The Allocative Channel of Cyclical UI

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Abstract

This paper explores the *allocative* channel of cyclical UI policy. Changes in UI generosity can affect worker-firm sorting by discouraging the formation of poor quality matches between worker and firms, but also by slowing down the speed at which employed workers can relocate towards their preferred job-type. We characterise the allocative effects of cyclical changes in UI generosity through the lens of a sorting model in the spirit of Lise and Robin (2017). After providing some novel empirical evidence consistent with key model mechanisms using worker panel data, we carefully calibrate the model to match micro-level evidence and use the resulting framework to quantify the allocative channel of UI, the role of cyclical UI policy for worker-firm sorting patterns over the business cycle, and the implications for welfare. We find that a one-time increase in UI generosity *improves* the allocation of workers across jobs, and that over the business cycle countercyclical UI policy plays a significant role in amplifying the cleansing effect of recessions and improving worker-firm sorting. Finally, we find that UI cyclicality generates welfare gains: procyclical UI stabilises job creation incentives and helps alleviate the slowdown in worker reallocation during recessions, whilst countercyclical UI strengthens the cleansing effect of recessions. Overall the welfare gains from UI cyclicality are small.

Keywords: Sorting, UI, Complementarities, On-the-job search

JEL Codes: E24, E32, J63, J64, J65

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1 Introduction

Unemployment insurance (hereafter: UI) is a key social security programme for supporting the incomes of workers who involuntarily lose their jobs across all advanced economies UI, and plays an important role as an automatic stabiliser during recessions. In the United States, a distinctive feature of the UI system is that the generosity of support provided to eligible workers has varies according to the state of the economy: UI becomes *more generous* during recessions. This is partly systematic, where at the state-level the maximum period of eligibility that workers can claim UI is increased automatically when the unemployment rate of the state rises above some threshold.[1] Additionally there have also been discretionary interventions at the Federal level. Recent examples of the latter include the Emergency Unemployment Compensation (EUC) programme in 2008 as well as the CARES act in 2020.[2] The scale of these interventions has precipitated much debate among economists regarding the appropriate use of UI as a cyclical tool to counteract the adverse effects of recessions on workers losing jobs.

Through the lens of a standard Mortensen-Pissarides framework, increasing UI support during downturns typically amplifies the decline in employment by increasing worker's reservation wages and disincentivising job search, to which firms respond in equilibrium by reducing job creation. Taken together these forces further reduce the flow rate of workers from unemployment to employment and amplify the increase in unemployment.[3] We refer to this well-known effect as the *employment channel* of UI. Moreover, to the extent that unemployment tends to be inefficiently high during recessions (and inefficiently low during expansions), a policymaker in a Mortensen-Pissarides environment would typically opt for a *procyclical* UI policy precisely because because the employment channel of UI helps to stabilise employment fluctuations over the business cycle.[4]

In a richer environment which features *complementarities* in production between heterogeneous firms and workers, search frictions generate equilibrium misallocation in the labour market. Even allowing workers to search on-the-job in order to find better matches, in general workers will not be matched to their preferred firm-type in equilibrium (and vice versa). In this envi-

[1] This has been the case at least since 1970 with the introduction of the Extended Benefits (EB) programme. This legislated that maximum UI duration within a given state is automatically extended when the state-level unemployment rate exceed a certain threshold.

[2] The EUC act in 2008 increased maximum UI duration to 99 weeks across all states, whilst the CARES act in 2020 instead provided more generous income replacement for workers losing jobs due to the Covid-19 pandemic.

[3] For example, Marinescu and Skaldalis (2021) 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. Hagedorn et al. (2019) provide quasi-experimental evidence that changes in UI policy have adverse general equilibrium effects on firm job creation.

[4] Key examples of this result in the literature are Mitman and Rabinovich (2015) and Jung and Kuester (2015), who use standard general equilibrium search & matching models with representative workers and firms. Though in both of these papers the policymaker also has insurance considerations (i.e. workers are risk-averse and cannot self-insure), they both find that stabilising employment is preferred in welfare terms.

ronment, changes in UI policy also affect the allocation of workers across jobs: we refer to this as the *allocative* channel of UI.

The impact of changes in UI on the allocation of workers is *ex ante* ambiguous. For instance, increasing UI generosity increases incentives for workers to wait and search for job offers to which they are better suited, rather than accepting lower quality matches which carry higher separation risk going forward (e.g. Marimon and Zilibotti 1999). In equilibrium firms respond through both the *type* and number of jobs they create, and exacerbating job creation incentives slows down worker reallocation such that workers spend more time in worse matches. Given the growing evidence documenting the large amount of reallocation in the US labour market over the business cycle, it is a natural step to consider the role cyclicality in UI policy plays for observed worker-firm sorting patterns.[5]

This paper studies the allocative channel of cyclical UI policy and its implications for policy design. We seek to address the following questions: How important is the allocative channel of UI for worker-firm sorting over the business cycle? What are the normative implications for UI policy design? Shedding light on these questions is important for contributing to the debates on the appropriate design of UI policy over the business cycle.

The analysis in the paper proceeds in three steps. Firstly, we outline a model of labour market sorting in the spirit of Lise and Robin (2017) featuring production complementarities between heterogeneous firms and workers, endogenous job creation, on-the-job search and aggregate shocks. Additionally we allow for cyclicality in UI policy and an explicit characterization of the wage distribution following Lentz et al. (2016) to facilitate mapping to cross-section evidence on wages. Secondly, using worker panel data we provide new empirical evidence which is consistent with key features of the sorting model. Finally, we discipline the model using this micro-level evidence and use the resulting framework to characterise the allocative channel of cyclical UI, quantify its importance for worker-firm sorting, and study the implications for policy design. To my knowledge, this is the first paper which attempts to quantify the impact of cyclicality in labour market policy design on worker-firm sorting patterns over the business cycle.

The first contribution of the paper is empirical. Using microdata from the Survey of Income and Programme Participation (SIPP), firstly we document some descriptive statistics about worker characteristics and unemployment risk across different worker 'types'. We document that whilst lower-type workers tend to earn lower wages and hold less liquid wealth, we do not find large differences in characteristics such education or occupation by worker rank, consistent with the assumption that workers are *ex ante* heterogeneous in the model. We also document

[5] Recent contributions to this literature have studied how worker-firm sorting behaves over the business cycle, and have tended to find that recessions are times when the worker-firm allocation *improves*. See, for example, Haltiwanger et al. (2022), Crane et al. (2023) and Baley et al. (2023).

that the 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.

The main empirical contribution is to provide new evidence of the labour market effects of UI. We use the panel version of Jorda's (2005) local projection methods to estimate the effects of UI on key variables of interest, using the state-level UI shock series identified by Chodorow-Reich et al. (2019) as our source of exogenous policy variation. Firstly, we document novel evidence in favour of a key mechanism in the model: that wages become less sensitive to changes in UI as (i) a worker becomes better-matched, and (ii) the worker's bargaining power increases, both of which are strongly correlated with time spent in continuous employment. We document that on average wages are insensitive to changes in UI policy, but digging deeper using the worker panel we provide novel evidence that the only characteristic which contributes increasing wage sensitivity to UI is having recently experienced an unemployment spell, consistent with the theoretical prediction. Secondly, we provide new estimates for the elasticity of labour market flow rates to changes in UI, finding that an unexpected 1 month increase in UI duration is associated with a fall in the state-level job finding rate on impact (which unwinds fairly quickly), whilst the response of separations is essentially flat. These elasticities are crucial for the model to match, as they determine the quantitative importance of the employment channel of UI.

Next, we bring the model to the data and characterise the allocative channel of UI in our environment. We discipline the model to match standard labour market stocks and flows, the cross-sectional dispersion in wages and wage growth within and across jobs, as well as our estimates for the flow elasticities and the average level and cyclicality of UI. The resulting framework is also able to broadly match several untargeted features of the data. Our first main result is that the allocative channel of UI acts in the *opposite* direction to the employment channel in the calibrated model. We find that average productivity increases in response to a one-time increase in UI generosity, as the effect of destroying the least productive matches dominates the effect from slowing down the job ladder. Our next key result is that countercyclical UI strongly contributes to countercyclical sorting between workers and firms. Simulating the baseline model (where the generosity of UI is countercyclical, as in the data) alongside the counterfactual case where UI generosity is *acyclical*, we find that the degree of worker-firm sorting is strongly countercyclical under our baseline calibration (-0.34 corr. with output), whilst sorting is essentially acyclical under the counterfactual. Dissecting this result reveals that whilst countercyclical UI amplifies both the 'cleansing' and 'sullying' forces of recessions, the former effect is stronger quantitatively and is driven by the relative improvement of the sorting of high-type workers (at the expense of low-type workers), whose employment share at high-type firms rises and low-type firms falls.

Finally, we explore the welfare implications of cyclicality in the design of UI policy. Our main result is that in this environment countercyclical UI policy *can* deliver welfare gains relative to acyclical policy by strengthening the cleansing effect of recessions, which improves worker-firm sorting over the business cycle in our simulations. This is a novel result. Decomposing these welfare gains, we find that workers benefit more from both countercyclical and procyclical UI policy, but for different reasons. In contrast firms are only better off under a procyclical UI policy as this policy stabilises fluctuations in profit-making opportunities. Finally, whilst we find that countercyclical UI policy does generate welfare gains in this environment, these gains are quantitatively small in output terms.

Related literature. This paper contributes to several strands of the macro labour literature.

On the empirical front, we contribute to a voluminous literature on the empirical effects of UI.[6] Whilst there is a consensus that raising UI generosity increases unemployment duration for recipients through its effect on job search and acceptance behaviour, there is less consensus on the broader macroeconomic effects of UI on labour market outcomes where some papers find very small effects and other find somewhat larger effects. Within this literature our paper is most closely related to contributions by Chodorow-Reich et al. (2019) and Jäger et al. (2020). Chodorow-Reich et al. (2019) utilise the state-monthly UI shock series that they identify and construct to estimate the responses of state-level labour market aggregates to UI shocks. We supplement their analysis by using their shocks to study the effects of UI on the wages of different types of workers using panel data, as well as estimating the effects on labour force flow rates rather than stocks. Our findings that UI has relatively small effects on labour market flows complements their findings that the effects on stocks are also small. Our evidence on wage insensitivity also complement the findings in Jäger et al. (2020) who use quasi-experimental evidence from UI reforms in Austria. Relative to their paper, our contribution is to document empirical evidence for the United States that wage sensitivity to UI policy appears to be most strongly linked to a worker's recent labour market history.

