggregate shock at the 90th percentile (outer lines), the ergodic steady state (middle lines), and the 10th percentile (inner lines). In general the matching set contracts during recessions towards the $y^*(x, 1)$ line, and expands during expansions. Again as in Lise and Robin (2017) despite the alternative production function specification we find that the firm threshold of the matching set is less sensitive to aggregate shocks than the worker threshold.

Distributions. Next, we plot the joint distribution of matches over worker- and firm-types $e(x, y)$ at the ergodic steady state in Figure 8a, as well as the distribution of workers and va-

Table 3. Summary of parameters

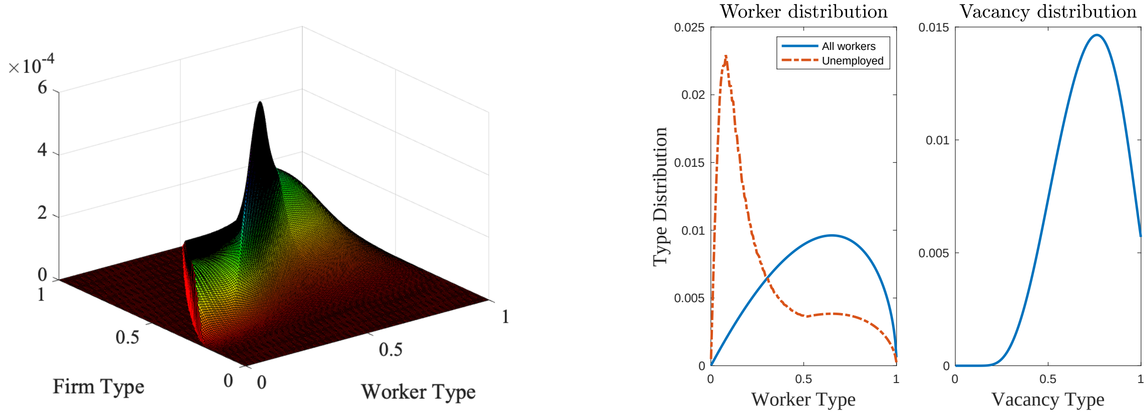
Parameter	Value	Description
Assigned:		
r	$\log(1.05)/52$	Weekly interest rate
ω	0.429	Matching function
σ	0.148	Dispersion of aggregate shock
ρ	0.992	Persistence of aggregate shock
Calibrated:		
α	0.554	Match efficiency
s	0.070	Relative search intensity of employed
δ	0.008	Exogenous separation rate
c_0	0.651	Vacancy cost scale
c_1	0.184	Vacancy cost convexity
b_0	0.696	UI constant
b_1	-0.984	UI elasticity
β_1	2.01	Worker shape 1
β_2	1.540	Worker shape 2
p_1	16.277	Returns to worker type
p_2	11.561	Returns to firm type
p_3	45.188	Mismatch cost



(a) Surplus function

(b) Matching sets

Figure 7. Surplus function and matching sets



(a) Distribution of matches, $e(x, y)$

(b) Worker and vacancy distributions

Figure 8. Model equilibrium distributions

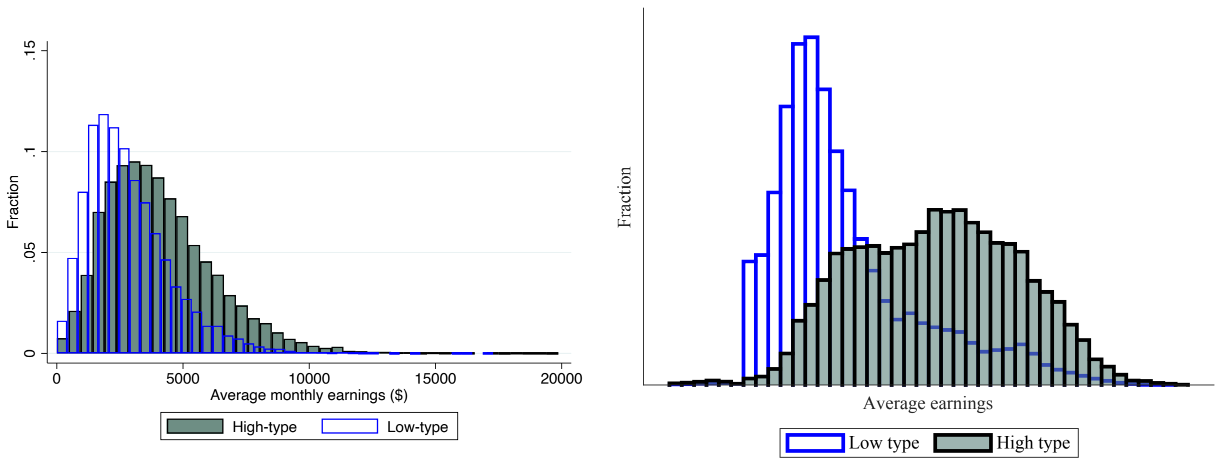
cancies in Figure 8b. Firstly, there is substantial mass along the optimal firm-type line $y^*(x)$, as well as at the boundary relating the the firm's reservation worker type. This suggests most mismatch between workers and firms in the model is driven by low-type workers being matched to high-type firms. Figure 8b illustrates that under the calibration the distribution of workers is slightly right-skewed but with most mass around the middle. Nevertheless the distribution of unemployment is highly left-skewed towards the lowest types in order to match the concentration of unemployment in the data, this is driven by the fact that the distribution of vacancies is concentrated around high-type firms, with relatively few low-type jobs created.

4.4 Untargeted outcomes

Despite being non-targeted it is instructive to see whether the calibrated model can replicate some of the key features of the data that we outline in the empirical section. Namely, the earnings distributions by worker-rank, differences in unemployment risk, and the differences in wage sensitivity to UI policy across workers.

Earnings distribution. Figure 9 plots compares the relative earnings distribution between high- and low-type workers in the model and in the data. We see that qualitatively the model replicates the same right-skewed of the earnings distribution for low-type workers, and that the mass of high-type earnings lies to the right, however the model does not generate the same right-skewed shape for the high-type worker earnings distribution.

Unemployment risk. Table 4 displays the ratios of EU and UE transition rates by worker type relative to the average rate (both of which are targeted moments). The patterns for the separation rate are very close to what we see in the data. However the pattern for the UE transition



(a) Data (b) Model

Figure 9. Earnings distribution by rank: Data vs. Model

Table 4. Unemployment risk: Model vs. Data

	Data			Model		
	Low	Mid	High	Low	Mid	High
EU	1.32	0.91	0.72	1.26	1.02	0.75
UE	1.08	1.01	0.93	0.55	1.87	2.30

rate is very different - in general, we find that in the model high-type workers find jobs at a much faster rate than low-type workers, which is not reflected in the data.

Wage sensitivity. (to be added)

5 The Anatomy of Sorting

In this section we examine the cyclical patterns of sorting in the model relative to the data. To do this we examine cyclical changes in employment shares of matches by worker-firm type relative to those documented by Crane et al. (2020) using data from the Longitudinal Employer-Household Dynamics (LEHD) data covering the same sample period.[18] Following the approach in Crane et al. (2020) we rank workers into terciles based on time spent in non-employment, and firms by their poaching share out of total hires in the economy. We then regress the first-difference in the tercile employment share on the first-difference in the aggregate unemployment rate.

