Essays on Cyclical Labour Market Dynamics and Policy



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This thesis consists of four self-contained chapters, all of which relate to topics on cyclical labour market dynamics and the appropriate design of labour market policies. In Chapter 1 we first compare alternative labour market policy responses to a recession, namely: (i) countercyclical UI expansions as used in the US, and (ii) match subsidies used in several European economies. Through the lens of a canonical matching model with endogenous separations and insurance considerations by risk-averse workers, whilst expanding UI reduces the consumption drop for workers who lose jobs we find that subsidising match continuation is more effective at providing insurance due to its stabilising effect on separations and tightness. Chapter 2 then studies the implications of countercyclical UI policy for the *allocation* of workers across jobs over the business cycle, through the lens of a matching model with sorting. After disciplining the model using novel evidence from worker panel data, we find that countercyclical expansions in UI significantly amplify the cleansing effect of recessions. Whilst this improves the average allocation of workers over the cycle, the associated welfare gains from the policy are small. Chapter 3 instead focuses on the role of fluctuations in labour force participation. Motivated by key empirical facts using worker flows data for the UK, we develop a tractable search & matching model where non-employed workers are heterogeneous in search effort and participation is determined relative to an exogenous threshold. Recessions are times when the composition of job searchers shifts towards workers with higher attachment, as in the data. Our framework is able to account for the estimated cyclical behaviour of all labour force flows, and we find that this composition channel of the participation margin is important for explaining the spike in unemployment at the onset of the Great Recession. Finally, Chapter 4 proposes a novel labour market amplification channel based on heterogeneity in stochastic discount factors across households. After outlining the key mechanism in a stylised matching environment, we embed this into a TANK model extended to allow for search frictions and quantify the direction and strength of amplification under a standard calibration, finding that amplification is significant for demand shocks but negligible for supply shocks.

Statement of Originality

Supervisors This thesis was supervised by Professor Francesco Zanetti and Professor Andrea Chiavari.

Total words This thesis contains approximately 71,890 words. This word count has been calculated by calculating the number of words on a representative page (455 words inc. footnotes, page 2) and multiplying by the number of pages, excluding the cover and the tables of contents (159 pages).

Notes for the reader Chapter appendices are provided for each chapter. These appendices contain additional details on models and data used in each chapter, as well as additional results and proofs.

Statement of authorship The work in this thesis is based solely on research carried out by myself as a doctoral student at the University of Oxford between October 2019 and April 2024. No part of this thesis has been submitted for a degree at the University of Oxford or any other university. Chapters 1, 2 and 4 are single-authored and are fully my own work. Chapter 3 is co-authored with Tomas Key and Bradley Speigner, both Bank of England. The views expressed in this chapter are those of its' authors, and not necessarily those of the Bank of England or its committees. This work has benefited greatly from feedback and discussions with faculty and fellow students at the Macro Working Group seminars in the Department, discussions with staff at the Bank of England during my time there as an intern, as well as at several external conferences and workshops I have presented at during the course of my time as a graduate student.

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Chapter 1

Insuring Matches or Workers? Labour Market Policy in Recessions

Abstract

Should policymakers increase direct insurance to workers during recessions as in the US, or seek to provide insurance to existing employment relationships by subsidising the continuation of matches as in Continental Europe? This paper seeks to shed light on this question through the lens of the matching framework developed in Jung and Kuester (2015) featuring risk-averse workers, who face uninsurable income risk in the labour market and make an endogenous search decision when non-employed, and endogenous job destruction. In this fairly environment, changes in UI and employment subsidies have opposite effects on labour market tightness via their effects on job creation and destruction, which has welfare implications through its effect on worker income risk. We use a calibrated version of the model to perform a policy experiment where we quantify the importance of the different effects of UI and employment subsidies on worker income risk during a recession. Overall, we find that although expanding UI reduces the cost of job separation to workers, increasing employment subsidies are more effective at offsetting heightened income risk during a recession via their effect on tightness. Moreover, we find that this result is robust to whether the labour market is 'flexible' and characterised by lower levels of policy support and higher worker turnover on average (e.g. the US), or more 'rigid' (e.g. Germany).

Keywords: *UI, Match subsidies, Risk aversion, Search & matching*
JEL Codes: *E24, E32, J63, J64, J65*

1.1 Introduction

Significant rises in job separations accompanied by large falls in labour demand during recessions has long been associated with inefficiencies which policy has a role in addressing. For instance, a large body of evidence documents that unemployed workers bear an excessive amount of the cost of downturns which they are unable to fully insure against (e.g. Jarosch 2021). Recognition of this concern has led to almost all advanced economies establishing some sort of unemployment insurance (hereafter: UI) system to provide partial income insurance for unemployed workers, though the nature of UI differs hugely across countries.[1] The resulting high levels of unemployment are also commonly thought to reflect an inefficient allocation of resources, or more specifically an under-utilization of labour (e.g. Michaillat and Saez 2021). In practice this has led some countries to adopt employment protection policies such as "short-time work" schemes (hereafter STWs) to incentivize firms to keep hold of workers during downturns by subsidising the costs of maintaining an employment relationship.[2]

In the face of very large recessions, policymakers have frequently sought to intervene to extend existing policy support to the labour market. This has been particularly evident during the last two major recessions: the Great Recession in 2008 and the Covid-19 pandemic recession in 2020. Though as recently emphasised by Giupponi et al. (2022), policymakers across advanced economies have made *different* choices regarding the nature of these interventions. More specifically, policymakers in the US have (for the most part) have tended to invest more resources in providing greater insurance directly to workers during recessions by making existing UI policy more generous.[3] In contrast, Western European economies in particular have opted to invest more resources into extending employment protection schemes in order to prevent 'excess' layoffs which would otherwise lead to higher unemployment and a greater under-utilization of labour.

A common reason put forward for cross-country differences in labour market policy responses to recessions is differences in underlying labour market institutions

[1] See Schmeider and von Wachter (2016) for a recent review of the UI literature.

[2] STWs are used in several major European economies, most notably Germany, France, and Italy. Compared to UI, such schemes are far from universal across advanced economies.

[3] As noted in Chapter 1, notable examples of this are the Emergency Unemployment Compensation (EUC) Act in 2008, as well as the Coronavirus Aid, Relief and Economic Security (CARES) act in 2020.

and structures.[4] For instance, compared to the US the German labour market is characterised by employment subsidies in the form of *Kurzarbeit* (a longstanding short-time work scheme), greater employment protection legislation, a higher degree of collective bargaining, and higher replacement rates, all of which contributes to lower turnover rates (separation and job finding) as well as higher average unemployment. The rationale is that in a more 'rigid' labour market with lower turnover rates (such as Germany) it takes unemployed longer to find new jobs, and therefore the welfare gains from preserving matches during downturns are potentially higher.[5]

This paper seeks to address the following questions: Should policy focus on providing insurance for workers or employment matches during downturns? Does this choice depend on existing design of labour market institutions? We answer these questions through the lens of a fairly standard general equilibrium matching model in the Mortensen and Pissarides (1994) tradition, calibrated to match standard labour market moments and then used to simulate policy counterfactuals during a recession and evaluate the welfare implications of policy alternatives. Furthermore, we repeat the analysis for alternative calibrations of the model ('flexible' vs. 'rigid' labour market) in order to examine the effect of existing labour market institutions for the findings.

Given our purposes, we adopt the framework developed in a series of papers by Jung and Kuester (2015), Ignaszak et al. (2020) and Jung et al. (2021), who extend a standard matching model to allow for endogenous job separations, risk-averse workers who are unable to insure income against unemployment risk, and an endogenous search decision. This environment has several important features for our purposes. Firstly, uninsurable endogenous income risk from unemployment allows a role for publicly-provided insurance to improve welfare of risk-averse workers by alleviating this risk. Secondly, allowing for an endogenous search choice captures the idea that search effort by non-employed workers is endogenous to UI, which captures the moral hazard concerns emphasised in the UI literature. Finally, endogenous separations are an important part of the analysis as a

[4]It is well documented that labour market institutions and policies differ hugely across economies, and that this goes some way to explaining cross-country differences in labour market outcomes. For notable contributions, see Lazear (1990) and Boeri (2010)).

[5]Historically, since Giersch (1985) the literature has often referred to this characterization of European labour markets compared to the US as 'eurosclerosis'.

key rationale of STWs as used in European economies is to preserve a number of existing job matches that would otherwise have separated during the downturn.

After calibrating the model to match salient features of the US labour market, we simulate a recession and study the welfare implications of adopting several policy alternatives: (i) increasing the level of UI, or (ii) investing the same amount of resources in subsidising existing employment relationships. In the model we find that whilst increasing UI directly reduces the income cost of job separations, it also *amplifies* the effect of the recession on income risk via its effect on job creation and tightness. In contrast, introducing employment subsidies dampens the effect of the recession by reducing job separations. Our first main result is that a cost-equivalent investment into subsidising matches is preferred to increasing the level of UI, as this more effectively insures the average consumption level of workers through the stabilization of labour market tightness which reduces income risk by ensuring that unemployed workers are reallocated into new jobs relatively faster.

In contrast, even though increasing UI provides more direct insurance to individual unemployed workers such that they enjoy a higher consumption level, a greater fraction of workers spend time in unemployment and the average duration of an unemployment spell is longer than otherwise. We find that this latter effect quantitatively dominates in terms of the overall effect on consumption insurance. Nevertheless, in this environment UI still achieves welfare gains via its effect on non-market channels, or more specifically the reduction in job search disutility and an increase in leisure utility enjoyed by the larger share of non-employed workers, which are typical features of models allowing for a search decision by non-employed workers (e.g. Mitman and Rabinovich 2015).

To examine the role of the underlying labour market institutions for our findings, we repeat the policy experiments after re-calibrating the model's structural and policy parameters to instead match key features of the German labour market, as an example of a more 'rigid' labour market (in comparison to the US). Our second main finding is that our results appear robust to underlying design of labour market institutions. If anything, the result goes in the other direction: we find that the destabilising effect from increasing UI is much smaller in a rigid labour market. In this environment where worker turnover is slower, increasing UI instead contributes positively to insuring average worker's consumption during a recession, as the direct benefits from higher consumption in unemployment are no longer offset by the increase in the share of workers spending more time in unemployment

during the downturn. As a result, the relative welfare gains from extending match subsidies versus expanding UI support are actually slightly smaller than for the US calibration.

Outline. The rest of the paper is structured as follows. The remainder of this section summarises the broadly related literature. Section 1.2 outlines the model framework we utilise for our policy experiments. Section 1.3 details the quantification. Section 1.4 outlines the baseline policy experiment and presents the main results. Section 1.5 studies the impact on the baseline results from an alternative calibration of the model to the German economy. Section 1.6 relates the key results to other key contributions in the literature. Section 1.7 concludes.

1.1.1 Related literature

The present paper is related to several different strands of literature studying the role of unemployment insurance and employment protection policies specifically, and their implications for the aggregate labour market from both a positive and a normative standpoint.

Unemployment insurance. There is a vast theoretical and empirical literature studying the effects of UI on the labour market and its optimal design. The key trade-off the theoretical literature has focused on has been the benefits of publicly providing income insurance to workers versus the implications of this for the labour market via changing job search incentives both for workers themselves (i.e. moral hazard concerns) as well as general equilibrium effects such as the job creation incentives for firms (via effects on wages and congestion externalities).[6] Empirically, whilst there is a large amount of evidence suggesting that in the case of individual workers an increase in UI is associated with longer spells in unemployment (Katz and Meyer 1990, Krueger and Meyer 2002), identifying the *macro* effects of UI is much more difficult owing to the challenge of identifying plausibly exogenous variation in UI at the market level (as opposed to the individual level).[7] As a result, there is no real consensus regarding the general equilibrium effects of UI. For instance, Landais et al. (2018) survey the literature and argue that as on average the *macro*-elasticity of UI is estimated to be lower than the *micro*-elasticity,

[6]Notable theoretical contributions characterising this trade-off (to name but a few) are: Baily (1978), Hopenhayn and Niccolini (1997), Chetty (2006), Shimer and Werning (2007, 2008), Coles (2008), Mitman and Rabinovich (2015), and Landais et al. (2018a, 2018b).