With regards to theory, in addition to the vast literature on UI design, the paper brings together two different literatures: (i) a literature which studies labour market sorting between heterogeneous workers and firms, and (ii) a smaller literature looking specifically at the *cyclical* design of UI policy, often motivated explicitly by the design of UI in the United States.

More recent contributions to the literature on sorting has evolved beyond an essentially theoretical literature based on key contributions from Shimer and Smith (2000) to become a quantitative literature bringing rich models featuring worker and firm heterogeneity to micro-data.[7]

[6]See, for instance, contributions by Krueger and Meyer (2002), Rothstein (2011), Farber and Valetta (2015), Schmeider and von Wachter (2016), Hagedorn et al. (2019), Marinescu (2017), Johnston and Mas (2018), Marinescu and Skandalis (2021), Acosta et al. (2023).

[7]Several notable examples are Lise and Robin (2017), Hagedorn et al. (2017), Bagger and Lentz (2018) and Crane

The key contribution of this paper relative to this existing literature is to study the interaction labour market policies with worker-firm sorting in this environment. More specifically, we quantify the role of changes in UI policy for worker-firm sorting and the implications of this for macroeconomic outcomes in the labour market using a fairly standard framework from this literature, calibrated to match the effects of UI on labour market flows as well as cross-sectional wage dispersion. The most closely related paper in this literature is Lise et al. (2016), who use a similar environment and also examine the welfare implications of UI policy, but in the absence of aggregate shocks.

Our contribution relative to the small literature studying the *cyclical* design of UI policy equilibrium matching models is to study this question in an environment with two-sided heterogeneity. For tractability this literature has tended to abstract from issues relating to worker or firm heterogeneity. We show that in the presence of production complementarities between workers and firms, countercyclical UI policy *can* deliver welfare gains, which contrasts with the results in Mitman and Rabinovich (2015) and Jung and Kuester (2015).

The remainder of the paper proceeds as follows. Section 2 outlines a random search model with two-sided heterogeneity and worker-firm production complementarities, and illustrates how a change in UI generosity can affect the allocation of workers. Section 3 presents some empirical facts consistent with the model structure, as well as some new elasticity estimates we use subsequently to disciplinet the model. Section 4 details how we bring the model to the data, as well as report the model fit relative to targeted and untargeted outcomes. Section 5 explores the role of UI policy design by using the calibrated model to perform a policy counterfactual. Section 6 quantifies the welfare gains from different UI policies and examines how welfare gains are distributed between workers and firms. Section 7 concludes.

2 A Model of Labour Market Sorting

In this section we briefly outline a tractable model of worker reallocation over heterogeneous jobs proposed by Lise and Robin (2017). We make two modifications to their environment: (i) we propose a more parsimonious production function, primarily in order to reduce the number of parameters we need to identify when we bring the model to the data, and (ii) we allow for a more general functional form for the workers flow value of unemployment (which we interpret as UI) to allow for cyclicality in UI generosity. We then outline how in this environment a change in UI generosity affects the allocation of workers across jobs. For more details of the model see the Model Description in Appendix A and also Lise and Robin (2017).

et al. (2023).

2.1 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.[8] 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.[9]

UI policy. All unemployed workers receive UI income $b(x,z)$, which given by[10]:

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

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).[11] The function $\Psi(z)$ determines the generosity of UI in the model and is allowed to depend on the aggregate state (in order to allow for cyclicality). We propose

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

[9]This functional form differs from that used in Lise and Robin (2017) and Crane et al. (2023), 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.

[10]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.

[11]Specifying UI income as a markdown on flow output $p(x,y,z)$, 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.

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, 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.

2.2 Solution

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 worker mobility and job creation decisions in the model. In the second stage we can compute the dynamics of distributions, aggregates and wages via simulation using the surplus function we solve for in the first stage. More formally:

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 paths for 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.

2.3 Characterizing the Allocative Channel of UI

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, $v(y)$.

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. More generous UI acts as a subsidy for workers to search for longer and wait for better quality matches. This is illustrated in Figure 1, 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 line plots the optimal choice of firm-type $y^*(x,1)$, sometimes referred to in the literature as the 'Beckerian' allocation.[12] Whilst workers would ideally like to be located along the blue-dashed line, search frictions in the market mean that this allocation cannot be achieved. 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

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

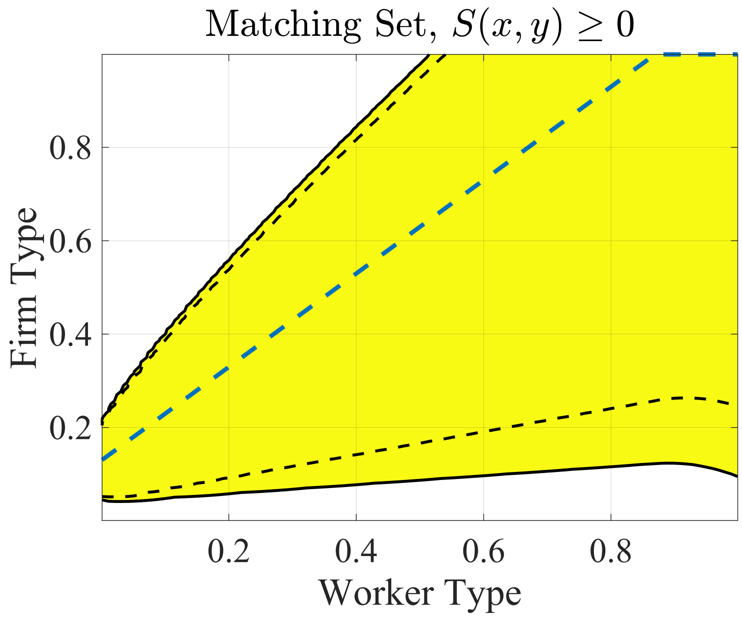


Figure 1. Illustrating how an increase in UI generosity $\Psi(z)$ contracts the matching set.

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 on the $y^*(x,z)$ plane. 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: workers will spend a longer time unemployed, and then spend more time in worse matches once they move into employment.

3 Empirical Evidence

In this section we document supporting evidence which is consistent with the model outlined in the previous section, as well as providing some new estimates of key elasticities we will use to calibrate the model. Firstly, we rank workers in the data following standard approaches in the literature and document facts about differences in characteristics and unemployment risk by worker rank. Secondly, we provide novel evidence that the key characteristic governing sensitivity of wages to changes in UI generosity is whether or not a worker has recently been unemployed, consistent with the predictions of the wage bargaining protocol assumed in the model with on-the-job search. Finally, we provide new estimates of the elasticities of separation and job finding rates to changes in UI generosity, which are key moments for our quantitative model to match.

3.1 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.[13] 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.

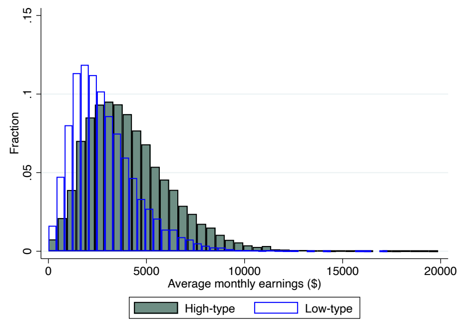
Sample construction. Following standard practice, we restrict our attention to workers between the ages 25-65 (i.e. prime age workers) who are not in the armed forces, who do not own businesses and are not self-employed. The resulting sample consists of 67,561 individuals observed for 30 months (2.5 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 B.

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.

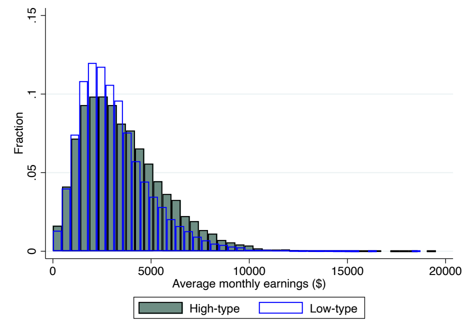
3.2 Ranking workers

To rank workers in the data 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 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, where higher-type workers will be able to earn higher wages in the labour market. More specifically, we regress real earnings on demographic characteristics and then rank workers by the average residuals of this

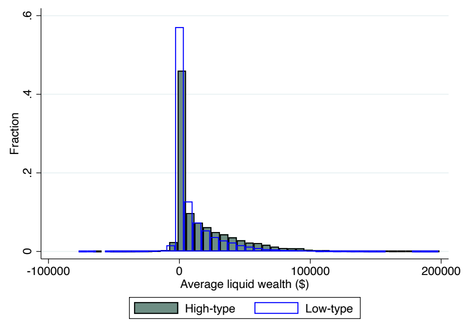
[13] Information regarding assets and liabilities is provided at a less than monthly frequency.



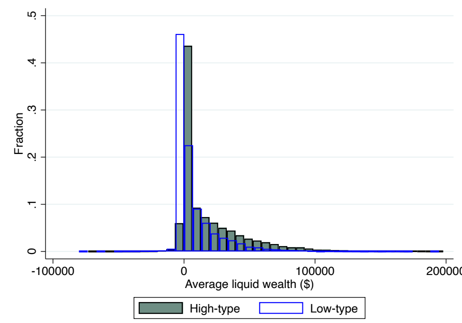
(a) Earnings (Ranking #1)



(b) Earnings (Ranking #2)



(c) Wealth (Ranking #1)



(d) Wealth (Ranking #2)

Figure 2. Earnings & wealth by worker rank

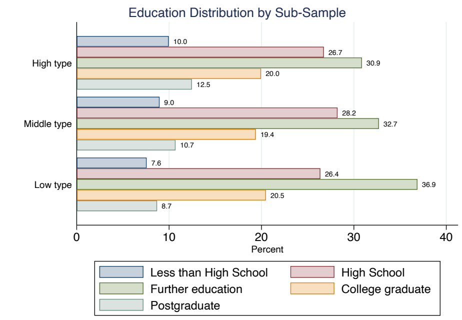
regression.