Secondly, we examine the effects of cyclical UI policy on sorting patterns by running the counterfactual of an acyclical UI policy, i.e. $b_1 = 0$. In both cases we first look at the cyclical

[18] The sample used by Cranet et al. (2020) is 1994-2014.

Table 5. Changes in worker and firm employment shares

Tercile	Data	Baseline	Acyclical
Workers:			
Low	-44.9	-10.65	-9.74
High	31.6	11.74	9.35
Firms:			
Low	12.0	17.13	12.0
High	-8.9	-7.31	-2.13

Notes: Table presents percentage change in employment shares in response to a 1 percent increase in unemployment rate. This is computed by regressing changes in employment shares on the first-difference of the unemployment rate.

behaviour of the worker and firm employment distributions separately, before studying the implications for the joint distribution.

Worker composition. The results for Low and High-type workers are presented in the upper panel of Table 5, as well as the empirical counterparts estimated in Crane et al. (2020). The calibrated model is qualitatively consistent with the cyclical patterns of the worker distribution in the data: recessions are times when the employment share of low-rank workers falls and that of high-rank workers increases.[19] We find that countercyclical UI policy *strengthens* this cleansing effect on the worker distribution, which is weaker under an acyclical UI policy. However the size of this difference is not quantitatively large.

Firm composition. We do the same exercise for the firm distribution. The results are displayed in the lower panel of Table 5. Again the calibrated model is qualitatively consistent with the empirical evidence. Although the distribution of vacancies shifts towards high-type jobs in recessions, the share of employment at low-type firms actually *increases* as in the data, i.e. there is a 'sullying' of the firm distribution. This is because during downturns the job ladder shuts down, meaning that the poaching of workers from low-type firms falls. We find that countercyclical UI policy also amplifies this effect compared to the scenario where UI is acyclical, and that this amplification appears to have a quantitatively more significant impact than on the worker distribution. In fact, our baseline model overstates the increase in the share of employment by low-type firms relative to the data, whilst being reasonably close to the fall in high-type firm employment share.

Joint composition. Finally, we consider the behaviour of the *joint* distribution of workers across firms. We do this by exploring the cyclical behaviour of the employment shares of different

[19] Note that a contribution of Crane et al. (2020) is to document that their empirical findings are broadly consistent with the Lise and Robin (2017) sorting framework.

Table 6. Changes in joint worker-firm employment composition

Tercile	Data	Baseline	Acyclical
High-type workers &:			
Low-type firms	9.80	-1.69	0.50
High-type firms	11.0	13.41	10.49
Low-type workers &:			
Low-type firms	-8.30	-3.47	-1.56
High-type firms	-18.1	1.99	-0.66

Notes: Table presents percentage change in employment shares in response to a 1 percent increase in unemployment rate. This is computed by regressing changes in employment shares on the first-difference of the unemployment rate.

combinations of worker and firm ranks. The results are displayed in Table 6. The calibrated model is able to match the strong increase in the share of high-type workers at high-type firms (which is over-stated) as well as the decline in low-type workers at low-type firms (which is under-stated). The former effect contributes to an improvement in worker-firm sorting, whilst the latter acts in the opposite direction. Both of these effects are weakened under an acyclical UI policy.

However the calibrated model fails to match the "off diagonal" patterns observed in the data. Namely, the model predicts that the share of high-type workers at low-type firms decreases during downturns, which contributes to improving sorting but is at odds with the data. Similarly, the model predicts that the share of low-type workers at high-type firms increases, which worsens sorting but is also counterfactual. As documented in Lise and Robin (2017), the model under acyclical UI policy is qualitatively consistent with these worker-firm sorting patterns but does not allow for countercyclical changes in the value of unemployment.

Summary. Overall, we find that in the model countercycical UI strengthens *both* the cleansing and sullying effects of downturns relative to an acyclical counterfactual. When UI is countercyclically generous, this amplifies the shift in the worker distribution towards high-type workers. This is driven by the relatively larger fall in the job finding rate of low-type workers, which is a result of a contraction in the feasible matching set and a shift in the distribution of vacancies $v(y)$ towards higher-type jobs. At the same time the increase in the employment share of low-type firms is also amplified under countercyclical UI. Although the vacancy distribution shifts away from low-type firms, the overall effect on job creation and the slowdown of the job ladder means that poaching hires fall significantly, and more low-type firm matches survive than otherwise. The effect on the joint distribution is ambiguous only looking at employment shares. Whilst countercyclical UI appears to improve the sorting of high-type workers, at the same time it seems to worsen the sorting of low-type workers.

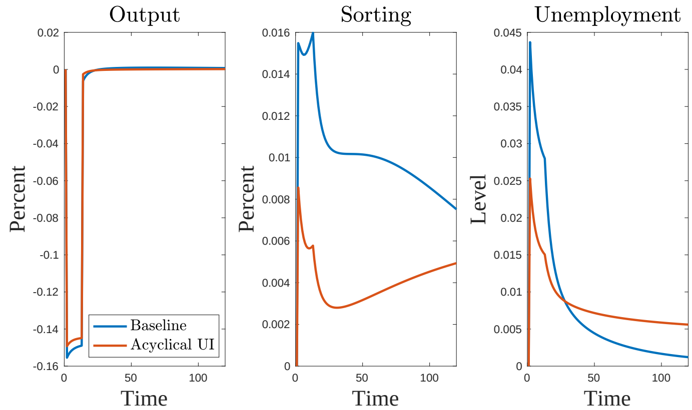


Figure 10. Recession experiment under alternative UI policies

6 Macroeconomic Implications

In this section we look at the effect of UI on the sorting patterns documented in the previous section on the overall degree of worker-firm agreement, in order to assess whether the amplification of the cleansing or sullying effect dominates. We then examine the macroeconomic implications of the interaction between UI policy and worker-firm sorting.

Aggregate sorting. On balance, does the amplification of the cleansing or sullying effect by countercyclical UI design dominate? In other words, does countercyclical UI improve or worsen the agreement between worker-firm types over the business cycle? To answer this, we propose as a measure of agreement the average within-match correlation between worker-type x and firm-type y: $\rho_{xy,t} = \text{corr}_t(x, y)$. This sorting index captures the degree of average worker-firm agreement within matches over time. The upper panel of Table 7 displays some of the cyclical properties of $\rho_{xy,t}$ under the baseline policy and the counterfactual, whilst the lower panel displays the volatilities of unemployment and value-added.

Overall under the baseline policy design fluctuations in $\rho_{x,y}$ are relatively small (around a third as volatile as aggregate output) and are countercyclical (-0.34 correlation with value-added). Under the counterfactual the volatility of the sorting index is increased by around 18% and is only very weakly countercyclical. This suggests that the amplification of the cleansing effect during recessions by countercyclically generous UI policy dominates the sullying effect, and moreover that the effect on overall sorting from the cyclical design of UI policy is quantitatively significant.