[7]For further discussion of these difficulties (and some proposed solutions), see Hagedorn et al. (2016) and Chodorow-Reich et al. (2019).

an increase in UI is associated with an increase in labour market tightness[8], whilst Mitman et al. (2022) use quasi-experiment evidence from Missouri and present findings that suggest the opposite is true.

Employment protection. A somewhat smaller literature exists studying employment protection policies. Early theoretical contributions include Hopenhayn and Rogerson (1993), Ljungqvist (2002), and Veracierto (2008), though these papers give mixed messages regarding the desirability of such policies.[9] Moreover, this literature tends to model employment protection legislation either in the form of a real resource cost paid by firms or as a 'layoff tax' which the government collects as revenue. Whilst this proxies for differences in legislation governing job separations displayed across countries, in practice these policies cannot be adjusted as easily as *subsidy* policies in recessions. A key example of this sort of policy are STWs, which forms the focus of its own small (but growing) literature. Balleer et al. (2016) and Cooper et al. (2017) provide theoretical contributions illustrating quantitatively that STWs are effective at reducing employment volatility as an automatic stabiliser, but potentially come at the cost of a reduction in allocative efficiency by impeding the reallocation of workers away from lower productivity firms. Empirical contributions by Giupponi and Landais (2018) and Cahuc et al. (2021) using administrative firm-level data provide stronger evidence for the role of STWs in protecting jobs during recessions.[10]

Joint policy design. Finally, there is a theoretical literature studying the overall design of labour market policy. An earlier series of contributions studied joint policy design in general equilibrium environments where search externalities are the only source of welfare losses, as in Mortensen and Pissarides (1994).[11] Blan-

[8]Landais et al. (2018) argue that the difference between these two elasticities reflects general equilibrium effects associated with changes in UI. The idea here is that the micro-elasticity identifies the effect of a change in UI on the unemployment duration of individual workers, taking aggregate conditions (i.e. job finding rates) as given. The macro-elasticity then captures any additional effects from changes in aggregate conditions. So if the macro-elasticity is less than the micro-elasticity, then aggregate job finding rates (and therefore tightness) must have increased.

[9]Quantitative results from these papers suggest that constraining firms' adjustment of their labour inputs can either increase or decrease the level and volatility of unemployment depending on modelling choices.

[10]Giupponi et al. (2022) survey evidence on the impacts of STWs on the aggregate labour market, finding that increases in their generosity are associated with higher tightness, mainly due to reducing the number of workers flowing into unemployment.

[11]Notable examples include Millard (1995), Millard and Mortensen (1997), Pissarides (2000), and Mortensen and Pissarides (2003). These papers study how policymakers can alleviate search externalities via a combination of layoff taxes, income taxes, hiring subsidies, and employment subsidies, but abstract from concerns about income insurance for workers.

chard and Tirole (2008) and Cahuc and Zylberberg (2008) study the joint design of employment protection policies with UI in a partial equilibrium setting where workers are risk-averse and cannot fully insure against unemployment. There are very few papers which study the joint design of UI and employment protection policies in general equilibrium environments where policy faces both insurance considerations and congestion externalities in the labour market. Two important exceptions to this are Michau (2015) and Jung and Kuester (2015).[12]

This paper is most closely related to recent contributions by Birinci et al. (2021) and García-Cabo et al. (2023), who conduct similar policy experiments looking at the effects of increases in employment subsidies (in the form of wage subsidies) versus UI during a downturn. Whilst both papers feature search frictions and endogenous labour demand, there are several key differences which are important for their results. Birinci et al. (2021) allow for match-specific productivity which grows stochastically over the duration of a match. They also abstract from moral hazard concerns and assume wages are unaffected by changes in the worker's outside option. In this environment UI and employment subsidies are complementary because they benefit different workers: employment subsidies benefit workers higher up the job ladder, whilst UI provides insurance for those workers towards the bottom of the job ladder who are less productive and face greater separation risk. García-Cabo et al. (2022) instead use a multi-sector model with job-specific stochastic productivity where workers are risk-neutral (i.e. there are no insurance considerations), and study the implications for the allocation of resources in response to a sector-specific productivity shock. In this case the labour market flexibility (i.e. the speed of allocation) is crucial for whether UI or employment subsidies are preferred. The analysis in this paper complements these papers by studying a similar policy experiment in an intentionally standard environment, where comparison reveals more clearly the role that these additional assumptions play for the results. We compare our results to these papers in more detail in Section 1.6.

[12]Michau (2015) illustrates how in the presence of search externalities and risk-averse workers, the steady state constrained-efficient allocation can be decentralised through a combination of hiring subsidies, layoff taxes and UI. Jung and Kuester (2015) extend this to a business cycle setting and find that there is a limited role for increasing UI during recessions once hiring subsidies and layoff taxes stabilise tightness via their effects on employment inflows and outflows respectively. Both of these papers rely on adjustments in 'layoff taxes' to reduce inefficiently high job separations and implement the optimal policy, however it is far from clear how this would be implemented in practice.

1.2 Model

In this section we briefly outline the theoretical framework we use to conduct policy analysis, which was developed in Jung and Kuester (2015), Ignaszak et al. (2020), and Jung et al. (2021). For the most part we retain their notation. The framework deviates in several key ways from the standard Mortensen-Pissarides (1994) framework from the perspective of our research question. Firstly, job separations are allowed to vary endogenously over the business cycle, which is a robust empirical fact (e.g. see Fujita and Ramey 2009) and allows a role for employment subsidies to stabilise job separations. Secondly, workers are risk-averse and are unable to insure income against unemployment risk so that UI can improve welfare by stabilising income fluctuations. Finally, non-employed workers make a job search decision such that job search incentives respond to changes in UI.

1.2.1 Environment

Workers. Time is discrete and runs forever. There exists a constant mass of *ex ante* identical, risk-averse workers. Workers can either be employed or unemployed.[13] Workers discount the future with the time-discount factor $\beta \in (0,1)$ and obtain utility from consumption $u(c)$, where $u'(c) \geq 0$, $u''(c) \leq 0$, additive flow utility $\bar{h}$ in non-employment, and idiosyncratic additive disutility $\iota_i \sim F_\iota$ conditional on being non-employed and choosing to actively search for a new match. Workers are unable to self-insure against unemployment risk and consume income hand-to-mouth in every period. Recently separated workers receive partial insurance in the form of a one-time severance payout equal to the value of the wage, whilst unemployed workers are paid unemployment insurance (UI) B_t. It is assumed that aggregate firm profits Π_t are redistributed to all workers equally, regardless of employment status. Taken together this implies that $c_{e,t} = w_t + \Pi_t$, and $c_{u,t} = B_t + \Pi_t$.

Firms. Firms post vacancies to form single-worker matches and produce output to earn profits. Vacancies are posted at per period cost $\kappa_v > 0$. If a firm entering period t matched with a worker will decide (jointly with the worker) whether or not to continue the match in the current period based on their idiosyncratic fixed costs of production $\varepsilon_j \sim F_\varepsilon$. There exists a threshold value of the cost ε^ξ at which

[13] Without loss of generality, we normalize the mass of workers in the economy to 1. This implies that $u_t = 1 - e_t$.

workers/firms are indifferent between the match continuing or separating.[14] If the worker-firm pair decide to terminate the match, the firm must pay a layoff tax τ_{ξ} (collected by the government as revenue) in addition to a one-time severance payment to the worker equal to the value of the wage w_t. If the match continues it produces $\exp\{a_t\}$ (where a_t is aggregate labour productivity) and receives employment subsidy $\tau_s \geq 0$, whilst the firm pays the worker wages w_t, the idiosyncratic production cost ε_j, and a production tax $\tau_{J,t}$ levied in order to balance the budget.

Matching. New matches m_t are formed by the meeting of non-employed searchers and job vacancies in the labour market via a constant returns to scale aggregate matching function:

$$m_t = m(v_t, s_t N_t) \tag{1.1}$$

where v_t are vacancies posted by new firms, s_t is the share of non-employed workers who search, N_t is the measure of non-employed workers, and therefore $s_t N_t$ is the relevant measure of "effective searchers". In any period the measure of non-employed is given by the measure of existing unemployed workers from the last period u_t plus the fraction of existing workers who are endogenously separated at the beginning of the period:

$$N_t = \xi_t e_t + u_t \tag{1.2}$$

where e_t is the measure of employed workers and ξ_t is the separation rate. We express the contact rates between workers and firms as a function of the ratio between vacancies and effective searchers (i.e. labour market tightness, θ_t) as standard:

$$\theta_t = v_t/(s_t N_t) \tag{1.3}$$

where the hiring and job finding rates are given by:

$$q_t = m_t/v_t = m(1, 1/\theta_t), \quad f_t = \theta_t q(\theta_t) \tag{1.4}$$

Overall the law of motion for aggregate employment is given by:

$$e_{t+1} = (1 - \xi_t)e_t + m_t \tag{1.5}$$

Timing. The timing of events within a model period is as follows:

[14] In general a separation can either be worker-initiated (a "quit"), firm-initiated (a "layoff"), or mutually agreed. This depends on the worker and firm surpluses, or more specifically how these surpluses respond to a shock that affects the profitability of the match. For simplicity, we will assume below that wages are determined by Nash bargaining such that workers/firm always enjoy a constant fraction of the joint match surplus, but an important implication of this is that *all* separations are mutually agreed by both workers and firms, i.e. bargaining is always efficient.

1. Aggregate uncertainty resolved.
2. Bargaining between existing worker-firm pairs occurs, determining wages & separation decisions.
3. Idiosyncratic shocks are drawn, determining how many matches separate & how many non-employed workers search for a job in current period.
4. Production, job creation and matching takes place. New matches do not produce until next period.

1.2.2 Equilibrium

Job creation. In equilibrium potential firms post vacancies until the expected value is equal to the cost. Job creation is therefore pinned down by the standard free entry condition, equating the cost of posting a vacancy with its expected gain:

$$\kappa_v = q_t \mathbb{E}_t Q_{t,t+1} J_{t+1} \tag{1.6}$$

where $Q_{t,t+1}$ is the appropriately defined stochastic discount factor.

Job search. Non-employed workers decide whether to search for a job based on their idiosyncratic cost of job search $\iota_i \sim F_\iota$, which is i.i.d. and drawn by all non-employed workers in every period. There exists a threshold cost ι^s at which point a non-employed worker is indifferent between searching or not, i.e. when the cost of searching is equal to the expected utility gain from searching:

$$\iota_t^s = f_t \beta \mathbb{E}_t \Delta_{t+1} \tag{1.7}$$

The share of non-employed who search is therefore given by:

$$s_t = Pr(\iota \leq \iota_t^s) = \int_{-\infty}^{\iota_t^s} \iota dF_\iota \tag{1.8}$$

Wages. Wages are assumed to be determined by Nash bargaining between workers and firms:

$$\underset{w_t x}{\text{argmax}} \ (\Delta_t)^{1-\eta_t} (J_t)^{\eta_t}$$

where $\eta_t \in (0,1)$ is the firm's (time-varying) bargaining power, J_t is the firm surplus and $\Delta_t := V_{e,t} - V_{u,t}$ is the worker's surplus, where $\{V_{e,t}, V_{u,t}\}$ are the values

of employment and unemployment respectively (defined below). The wage paid to workers w_t satisfies the usual Nash sharing rule:

$$(1-\eta_t)J_t = \eta_t \frac{\Delta_t}{u'(w_t+\Pi_t)} \tag{1.9}$$

Separations. The separation threshold ε_t^{ξ} is defined as the level of ε_j at which a worker-firm pair are indifferent between continuing the match or separating, i.e. ε_t^{ξ} satisfies the following indifference condition:

$$J_t(\varepsilon_t^{\xi}) = \Delta_t(\varepsilon_t^{\xi}) = 0 \tag{1.10}$$

We can then define the share of matches which separate ξ_t (i.e. the separation rate) as:

$$\xi_t = Pr(\varepsilon_j > \varepsilon_t^{\xi}) = \int_{\varepsilon_t^{\xi}}^{\infty} \varepsilon_j dF_{\varepsilon} \tag{1.11}$$

Market clearing. Total resources are allocated between consumption, (fixed) production costs, and the cost of new job creation:

$$Y_t = e_t \cdot (w_t + \Pi_t) + u_t \cdot (B_t + \Pi_t) + e_t \int_{-\infty}^{\varepsilon_t^{\xi}} \varepsilon_j dF_{\varepsilon}(\varepsilon_j) + \kappa_v v_t \tag{1.12}$$

where aggregate firm profits can be expressed as:

$$\Pi_t = e_t(1-\xi_t)[\exp\{a_t\} - \tau_{J,t} - w_t - \int_{-\infty}^{\varepsilon_t^{\xi}} \varepsilon_j dF_{\varepsilon}(\varepsilon_j)] - e_t\xi_t[w_t + \tau_{\xi}] - \kappa_v v_t \tag{1.13}$$

Definition 2.1 (Equilibrium)**.** *For a given realization of $\{a_t\}_{t=0}^{T}$, initial unemployment level u_0, and policy rules for $\{\tau_{\xi,t}, B_t, \tau_{s,t}\}$, an equilibrium is defined as a sequence for the threshold production cost ϵ_t^{ξ} and separation rate ξ_t, the threshold job search cost ι_t^s and share of non-employed searchers s_t, wages w_t, firm profits Π_t, vacancies v_t, tightness θ_t, labour market stocks $\{e_t, u_t, N_t\}$ which satisfy: the job creation condition in 1.6, the Nash sharing rule in 1.9, the separation condition in 1.10 and definition of separation rate in 1.11, the job search condition in 1.7 and definition for share of non-employed searchers in 1.8, the market clearing condition in 1.12 and the definition of firm profits in 1.13.*

In the baseline case we assume that policy instruments remain constant over the business cycle.[15]

[15]One slight deviation here from Jung and Kuester (2015) is that in their baseline case they assume the government ensures that $b := c_u/c_e$ is constant, rather than B. This requires the policymaker to constant adjust B in order to ensure the consumption replacement rate b is constant in response to aggregate shocks.