3.3 Descriptive statistics by worker rank

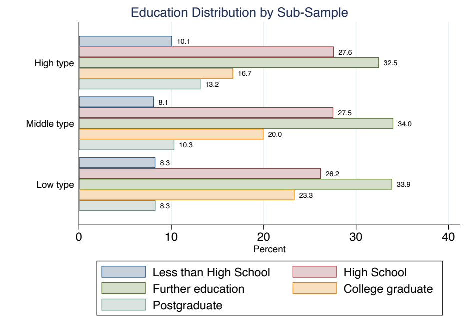
Characteristics. How do worker characteristics vary by rank? Figure 2 plots the earnings and liquid wealth distributions by worker rank, whilst Figure 3 plots the distribution across educational attainment and occupation by worker rank group. Overall lower rank workers on average have lower wages and accumulate lower liquid wealth, but there are not huge differences across worker ranks in terms of educational attainment or occupations.[14] This finding is broadly consistent with other recent literature (e.g. Gregory et al. 2022) who find observable worker characteristics do not account for the vast majority of the variation in labour market experiences across workers in the data, which is used to justify the same assumption of *ex ante* heterogeneity across workers.

Unemployment risk. By 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 these key flow rates vary across worker ranks. Across both ranking methods we find that the main driver of differences in unemployment risk is in the separation rate, where

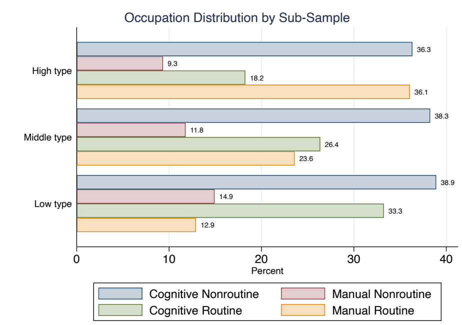
[14] In general we do not find any significant differences by worker rank across demographic characteristics.



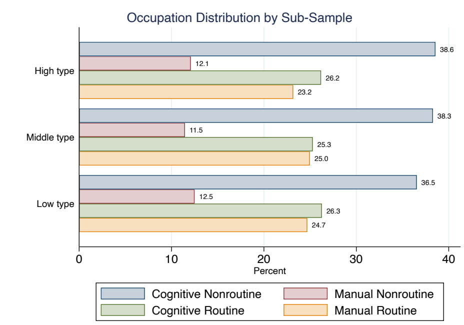
(a) Education (Ranking #1)



(b) Education (Ranking #2)



(c) Occupation (Ranking #1)



(d) Occupation (Ranking #2)

Figure 3. Education & occupation by worker rank

Table 1. Unemployment risk by worker rank

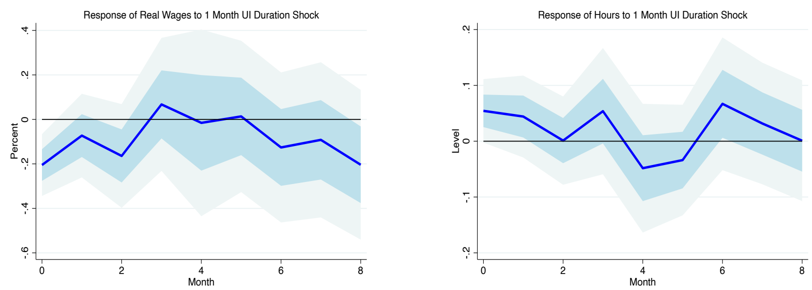
	Average (%)	Ranking #1			Ranking #2		
		Low	Mid	High	Low	Mid	High
EU	1.0	1.32	0.91	0.72	1.48	0.77	0.97
UE	27.10	1.08	1.01	0.93	0.94	0.93	0.71

low-rank workers face a separation rate that is more 30% higher than the sample average.[15] Through the lens of the theoretical model, this suggests that lower-ranked workers are on average located in matches that they are not well-suited to.

3.4 Wage sensitivity to UI

In the standard Mortensen-Pissarides paradigm the value of unemployment is a key determinant of the workers outside option and therefore wages via bargaining. In our environment where heterogeneous workers search on-the-job, equation (1) implies that the elasticity of the

[15]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.



(a) Real Wages

(b) Hours

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

wages to changes in $b(x,z)$ is given by:

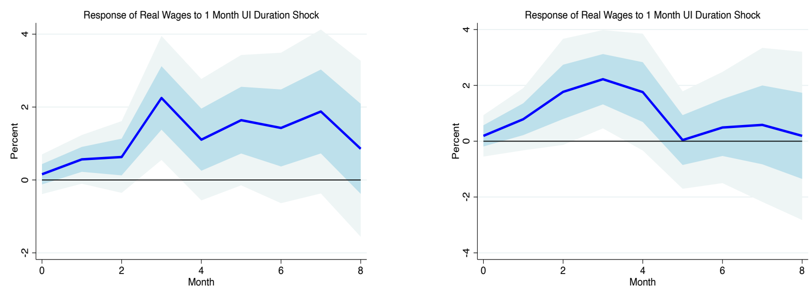
$$\varepsilon_{w,UI} = (1-\sigma) \cdot \frac{b(x,z)}{p(x,y,z)}$$

where σ is the worker's share of the match surplus, and $\frac{b(x,z)}{p(x,y,z)}$ is the flow value of UI as a fraction of total match output. Both objects are heterogeneous across workers. In the model, σ is assumed to be zero when a worker is hired from unemployment but then subsequently increases endogenously whilst workers are employed and therefore are able to search on-the-job and use credible offers to bargain up their share of the surplus. At the same time $\frac{b(x,z)}{p(x,y,z)}$ falls for an individual worker during an employment spell as they become better matched via on-the-job search such that $p(x,y,z)$ increases relative to $b(x,z)$. Overall the model predicts higher wage sensitivity to UI for workers who have recently been hired from unemployment, as these workers are more likely to have lower bargaining power σ and to be mismatched relative to their preferred job-type (lower $p(x,y,z)$).

To test the model's predictions, we estimate impulse responses to Chodorow-Reich et al. (2019) UI shocks using a panel version of Jordà's (2005) local projections. More specifically, we estimate the following regression specification for each time horizon $h \geq 0$:

$$(\Delta_h)y_{i,s,t+h} = \left(\sum_{k=-\kappa}^{h} \gamma_h \varepsilon^{UI}_{s,t+k}\right) \times \mathbb{1}_{i\in\mathcal{I}^x} + \sum_{j=1}^{L} \delta_h' \mathbf{X_{i,s,t-j}} + \phi_{i,h} + \phi_{s,h} + \phi_{t,h} + \nu_{i,t+h} \tag{3}$$

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, $\mathbb{1}_{i\in\mathcal{I}^x}$ is an indicator function for whether or not an individual worker is part of a sub-sample of the data, where $\mathcal{I}^x$ 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

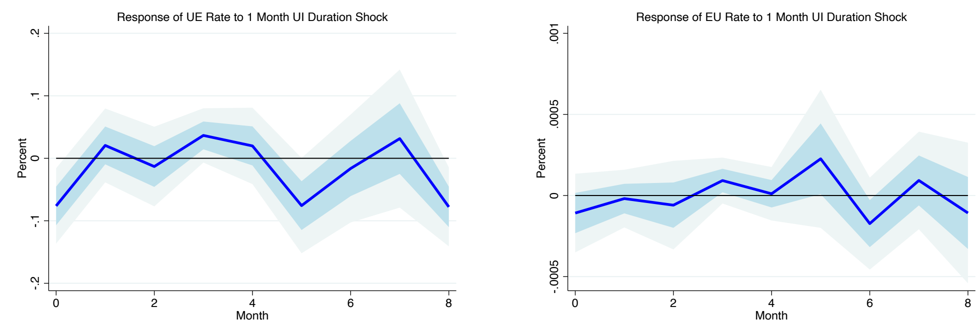
Average effect. The left panel of Figure 4 plots the responses of wages worked using the whole sample to identify the average effect of an increase in UI generosity.[16] The response on impact is very small (if anything actually slightly *negative*) and is statistically insignificant thereafter. To assess the response of overall earnings to a UI shock in the data on average we also identify the average effect on hours worked, which we also find is highly insensitive to changes in UI. Overall through the lens of the model the insensitivity of wages to changes in UI suggest both that on average workers are able to command a sizeable share of the match surplus and/or are reasonably well-matched such that the flow value of unemployment relative to employment is small.

Effect by worker characteristic. Which worker characteristics are important for determining the sensitivity of wages to changes in UI in the data? To address this we re-estimate the wage responses by sub-sample according to characteristics such as worker rank, education, occupation, wealth, and finally labour market experience. In the almost all instances we do not find significantly different estimates relative to the full sample based on these observed characteristics.[17] Figure 5 instead plots the estimated wage responses for the sub-samples of workers who report claiming UI or being unemployed during 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 suggests that whether or not a worker experiences unemployment (in the short-time they are in the SIPP) is a key characteristic in determining the sensitivity of wages to UI, consistent with the predictions of the sorting model.[18]

[16] We estimate the cumulative changes in the variables, though 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.

[17] See Appendix ? for these results.

[18] Note that we do not identify whether this result in the data is driven by the fact that recently unemployed workers have lower bargaining power or because they are more likely to be mismatched.



(a) UE Rate

(b) EU Rate

Figure 6. Estimated responses of job finding and separation rates

3.5 Estimating flow elasticities to UI

Finally, we also provide new estimates for the response of unemployment risk to UI. More specifically, we estimate the elasticity of the separation (EU) and job finding (UE) rates to changes in UI generosity. For our purposes, these elasticities are crucial for the model to match as they determine how changes in UI affect average unemployment risk for workers, and therefore the overall adverse effect on employment from an increase in UI. First, we construct state-level flow rates from our panel sample based on standard definitions (e.g. Fujita and Ramey 2009).[19] We then estimate the elasticities via panel local projections again using the general specification in (3). Figure 6 plots the estimated impulse responses of state-level job finding and separation rates to an unanticipated increase in UI duration. We find that a significant fall in the UE rate on impact (-0.075 p.p), 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, raising by around 0.0003 p.p.[20] In the next section we use these estimates to discipline the quantitative model.