Unemployment & value-added: What are the implications for the effects of UI on sorting for unemployment and value-added over the business cycle? We simulate a recession experiment by analysing the response of these variables to a 1 quarter negative standard deviation shock to aggregate productivity that then returns to its steady state value. The impulse responses are plotted in Figure 10

Table 7. Cyclical behaviour of sorting: Baseline vs. Acyclical

Moment	Baseline	Acyclical
Sorting:		
$\mathrm{sd}[\rho_{x,y}]$	0.039	0.046
$\mathrm{corr}[\rho_{x,y}, VA]$	-0.338	-0.011
Macro:		
$\mathrm{sd}[U]$	0.178	0.125
sd[VA]	0.092	0.089

The response of value-added is driven by the joint behaviour of sorting in the labour market and the overall number of productive matches (i.e. employment). Downturns decrease the measure of active matches (which reduces value-added), but are also associated with an improvement in sorting between workers and firms (which increases value-added). Upon the onset of the recession the larger spike in unemployment under countercyclical UI is associate with greater output losses. However during the recovery phase we find that output overshoots steady state by more under countercyclical UI as those matches formed in recessions under this policy are better-matched on average and therefore more productive. This is also reflected in the cyclical properites of these variables, displayed in Table 7. In the model acyclical UI policy reduces unemployment volatility by around 30% but (as documented above) substantially weakens the cleansing effect of recessions. Overall we find in the simulation these effects approximately cancel each other out in terms of their effect on output volatility.

7 Welfare quantification

Is cyclicality in the design of UI policy desirable from a welfare perspective? In this section we use the model to quantify welfare gains/losses from the cyclical design of UI policy. As standard we can define overall social welfare Ω as the present discounted value of social output (production + UI receipts), net of the costs of job formation. Formally:

$$\Omega \quad = \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \left\{ \int p(x,y,z) de_t(x,y) + \int b(x,z) du_t(x) - \int c(v) dv_t(y) \right\}$$

Social welfare. We evaluate social welfare Ω at the ergodic distribution of the model for a range of values of b_1. Figure 11 plots the difference in social welfare $\Delta\Omega$ relative to the acyclical case (i.e. $b_1 = 0$) as a fraction of annual GDP. We find that social welfare appears to be U-shaped in the cyclicality of UI design. As in the existing literature (e.g. Mitman and Rabinovich 2015) strongly procyclical UI delivers welfare gains from reducing fluctuations in employment. In

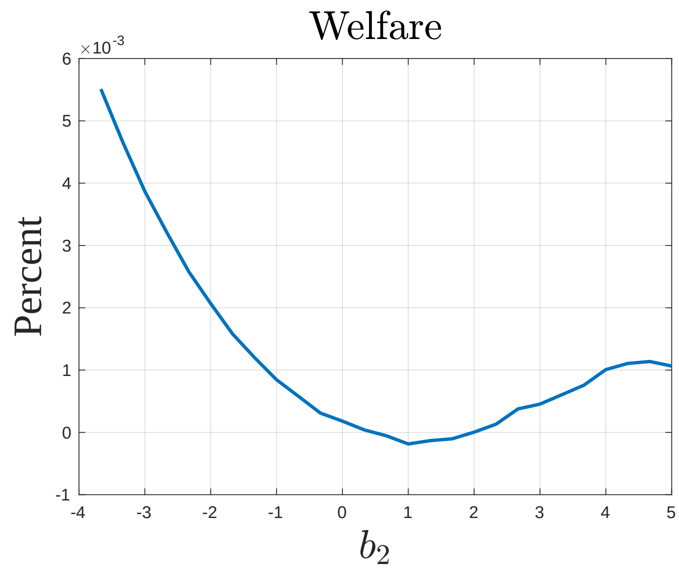


Figure 11. Social welfare and UI cyclicality

this environment UI must be *sufficiently* procyclical to outweigh the losses from greater worker-firm mismatch. However we find that strongly countercyclical UI can *also* deliver welfare gains, driven by its effects on worker-firm sorting. This is a novel result. Under countercyclical UI, the welfare gains from improving worker-firm sorting outweigh the costs of greater unemployment volatility. Overall, whilst changing the cyclical design of UI policy has implications for social welfare, quantitatively the welfare gains from the policy in the model are very small, i.e. $< 0.1\%$ annual GDP.

Decomposing welfare gains. Who accrues the welfare gains from the design of UI policy in the model? We can decompose overall social welfare into welfare for workers and firms.

For workers, welfare is simply the present discounted value of all wage contracts and UI receipts:

$$\Omega^w = \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \left\{ \int w(\sigma, x, y) d\mathcal{W}_t(\sigma, x, y) + \int b(x, z) du_t(x) \right\}$$

For firms, welfare is the present discounted value of all match profits, net of the vacancy creation costs:

$$\Omega^f = \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \left\{ \int (p(x, y, z) - w(\sigma, x, y)) d\mathcal{W}_t(\sigma, x, y) - \int c(v) dv_t(y) \right\}$$

Figure 12 plots the decomposition of welfare gains between workers and firms for the same

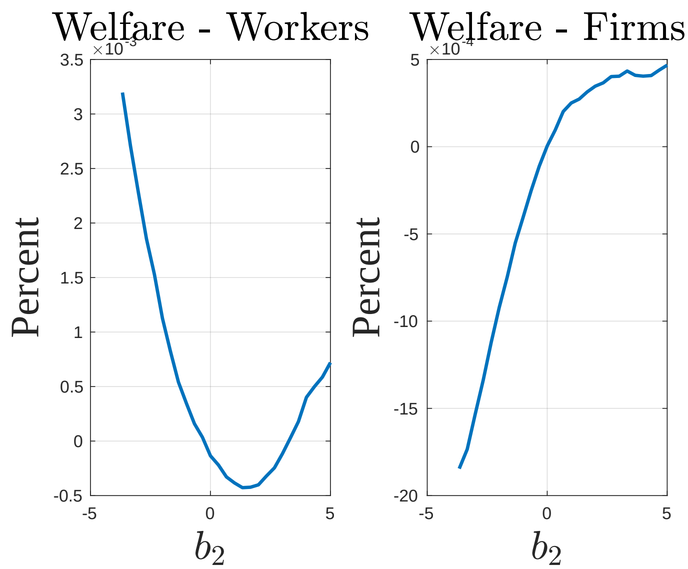


Figure 12. Distribution of welfare gains: Workers vs. firms

exercise as above. We can see instantly from the left panel that for workers the pattern follows the aggregate picture in Figure 11. When UI is countercyclical the welfare gains accruing to workers are driven by reducing worker-firm mismatch and therefore increases wages, whilst when UI is procyclical the welfare gains are driven by reducing the share of workers receiving UI. In the case of firms the picture is very different, where in contrast firms are worse-off under countercyclical UI policy on average (due to having to pay higher wages) but are relatively better-off under procyclical UI, which improves the set of feasible matches and therefore opportunities to make profits.

Welfare in a recession. Finally, we repeat the same exercise but instead evaluate social welfare during a recession rather than at the ergodic distribution. This time we compute the change in social welfare $\Delta\Omega$ relative to the absence of an aggregate shock, as a fraction of annual GDP, again for a range of values for UI cyclicality b_1. Figure 13 illustrates that in the model welfare is *increasing* in the countercyclicality of UI generosity. Whilst in all cases the initial rise in unemployment is decreasing in the degree of procyclicality, the subsequent benefits from higher productivity matches formed during the recession are *increasing* in UI countercyclicality. Overall the latter effect dominates the former over the simulation period, and welfare *gains* can be achieved if UI is sufficiently countercyclical.