1.3 Quantification

In this section, we first outline a calibration of the model to fit key moments in the US labour market, following the strategy in Jung and Kuester (2015). Next, we compare the decentralized stationary allocation to that which would be implemented by a social planner and comment on the inefficiencies generated by the presence of search frictions and incomplete markets.

1.3.1 Calibration

A model period is equal to 1 month. A summary of calibration is provided in Table 1.8. Details of the calibration are provided below.[16]

Functional forms. The aggregate matching function is assumed to be Cobb-Douglas:

$$m_t = \chi v_t^{\alpha} (s_t N_t)^{1-\alpha}$$

where $\alpha \in (0,1)$ is the elasticity of matches with respect to vacancies, and $\chi > 0$ is a match efficiency constant. This implies the following expressions for the job finding and hiring rates:

$$f(\theta) = \chi \theta^{\alpha}, \;\; q(\theta) = f(\theta)/\theta$$

The utility function for consumption is assumed to be a simple log utility function:

$$u(c) = \log(c)$$

Idiosyncratic shocks $\{\iota_i, \varepsilon_j\}$ are logistically distributed, i.e. F_ι and F_ε are given by:

$$F_\iota = F\Big(0, \pi\frac{\psi_s^2}{3}\Big), \;\; F_\varepsilon = F\Big(\mu_\varepsilon, \pi\frac{\psi_\varepsilon^2}{3}\Big)$$

where F is the logistic CDF, $\{\psi_s, \psi_\varepsilon\}$ control dispersion, and π is the mathematical constant.[17] The share of non-employed searchers s_t and the separation rate ξ_t are

[16] For the purposes of simulating the model for calibration purposes, we impose the strict condition in equilibrium that $\tau_{J,t}$ fluctuates in order to balance the budget in every period (i.e. there is no tax smoothing).

[17] The logistic distribution is a convenient choice as it permits a closed-form expression for the conditional expectation. For instance, the average production costs paid by continuing matches in any period are given by:

$$\int_{-\infty}^{\tilde{\varepsilon}_t^{\xi}} \varepsilon_j dF_\varepsilon(\varepsilon_j) = \Psi(\xi_t) = -\psi_\varepsilon \Big[(1-\xi_t)\log(1-\xi_t) + \xi_t \log(\xi_t) \Big]$$

whilst average disutility costs of job search can be defined analogously, denoted by the function $\Psi(s_t)$.

therefore given by the following expressions:

$$s_t = \frac{1}{1+\exp\{\frac{-f_t\beta\mathbb{E}_t\Delta_{t+1}}{\psi_s}\}}, \quad \xi_t = \frac{1}{1+\exp\{(\varepsilon_t^{\xi}-\mu_\varepsilon)/\psi_\varepsilon\}}$$

Externally calibrated parameters. Several parameters are set to standard values in the literature. The discount factor is set to $\beta = 0.996$. The elasticity of matches with respect to vacancies is set to $\alpha = 0.3$ based on Pissarides and Petrongolo (2001). The steady state value of the firm's share of the joint surplus is set to α.[18]

Internally calibrated parameters. Remaining parameters are set to match key moments in the data for the US labour market. Flow utility from non-employment is set to $\bar{h} = 0.382$ to match a non-employment rate of 7.5%. The dispersion parameter for the job search cost shock is set to $\psi_s = 0.216$ to target an elasticity of average unemployment duration to a change in UI equal to 0.8 based on Meyer (1990). The vacancy posting cost is set to $\kappa_v = 0.176$ to match a 6.4% average unemployment rate. The match efficiency constant is set to $\chi = 0.298$ to match a 71% quarterly hiring rate as in Den Haan et al. (2000). The location parameter for the production cost distribution is set to $\mu_\varepsilon = 0.063$ such that the mean production costs of surviving firms is zero. The dispersion parameter for the production cost shock is set to $\psi_\varepsilon = 0.659$ to target a 28% monthly job finding rate.

Policy. Policy parameters are set to replicate US labour market institutions. The level of match subsidies is set to zero, i.e. $\tau_s = 0$. The level of UI is set to $B = 0.425$ to target a 45% wage replacement rate as in Engen and Gruber (2001). The layoff tax is set to $\tau_{\bar{\xi}} = 0.680$ to target a value equal to 50% of UI payments a worker receives during an average unemployment spell. Finally, the production tax is set to ensure the government budget constraint is satisfied.

Wage rigidity. The firm's share of the joint match surplus (i.e. bargaining power) η_t varies procyclically over the business cycle in order to ensure a degree of wage rigidity that generates realistic volatility in labour market tightness.[19] Specifically, η_t evolves according to:

$$\eta_t = \eta \exp\{\gamma_w a_{t-1}\}$$

[18] This is assumed for convention. In this particular model the Hosios' (1990) condition does not ensure efficiency of the stationary equilibrium as the social planner is no longer trying to maximise output, but has to take into account insurance concerns of risk-averse workers.

[19] This is a convenient way of allowing for wage rigidity without introducing the possibility of privately inefficient job separations.

where γ_w controls the degree of wage rigidity and is set to target the unconditional volatility in the job finding rate in the data.[20] This requires setting $\gamma_w = 14.81$.[21]

1.3.2 Stationary Equilibria: Baseline vs. Constrained-efficient

Variable	Baseline	Efficient
c_e	0.945	0.945
c_u	0.427	0.429
θ	0.834	2.050
v	0.053	0.054
f	0.282	0.369
s	0.843	0.846
N	0.075	0.031
ξ	0.019	0.010
$urate$	0.064	0.026

Table 1.1. Stationary equilibrium: Baseline vs. Efficient

How does the baseline stationary equilibrium compare to the constrained-efficient allocation chosen by a social planner? Overall the social planner has to trade-off two sources of welfare losses: (i) excess volatility in worker consumption due to incomplete markets, and (ii) congestion externalities due to search frictions in the matching market. Moreover, the planner is unable to provide full insurance to workers due to the presence of the endogenous job search decision.

Table 1.1 compares the values of key endogenous variables in the stationary equilibrium with their corresponding values in the constrained-efficient allocation.[22] The social planner only chooses to provide marginally more direct insurance to unemployed workers, where c_u is 0.47% higher in the efficient allocation whilst c_e is unchanged. Instead the planner prefers a much tighter labour market than

[20] To calibrate γ_w we need to simulate a process for a_t and compute theoretical moments based on a stochastic solution of the model. Following Jung and Kuester (2015) we assume that a_t follows an AR(1) with $\rho_a = 0.983$ and $100 \cdot \sigma_a = 3.4$, and solve for a log-linear stochastic solution of the model. We report moments and correlations from model simulations compared to the data in Table 1.9 in the Appendix.

[21] Note that this is different from the value computed by Jung and Kuester (2015). This is because in their simulations they assume that the policymaker keeps the consumption replacement rate constant, i.e. $b = \frac{c_u}{c_e} = \frac{B+\Pi}{w+\Pi}$, rather than the level of UI, B. Interestingly, this actually slightly reduces the ability of the model to fit the data by increasing the volatility of wages relative to the simulated model in Jung and Kuester (2015), which then leads to separations and unemployment being too volatile compared to the data.

[22] We compute the allocation chosen by the social planner utilising the results derived in Jung and Kuester (2015) relating to the stationary equilibrium of the model.

achieved in the decentralised equilibrium on average. This has the effect of easing search congestion on the worker side (the job finding rate f is significantly higher) which indirectly provides insurance by significantly reducing unemployment, average unemployment duration, and therefore income risk faced by workers in equilibrium. This is achieved partly through more job creation (i.e. higher levels of vacancy posting, v), but mostly through the reduction in effective searchers via the number of non-employed N, driven by the reduction in the separation rate, ξ, which is inefficiently high in the decentralised equilibrium.[23]

1.4 Model Simulation: A Simple Policy Experiment

In this section we use the calibrated framework outlined above to conduct a simple policy experiment. More specifically, we simulate a recession and assess the implications of 4 different policy responses:

1. No policy response, government balances budget
2. No policy response, government runs deficit (i.e. automatic stabilisers)
3. An increase in UI
4. Introduction of (cost-equivalent) match subsidies

The shock driving the recession is a 1% fall in labour productivity $\exp\{a_t\}$ which lasts for T periods before returning to steady state:

$$\exp\{a_t\} = \begin{cases} 0.99 & \text{for } t = 1, ..., T \\ 1 & \text{for } t = T+1, ... \end{cases} \tag{1.14}$$

where it is assumed that the shock is unexpected but its structure is common knowledge after the shock arrives (i.e. agents have perfect foresight).

1.4.1 Policy Alternatives in a Recession

Figure 1.1 presents the responses of key endogenous variables under the 4 different policy responses discussed above. We review each one in turn.

[23] As an aside, this is a key difference from the standard matching model with risk-neutral workers (e.g. Pissarides 2000). In that standard environment it is well-understood that separations can only be inefficiently *low*, and are maximised in the efficient equilibrium (i.e. when the Hosios (1990) condition is satisfied). In the present environment, the fact that workers are risk-averse and unable to insure means that separations can be inefficiently *high*.

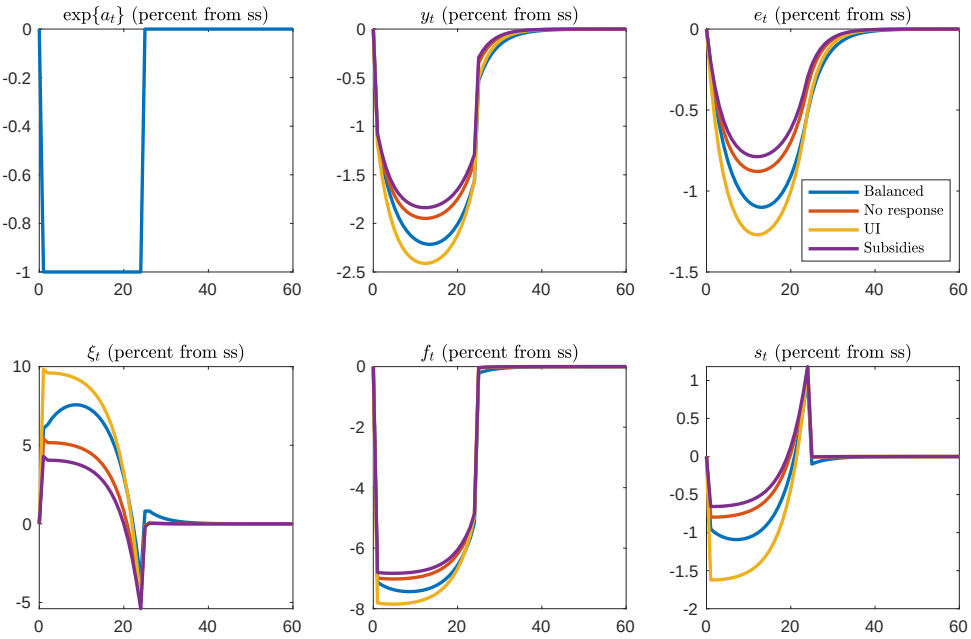


Figure 1.1. Labour market responses under different policies.