3.6 Summary

This section has documented some new facts which are consistent with some of the key assumptions and mechanisms in the model of sorting, as well as providing some new estimates of key elasticities for the purpose of carefully calibrating the effects of UI in our model. Firstly, ranking workers using standard methods in the literature reveals that worker rank is not strongly correlated with other standard demographic characteristics among workers, whilst heterogeneity separation risk is the key driver of heterogeneity in unemployment risk across different types of workers in the labour market, consistent with our model of sorting. Secondly, we document the

[19]Unfortunately we are not able to look at disaggregated 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.

[20]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 again robust to adding a large number of individual-level controls, allowing for lagged/future shocks, and controlling for seasonality.

insensitivity of the wage on average whilst finding that only recent experience of unemployment or claiming UI matter for the sensitivity of wages to UI, again consistent with the model of sorting and in particular the assumptions around wage bargaining. Finally, estimating the elasticities of key labour market flow rates to UI which determine unemployment risk, we find a significant response on the job finding rate but a flat response on separations.

4 Quantification

This section outlines how we bring the model to the data. We present the strategy for parameterizing the model, before examining both targeted and untargeted model outcomes under the baseline parameterization.

4.1 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. As is well-known this choice of matching function ensures that worker-firm contact rates are always bounded between $(0, 1)$. Firm and worker contact rates as a function of tightness θ_t are given respectively 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. The interest rate 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).[21] 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 remaining set of parameters using the method of moments, with weights chosen to minimize the relative distance between the model and empirical moments. All parameters are estimated jointly. In this environment there is not a straight-forward one-to-one mapping from some parameters to moments in the data. In what follows, we instead provide a heuristic argument of which parameters are most relevant for each moment 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.[22]

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.[23]

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 replacement rate of $\mathbb{E}[b/w]$ equal to the average replacement rate in the SIPP, which is 0.47. We

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

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

[23] 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 choose we target the value reported in Morchio (2020) for the NLSY79 as this sample observes worker histories for a longer duration than in the SIPP. On average in our sample an individual is observed 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.

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 over our sample period equal to -0.4621, indicating that UI generosity in the data is indeed strongly countercyclical.

The vacancy cost function $c(v)$ controls how job creation responds to changes in the profitability of producing, as well as determining the shape of the equilibrium employment and unemployment distributions. As changes in UI policy affect match profitability and the behaviour of job creation is a key determinant of unemployment risk in the mdoel, we identify the parameters in $c(v)$ by targeting the estimated elasticities of the EU and UE flow rates to a UI policy shock presented in the previous section.

Identifying the shape of the production function $p(x, y)$ in the presence of worker-firm complementarities is notoriously challenging. Hagedorn et al. (2017) and Bagger and Lentz (2018) show that worker-firm complementarities can be identified using information of job-side information on productivity and duration. However given that we only use panel data on workers we adopt the approach taken in Lise et al. (2016) who emphasise that the production function parameters can be identified in a similar environment using information on the variances of wages and wage growth, both within and across jobs. The relative returns to x and y captured by the parameters $\{p_1, p_2\}$ are related to the variances of wage growth from both staying and switching jobs, whilst the strength of complementarities p_3 can be identified using information on cross-sectional wage inequality, as the wages of workers who are searching on-the-job for better matches will diverge.

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 reasonably satisfactory, except for a few targets: the concentration of unemployment, the replacement rate, and the degree of wage inequality. Despite featuring two-sided heterogeneity, the model is still unable to generate sufficient unemployment concentration in the cross-section. The model struggles to match the level of unemployment whilst getting the wage replacement rate correct. Finally, the model struggles to generate sufficient wage dispersion relative to the data.

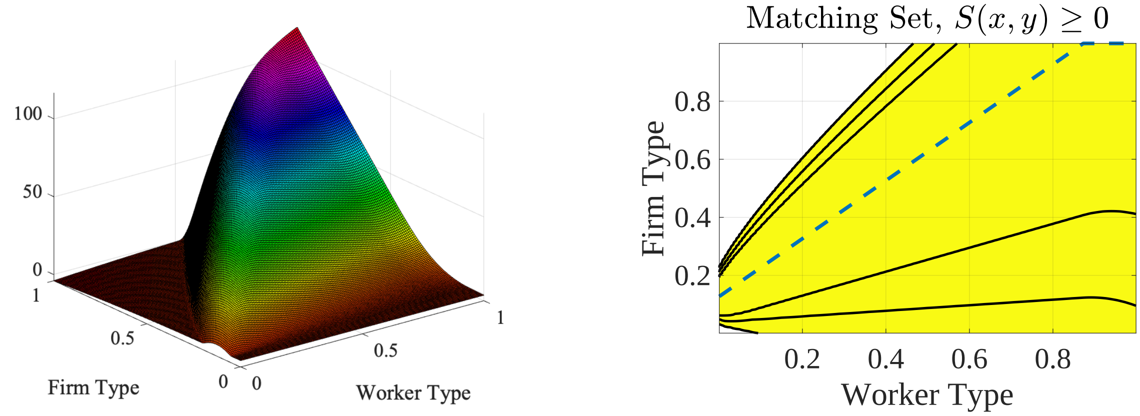
The calibrated parameters are listed in Table 3. UI policy in the model is countercyclically generous ($b_1 = -0.984$) in order to match the features of the data. The distribution of worker heterogeneity differs from Lise and Robin (2017) and Crane et al. (2020), with most workers being located in the middle of the range for $x \in [0, 1]$ rather than being right-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. We also estimate significantly more convex costs of job creation, in order to match our estimated UI elasticities.

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
$\mathbb{E}[U]$	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)
$\epsilon_{UE,b}$	-0.075	-0.059	SIPP
$\epsilon_{EU,b}$	0.0003	0.0003	SIPP
$\mathbb{E}[\text{sd } w]$	0.650	0.538	SIPP
$\mathbb{E}[\text{sd } \Delta w]$	0.216	0.151	SIPP
$\mathbb{E}[\text{sd } \Delta w \| EE]$	0.403	0.360	SIPP

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

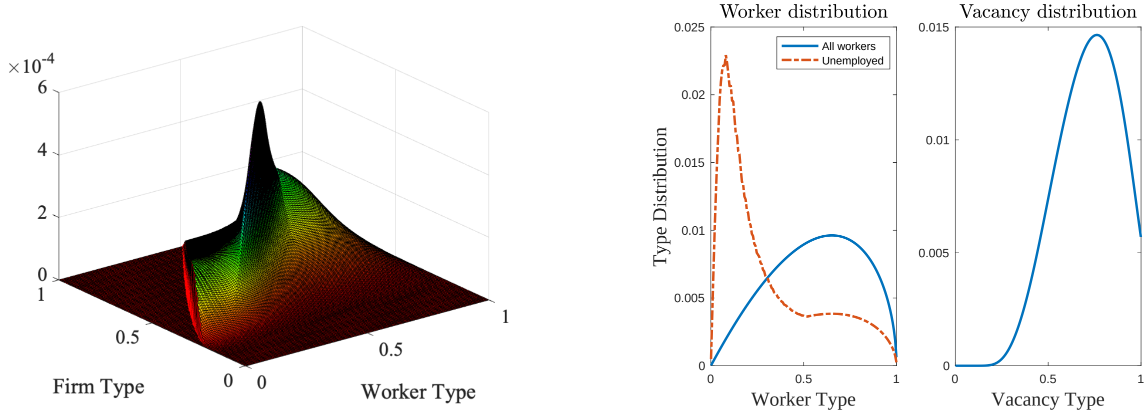
Figure 7. Surplus function and matching sets

4.2 Model outcomes

In this section we examine 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 vacancies in Figure 8b. 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 equilibrium is driven by low-type workers being matched to high-type firms. Figure 8b illustrates that under our baseline calibration the distribution of workers is slightly right-skewed but with most mass around the middle. Nevertheless, the dis-



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

(b) Worker and vacancy distributions

Figure 8. Model equilibrium distributions

tribution of unemployment is highly left-skewed towards the lowest types in order to match the concentration of unemployment in the data. This left-skewness itself is driven by the fact that the distribution of vacancies is concentrated around high-type firms, with relatively few low-type jobs created.

4.3 Untargeted outcomes

Despite being untargeted it is instructive to see whether the calibrated model can replicate some other key features of the data. Namely, we examine the implications of the model for: (i) differences in unemployment risk across workers by rank, (ii) the earnings distributions by worker rank, and (iii) the model-implied sorting patterns across worker-firm matches.

Unemployment risk. Table 4 displays the ratios of EU and UE transition rates by worker type relative to the average rate.[24] The patterns for the separation rate are very close to what we see in the data, where separation risk is declining in a worker's type. However the pattern for the UE transition 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. This is not reflected in the data, where we found that job finding rates do not strongly correlate with worker rank.