8 Conclusion

(to be added)

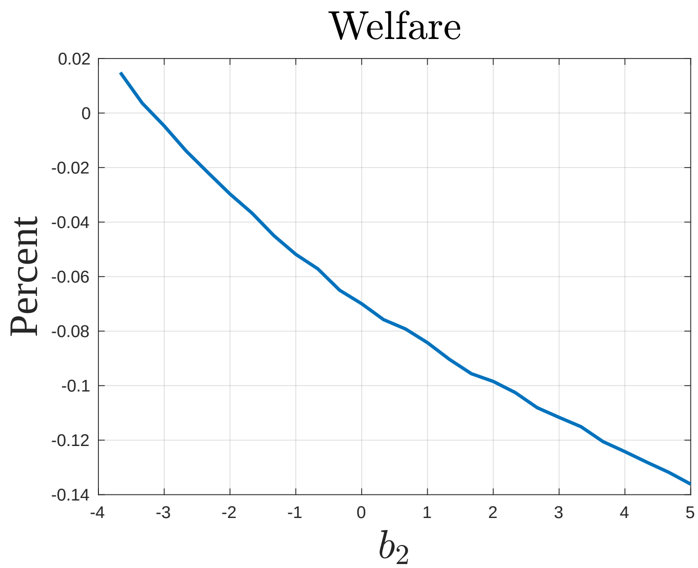


Figure 13. Social welfare in a recession under different UI policies

References

(to be added)

A Data Description

A.1 Panel Data on Workers

For the empirical analysis, we use individual-level data from the Survey of Income and Programme Participation (SIPP). This is a longitudinal dataset based on a representative sample of the US civilian non-institutionalized population. To construct our sample we consider the period 1996-2013, which requires linking together the 1996, 2001, 2004 and 2008 SIPP panels. Each panel consists of a new sample of individuals and is divided in four rotation groups. Individuals within a rotation group are interviewed every four months so that information for each rotation group is collected for each month. In each interview individuals are asked to provide information about, among other things, their employment status, occupation, earnings, and income from government support programmes. The SIPP also provides topical module files providing detailed information on the assets and liabilities of individuals. We restrict the sample to those aged between 25-65 and not in the armed forces. We also exclude individuals who are self-employed or business owners. We also drop all observations after the first missing value for key variables of interest. All analysis is weighted according to the "wpfinwgt" weights.

Worker earnings. The SIPP allows workers in employment to provide information on earnings and hours for up to two current jobs. To estimate the worker's wage in a job, we simply set this to be their average nominal hourly pay. To get real wages we then deflate nominal wage estimates by the PCE price index.

UI income. We define the nominal UI income of an individual as the amount of state UI compensation the individual received in a month for individuals who reported being in receipt of UI income. We drop individuals for whom the amount of UI income or their UI receipt status are imputed, as well as any spurious UI observations. We deflate using the PCE price index to arrive at a measure for real UI income.

Labour force status & transitions. We follow Birinci and See (2023) when classifying workers into labour force states. Specifically, we classify an individual as employed (E) if they report having a job and is either working or not on layoff, but is absent without pay for the first week of the month. We classify an individual as unemployed (U) if they report either having no job and active searching for work, or having a job but is currently laid off in the first week of the month. Finally, we classify individuals as inactive (N) if they are not classified as either employed or unemployed. To compute transition rates between any of the labour force states between period t and $t+1$, for example the EU rate, we compute total transitions from employment to unemployment between t and $t+1$, divided by total employment at t, and then control for seasonality by removing monthly fixed effects.

Liquid wealth. The topical modules of the SIPP containing "Assets and Liabilities" variables provides detailed information on the assets and liabilities of individuals. These topical module files typically cover 2-3 waves of each SIPP panel. Importantly, this gives us information on the *market value* of assets held by workers, rather than just asset-based income (which is available in the core monthly files). As data on assets/liabilities is not observed at the same frequency as the labour market data we assign to months with missing data the asset information from the nearest available data point (i.e. nearest neighbour interpolation).

To construct a measure of *liquid* wealth, we define this as the sum of all financial (liquid) assets, net of all debts/liabilities in this asset class. Importantly, we exclude information about illiquid assets such as property. We then deflate by the PCE price index. More specifically, we define liquid wealth as:

- Financial assets = "Value of joint non-interest checking account" + "Value of own non-interest checking account" + "Face value of US saving bonds owned" + "Market value of IRA account in own name" + "Market value of KEOUGH account" + "Market value of 401K in own name"
- Financial liabilities = "Amount of loans owed in own name" + "Amount of other debt owed in own name" + "Amount owed for store bills/credit cards in own name" + "Amount owed jointly in other debt" + "Amount owed for credit cards with spouse" + "Amount owed for loans with spouse" + "Money owed with spouse for loans" + "Money owed with spouse for store bills/credit cards"
- Liquid wealth = "Financial assets" $-$ "Financial liabilities"

Following Lise (2012) and Baley et al. (2023) we trim the top and bottom 0.5% of the distribution to reduce the influence of outliers on the results.

Occupation. The SIPP uses the Census of Population Occupational System to provide 3-digit occupation codes for individuals, which is closely related to the Standard Occupational Code (SOC) system for classifying worker occupations. One issue when using data from different SIPP panels is that the later panels (2004 and 2008) use the 2000 census occupational classification, whereas the earlier panels use the 1990 occupational classification. These two classification systems differ quite substantially. Following Carillo-Tudela et al. (2022), we use the IPUMS re-coding of the 2000 Census Occupational Classification to create a uniform 3-digit coding system across our sample. The resulting classification is very similar to that used in Dorn (2009) and Autor et al. (2013). From these 3-digit codes we then aggregate to 2-digit codes following the 22 Standard Occupational Codes. From this we then aggregate to 1-digit codes based on the four well-known task-based categories: Cognitive Nonroutine, Manual Nonroutine, Cognitive Routine and Manual Routine. Worker occupations in any given reference month in the sample are then assigned occupations based on their "main job". For workers with one job this is straightforward. When workers have multiple jobs we define their "main job" as the job which they spend most hours working at in a month. In the event of a tie, we assign the job with higher earnings as the main job.

State-level aggregation. To estimate panel local projections using Chodorow-Reich et al. (2019) UI shocks, we generate state-level estimates for key variables. To obtain state-level measures of wages and UI income we simply use the weighted average across all individuals in the sample by state. We compute state-level transition rates by dividing the number of transitions by the estimated state population in a given reference month (using the wpfinwgt weights).

A.2 Unemployment Insurance Shocks

To estimate the effects of changes in UI duration on key variables of interest, we utilise the series of UI duration shocks identified in Chodorow-Reich et al. (2019). This is a monthly series of shocks at the state-level covering the sample period 1996-2015. The strategy for identifying plausibly exogenous variation in UI duration at the state-level exploits the fact that UI duration in the US is determined at the state-level endogenously responds to real-time estimates of the state-level unemployment rate, but that estimates of the state-level unemployment rate are revised *ex post* which reveals episodes where state-level UI duration based on real-time and revised data differ. In essence, this strategy relies on randomness in the duration of UI with respect to fundamentals caused by measurement error in the fundamentals.