Balanced budget. We first analyse the response of the economy where the policymaker does not adjust policy tools in response to the aggregate shock, apart from adjusting τ_J to balance the budget. The main effect of the aggregate shock is to reduce the value of a filled job, J_t. This has implications for both existing jobs and new job creation. In the first instance, the fall in aggregate productivity makes many marginal matches unviable that would have otherwise produced (i.e. the separation threshold $\varepsilon_t^{\tilde{\xi}}$ increases), increasing the number of separations (bottom left panel, Figure 1.1). Secondly, the reduction in J_t disincentivises new job creation. This drives the fall in labour market tightness, reflected in the falling job finding rate (bottom middle panel). The overall outcome of an increase in separations and a reduction in job finding is an increase in the number of unemployed workers (i.e. employment falls, top right panel) and a fall in aggregate output (top middle panel).

How does the production tax $\tau_{J,t}$ respond to balance the budget? The increase in the number of unemployed means a greater amount of resources spent on UI even though B is held constant, whilst an increase in separations increases the amount of revenue taken from the layoff tax. Quantitatively the former dominates the latter so $\tau_{J,t}$ has to rise to balance the budget. This puts further downward pressure on J_t

as the production tax also reduces the flow benefit from a filled job, and therefore amplifies the effect of the initial shock on the labour market.

No response. Next we analyse how the labour market responds when the policymaker doesn't change *any* policy instruments, including $\tau_{J,t}$. That is to say, we allow the government to run a deficit to meet the additional fiscal expenditure from rising unemployment. This exercise effectively identifies the contribution of increasing $\tau_{J,t}$ to the dynamic response of the labour market in the previous scenario. Relative to the balanced-budget case, the increase in separations and fall in job finding rate are reduced as the impact of the shock is dampened. This highlights the benefits associated with the government being able to smooth taxes over time, rather than being forced to balance the budget.

UI. How do the things change when the government increases the generosity of UI during the recession? In the experiment we assume the level of UI increases by 1% in response to the recession. Figure 1.1 illustrates that under the baseline calibration an increase in UI *amplifies* the effect of the recession in the labour market. This occurs through the effect on the worker's surplus - as wages are determined via Nash bargaining, a reduction in the worker's flow surplus from working increases the bargained wage, which in turn reduces the value of a filled job, increases separations and reduces job creation. Moreover, the reduction in the worker's surplus also amplifies the fall in the share of non-employed workers who search (bottom left panel, Figure 1.1), which exacerbates the congestion externalities faced by firms and further reduces job creation incentives relative to an environment where the share of non-employed searchers was constant over time.

Match subsidies. What would be the effect if instead the government decided to invest the same amount of resources into subsidising existing employment relationships? We analyse the responses when the policymaker introduces match subsidies $\tau_s > 0$, where τ_s is chosen such that the policy is cost-equivalent to the increase in UI over the simulation period. Increasing match subsidies at the onset of the recession directly counteracts the effects of the aggregate shock by reducing the fall in the job value ,J_t. As a result there are fewer separations, the fall in tightness is dampened, and the increase in unemployment is not as large relative to the no response case. Quantitatively, the dampening on unemployment appears to predominantly come from the reduction in job separations, as the impact on tightness itself is quite small.

Summary. Overall the results suggest that under a fairly standard calibration of the model for the US labour market, the introduction of match subsidies dampens labour market volatility by both reducing unemployment inflows and supporting unemployment outflows, whilst in contrast increasing UI amplifies the effect of the recession by reducing the worker's employment surplus, adding upward pressure to market wages and exacerbating the fall in new job creation.

1.4.2 Welfare

Which policy response is preferred in welfare terms? In this environment the period social welfare function is given by the following:

$$\mathbb{W}_t = \underbrace{e_t \log(w_t + \Pi_t) + u_t \log(B_t + \Pi_t)}_{\text{Consumption}} + \underbrace{(\xi_t e_t + u_t)\Psi(s_t)}_{\text{Job search}} + \underbrace{(\xi_t e_t + u_t)\bar{h}}_{\text{Leisure}}$$

Welfare can be decomposed into three constituent elements:

1. Utility from consumption
2. Disutility from job search
3. Utility from non-employment (i.e. leisure)

In general, policy alternatives will affect social welfare in different ways depending on how they influence these three channels.

	Consumption	Job search	Non-employment
Equilibrium:			
Decentralised	74.0%	5.1%	20.9%
Efficient	83.3%	3.3%	13.4%

Table 1.2. Welfare decomposition: Shares

Stationary equilibrium. Table 1.2 displays the contribution shares of the (absolute) value of social welfare for each constituent element in both the decentralised equilibrium and the efficient equilibrium. In both cases, utility from consumption is the main contributor to social welfare. Flow utility from non-employment plays a smaller role, whilst (dis)utility from job search turns out to be a very small determinant of social welfare. Overall we find that in the calibrated model welfare losses from congestion externalities and incomplete markets amount to around 11.4% in the stationary equilibrium. The results in Table 1.2 suggest that the social planner achieves these welfare gains primarily by reducing the share of workers

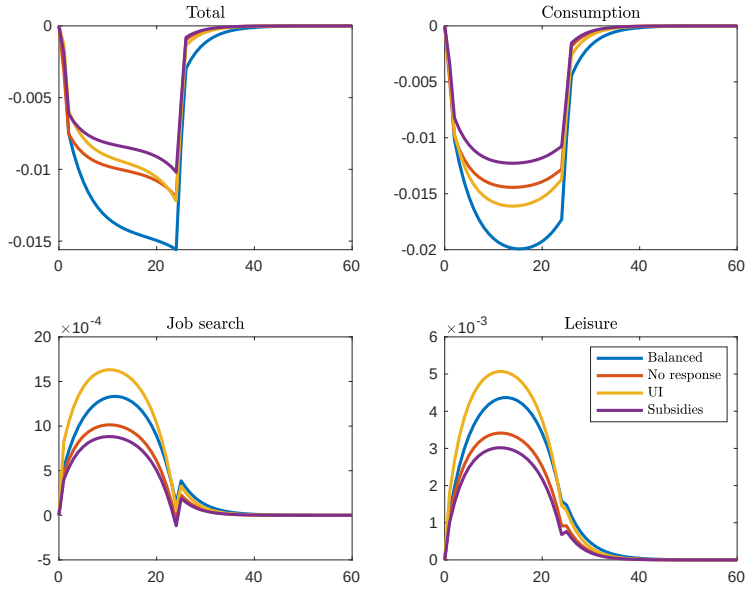


Figure 1.2. Decomposing the social welfare response

in non-employment, and thereby increasing the average worker's consumption utility.

Policy experiment. Figure 1.2 plots the responses of each component of social welfare (in deviation from steady state) for each of the policy responses studied in the previous section, whilst Table 1.3 summarises the welfare gains under different policy alternatives.[24] In all cases social welfare falls during the recession, again driven primarily by the falling level of average consumption due to the fall in employment, but is partially offset by reduced job search disutility and increased flow utility from non-employment. Relative to a balanced-budget response, no response achieves welfare gains of 1.43% mainly through higher average consumption of workers, despite this resulting in lower utility from the job search and leisure channels. This isolates welfare benefits of being able to tax smooth for the government during recessions.

Both an increase in UI and an introduction of match subsidies during the recession achieve further welfare gains on top of this, but for different reasons. Despite reducing the consumption fall upon separation, increasing UI during the recession actually delivers a *larger* peak fall in average consumption utility due to indi-

[24]Welfare gains are reported as a percentage relative to the balanced-budget scenario over the simulation period.

rect effects amplifying the fall in tightness, though this is counteracted by reduced disutility from job search and increase utility from leisure which actually dominate quantitatively. In contrast, introducing match subsidies reduces the welfare gains associated with reduced job search and increased utility from leisure, but overall provides better overall insurance of average worker consumption via the stabilisation of tightness. Under the baseline calibration, we find that the welfare gains from introducing match subsidies are quantitatively larger than those from increasing UI (+ 0.64% compared to 0.23%).

Policy response	None (deficit)	UI	Subsidies
Welfare gain (%)	1.43	1.66	2.07
	-	(+0.23)	(+0.64)

Table 1.3. Welfare gains under alternative policy responses.

1.5 Flexible vs. Rigid Labour Markets?

A common reason put forward for cross-country differences in the responses of labour market policies to recessions is because of differences in existing institutions and underlying structures. For instance, compared to the US the German labour market is characterised by employment subsidies in the form of *Kurzarbeit* (a longstanding short-time work scheme), greater employment protection legislation, a higher degree of collective bargaining, and higher replacement rates. These differences in institution contribute to lower turnover rates (separation and job finding) as well as higher average unemployment. In other words, the German labour market is more 'rigid' compared to the relative 'flexibility' of the US. In a rigid labour market with lower turnover rates, it takes unemployed longer to find new jobs and therefore the welfare gains from preserving matches during downturns are potentially higher.

In this section we test this hypothesis by repeating the analysis above using alternative calibration for the model, where we instead target key moments of the German labour market based on comparative evidence presented in Jung and Kuhn (2014). We first outline the alternative calibration, retaining the same choices for functional forms as used above to facilitate comparison. We then present the responses of the labour market to the same aggregate shock and compare with the US calibration, before presenting welfare results.

1.5.1 Alternative Calibration

Below we outline details of the alternative calibration of the model.[25] Table 1.4 compares the implied values of the structural parameters used in the two different calibrations, whilst Table 1.5 presents the values of key endogenous variables in the stationary equilibrium for the two different calibrations.

Externally calibrated parameters. We retain the same value for the time discount factor β. The elasticity of matches with respect to vacancies is instead set to $\alpha = 0.25$, based on the aggregate matching function estimation in Jung et al. (2021), and again we fix $\eta = \alpha$ for convention.

Steady state targets. Remaining structural parameters are set to target moments corresponding to the German labour market based on evidence on German labour market flows, stocks and transitions data between 1980-2004 as documented in Jung and Kuhn (2014) (unless otherwise stated). We match the following steady state moments: an 8.4% average unemployment rate; a 6.2% monthly job finding rate; a 70% quarterly hiring rate based on Christoffel et al. (2009); 81% non-employed workers search, based on Jung et al. (2021); an elasticity of unemployment duration to a change in benefits $\epsilon_{D_u} = 0.5$, based on the range of estimates reported in Schmeider and von Wachter (2016).

Policy. Policy parameters are set to match salient features of German labour market institutions. We set B to target a 67% wage replacement rate. The layoff tax τ_{ξ} is set to equal 6 times the monthly equilibrium wage, again based on Jung et al. (2021). Finally we set τ_s to match the average employment support provided by *kurzarbeit*. As documented in Balleer et al. (2016), since its inception in 1975 an average of 0.83% of the workforce have been enrolled on the STW scheme, where the government covers 60% of their wage.

Wage rigidity. We set the degree of wage rigidity γ_w in the same way as before, this time targeting $100 \cdot \sigma_f = 10.4$.[26]

Discussion. In order to generate higher unemployment and a lower job finding rate, the model requires a much lower level of labour market tightness in equilibrium which is achieved through a combination of lower vacancy posting (requiring a higher vacancy cost κ_v) and a lower degree of match efficiency χ. The separation

[25] A summary of the calibration is given in Table 1.10.

[26] Table 1.11 reports moments and correlations compared to what we see in the data.