Earnings distribution. Figure 9 compares the relative earnings distribution between high- and low-type workers in the model with the equivalent in the SIPP data. Qualitatively we see that the model is able to replicate the same right-skewness of the earnings distribution for low-type workers that we find in the data. It also generates the higher average earnings of high-type workers.[25] However the model does not generate the same right-skewed shape for the high-

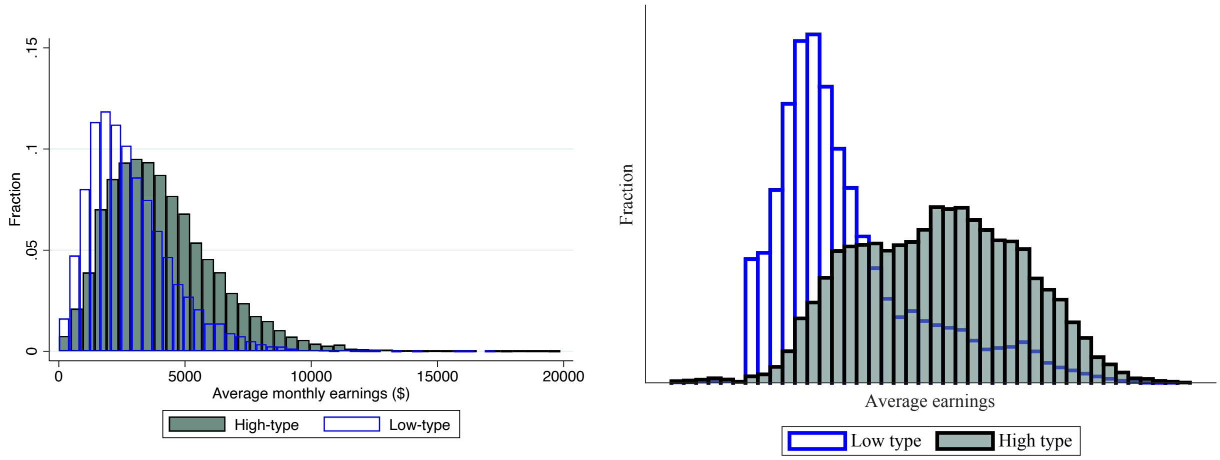
[24]Note that we target these rates but instead use values from the BLS rather than the SIPP.

[25]Note that the ranking method being used in this case is not based on earnings, but instead on time spent in

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

Notes: Table presents ratios of worker transition rates to average transition rate by worker rank, where average the EU and UE rates are targeted moments.



(a) Data

(b) Model

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

type worker earnings distribution. This is potentially one of the sources of difficulty the model has in generating sufficient wage dispersion in the estimation.

Worker-firm sorting. We compare the model-implied patterns of worker-firm sorting with values reported in the literature.[26] The results for Low and High-type workers are presented in the upper panel of Table 5. The 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. In the middle panel of Table 5 report the results from the same exercise for the firm distribution. 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 due to declining worker contact rates, meaning that the

non-employment.

[26]Specifically, we use the empirical moments presented in Crane et al. (2020) using linked employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD) covering the same sample period, i.e. is 1994-2014. Following the same approach we rank workers as before, and rank firms by their poaching share out of total hires in the economy. We then regress the first-difference in the worker/firm tercile employment share on the first-difference in the aggregate unemployment rate as the cyclical indicator used in their empirical exercise.

Table 5. Sorting patterns: Data vs. Model

Tercile	Data	Model
Worker distribution:		
Low	-44.9	-10.65
High	31.6	11.74
Firm distribution:		
Low	12.0	17.13
High	-8.9	-7.31
High-type workers &:		
Low-type firms	9.80	-1.69
High-type firms	11.0	13.41
Low-type workers &:		
Low-type firms	-8.30	-3.47
High-type firms	-18.1	1.99

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. Empirical moments taken from Crane et al. (2020).

poaching of workers from low-type firms falls.[27]

Finally, in the bottom panel we consider the behaviour of the *joint* distribution of workers across firms. 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. 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 this 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 relative to what Crane et al. (2020) document.

5 Characterising the Allocative Effects of UI

In this section we first characterise the effect of UI on the overall allocation of workers across jobs. We then quantify its role for worker-firm allocation patterns over the cycle by using the

[27]Note that one of the contributions of Crane et al. (2020) is to document that their empirical findings are broadly consistent with the Lise and Robin (2017) sorting framework we use in this paper.

calibrated model to run a counterfactual experiment. Finally, we then document the implications for aggregate outcomes such as employment, productivity and output.

5.1 UI shock

How does the worker-firm allocation respond to a one-time increase in UI generosity? Figure 10 plots the impulse responses of several key model aggregates. These are responses to an unexpected increase in the average level of UI generosity b_0, which is comparable to the empirical UI shock we previously used to estimate elasticities.[28] We find that average worker productivity *increases* in response to an increase in UI generosity, which pushes up on output. In other words, the allocative channel of UI acts in the opposite direction to the employment channel under the baseline calibration. For the overall allocation of workers across jobs, the contraction of the matching set towards the optimum allocation (such that the least productive matches are no longer profitable for either firms or workers) dominates the slowing down of job-to-job reallocation from declining job creation. Figure 10 also illustrates the standard employment channel of UI, which pushes down on output. Overall the employment channel still dominates quantitatively such that aggregate output falls. Moreover, whilst the effect of the UI shock on both channels is increasing for lower levels of aggregate productivity z, quantitatively the contribution of the employment channel increases by more. In isolation these results suggest that even in this richer environment, although increasing UI improves the allocation of workers across jobs the effect on employment still dominates, and that this even more the case during downturns.

5.2 Cyclical worker-firm sorting

Does cyclicality in UI policy matter for the dynamics of the worker-firm allocation? To answer this question we simulate the model and compare outcomes to those under the alternative policy where UI is *acyclical*, i.e. $b_1 = 0$. We use the within-job correlation between worker and firm-types (x, y) as a simple measure to keep track of how well allocated workers are across jobs. More specifically, we define $\rho_{xy,t} = \text{corr}_t(x, y)$ as a sorting index at time t. Table 6 reports the cyclical behaviour of the sorting index under the baseline policy and counterfactual. Our headline result is that moving from a countercyclical to an acyclical UI policy significantly reduces the countercyclicality of worker-firm sorting in the calibrated model, from being strongly countercyclical ($\text{corr}[\rho_{xy}, Y] = -0.34$) to being almost acyclical ($\text{corr}[\rho_{xy}, Y] = -0.01$). Cyclicality in the design of UI policy therefore appears to have a significant impact for the dynamics of worker-firm sorting through the lens of the model.

[28]The UI shocks in the data are unexpected 1 month increases in the *duration* of UI income, rather than increases in its level. Unlike in the data, in the model UI income does not expire. To address this discrepancy between model and data, we compute the equivalent value of one additional month of UI income as a fraction of the average wage

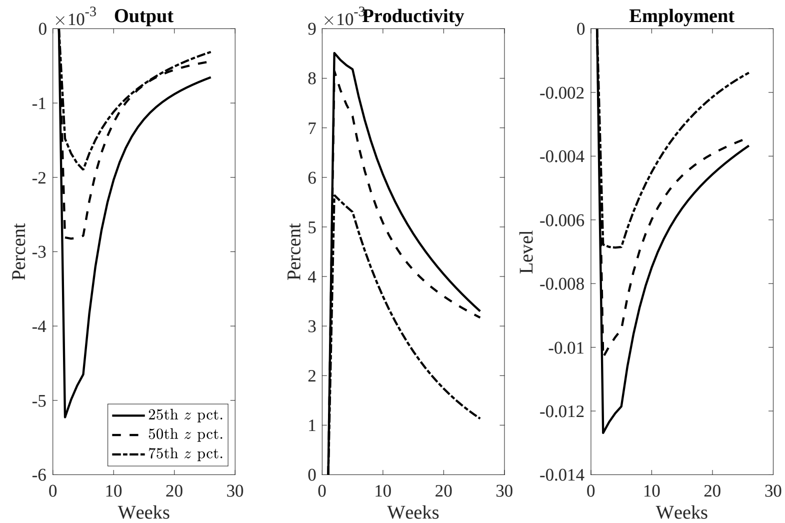


Figure 10. Impulse response to a 1 month increase in UI generosity

Table 6. Cyclicality of sorting

Moment	$b_1 = -0.984$	$b_1 = 0$
$\text{sd}[\rho_{xy}]$	0.039	0.046
$\text{corr}[\rho_{xy}, Y]$	-0.338	-0.011

To understand what drives this result, we look deeper into how worker-firm sorting patterns change with b_1. The results are reported in Table 7. As before, the top two panels document the effects on the worker and firm distributions in isolation, whilst the bottom panels examine the the joint worker-firm match distribution. Moving to an acyclical UI policy leads to the cleansing effect on the worker distribution being somewhat muted. The fall in low-type and increase in high-type employment shares in recessions are both smaller, though quantitatively these differences do not appear to be large. On the firm side, moving to an acyclical UI also appears to reduce 'sullying' forces, where the increase (fall) in the employment share of low(high)-type workers is significantly muted relative to $b_1 < 0$. Taken together, moving to an acyclical from a countercyclical UI policy is associated with a weakening of worker distribution cleansing and a reduction in firm distribution sullying during recessions.

Examining the sorting patterns across worker-firm matches, moving to an acyclical UI policy dampens the increase in high-worker/high-firm matches during recessions, whilst the share of high-worker/low-firm matches increases (rather than decreases). Both these effects contribute to worse overall sorting via its effect on high-type workers.[29] In contrast, moving to an acycli-

in the data. We then assume that the shock is an increase the replacement rate by this amount.

[29] Note that whilst in the model this channel contributes to acyclical UI dampening the cleansing effect of the recession relative to the baseline policy, this pattern is actually consistent with the evidence in Crane et al. (2020).

Table 7. Sorting patterns: Counterfactual

Tercile	$b_1 = -0.984$	$b_1 = 0$
Worker distribution:		
Low	-10.65	-9.74
High	11.74	9.35
Firm distribution:		
Low	17.13	12.0
High	-7.31	-2.13
High-type workers &:		
Low-type firms	-1.69	0.50
High-type firms	13.41	10.49
Low-type workers &:		
Low-type firms	-3.47	-1.56
High-type firms	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.

cal UI policy is also associated with dampening the decline in low-worker/low-firm matches during recessions, as well as a declining share of low-worker/high-firm matches, both of which contribute to improving overall sorting via the effect on low type workers.

Overall therefore we find that the impact of the allocative channel of UI on high-type workers is what drives the overall pattern in the sorting index. In contrast, as low-type workers are relatively more constrained in terms of the amount of firms they are productive at, they are relatively more affected by the larger fall in job creation and worker reallocation.