B Model Description

Matching. At the beginning of period t there is a measure $u_t(x)$ of unemployed workers over productivity types, and a measure $e_t(x,y)$ of employed workers over productivity and firm-type. Following Lise and Robin (2017) we assume that in response to the realization of the aggregate productivity shock separations and meetings between workers and firms occur sequentially. Specifically, separations occur first either in response to the change in the aggregate state or due to an idiosyncratic job destruction shock with probability $\delta \in (0,1)$. Then subsequently unemployed workers and surviving employees have the chance to match with a new employer.

Job search is random and all workers, employed and unemployed, sample from the same (endogenous) offer distribution $v(y)$, which denotes the number of job opportunities created over firm-type. Defining $u_{t+}(x)$ and $e_{t+}(x,y)$ as the measures of unemployed and employed workers after the separation stage (i.e. at time $t+$), we can then define effective searchers as:

$$L_t = \int u_{t+}(x)dx + s \int \int e_{t+}(x,y)dxdy$$

The aggregate number of job opportunities can be expressed as $V_t = \int v(y)dy$. We can then define aggregate labour market tightness as:

$$\theta_t = \frac{V_t}{L_t}$$

Unemployed workers meet vacancies with probability $f(\theta_t)$, where $f(\cdot)$ is a strictly increasing and concave function such that $f(0) = 0$ and $f'(0) > 0$, whilst for employed workers the probability is instead $s \cdot f(\theta_t)$. Firms with recruiting intensity $v(y)$ meet workers with probability $q(\theta_t)$, where $q(\cdot)$ is a strictly decreasing and convex function such that $q(\theta) = f(\theta)/\theta$, $q(0) = 0$, $q'(0) < 0$ and $f(q^{-1}(\cdot))$ is concave. Again for brevity we suppress dependence on tightness in our notation.

Production. Firms are single-worker entities who produce the single good. Firms have access to a production technology at the match level $p_t(x,y)$ which depends on the worker's productivity x, the firm's own productivity y, and aggregate productivity z. We allow for the productivity of the match to depend on the relative distance between x and y such that there are complementarities in production between high-type workers and high-type firms: $p_{x,y} \neq 0$.

Wage bargaining. To pin down wages in this environment we assume that wages are restricted to fixed wage contracts which can only be renegotiated when either party has a credible threat, following the sequential auction framework of Postel-Vinay and Robin (2002). When workers search on-the-job, employed workers can receive job offers from other firms in the market which triggers competition between the incumbent and prospective firm. We assume that firms engage in Bertrand competition for the worker, which ensures that the worker receives a continuation value equal to the second highest bid and always goes to the match with the highest overall surplus.

Denote the joint value of a match by $P_t(x,y)$ and the value of unemployment $U_t(x)$. The surplus of a match is then given by $S_t(x,y) = P_t(x,y) - U_t(x)$. Bilateral efficiency ensures that workers and firms only stay together if it is mutually beneficial, i.e. $S_t(x,y) \geq 0$. We also assume that initially the match surplus is entirely appropriated by the firm when matched with an unemployed worker. Let $W_{1,t}(x,y,y')$ be the value offered at time t by a firm of type y to a worker of type x who has received some alternative employment opportunity of type y'. If an employed worker matches with a new firm with match value $P_t(x,y')$, one of two things happen. Either $P_t(x,y') > P_t(x,y)$ and the worker moves to the new firm and receives the old match value $W_{1,t}(x,y',y) = P_t(x,y)$ as continuation; or $P_t(x,y') \leq P_t(x,y)$ and the worker stays with their current employer but uses the offer to force a renegotiation to earn a minimum continuation value equal to $W_{1,t}(x,y,y') = P_t(x,y')$.

One issue with the standard sequential auction protocol is that wages cannot usually be solved for exactly. Following Lentz et al. (2016) we instead consider contracts with limited commitment stipulating a fixed share of the match surplus that the employer commits to, which we denote by $\sigma \in (0,1)$. We discuss this in detail below.

B.1 Value Functions

Being unemployed with productivity x and aggregate productivity z has value

$$\begin{aligned} U_t(x) &= b_t(x) + \beta \mathbb{E}_t \left[(1 - f_{t+1}) U_{t+1}(x) + f_{t+1} \int E_{0,t}(x,y) \frac{v_{t+1}(y)}{V_{t+1}} dy \right] \\ &= b_t(x) + \beta \mathbb{E}_t U_{t+1}(x) \end{aligned} \tag{3}$$

where $f_{t+1} \frac{v_{t+1}(y)}{V_{t+1}}$ is the probability a worker meets a job opportunity posted by firm type y, and the second equality follows from the assumption that the firm hiring an unemployed workers appropriate the full value of the match, i.e. $E_{0,t}(x,y) = U_t(x)$.

The probability of a match being destroyed in any period t is given by:

$$\mathbb{1}\{P_t(x,y) < U_t(x)\} + \delta \times \mathbb{1}\{P_t(x,y) \geq U_t(x)\}$$

A match between a worker of type x and a firm of type y has value

$$\begin{aligned}
P_t(x,y) &= p_t(x,y) \\
&\quad +\beta\mathbb{E}_t\bigg[(1-(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}U_{t+1}(x) \\
&\quad +(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}\bigg((1-sf_{t+1})P_{t+1}(x,y) \\
&\quad +sf_{t+1}\int \max\{P_{t+1}(x,y),W_{1,t+1}(x,y',y)\}\frac{v_{t+1}(y')}{V_{t+1}}dy'\bigg] \\
&= p_t(x,y) \\
&\quad +\beta\mathbb{E}_t\bigg[(1-(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}U_{t+1}(x) \\
&\quad +(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}P_{t+1}(x,y)\bigg]
\end{aligned} \tag{4}$$

where the second equality follows by imposing the sequential auction conditions.[20] Defining the match surplus as $S_t(x,y)=P_t(x,y)-U_t(x)$, and combining the values defined above, we have

$$S_t(x,y)=p_t(x,y)-b_t(x)+(1-\delta)\beta\mathbb{E}_t\max\{S_{t+1}(x,y),0\} \tag{5}$$

where $S_t(x,y)\geq 0$ defines the conditional *acceptance* set for workers and firms matching, condition on the realization of z at time t.

B.2 Job Creation

In each period firms can post job opportunities v at per period cost $c(v)\geq 0$, where $c(\cdot)$ is independent of firm type y, increasing and convex.[21] In equilibrium firms will create new job opportunities to the point at which the expected value of a job is equated to its' marginal cost

$$c'(v(y))=q(\theta_t)J_t(y) \tag{6}$$

[20]As pointed out in Lentz et al. (2016) and Lise and Robin (2017), in this environment Bertrand competition for workers who search on the job has the nice property that it makes the joint match value independent of whether or not the employee is actually poached.

[21]Convexity in vacancy posting costs is required in this environment to ensure that the endogenous job offer distribution $v(y)$ is non-degenerate.

where the expected value of a contact is given as

$$
\begin{aligned}
J_t(y) &= \int \frac{u_{t+}(x)}{L_t} \max\{S_t(x,y),0\}dx \\
&+ \int\int \frac{se_{t+}(x,y)}{L_t} \max\{S_t(x,y) - S_t(x,y'),0\}dxdy'
\end{aligned} \tag{7}
$$

B.3 Wage Contracts

Following Lentz et al. (2016) and Lise and Postel-Vinay (2020), we consider employment contracts with limited commitment from the employer to give the worker a fixed share of the match surplus. Contracts can only be renegotiated if both parties agree.