Parameter	Symbol	US	Germany
Preferences:			
Discount factor	β	0.996	0.996
Non-employment flow utilty	$\bar{h}$	0.382	-0.349
Firm bargaining power	η	0.3	0.25
Search cost dispersion	ψ_s	0.216	0.395
Labour market:			
Match elasticity	α	0.3	0.25
Match efficiency	χ	0.298	0.094
Vacancy cost	κ_v	0.176	0.930
Production cost location	μ_ϵ	0.063	0.117
Production cost dispersion	ψ_ϵ	0.659	3.33
Policy:			
UI	B	0.425	0.605
Match subsidies	τ_s	0	0.005
Layoff tax	$\tau_{\tilde{\xi}}$	0.680	5.415
Production tax	τ_J	0.013	0.039

Table 1.4. Structural parameters under alternative calibrations

rate consistent with this is comparable with that the data[27], and is achieved by a significantly higher cost of job separation for firms, $\tau_{\tilde{\xi}}$. The higher level of B ensures that unemployed workers are much better off under the German calibration (around 37% in consumption utility terms). In order to match the higher level of UI support with a share of non-employed searchers equal to 81%, the model requires $\bar{h} = -0.349$. Finally, to achieve a lower elasticity of unemployment duration with respect to UI the model requires a higher degree of dispersion in the job search utility cost ψ_s.

1.5.2 Model Assessment

Stationary equilibria. How does the competitive stationary equilibrium compare to the efficient equilibrium for the calibration of the model to the German labour market? Table 1.5 compares the decentralised stationary equilibrium to the constrained-efficient allocation (as well as for the US calibration). Tightness is still inefficiently low in the German calibration, though not by as much as for the

[27]The average EU transition rate in the data is reported to be 0.005 in Jung and Kuhn (2014), whilst in the EU rate ($\tilde{\xi}$) implied by the model under this calibration is 0.006.

US calibration. The social planner chooses to increase tightness by significantly reducing the amount of non-employed workers (and hence the unemployment rate), rather than by stimulating more job creation on the firm side (vacancies are actually inefficiently *high* in the decentralised equilibrium). Increased tightness is achieved primarily through a much lower amount of job separations, which requires existing matches to pay higher costs of production and for workers to consume less in absolute terms (which is partly achieved by lowering the replacement rate, which is inefficiently high).

Table 1.6 presents the decomposition of social welfare into its three distinct channels in the stationary equilibria as before. Again utility from consumption is the key determinant of social welfare, though job search disutility now plays a more significant role under the German calibration compared to the US.

	US		Germany	
Variable	Decentralised	Efficient	Decentralised	Efficient
c_e	0.945	0.945	0.913	0.899
c_u	0.427	0.429	0.615	0.601
θ	0.834	2.050	0.188	0.440
v	0.053	0.054	0.016	0.009
f	0.282	0.369	0.062	0.077
s	0.843	0.846	0.810	0.832
N	0.075	0.031	0.102	0.026
ξ	0.019	0.010	0.006	0.002
$urate$	0.064	0.026	0.084	0.021

Table 1.5. Comparing stationary equilibria

Dynamic responses. Figure 1.3 plots the responses of the labour market under the two different calibrations to the same recession shock. Overall labour market volatility (and hence the job finding rate) is lower under the German calibration.[28] This leads to a less severe recession in terms of employment and output deviations from steady state. This is also driven by the dynamics of job separations, which spike immediately in response to the recession but do not remain elevated for as long. Crucially, the recovery in employment and output is much more protracted under the German calibration, reminiscent of the results in Jung and Kuhn (2013). This is due to the monthly job finding rate being much lower in the German calibration. For a given level of tightness, it takes much longer on average for the

[28] This is by construction as we target the lower observed volatility in the data when determining the degree of wage rigidity.

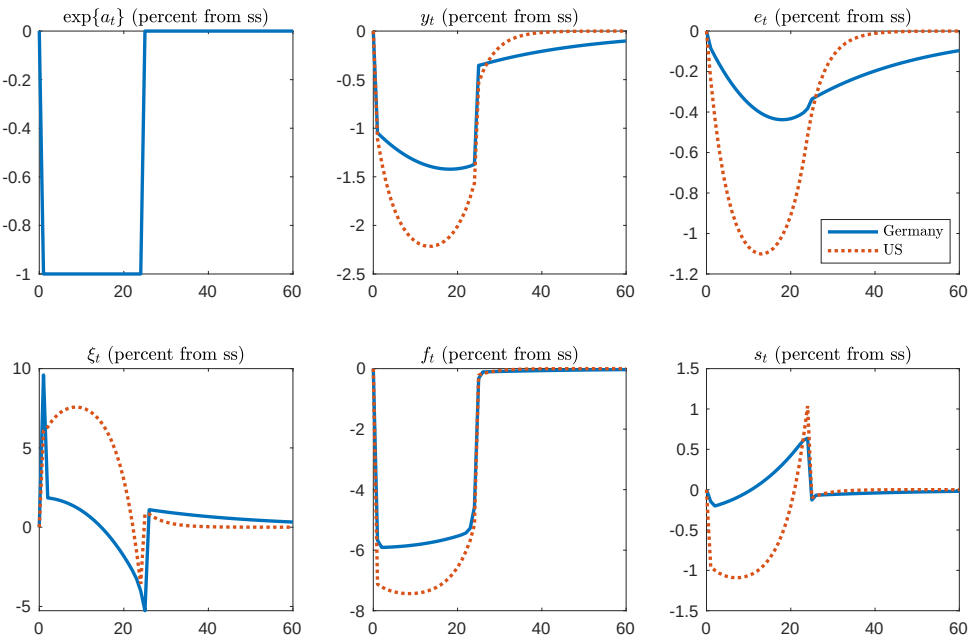


Figure 1.3. Comparing the response of the labour market under different calibrations.

non-employed to find jobs and therefore for the stock of non-employed workers to reduce back to its equilibrium level.

1.5.3 Policy experiment

We present results from same policy experiment as above under the alternative rigid labour market calibration.[29]

Labour market responses. Figure 1.4 plots the labour market responses under alternative policies. In general we see a fairly similar picture to the US calibration in Figure 1.1. Allowing the government to run a deficit dampens the recession, but in this case also significantly reduces the persistence of the effects of the aggregate shock on the labour market due to the lower average flow rates between employment and unemployment. Increasing the existing employment subsidies directly counteracts the effects of the negative shock, whilst the increase in UI again amplifies the shock through its effect on the worker's employment surplus (though this

[29]There is one slight difference in our policy experiments. We instead assume that for the subsidy response, the employment subsidy increases by 10% in response to the 1% negative shock to aggregate productivity. We then compute the cost-equivalent increase in the level of UI for the increase in UI scenario. This turns out to be equivalent to a 0.83% increase in the level of UI.

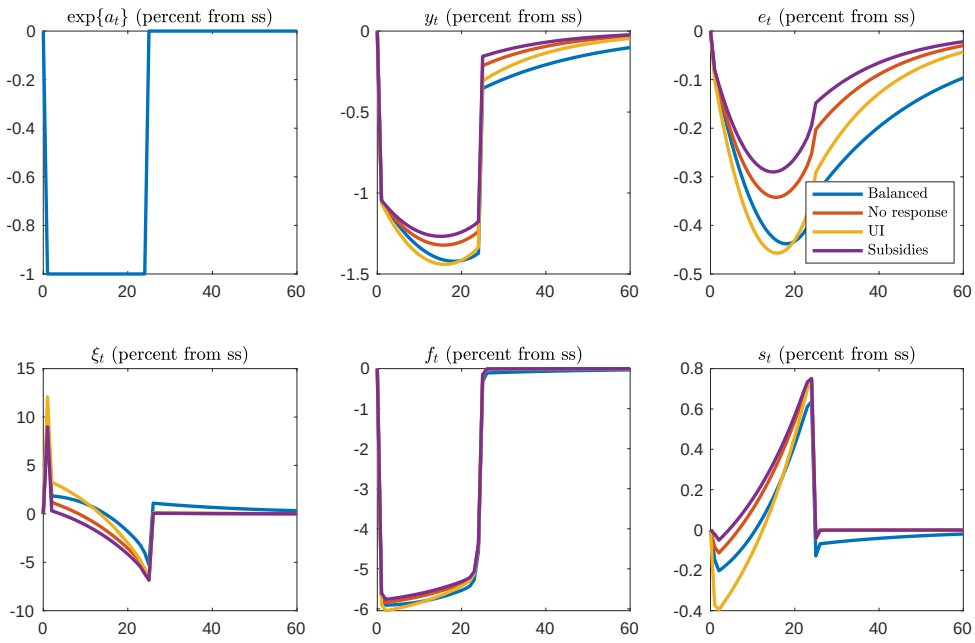


Figure 1.4. German calibration: Policy responses

	Consumption	Job search	Non-employment
Equilibrium:			
Decentralised	70.2%	10.6%	19.2%
Efficient	89.6%	3.5%	6.9%

Table 1.6. Welfare decomposition: Shares

channel is less strong relative to the US calibration for a comparable increase in UI in percentage terms).

Welfare. The dynamic response of social welfare - as well as each distinct channel - are plotted in Figure 1.5. We find in all cases that aggregate social welfare is driven by the dynamics of average consumption, whilst contributions of leisure and job search appear to be quantitatively irrelevant.[30] The average consumption level actually *rises* upon the impact of the shock due to the assumption that the firm's bargaining power sharply falls in line with a_t, which increases wages for

[30]Note that under the German calibration we actually required a *negative* flow utility value associated with non-employment, $\bar{h}$. This is in line with Jung et al. (2021). This means that this channel now contributes negatively to welfare, rather than positively in the US case where we needed $\bar{h} > 0$. One could interpret $\bar{h} < 0$ instead as disutility associated with non-employed independent of that induced from active job search.

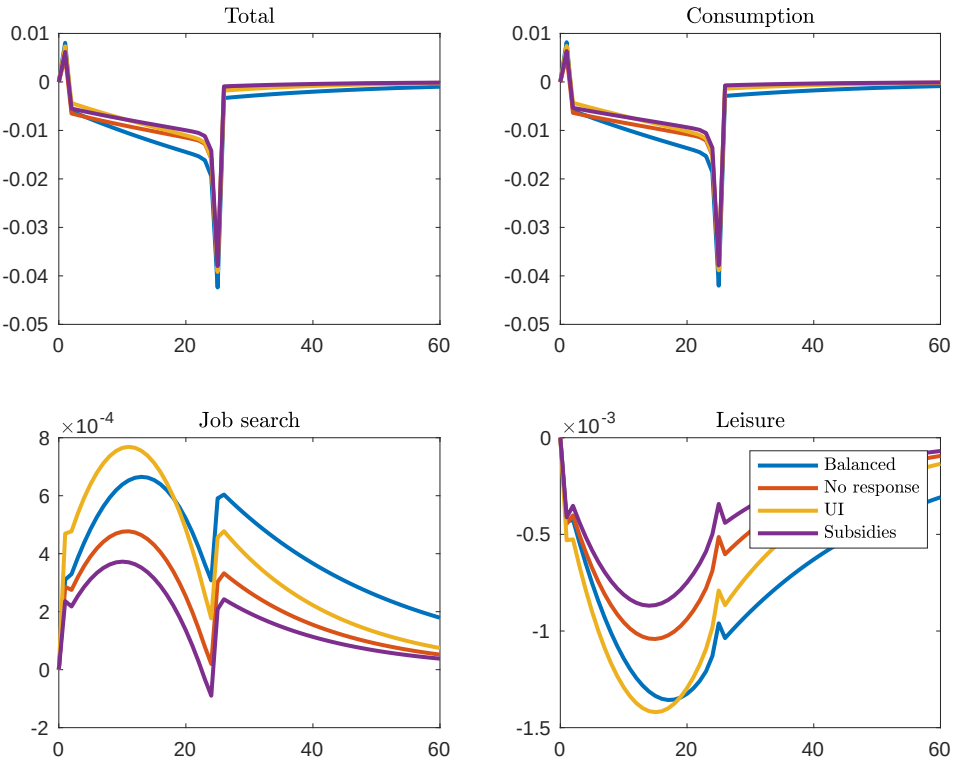


Figure 1.5. German calibration: Welfare decomposition

Policy response	None (deficit)	UI	Subsidies
Welfare gain (%)	0.74	0.88	1.03
	-	(+0.14)	(+0.29)

Table 1.7. Welfare gains under alternative policy responses.

one period before they subsequently decline in line with the present discounted value of the joint surplus.[31]

As with the flexible US calibration, we find that the fall in average consumption is mitigated more significantly when policy acts to stabilise labour market tightness, rather than seeking to provide direct insurance. However as the increase in UI has a less destabilising effect under this alternative calibration (e.g. see the top right panel of Figure 1.5), welfare losses from consumption are actually mitigated by the increase in direct insurance provision to workers.[32]

Finally, Table 1.7 reports the computed welfare gains of each of the policy responses relative to the balanced budget case. Again the ordering of policy preference is not altered by the calibration - increasing employment subsidies is still preferred, as we find they are more effective at insuring average consumption via the stabilisation tightness relative to reducing the consumption cost of separation via increasing UI. However in this calibration we find that a cost-equivalent expansion in UI *does* achieves welfare gains through its role in insuring workers' consumption, rather than through its effects on reducing job search disutility or increasing leisure/non-employment flow utility.[33] As a result, the *relative* gains from employment subsidies compared to a cost-equivalent increase the level of UI support are smaller for the German calibration than for the US calibration. If anything, this result goes in the opposite direction to the hypothesis that employment subsidies in recession are more desirable in the context of more rigid labour markets.