5.3 Aggregate implications

The results from the previous section documented that the cyclical design of UI has a significant impact on the allocation of workers across jobs over the business cycle in the calibrated model. What are the implications of this for aggregate outcomes?[30] To address this, we present quantitative results from: (i) the responses of the economy to a one-time recessionary shock lasting for 1 quarter (12 weeks) under the different UI policies, and (ii) simulation evidence from the same counterfactual experiment as the previous section.[31]

[30] Ultimately, the implications of worker-firm allocations for aggregate productivity and output crucially depend on the production function, and in particular the costs of misallocation (captured by the p_3 parameter). In following section where we look at welfare we therefore take this into account by computing welfare for different values of p_3.

[31] For the recession experiment, we set the size of the shock equal to one standard deviation of z in the model, σ.

Figure 11 presents the response of the economy to a recessionary shock under the two different policy scenarios. The shock is unexpected from the perspective of all agents in the economy and its duration is assumed to be unknown. The responses again illustrate the two different channels of countercyclical UI policy, i.e. the employment channel and the allocative channel. In the recession, the employment channel generates higher unemployment (around 1.5 p.p extra) relative to the acyclical counterfactual, which amplifies the fall in output driven. At the same time the improvement in worker-firm sorting via the allocative channel dampens the fall in average worker productivity (and therefore output). Consistent with the previous finding for the UI shock, we find that the employment channel dominates in our simulation on impact such that output falls by more in the recession under countercyclical UI policy. However overall the quantitative difference between the two policies in terms of the output effect is small ($< 0.01\%$).

Upon the unwinding of the recession after 1 quarter, we find that unemployment unwinds much faster under countercyclical UI policy whilst productivity overshoots its steady state level. The faster employment recovery is associated with a larger expansion in the size of the feasible matching set as the recession unwinds and additional UI support is withdrawn. Productivity overshoots because at the point the shock unwinds there is now a greater share of matches located closer to the optimal allocation, meaning the recovery in aggregate productivity z generates higher output returns than otherwise. Moreover, the improvement in worker-firm sorting from countercyclical UI is very persistent, as once better matches are formed it takes the exogenous destruction of productive matches to reduce $\text{corr}_t(x, y)$ (in the absence of any further shocks to z).[32]

Finally, the simulated moments from the model under the baseline UI policy and the counterfactual reported in Table 8 tell a similar story. Acyclical UI policy reduces unemployment and job creation volatility, but is also associated with an increase in the volatility of average labour productivity in the economy due to the weakening of the cleansing effect during recessions (and therefore matches on average being further away from the optimal allocation). Overall, we find that output volatility is marginally reduced under an acyclical UI policy, though the difference is quantitatively small.

5.4 Summary

In summary, results from the quantitative model suggest that: (i) increasing UI tends to *improve* the worker-firm allocation in quantitative model, i.e. the allocative channel of UI acts in the opposite direction to the employment channel, (ii) cyclicality in UI policy appears to have a sig-

[32] Note that under acyclical UI we find that the improving in sorting initially declines upon the unwinding of the shock, but then begins to improve again as the job ladder recovers and workers begin moving towards better matches via on-the-job search.

Table 8. Cyclical moments: Counterfactual

Moment	$b_1 = -0.984$	$b_1 = 0$
sd$[U]$	0.178	0.125
sd$[V]$	0.224	0.165
sd$[EU]$	0.291	0.298
sd$[UE]$	0.336	0.342
sd$[w]$	0.135	0.080
sd[prod.]	0.079	0.085
sd$[Y]$	0.092	0.089
corr[prod., Y]	0.973	0.975
corr$[EU, Y]$	-0.042	-0.017
corr$[UE, Y]$	0.481	0.348

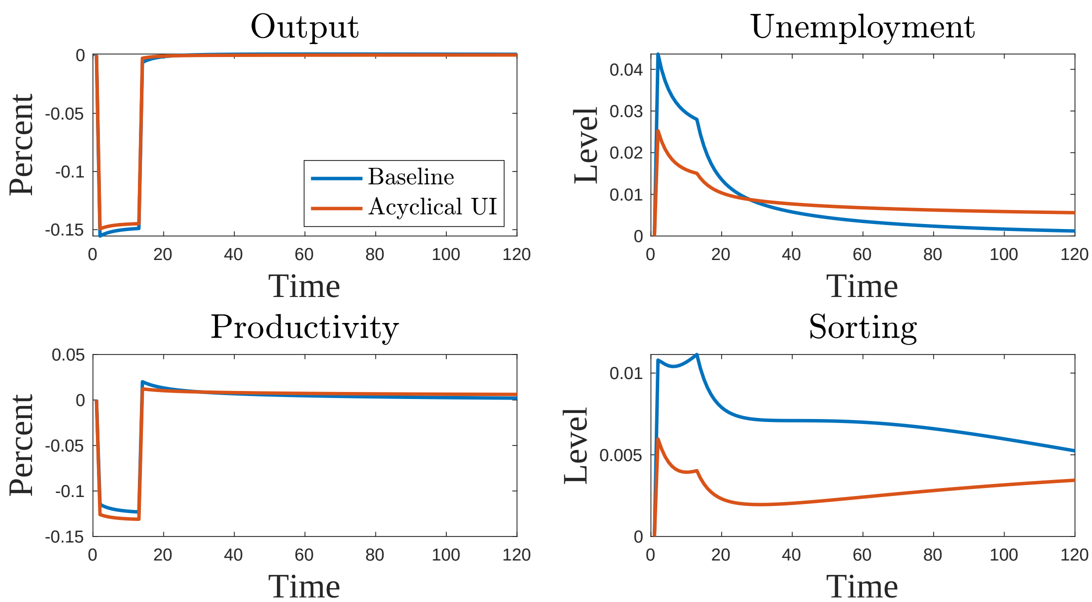


Figure 11. Recession under alternative UI policies

nificant impact on worker-firm sorting patterns over the business cycle, where countercyclical UI strengthens the cleansing effect of recessions, and (iii) taking into account allocative effects, countercyclical UI is still associated with an increase in output volatility, though this increase in quantitatively small. In the next section we move on to conduct more formal welfare analysis to assess the desirability of cyclicality in UI design.

6 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 performance of different cyclical designs of UI policy in this environment. We also examine how this is affected by the importance of worker-firm complementarities in production, captured by the p_3 parameter, which controls the importance of the worker-firm allocation for aggregate output in the model.

6.1 Computing social welfare under alternative UI policies

Social welfare Ω is defined as standard, i.e. the present discounted value of social output (output + UI income of unemployed), net of the costs of job creation. In our environment this can be written formally as:

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

Figure 12 plots the difference in social welfare ($\Delta\Omega$) relative to the acyclical case (i.e. $b_1 = 0$), normalized by steady state annual GDP.[33] We compute Ω for a range of values of b_1 and p_3. The first panel illustrates the full shape of social welfare as a function of $\{b_1, p_3\}$, whilst the second panel only illustrates this for selected values of p_3 to more easily show the role of changing the strength of worker-firm complementarities for social welfare.

Our main result is that for all values of p_3, we find that welfare gains relative to an acyclical policy are U-shaped in UI cyclicality, b_1. As has been emphasised in existing literature, procyclical UI ($b_1 > 0$) delivers welfare gains in the presence of search frictions and endogenous job creation via the employment channel by stabilising fluctuations in employment.[34] Reducing UI generosity during downturns increasing the size of the feasible matching set and therefore allows more jobs to be profitable than otherwise (though these jobs are located further from the optimal allocation). Whilst this worsens the cleansing effect of recessions, by stabilising job creation incentives this policy also dampens the decline in job-to-job transitions during recessions, which tapers the sullying effect. One caveat to this in our environment is that UI must be *sufficiently* procyclical (relative to $b_1 = 0$) to generate sufficient gains to outweigh the losses from weakening the cleansing effect of recessions.

Contrary to existing literature, we also find that *countercyclical* UI delivers welfare gains in this environment. To our knowledge this is a novel result. In a standard Mortensen-Pissarides environment an increase in UI generosity increases total UI income both directly and indirectly (via the employment channel), as well as reducing output costs from reduced job creation. But in terms of the overall impact on social welfare over the business cycle these effects are dominated by the effect on aggregate output via the employment channel such that countercyclical UI generates welfare losses. In this environment the negative impact on output during downturns is

[33] Here we follow the approach taken in Garcia-Cabo et al. (2023), though we define $\Delta\Omega$ in deviations from the acyclical case rather than from steady state. Note that under both policies the model steady state is identical. We compute welfare over the same simulated series for z.

[34] For example, see the results in Mitman and Rabinovich (2015) and Jung and Kuester (2015).

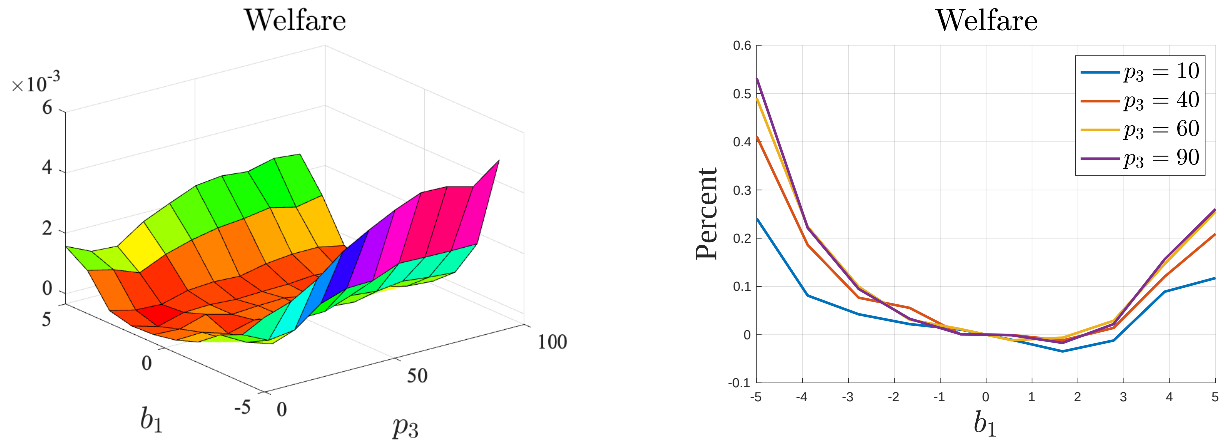


Figure 12. Social welfare under different $\{b_1, p_3\}$ combinations

mitigated by the presence of the allocative channel of UI.The strengthening of the cleaning effect of recessions in the presence of countercyclical UI policy means that the joint distribution over worker-firm matches $e(x, y)$ on average lies closer to the optimal allocation. Overall, consistent with the findings from the previous section on the aggregate implications of the allocative effects of UI, we find that quantitatively the welfare gains from cyclicality in UI policy are not large.[35]

Secondly, we find that in both cases the relative welfare gains from either procyclical or countercyclical UI policy are increasing in the strength of production complementarities. When p_3 is relatively large, the output costs from misallocation are higher and the feasible matching set is smaller on average. For procyclical UI policy, as equilibrium unemployment is higher for larger values of p_3 the welfare gains via the employment channel from countercyclically increasing the size of the matching set will consequently be larger, whilst the benefits from preserving job creation incentives (and therefore greater worker reallocation) are also increasing in p_3. For countercyclical UI policy, again the productivity gains from improved worker-firm allocation via the strengthening of the cleansing effect of recessions will also be larger when the output costs of misallocation are higher.