We denote the present value for a worker of type x employed at type y on a contract that delivers a share σ of the match surplus to the worker as $W_t(x,y,\sigma)$. By definition it follows that:

$$
W_t(x,y,\sigma) = U_t(x) + \sigma S_t(x,y)
$$

As stated above, matches formed when a worker is hired from unemployment have $\sigma = 0$ (i.e. firm receives all the match surplus). For workers in existing matches who search on the job, a match with an alternative firm y' generates a renegotiation of σ to:

$$
\sigma' = \begin{cases} S_{t+1}(x,y)/S_{t+1}(x,y') & \text{if } S_{t+1}(x,y') > S_{t+1}(x,y), \\ S_{t+1}(x,y')/S_{t+1}(x,y) & \text{if } \sigma S_{t+1}(x,y) < S_{t+1}(x,y') \leq S_{t+1}(x,y), \\ \sigma & \text{if } S_{t+1}(x,y') \leq \sigma S_{t+1}(x,y) \end{cases} \tag{8}
$$

In practice aggregate shocks do not lead to a contract renegotiation, apart from in the case where $S_t(x,y) < 0$ in which case both the worker and firm mutually agree to terminate the match.

A contract σ induces a wage $w_t(\sigma,x,y)$ such that:

$$
\begin{aligned}
W_t(\sigma,x,y) &= w_t(\sigma,x,y) + \beta\mathbb{E}_t U_{t+1}(x) \\
&+(1-\delta)\beta\mathbb{E}_t\left[\mathbb{1}\{S_{t+1}(x,y) \geq 0\}\left(sf(\theta_{t+1})\int I_{t+1}(\sigma,x,y,y')\frac{v_{t+1}(y')}{V_{t+1}}dy'\right.\right. \\
&\left.\left.+(1-sf(\theta_{t+1}))\sigma S_{t+1}(x,y)\right)\right]
\end{aligned}
$$

A worker employed today receives the wage as the flow value, whilst the appropriate continuation value is $\beta\mathbb{E}_t W_{t+1}(\sigma,x,y,) = \beta\mathbb{E}_t U_{t+1}(x) + \beta\mathbb{E}_t\sigma S_{t+1}(x,y)$. The appropriate surplus share in the continuation value depends on whether or not the match survives the exogenous job destruction shock, and then conditional on survival whether or not the worker receives another job offer and the relative value of that match relative to the current match. This is captured by the function $I_{t+1}(\sigma, x, y, y')$, which takes the value of the second-best of the three values: $\{S_{t+1}(x,y), S_{t+1}(x,y'), \sigma S_{t+1}(x,y)\}$. More explicitly:

$$I_{t+1}(\sigma, x, y, y') = \begin{cases} S_{t+1}(x,y) & \text{if } S_{t+1}(x,y') > S_{t+1}(x,y), \\ S_{t+1}(x,y') & \text{if } \sigma S_{t+1}(x,y) < S_{t+1}(x,y') \leq S_{t+1}(x,y), \\ \sigma S_{t+1}(x,y) & \text{if } S_{t+1}(x,y') \leq \sigma S_{t+1}(x,y) \end{cases}$$

For any given match (x, y) with contract σ, Lentz et al. (2016) illustrate that the piece rate wage takes the following form:

$$\begin{aligned} w_t(\sigma, x, y) &= \sigma p_t(x,y) + (1-\sigma) b_t(x) \\ &\quad -(1-\delta)\beta \mathbb{E}_t \left[\mathbb{1}\{S_{t+1}(x,y) \geq 0\} s p(\theta_{t+1}) \int \left[I_{t+1}(\sigma, x, y, y') - \sigma S_{t+1}(x,y) \right] \frac{v_{t+1}(y')}{V_{t+1}} dy' \right] \end{aligned} \tag{9}$$

B.4 Labour Market Flows

The law of motion for unemployment is

$$u_{t+1}(x) = u_{t+}(x) \left[1 - \int f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} dy \right] \tag{10}$$

and for employment

$$\begin{aligned} e_{t+1}(x,y) &= e_{t+}(x,y) \left[1 - \int s f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y') \geq S_t(x,y)\} dy' \right] \\ &\quad + \int e_{t+}(x,y') s f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq S_t(x,y')\} dy' \\ &\quad + u_{t+}(x) f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} \end{aligned} \tag{11}$$

where the first line accounts for matches dissolved due to poaching by more productive firms, the second line accounts for new jobs added due to poaching from less productive, and the final line accounts for new matches formed by hiring directly from unemployment. Finally, as illustrated in Lentz et al. (2016), we can analogously define the law of motion for the cross-sectional distribution function of contracts $\mathcal{W}_t(\sigma, x, y)$:

$$\begin{aligned}\mathcal{W}_{t+1}(\sigma,x,y) &= \mathcal{W}_{t+}(\sigma,x,y)\left[1 - sf_t + \int sf_t \frac{v_t(y)}{V_t}\mathbb{1}\{S_t(x,y') \le \sigma S_t(x,y)\}dy'\right] \\ &\quad + \int e_{t+}(x,y')sf_t\frac{v_t(v)}{V_t}\mathbb{1}\{\sigma S_t(x,y) > S_t(x,y')\} \\ &\quad + u_{t+}(x)f_t\frac{v_t(y)}{V_t}\mathbb{1}\{S_t(x,y) \ge 0\}, \qquad (12)\end{aligned}$$

where the first row indicates the stock of matches with contract less than σ which remain unchanged. The second row accounts for all instances of poaching, which occurs when a match (x, y') draws an alternative offer y such that $S(x, y) > S(x, y')$ that then delivers a contract $\sigma = S(x, y')/S(x, y)$. The last row accounts for all hires from unemployment, which adds to the measure of workers $\mathcal{W}_t(0, x, y)$.

B.5 Equilibrium

C Identification

The convexity of vacancy posting costs c_1 is key for the dispersion of the equilibrium job offer distribution $v(y)$ which workers face, and therefore the rate at which workers receive job offers used to improve their wage contract, σ. To identify this parameter we target the average wage elasticity with respect to UI that we estimate using the SIPP in the previous section. To illustrate the logic, the wage elasticity with respect to a change in UI for a worker of type x matched with firm-type y with current wage contract σ is given by[22]:

$$\varepsilon_{w,UI} = \frac{dw(\sigma,x,y)}{db(x)} \cdot \frac{b(x)}{w(\sigma,x,y)}$$