[31] This is a result of the fact that under the German calibration the degree of wage rigidity required to match the observed volatility in labour market tightness and job finding rate is larger ($\gamma_w = 17.78$) than it is for the US calibration ($\gamma_w = 14.81$).

[32] This contrasts with the US calibration, where providing greater direct insurance via increasing UI actually worsened the outcome for average consumption.

[33] This is a direct result of the fact that the destabilising effect of UI through the job creation channel is much weaker under a calibration targeting a lower elasticity of unemployment duration to changes in UI, as well as lower average worker flow rates.

1.6 Relationship to the Literature

In this section we discuss in detail the relationship between the results presented above and those presented in Birinci et al (2021) and Garcia-Cabo et al. (2023), who perform a very similar policy experiment comparing the relative benefits of an expansion in UI during a downturn versus employment protection.

Birinci et al. (2021). Whilst also allowing for risk-averse workers and endogenous separations, the framework in Birinci et al. (2021) deviates in two important ways. Firstly, matches become more productive over time, capturing the idea that employment subsidies deliver benefits by protecting matches that have accumulated more 'match-specific capital' which would otherwise be lost upon separation.[34] Secondly, wages are downwardly rigid and assumed to be an exogenous function of productivity, rather than endogenously determined as a function of the joint match surplus. This is important because a key channel in our analysis is the effect of UI on tightness via the job creation channel operating through the effect on wages, which is absent in Birinci et al. (2021) and therefore dampens the adverse effects from UI expansions.[35] In both environments increasing UI amplifies the effect of the downturn on unemployment and aggregate output, whilst employment subsidies act in the opposite direction. In Birinci et al. (2021) this is because increasing UI reduces the worker's surplus, generating an increase in worker-initiated separations which amplifies the increase in unemployment, whilst increasing payroll subsidies reduces the number of layoffs such that more higher productivity matches are saved and the fall in aggregate output is less severe.[36]

Birinci et al. (2021) similarly find that in isolation a cost-equivalent increase in employment subsidies delivers better welfare outcomes than an expansion in UI. However they emphasise that this is because payroll subsidies protect higher productivity matches, whilst increasing UI leads to losses in match capital despite providing consumption insurance for those workers who lose their jobs. Moreover, they emphasise that in this environment the two policies are *complements* as

[34] For a discussion of this in the context of Covid-19, see Fujita et al. (2020): https://cepr.org/voxeu/columns/labour-market-policy-response-covid-19-must-save-aggregate-matching-capital.

[35] Both environments also do not feature an endogenous search decision, which means the adverse effects from expanding UI are dampened even further relative to the baseline framework we use in this paper.

[36] Birinci et al. (2021) actually make a modelling distinction between matches that are temporarily inactive ('temporary layoffs') with a positive probability of recall, and permanently separated matches with zero possibility of recall.

they benefit different types of workers: employment subsidies benefit workers in matches with high match-capital, whilst more generous UI benefits the rest. Solving for the optimal allocation of a fixed budget between the two policies, they actually find that only 20% should be allocated to payroll subsidies and the rest to greater UI.[37] In contrast, in the Jung-Kuester environment with homogeneous matches, we find that UI and employment subsidies are *substitutes*: employment subsidies provide greater consumption insurance by reduced volatility in tightness but reduce utility from non-employment and higher job search disutility, whilst higher UI leads to worse average consumption insurance outcomes.

Garcia-Cabo et al. (2023). Using a multi-sector model, the focus of this paper is purely on how different policy alternatives can improve the reallocation of workers during a downturn precipitated by a negative productivity shock to one sector. Again in contrast to our approach, matches are characterised by persistent job-specific productivity shocks whilst workers are assumed to be risk-neutral so insurance concerns play no role in evaluating the desirability of the policy alternatives from a welfare perspective. Although each policy alternative has similar effects on aggregates as in Birinci et al. (2021) and our framework, their effect on the overall allocation of workers across sectors and jobs is crucial for the desirability of each policy alternative. Expanding UI generates more job separations and a higher initial fall in output (due to higher unemployment), but potentially speeds up the process of reallocating workers away from low productivity matches towards new, higher productivity jobs in the unaffected sector. Increased employment protection (in this case wage subsidies) dampens the initial fall in output by protecting employment matches, but hinders the reallocation of workers away from the affected sector.

The key takeaway from Garcia-Cabo et al. (2023) is that when the labour market is 'flexible' (i.e. the job finding rate is higher) UI policies are preferred, as the benefits from speeding up worker reallocation are larger than the costs of amplifying the initial effect of the recession. Otherwise, employment protection policies are preferred in environments where worker reallocation is slower. In contrast, in our single-sector environment with homogeneous productivity across matches there are no gains from reallocation, whilst instead there are additional welfare gains

[37] This is because there are high diminishing returns to payroll subsidies: once the highest productivity matches are saved, the gains from preserving lower productivity matches diminish, and it is better to let these matches separate but provide workers with greater insurance.

from reducing income risk faced by workers. In this case, employment subsidies are always preferred as they are more effective at mitigating the increase in risk.

1.7 Conclusion

In this chapter, we have sought to address a question that has gained recent salience: Should we insure workers or employment matches during a recession? Through the lens of a relatively standard equilibrium matching model with risk-averse workers, an endogenous job search decision and endogenous job separations, we find that subsidising matches is preferred in welfare terms. This is because increasing worker insurance through expanding UI, although reducing the cost of job separation for an individual worker, has adverse effects on tightness through its effects on search effort and job creation which exacerbates income risk faced by workers. In contrast, increasing employment protection during a recession directly offsets some of the increase in income risk. Moreover, this finding is robust to whether we calibrate the model to match a 'flexible' labour market (such as the US) or a more 'rigid' labour market (such as Germany) characterised by more generous policy support and lower turnover.

Chapter 1: Appendices

1.A Model Appendix

1.A.1 Value functions

Employment value An employed worker at the beginning of period t will either continue to be employed with probability $(1 - \xi_t)$ or will separate with probability ξ_t. Upon separation the worker receives the value of unemployment plus the difference in the flow consumption utility between the employed and unemployed (due to the severance payment). The value of employment can therefore be written as:

$$V_{e,t} = (1 - \xi_t)\big[u(w_t + \Pi_t) + \beta \mathbb{E}_t V_{e,t+1}\big] + \xi_t\big[V_{u,t} + u(w_t + \Pi_t) - u(B_t + \Pi_t)\big] \tag{1.15}$$

Unemployment value An unemployed worker at the beginning of period t consumes and enjoys leisure, and makes a decision about whether to search in the current period or not based on their idiosyncratic utility cost of job search ι_i. If the unemployed worker decides to search for a job they successfully find a match with probability f_t, otherwise they will remain in unemployment. The value of unemployment can therefore be written as:

$$\begin{aligned} V_{u,t} &= u(B_t + \Pi_t) + \bar{h} + \int_{-\infty}^{\iota_t^s} [-\iota_i + f_t \beta \mathbb{E}_t V_{e,t+1} + (1 - f_t)\beta \mathbb{E}_t V_{u,t+1}] dF_\iota(\iota_i) \\ &\quad + \int_{\iota_t^s}^{\infty} \beta \mathbb{E}_t V_{u,t+1} dF_\iota(\iota_i) \end{aligned} \tag{1.16}$$

$$\tag{1.17}$$

Job value. At the beginning of the period upon realization of idiosyncratic production costs ϵ_j the worker-firm pair decide whether or not to continue the match. If $\epsilon_j > \epsilon_t^\xi$ then the match is terminated and the firm has to pay layoff tax τ_ξ as

well as a severance payment to the worker. Otherwise, the match produces output $\exp\{a_t\}$ and receives employment subsidy τ_s. The firm pays the worker wages w_t, the production cost ϵ_j, and a production tax $\tau_{J,t}$. The value of a filled job can therefore be written as:

$$\begin{aligned} J_t &= -\int_{\varepsilon_t^{\bar{\xi}}}^{\infty} [\tau_{\bar{\xi}} + w_t] dF_\varepsilon(\varepsilon_j) \\ &\quad + \int_{-\infty}^{\varepsilon_t^{\bar{\xi}}} [\exp\{a_t\} + \tau_s - \varepsilon_j - w_t + \tau_{J,t} + \mathbb{E}_t Q_{t,t+1} J_{t+1}] dF\varepsilon(\varepsilon_j) \end{aligned} \tag{1.18}$$

where $Q_{t,t+1}$ is the relevant stochastic discount factor for the firm:

$$Q_{t,t+s} = \beta \frac{\lambda_{t+s}}{\lambda_t} \tag{1.19}$$

and λ_t is the weighted marginal utility of firm owners (which comprises both employed and unemployed workers):

$$\lambda_t = \left(\frac{e_t(1-\xi_t)}{u'(w_t + \Pi_t)} + \frac{u_t}{u'(B_t + \Pi_t)} \right) \tag{1.20}$$

1.B Additional Tables & Figures

1.B.1 US Calibration

Table 1.8 provides a summary of the parameterization of the model to match US labour market data, as outlined in Section 1.3. Table 1.9 compares the second moments from simulating the baseline model to those in the data.

1.B.2 German Calibration

Table 1.10 provides a summary of the parameterization of the model to match US labour market data, as outlined in Section 1.3. Table 1.11 compares the second moments from simulating the baseline model to those in the data.

Parameter/Value	Description	Source/Target
Externally calibrated:		
$\beta = 0.996$	Discount factor	Standard
$\alpha = 0.3$	Match elasticity	Petrongolo and Pissarides (2001)
$\eta = 0.3$	Firm's joint surplus share	Hosios' (1990) condition
Internally calibrated:		
$\bar{h} = 0.382$	Leisure utility	$N = 0.075$
$\psi_s = 0.216$	Job search cost dispersion	$\varepsilon_{D_u} = 0.8$
$\kappa_v = 0.176$	Vacancy posting cost	6.4% unemp. rate
$\chi = 0.298$	Match efficiency	71% (quarterly) hiring rate
$\mu_\varepsilon = 0.063$	Production cost scale	$\int^{\varepsilon^\xi} \varepsilon F_\varepsilon(\varepsilon) = 0$
$\psi_\varepsilon = 0.659$	Production cost dispersion	$f = 0.282$
Policy:		
$\tau_s = 0$	Match subsidies	-
$\tau_\xi = 0.680$	Layoff tax	50% average UI claims
$\tau_J = 0.013$	Production tax	Balanced budget
Wage rigidity:		
$\gamma_w = 14.81$	Wage rigidity	$100 \cdot \sigma_f = 12.29$

Table 1.8. Calibration: US Labour market

Variable		y	a	$urate$	v	f	ξ	w	θ
σ_x	*Model*	3.43	1.59	22.20	21.36	12.29	12.15	2.74	40.96
	Data	3.34	1.85	17.46	18.55	12.29	8.52	1.94	13.85
$\rho_{x,y}$	*Model*	1	0.98	-0.99	0.88	0.99	-0.99	0.61	0.99
	Data	1	0.62	-0.89	0.80	0.86	-0.73	0.64	0.87

Notes: The table reports second moments in both the model and the data. Data moments are taken directly from those reported in Jung and Kuester (2015). Simulated series from the model are monthly averages, in logs, and multiplied by 100 to express them in percent deviation from steady state. The top panel compares unconditional standard deviations, whilst the bottom panel compare correlation with GDP.