[35]In all cases considered, welfare gains from cyclical UI policy are $<$ 1% annual GDP.

6.2 Decomposing welfare gains from cyclical UI

How are the welfare gains from cyclical UI policy distributed? We can decompose overall social welfare into welfare for workers and firms:

$$\Omega \equiv \Omega^w + \Omega^f$$

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

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

For firms, welfare is the present discounted value of all match profits (match output minus wage costs), net of the costs of creating jobs:

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

Figure 13 plots the decomposition of welfare gains between workers and firms for the same exercise as above. The main takeaway from this exercise is that the distribution of welfare gains from UI cyclicality differs across workers and firms.

We can see instantly from the left panel of Figure 13 that for workers the pattern of welfare gains follows that of the aggregate (Figure 12). When UI is procyclical the welfare gains are again driven by stabilising the share of workers receiving UI. Under this policy workers on average spend longer in employment (where they earn wages) versus unemployment, whilst the slowdown in job-to-job transitions during recessions is mitigated. In the case of countercyclical UI, the welfare gains accruing to workers are instead driven by improving the average allocation of workers across jobs via the strengthening of the cleansing effect of recessions. Workers may spend less time in employment on average, but among those workers who are employed they are on average located in better matches, which improves average productivity and wages (via sequential bargaining). Again we find the gains from countercyclical UI for workers are increasing in the output cost of misallocation, p_3.

For firms the picture is very different. In contrast to workers, firms are unambiguously worse-off under countercyclical UI policy. This is driven by the fact that firms do not have an outside option other than being matched with a worker, and under this policy the size of the feasible matching set (and therefore opportunities for making profits) is strongly procyclical. Welfare gains for firms are instead increasing in the procyclicality of UI, as reducing UI generosity when aggregate productivity decreases expands the set of feasible matches during downturns and increases opportunities for firms to make profits.

6.3 Welfare in a recession

Finally, we compute welfare losses in the model from the same recession experiment from before under alternative UI policies. We use the same recession exercise from the previous section. In this case, we compute the change in social welfare $\Delta\Omega$ relative to the absence shocks as a fraction of annual GDP. Again we compute $\Delta\Omega$ for a range of values for $\{b_1, p_3\}$. The results are plotted in Figure 14. In contrast to the welfare results under stochastic simulation, we find that for a one-off unexpected fall in aggregate productivity, welfare losses are *decreasing* in the countercyclicality of UI generosity. Whilst the initial rise in unemployment is decreasing in the degree of procyclicality b_1, the subsequent benefits from higher productivity matches formed during the recession and the faster recovery in employment when the shock returns to steady state are *increasing* in the degree of UI countercyclicality. Overall, we find that for our calibration the latter effects of countercyclical UI during the recovery phase dominate over the simulation period. Finally, the importance of worker-firm complementarities for productivity captured in p_3 only serve to amplify this result.

7 Conclusion

In this paper, we have explored the role of the allocative channel of UI for worker-firm sorting patterns, as well as its' normative implications for the design of UI policy. Using panel data on workers, we provide new evidence for several key assumptions underpinning the relatively standard model of labour market sorting we use to address these issues. After disciplining the model using this micro-level evidence, we use the calibrated framework to characterise the allocative channel of UI, quantify its impact for worker-firm sorting patterns over the cycle using counterfactual simulations, and study its' welfare implications. Overall we found that the effects of cyclical UI policy on worker-firm sorting dynamics appear significant through the lens of the model, and that countercyclical UI policy can achieve welfare gains in this environment by strengthening the cleansing effect of recessions and improving the average allocation of workers across jobs.

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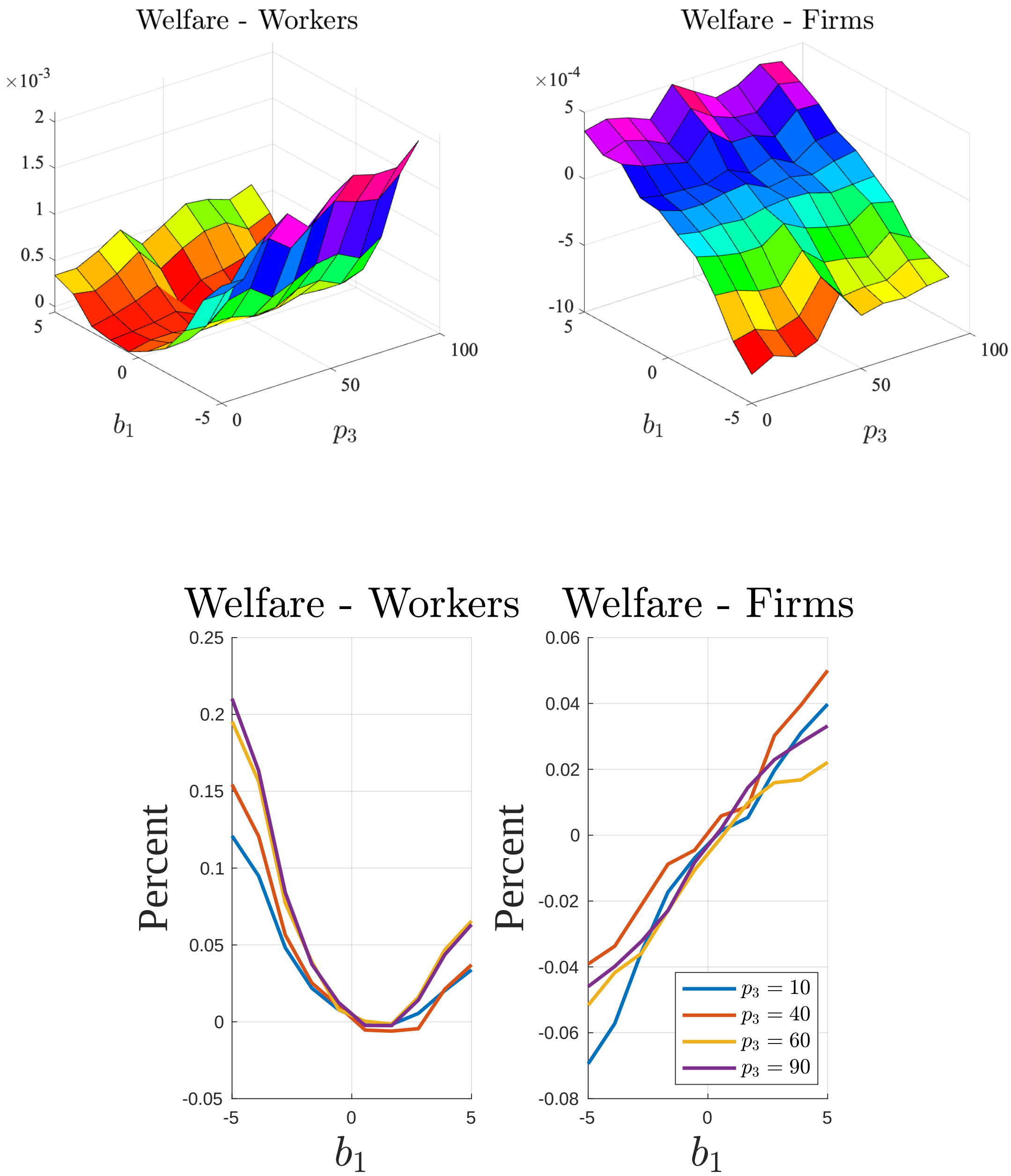

Figure 13. Distribution of welfare gains: Workers vs. Firms

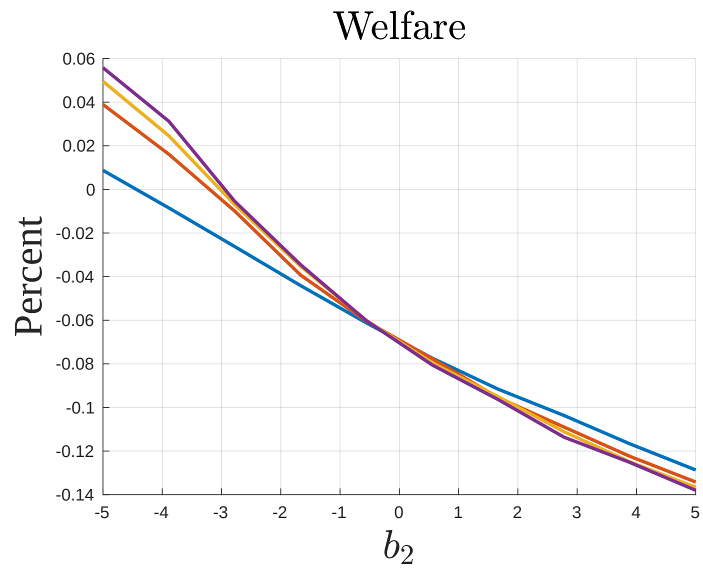

Figure 14. Social welfare in a recession under different UI policies

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A Model Appendix

A.1 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.