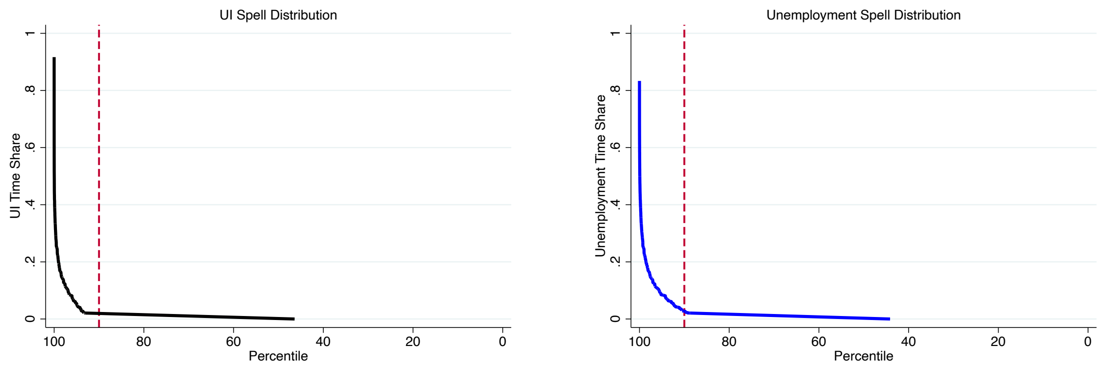
where:

$$\frac{dw(\sigma,x,y)}{db(x)} = \overbrace{1-\sigma}^{\text{Current wage contract}} - \overbrace{\frac{d\Delta(\sigma,x,y)}{db(x)}}^{\text{Change in renegotiation possibilities}}$$

$$\Delta(\sigma,x,y) = (1-\delta)\beta s f(\theta) \cdot \int \left[I(\sigma,x,y,y' - \sigma S(x,y)\right]\frac{v(y')}{V}dy'$$

Identifying the parameters of the production function $p(x, y)$ is more challenging as this controls the shape of the feasible *matching set*. Changes in UI policy also expand or contract the matching set in (x, y) space, which affects flows between employment and unemployment,

[22] Note that this definition of the wage elasticity is conditional on the continuation of the match. For matches on or close to the thresholds of the matching set the increase in $b(x)$ will lead to a separation, in which case the wage effectively becomes zero.



(a) UI Time Distribution

(b) Unemployment Time Distribution

Figure 14. Labour force status: Distributions by time

and so can also be used to identify the parameters in $p(x, y)$. To identify the return to firm-type η we target the EU rate elasticity to UI. This parameter varies the upper threshold of the matching set, where there is typically a large mass of worker-firm pairs are located in equilibrium. For the mismatch cost χ we target the observed wage dispersion in the SIPP. Mismatch costs χ influences both thresholds of the matching set, as well as the size of output losses from having matches located away from their optimal $y^*(x)$ pair. Finally, to identify the complementarity parameter ξ we target the average cross-sectional variation in value-added reported in Bloom et al. (2014).

D Additional Figures & Tables

Incidence of UI claims. How many workers claim UI in the data? We compute the fraction of time in the sample that an individual receives UI, as well as for time spent unemployed in order to compare with results in Morchio (2020).[23] Figure 14 plots the resulting distributions. It can immediately be seen that time spent receiving UI is extremely concentrated among relatively few individuals in the data. Table 8 quantifies the extent of this concentration. Overall in our sample the vast majority of workers never experience unemployment (85%) or claim UI (92%). The top 5% of workers by time spent in unemployment account for around 36% total time unemployed in the sample, whilst the same figure of UI recipients is only 14%. In other words, UI claims are *even more* concentrated than unemployment in the data. The vast majority of workers never interact with the policy.

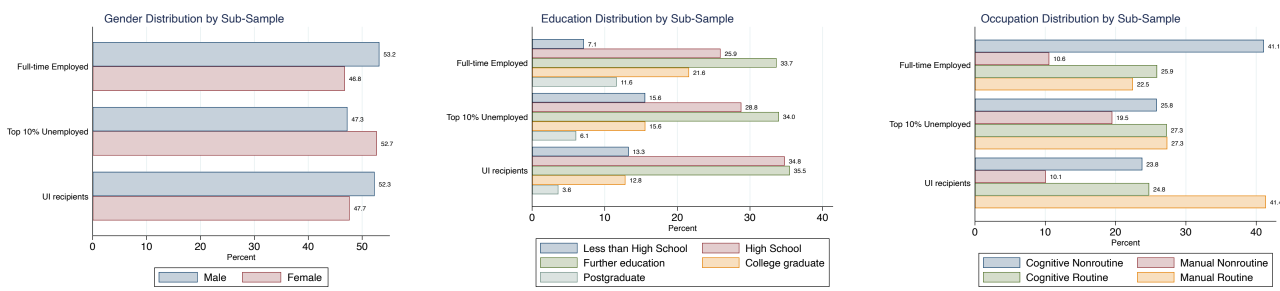
Characteristics of UI recipients. What are the characteristics of the workers who receive UI in our sample? Figure 15 plots selected demographic characteristics by sub-sample, whilst

[23]Morchio (2020) computes this same distribution using NLSY79 data. Using SIPP data we actually find that unemployment is even more concentrated, however we have a shorter time sample and the definition of unemployment that we use is slightly different compared to Morchio (2020).

Table 8. US labour market experiences: SIPP 1996-2013

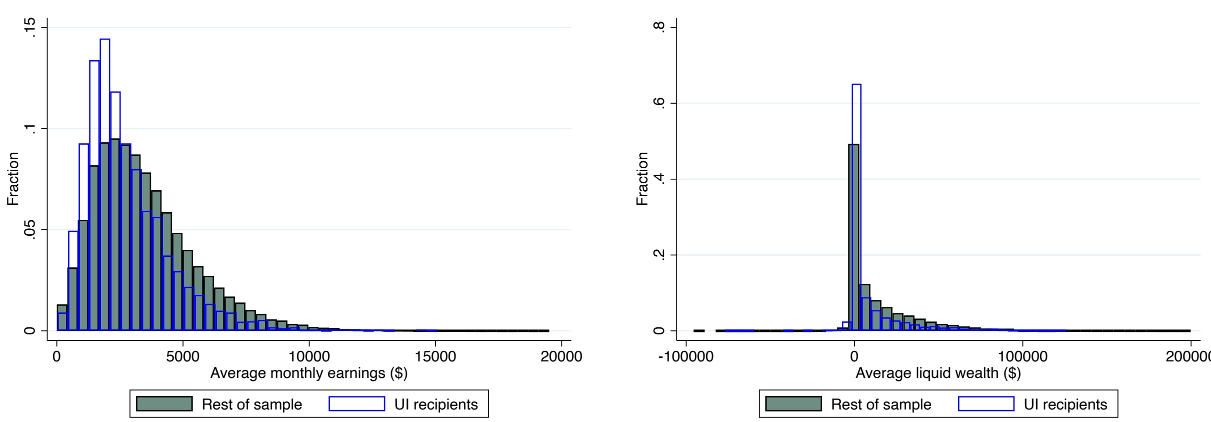
	Unemployment	UI Recipient
Avg. % time	1.8	1.0
Avg. % time, excluding top 10%	0.08	0
Avg. % time, excluding top 5%	0.65	0.14
% never	85.2	91.6

Notes: Table presents statistics summarising labour market experiences of workers in the SIPP sample during the period 1996-2013. Column (1) refers to being in unemployed, which includes unemployed worker receiving UI but also those who do not. Column (2) refers only to workers receiving UI.



(a) Gender (b) Education (c) Occupation

Figure 15. Worker characteristics by sub-sample



(a) Earnings (b) Liquid wealth

Figure 16. Average earnings & wealth distributions: UI recipients vs. Rest of sample

Table 9. Transition rates by group: SIPP 1996-2013

Transition rate	Aggregate (%)	Gender		Education		Occupation		Earnings		Wealth	
		Male	Female	>College	<College	Cognitive	Manual	<50th pct.	> 50pct	<50th pct.	>50th pct.
E-U	0.10	1.13	0.79	0.24	1.21	0.92	1.22	1.87	0.42	1.50	0.62
U-E	27.10	0.94	0.96	1.08	0.94	1.02	1.02	1.04	1.04	1.10	0.85

Notes: Table presents transition rates between employment and unemployment. Transition rates are computed as the average transition rate by group across the full sample period 1996m1-2013m11. The table reports the average transitions rates across the whole sample, and then reports ratios of transition rates for sub-groups over the whole sample.