Table 1.9. Model evaluation: Theoretical vs. Empirical Moments

Parameter/Value	Description	Source/Target
Externally calibrated:		
$\beta = 0.996$	Discount factor	Standard
$\alpha = 0.25$	Match elasticity	Jung et al. (2021)
$\eta = 0.25$	Firm's joint surplus share	Hosios' (1990) condition
Internally calibrated:		
$\bar{h} = -0.349$	Leisure utility	$s = 0.81$
$\psi_s = 0.395$	Job search cost dispersion	$\varepsilon_{D_u} = 0.5$
$\kappa_v = 0.930$	Vacancy posting cost	8.4% unemp. rate
$\chi = 0.094$	Match efficiency	70% (quarterly) hiring rate
$\mu_\varepsilon = 0.117$	Production cost scale	$\int^{\bar{\varepsilon}^\xi} \varepsilon F_\varepsilon(\varepsilon) = 0$
$\psi_\varepsilon = 3.334$	Production cost dispersion	$f = 0.062$
Policy:		
$\tau_s = 0.005$	Match subsidies	$\tau_s = 0.6 \cdot 0.0083 \cdot w$
$\tau_\xi = 5.415$	Layoff tax	$\tau_\xi = 6 \cdot w$
$\tau_J = 0.039$	Production tax	Balanced budget
Wage rigidity:		
$\gamma_w = 17.78$	Wage rigidity	$100 \cdot \sigma_f = 10.4$

Table 1.10. Calibration: German Labour market

Variable		y	a	$urate$	v	f	ξ	w
σ_x	*Model*	3.3	1.6	16.5	30.7	10.4	11.3	14.3
	Data	2.4	1.6	18.1	33.1	10.4	15.1	1.7
$\rho_{x,y}$	*Model*	1	0.93	-0.94	0.78	0.94	-0.97	0.06
	Data	1	0.77	-0.76	0.82	0.40	-0.81	0.84

Notes: The table reports second moments in both the model and the data. Data moments are taken directly from those reported in Jung and Kuhn (2014). Simulated series from the model are monthly averages, in logs, and multiplied by 100 to express them in percent deviation from steady state. The top panel compares unconditional standard deviations, whilst the bottom panel compare correlation with GDP.

Table 1.11. German calibration: Model evaluation

Chapter 2

The Allocative Channel of Cyclical UI

Abstract

This chapter explores the *allocative* channel of cyclical UI policy in an environment where there are heterogeneous workers and firms. Changes in UI generosity can improve worker-firm sorting by discouraging the formation of poor quality matches between worker firms, as well as adversely affect sorting by discouraging job creation and slowing down the speed at which employed workers can relocate towards their preferred job-type. We characterise the allocative effects of UI through the lens a model of labour market sorting in the spirit of Lise and Robin (2017) extended to allow for cyclicality in UI policy. After providing novel empirical evidence consistent with several key assumptions in the model using worker panel data, we carefully calibrate the model to match this micro-level evidence and use the resulting framework to characterise 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. In the model, we find that increasing 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. Finally, we find that cyclicality in UI policy generates welfare gains, but for different reasons: procyclical UI policy stabilises job creation incentives and helps alleviate the slowdown in worker reallocation during recessions, whilst countercyclical UI strengthens the cleansing effect of recessions. Overall welfare gains from UI cyclicality are small.

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

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

2.1 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 has been that the generosity of support provided to eligible unemployed workers has varied 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.

Through the lens of a standard Mortensen-Pissarides framework, increasing UI support during downturns typically only serves to amplify the effects of the recession on 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 during the downturn and therefore 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 prefer a *procyclical* UI policy precisely because because the employment channel of UI helps to stabilise employment fluctuations over the business cycle.[4]

[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

Allowing for *complementarities* in production between heterogeneous firms and workers who can search on-the-job, search frictions generate equilibrium misallocation in the labour market, i.e. workers will not in general be matched to their preferred firm-type (and vice versa). In this environment, changes in UI policy will affect the allocation of workers across jobs: we refer to this as the *allocative* channel of UI. However impact of changes in UI on the allocation of workers is *ex ante* ambiguous. For instance, increasing UI generosity will mean workers prefer 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 general equilibrium firms respond to the change in worker search behaviour through both the *type* and number of jobs they create. If workers use on-the-job search to relocate towards better matches, exacerbating job creation incentives slows this process down such that employed workers spend longer in worse matches. In the context of a growing empirical literature documenting the large degree of worker 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 chapter 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 chapter 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. We additionally allow for cyclicality in UI policy and an explicit characterization of the wage distribution following Lentz et al. (2016). Secondly, using worker panel data we provide new empirical evidence which is consistent with several key assumptions of the sorting

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.

[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).

model. Finally, we discipline the model using this micro-level evidence and use the resulting framework to characterise the allocative channel of 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 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 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 chapter 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] 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

[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 et al. (2023).

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 chapter proceeds as follows. Section 2.2 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 2.3 presents some empirical facts consistent with the model structure, as well as some new elasticity estimates we use subsequently to discipline the model. Section 2.4 details how we bring the model to the data, as well as report the model fit relative to targeted and untargeted outcomes. Section 2.5 explores the role of UI policy design by using the calibrated model to perform a policy counterfactual. Section 2.6 quantifies the welfare gains from different UI policies and examines how welfare gains are distributed between workers and firms. Section 2.7 concludes.

2.2 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 2.A and also Lise and Robin (2017).

2.2.1 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]:

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

[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.

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 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:

$$w(\sigma, x, y, z) = \sigma p(x, y, z) + (1 - \sigma) b(x, z) - \Delta \tag{2.1}$$

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:

$$S_t(x, y) = p_t(x, y) - b_t(x) + \frac{1 - \delta}{1 + r} \mathbb{E}_t \max\{S_{t+1}(x, y), 0\} \tag{2.2}$$

This result delivers tractability in the model whilst allowing for two-sided heterogeneity. This depends on several key assumptions: (i) transferable (linear) utility

[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.

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.

2.2.2 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).

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.

2.2.3 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

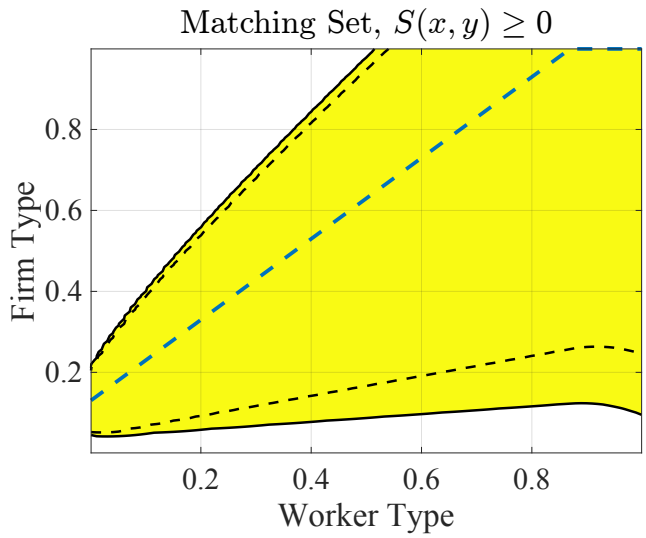


Figure 2.1. Illustrating how an increase in UI generosity $\Psi(z)$ contracts the matching set.

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 2.1, 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 sorting by encouraging the formation of better matches from the unemployment pool whilst reducing mismatches.

[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.

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.

2.3 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.

2.3.1 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.

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

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 2.B.

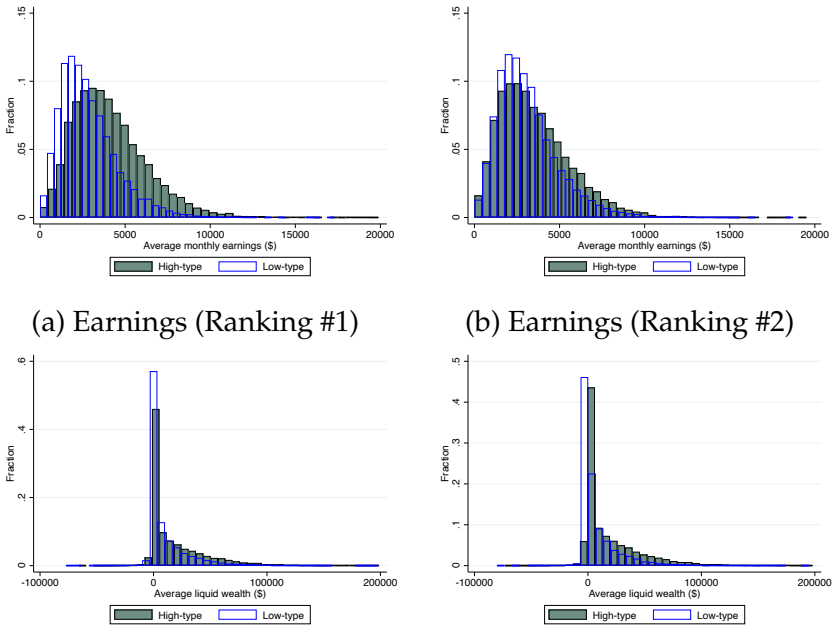
UI shocks. For a measure of exogenous variation in UI duration we adopt the shock series identified in Chodorow-Reich et al. (2019). Their methodology exploits the design of UI in the United States, where UI is administered at the state-level and responds endogenously to changes in real-time estimates 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.

2.3.2 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 regression.

2.3.3 Descriptive statistics by worker rank

Characteristics. How do worker characteristics vary by rank? Figure 2.2 plots the earnings and liquid wealth distributions by worker rank, whilst Figure 2.3 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



(a) Earnings (Ranking #1)

(b) Earnings (Ranking #2)

(c) Wealth (Ranking #1)

(d) Wealth (Ranking #2)

Figure 2.2. Earnings & wealth by worker rank

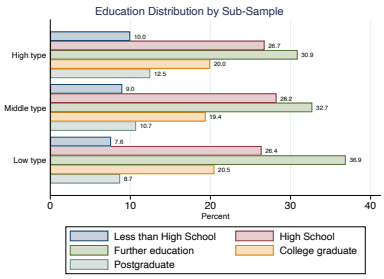
ranks in terms of educational attainment or occupations.[14] This finding is broadly consistent with other recent literature (e.g. Gregory et al. 2022) who find observable worker characteristics do not account for the vast majority of the variation in labour market experiences across workers in the data, which is used to justify the same assumption of *ex ante* heterogeneity across workers.[15]

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 2.1 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 low-rank workers face a separation rate that is more 30% higher than the sample average.[16] Through

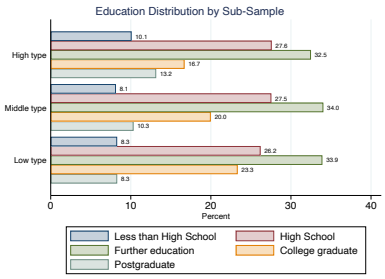
[14] In general we do not find any significant differences by worker rank across demographic characteristics.

[15] In Appendix 2.B.3 we examine which worker characteristics are most strongly correlated with being a UI recipient or experiencing unemployment in the data. Evidence from panel logit regressions suggests labour market experience, education and occupation are strongly correlated with UI claims, whilst overall cross-sectional variation in labour market experience is not well-explained by characteristics in the SIPP.

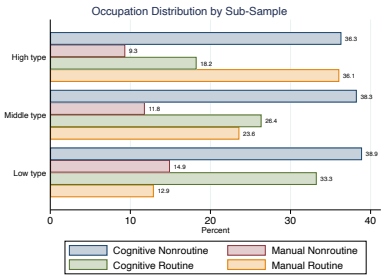
[16] This is consistent with results in Birinci and See (2023) who using the same sample document differences in unemployment risk by earnings and wealth only.