A.2 Value Functions

Being unemployed with productivity x and aggregate productivity z has value

$$\begin{aligned} U_t(x) &= b_t(x) + \beta \mathbb{E}_t \left[(1 - f_{t+1}) U_{t+1}(x) + f_{t+1} \int E_{0,t}(x,y) \frac{v_{t+1}(y)}{V_{t+1}} dy \right] \\ &= b_t(x) + \beta \mathbb{E}_t U_{t+1}(x) \end{aligned} \tag{4}$$

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

$$
\begin{aligned}
P_t(x,y) &= p_t(x,y) \\
&+\beta\mathbb{E}_t\Bigg[(1-(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}U_{t+1}(x) \\
&+(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}\Bigg((1-sf_{t+1})P_{t+1}(x,y) \\
&+sf_{t+1}\int \max\{P_{t+1}(x,y), W_{1,t+1}(x,y',y)\}\frac{v_{t+1}(y')}{V_{t+1}}dy'\Bigg] \\
&= p_t(x,y) \\
&+\beta\mathbb{E}_t\Bigg[(1-(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}U_{t+1}(x) \\
&+(1-\delta)\mathbb{1}\{P_{t+1}(x,y)\geq U_{t+1}(x)\}P_{t+1}(x,y)\Bigg]
\end{aligned} \tag{5}
$$

where the second equality follows by imposing the sequential auction conditions.[36] Defining the match surplus as $S_t(x,y) = P_t(x,y) - U_t(x)$, and combining the values defined above, we have

$$S_t(x,y) = p_t(x,y) - b_t(x) + (1-\delta)\beta\mathbb{E}_t \max\{S_{t+1}(x,y), 0\} \tag{6}$$

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.

A.3 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.[37] 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

$$c'(v(y)) = q(\theta_t)J_t(y) \tag{7}$$

[36] 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.

[37] 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

$$\begin{aligned} J_t(y) &= \int \frac{u_{t+}(x)}{L_t} \max\{S_t(x,y),0\}dx \\ &+ \int\int \frac{se_{t+}(x,y)}{L_t} \max\{S_t(x,y) - S_t(x,y'),0\}dxdy' \end{aligned} \tag{8}$$

A.4 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:

$$\sigma' = \begin{cases} S_{t+1}(x,y)/S_{t+1}(x,y') & \text{if } S_{t+1}(x,y') > S_{t+1}(x,y), \\ S_{t+1}(x,y')/S_{t+1}(x,y) & \text{if } \sigma S_{t+1}(x,y) < S_{t+1}(x,y') \leq S_{t+1}(x,y), \\ \sigma & \text{if } S_{t+1}(x,y') \leq \sigma S_{t+1}(x,y) \end{cases} \tag{9}$$

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:

$$\begin{aligned} w_t(\sigma, x, y) \quad = \quad & \sigma p_t(x,y) + (1-\sigma) b_t(x) \\ & -(1-\delta)\beta \mathbb{E}_t \left[\mathbb{1}\{S_{t+1}(x,y) \geq 0\} s p(\theta_{t+1}) \int \left[I_{t+1}(\sigma, x, y, y') - \sigma S_{t+1}(x,y) \right] \frac{v_{t+1}(y')}{V_{t+1}} dy' \right] \end{aligned} \tag{10}$$

A.5 Labour Market Flows

The law of motion for unemployment is

$$u_{t+1}(x) = u_{t+}(x) \left[1 - \int f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} dy \right] \tag{11}$$

and for employment

$$\begin{aligned} e_{t+1}(x,y) \quad = \quad & e_{t+}(x,y) \left[1 - \int s f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y') \geq S_t(x,y)\} dy' \right] \\ & + \int e_{t+}(x,y') s f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq S_t(x,y')\} dy' \\ & + u_{t+}(x) f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} \end{aligned} \tag{12}$$

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 $\mathcal{W}_t(\sigma, x, y)$:

$$\begin{aligned} \mathcal{W}_{t+1}(\sigma, x, y) \quad = \quad & \mathcal{W}_{t+}(\sigma, x, y)\left[1 - sf_t + \int sf_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x, y') \leq \sigma S_t(x, y)\} dy'\right] \\ & + \int e_{t+}(x, y') sf_t \frac{v_t(v)}{V_t} \mathbb{1}\{\sigma S_t(x, y) > S_t(x, y')\} \\ & + u_{t+}(x) f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x, y) \geq 0\}, \end{aligned} \tag{13}$$

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 $\mathcal{W}_t(0, x, y)$.

A.6 Equilibrium

(to be added)

B Data Description

B.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"

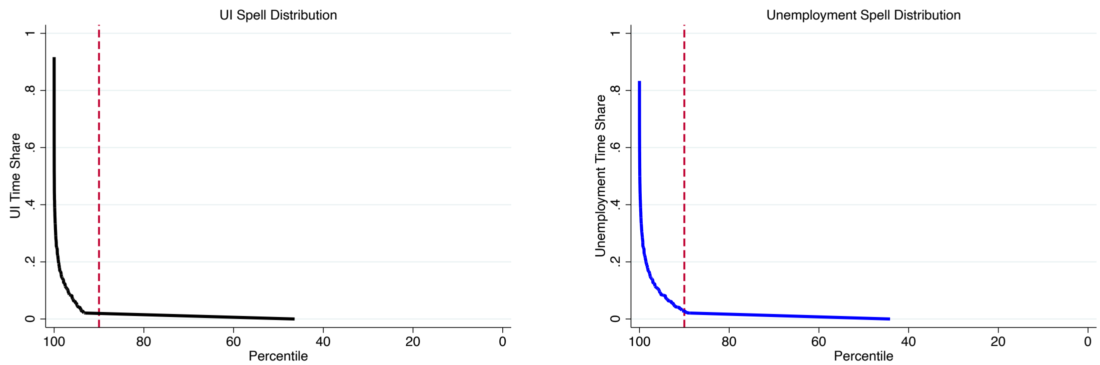
Following Lise (2012) and Baley et al. (2023) we trim the top and bottom 0.5% of the distribution to reduce the influence of outliers on the results.

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 recoding 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).

B.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.



(a) UI Time Distribution

(b) Unemployment Time Distribution

Figure 15. Labour force status: Distributions by time

Table 9. 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

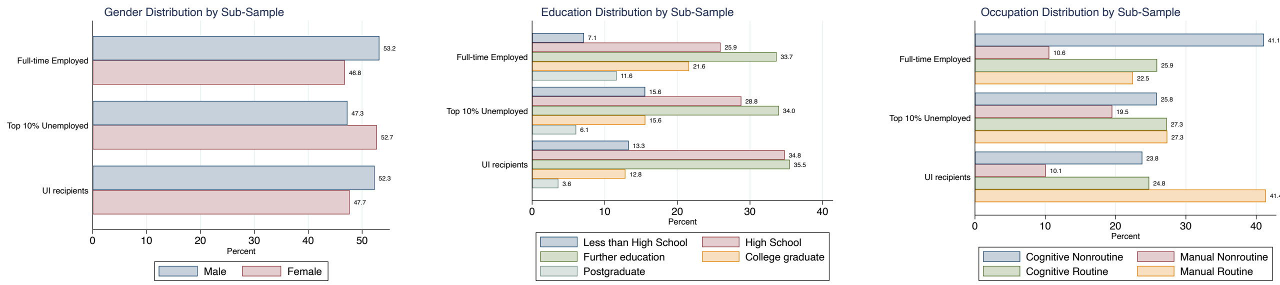
Notes: Table presents statistics summarising labour market experiences of workers in the SIPP sample during the period 1996-2013. Column (1) refers to being in unemployed, which includes unemployed worker receiving UI but also those who do not. Column (2) refers only to workers receiving UI.

C 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).[38] Figure 15 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 9 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.

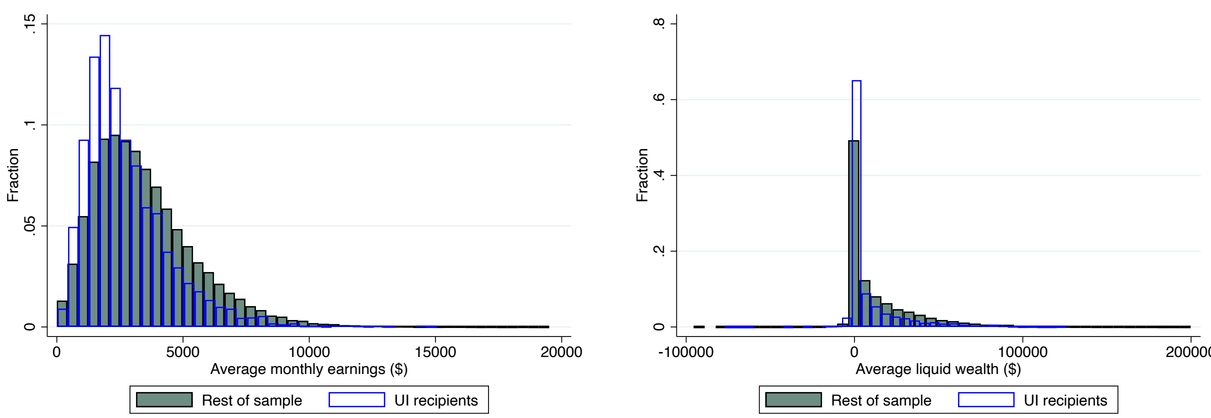
Characteristics of UI recipients. What are the characteristics of the workers who receive UI in our sample? Figure 16 plots selected demographic characteristics by sub-sample, whilst Figure 17 plots earnings and wealth distributions. There are no marked differences in gender and educational attainment across the sub-samples. In terms of occupation, workers who are

[38] 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).



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

Figure 16. Worker characteristics by sub-sample



(a) Earnings (b) Liquid wealth

Figure 17. Average earnings & wealth distributions: UI recipients vs. Rest of sample

Table 10. 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.

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 10 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.[39] 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 11. 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 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

[39] 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 11. 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.

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 12. 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.[40]

[40]We find a similar story when we look at time spent in unemployment. See results in Table 13 in Appendix C.

Table 12. 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 13. 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.