Figure 16 plots earnings and wealth distributions. There are no marked differences in gender and educational attainment across the sub-samples. In terms of occupation, workers who are always employed for the duration of their time in the sample ('full-time employed') are much more likely to be in an occupation classed as cognitive nonroutine, whilst UI recipients are over-represented in manual routine occupations. Finally, UI recipients typically have lower average monthly (real) earnings and hold less liquid wealth.

These patterns are reflected when we examine worker transition rates between employment and unemployment in the SIPP sample by worker characteristic, in order to understand which worker characteristics are important for accounting for heterogeneity in unemployment risk. Table 9 displays the transition rates by worker characteristic as a ratio relative to the average transition rate for the sample. Notably, separations into unemployment from employment (the EU rate) vary substantially across worker characteristics. In addition to earnings and wealth (as documented in Birinci and See 2023), differences in educational attainment and occupation are also strongly associated with differences in separation risk, where workers with attainment greater than a college degree on average face much lower separation risk whilst workers in manual occupations (notably manual routine) face substantially higher separation risk. In contrast, there is much less heterogeneity in job finding rates by worker characteristic, where only educational attainment and wealth seem to display significant differences.

Only examining heterogeneity in flow rate between employment and unemployment ignores the fact that not all workers who are classified as unemployed or eligible for UI, or decide to claim UI even if they are eligible.[24] To quantify the relative importance of these characteristics for the likelihood that a worker claims UI in the sample we estimate cross-sectional logit regressions where the dependent variable is equal to 1 if the worker receives UI in the sample, and 0 if they do not. For observables that can change over time (such as educational attainment, occupation etc.) we take the value observed at the start of the period for which the individual is in the sample. We estimate various specifications, incrementally adding further worker-level observables. The results are displayed in Table 10. The most strongly associated characteristic (unsurprisingly) is the fraction of time spent a worker spends in unemployment. The results further suggest that having educational attainment beyond a College degree and being employed in a nonroutine occupation are key factors in reducing a worker's likelihood of

[24] Birinci and See (2023) calculate using the SIPP that on average only 57% of unemployed workers are elgible to claim for UI, and within those eligible only 61% actually claim UI.

Table 10. Effects of worker-level observables on UI receipt status

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-2.602***	-2.199***	-2.707***	-2.171***	-2.085***	-3.141***
Age	0.00223	0.000414	0.00103	-0.000587	0.000985	0.00697***
Experience	-0.00146***	-0.00121***	-0.00124***	-0.000111	-4.20e-05	0.000331*
Education						
High school		-0.159***	-0.115**	0.0246	0.0292	0.179***
Some further		-0.352***	-0.217***	-5.97e-05	0.00247	0.177***
College		-0.870***	-0.588***	-0.240***	-0.225***	-0.0369
>College		-1.367***	-1.042***	-0.619***	-0.593***	-0.447***
Occupation						
Manual Nonroutine			-0.150***	-0.411***	-0.422***	-0.414***
Cognitive routine			0.113***	-0.0425	-0.0407	-0.0483
Manual routine			0.671***	0.524***	0.521***	0.568***
Earnings & wealth						
Earnings percentile				-0.0160***	-0.0151***	-0.00794***
Liquid wealth percentile					-0.00429***	-0.00404***
% Unemp						13.31***
Standard controls	X	X	X	X	X	X
Observations	67,561	67,561	67,561	67,561	67,561	67,561

Notes: Standard additional controls for each logit model include gender, race & state of residence. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ using robust standard errors.

claiming UI in the sample. Interestingly, the position of a worker within the earnings or wealth distributions appear to be much less strongly correlated with claiming UI when we account for other observables.

Finally, we quantify the relative importance of worker characteristics in accounting for cross-sectional variation in the duration of UI spells by estimating a simple cross-sectional regression on the fraction of time spent claiming UI (conditional on claiming UI). The results for various specifications are presented in Table 11. The main takeaway is that whilst the estimated signs are as expected, the R^2 when we include all worker-level characteristics is still very low (0.031). These findings suggest that whilst there is significant heterogeneity in UI spell duration across workers, this does not appear to be well-explained by worker observables.[25]

[25] We find a similar story when we look at time spent in unemployment. See results in Table 12 in Appendix D.

Table 11. Accounting for fraction (%) time receiving UI

	(1)	(2)	(3)	(4)	(5)
Constant	0.0798***	0.0938***	0.0868***	0.0917***	0.0923***
Age	0.000517***	0.000503***	0.000549***	0.000539***	0.000547***
Experience	2.60e-05	2.73e-05	2.23e-05	2.93e-05*	2.97e-05*
Education					
High school		-0.0125**	-0.0125**	-0.0116**	-0.0116**
Some further		-0.0175***	-0.0168***	-0.0156***	-0.0157***
College		-0.0185***	-0.0167**	-0.0143**	-0.0141**
>College		-0.0200**	-0.0186**	-0.0152*	-0.0150*
Occupation					
Manual Nonroutine			-0.0183***	-0.0208***	-0.0209***
Cognitive routine			-0.00392	-0.00548	-0.00552
Manual routine			0.00978**	0.00810*	0.00805
Earnings & wealth					
Earnings percentile				-0.000126**	-0.000121*
Liquid wealth percentile					-2.68e-05
Standard controls	X	X	X	X	X
R^2	0.022	0.023	0.027	0.030	0.031
Observations	3,885	3,885	3,885	3,885	3,885

Notes: Standard controls for each regression model include gender, race & state of residence. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ using robust standard errors.

Table 12. Accounting for share (%) time unemployed

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0806***	0.101***	0.0961***	0.104***	0.103***	0.102***
Age	0.000412***	0.000391***	0.000398***	0.000386***	0.000371***	1.72e-05
Experience	-3.58e-05***	-3.13e-05***	-3.22e-05***	-1.78e-05	-1.83e-05	-3.79e-05***
Education						
High school		-0.0150***	-0.0150***	-0.0134***	-0.0134***	-0.0131***
Some further		-0.0254***	-0.0246***	-0.0226***	-0.0225***	-0.0210***
College		-0.0371***	-0.0351***	-0.0309***	-0.0310***	-0.0262***
>College		-0.0370***	-0.0351***	-0.0298***	-0.0301***	-0.0193***
Occupation						
Manual Nonroutine			-0.00686*	-0.0110***	-0.0109***	-0.000130
Cognitive routine			0.000320	-0.00257	-0.00253	-0.000898
Manual routine			0.00820**	0.00545	0.00548	0.000639
Earnings & wealth						
Earnings percentile				-0.000233***	-0.000241***	-0.000328***
Liquid wealth percentile					4.32e-05	4.79e-05
% time UI						0.507***
Standard controls	X	X	X	X	X	X
R^2	0.022	0.032	0.034	0.037	0.037	0.186
Observations	10,030	10,030	10,030	10,030	10,030	10,030

Notes: Standard controls for each regression model include gender, race & state of residence. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ using robust standard errors.