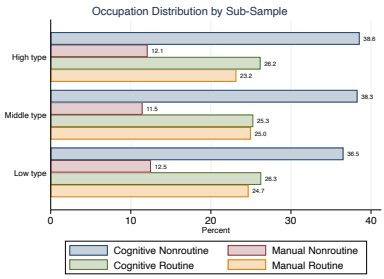
(a) Education (Ranking #1)



(b) Education (Ranking #2)



(c) Occupation (Ranking #1)



(d) Occupation (Ranking #2)

Figure 2.3. Education & occupation 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

Table 2.1. Unemployment risk by worker rank

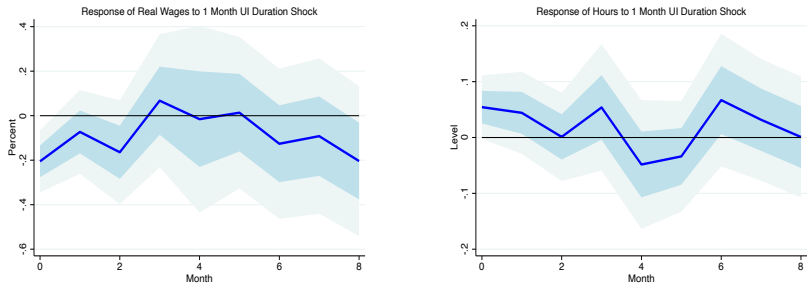
the lens of the theoretical model, this suggests that lower-ranked workers are on average located in matches that they are not well-suited to.

2.3.4 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 (2.1) implies that the elasticity of the 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 work-



(a) Real Wages (b) Hours

Figure 2.4. Impulse Responses of (Log) Real Wages and Hours

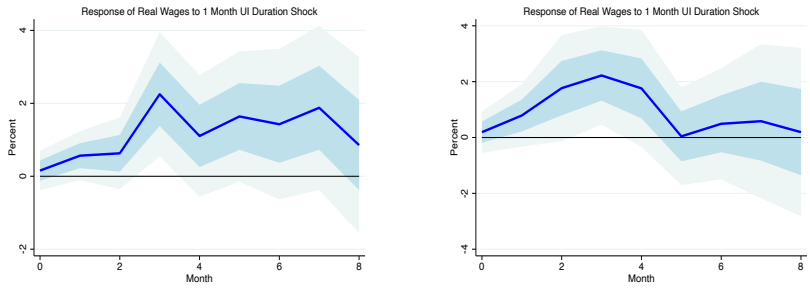
ers. In the model, σ is assumed to be zero when a worker is hired from unemployment but then subsequently increases endogenously whilst workers are employed and therefore are able to search on-the-job and use credible offers to bargain up their share of the surplus. At the same time $\frac{b(x,z)}{p(x,y,z)}$ 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 $h \geq 0$:

$$(\Delta_h) y_{i,s,t+h} = \left(\sum_{k=-\kappa}^{h} \gamma_h \varepsilon_{s,t+k}^{UI} \right) \times \mathbb{1}_{i \in \mathcal{I}^x} + \sum_{j=1}^{L} \delta_h' \mathbf{X}_{\mathbf{i,s,t-j}} + \phi_{i,h} + \phi_{s,h} + \phi_{t,h} + \nu_{i,t+h} \tag{2.3}$$

where $(\Delta_h) y_{i,s,t+h}$ is the (cumulative change in) worker-level variable of interest, $\varepsilon_{s,t}^{UI}$ 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), $\mathbf{X}_{\mathbf{i,s,t}}$ 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.

Average effect. The left panel of Figure 2.4 plots the responses of wages worked using the whole sample to identify the average effect of an increase in UI generos-



(a) UI Recipients (b) Unemployed

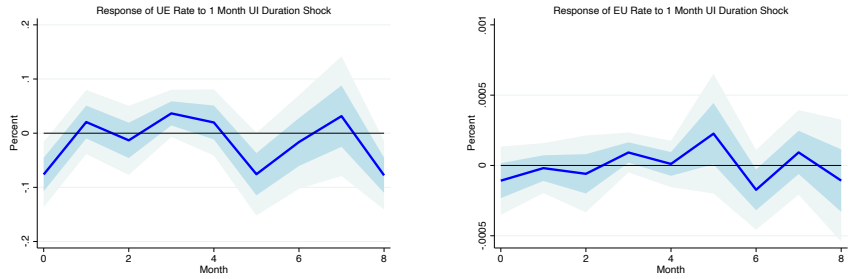
Figure 2.5. Wage elasticities by labour market experience in sample

ity.[17] 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.[18] Figure 2.5 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 subgroups 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

[17] 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.

[18] See Appendix ? for these results.



(a) UE Rate (b) EU Rate

Figure 2.6. Estimated responses of job finding and separation rates

(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.[19]

2.3.5 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).[20] We then estimate the elasticities via panel local projections again using the general specification in (2.3). Figure 2.6 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.[21] In the next section we use these estimates to discipline the quantitative model.

[19]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.

[20]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.

[21]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.

2.3.6 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 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.

2.4 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.

2.4.1 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 Den Haan et al. (2000) 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).[22] 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

[22] 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.

flow from unemployment to employment, between jobs, and from employment to unemployment, as standard in the literature.[23]

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.[24]

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 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 model, 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. How-

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

[24] 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.

ever 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 2.2 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 2.3. 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.

2.4.2 Model outcomes

In this section we examine additional model outcomes to inspect the properties of the calibrated model.

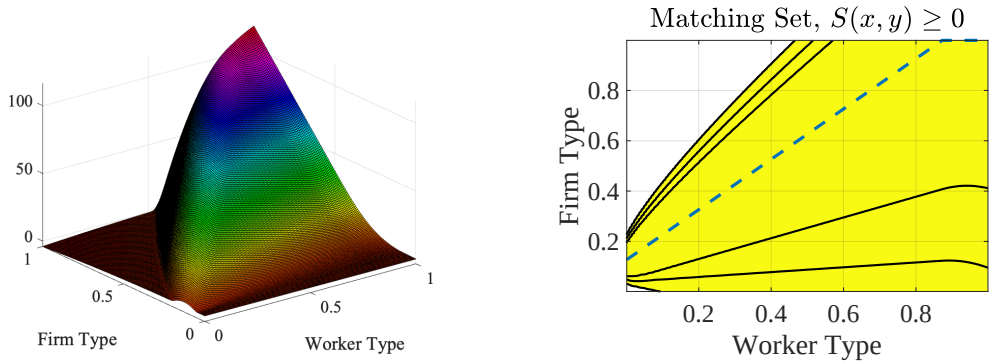
Surplus function. Figure 2.7a plots the solution for the surplus function $S(x, y)$ at the ergodic steady state, whilst Figure 2.7b plots the feasible matching sets for different values of the aggregate shock z. Inspecting the surplus function it can be seen that whilst mismatch is costly in either dimension, 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)

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
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
$\mathbb{E}[\text{sd } \Delta w \vert EE]$	0.403	0.360	SIPP

Table 2.2. Targeted moments

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

Table 2.3. Summary of parameters



(a) Surplus function

(b) Matching sets

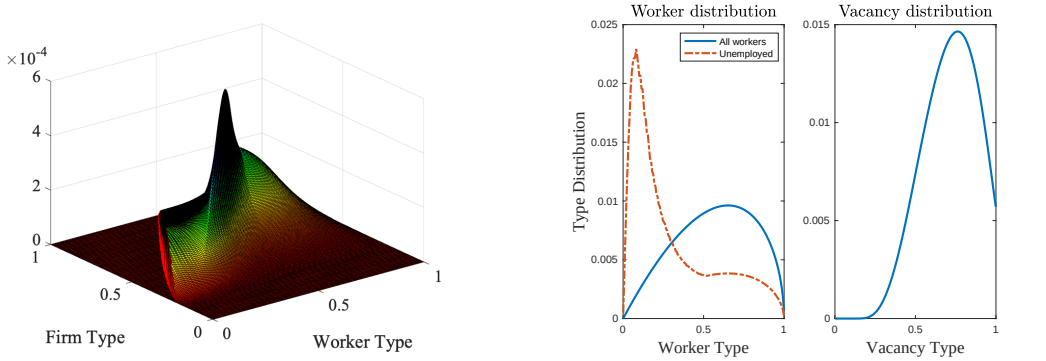
Figure 2.7. Surplus function and matching sets

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 2.8a, as well as the distribution of workers and vacancies in Figure 2.8b. 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 2.8b illustrates that under our baseline calibration the distribution of workers is slightly right-skewed but with most mass around the middle. Nevertheless, the distribution of unemployment is highly left-skewed towards the lowest types in order to match the concentration of unemployment in the data. This 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.

2.4.3 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



(a) Distribution of matches, $e(x, y)$ (b) Worker and vacancy distributions

Figure 2.8. Model equilibrium distributions

	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.

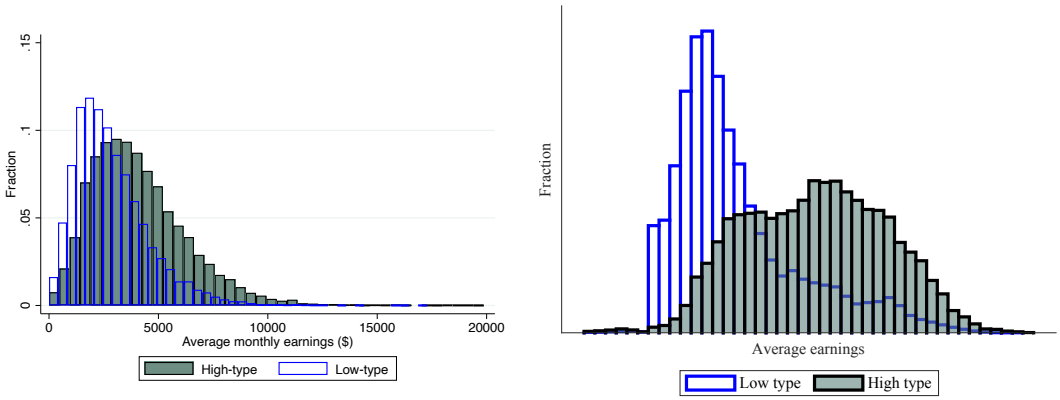
Table 2.4. Unemployment risk: Model vs. Data

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 2.4 displays the ratios of EU and UE transition rates by worker type relative to the average rate.[25] 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 2.9 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

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



(a) Data (b) Model

Figure 2.9. Earnings distribution by rank: Data vs. Model

generates the higher average earnings of high-type workers.[26] However the model does not generate the same right-skewed shape for the high-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.[27] The results for Low and High-type workers are presented in the upper panel of Table 2.5. 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 2.5 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 poaching of workers from low-type firms falls.[28]

[26]Note that the ranking method being used in this case is not based on earnings, but instead on time spent in non-employment.

[27]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.

[28]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

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).

Table 2.5. Sorting patterns: Data vs. Model

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.

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

2.5.1 UI shock

How does the worker-firm allocation respond to a one-time increase in UI generosity? Figure 2.10 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.[29] 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

paper.

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

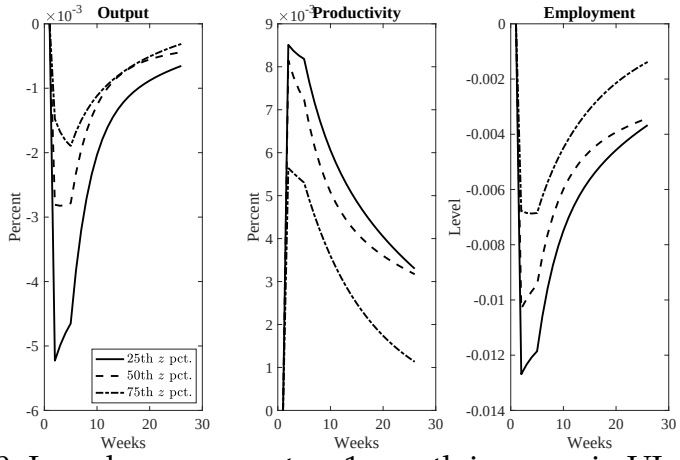


Figure 2.10. Impulse response to a 1 month increase in UI generosity

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 2.10 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.

2.5.2 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 2.6 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 ap-

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

Table 2.6. Cyclicality of sorting

pears to have a significant impact for the dynamics of worker-firm sorting through the lens of the model.

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 2.7. 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.[30] In contrast, moving to an acyclical 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

[30]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).

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.

Table 2.7. Sorting patterns: Counterfactual

they are productive at, they are relatively more affected by the larger fall in job creation and worker reallocation.

2.5.3 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?[31] 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.[32]

Figure 2.11 presents the response of the economy to a recessionary shock under

[31] 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.

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

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).[33]

Finally, the simulated moments from the model under the baseline UI policy and the counterfactual reported in Table 2.8 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.

[33]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.

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

Table 2.8. Cyclical moments: Counterfactual

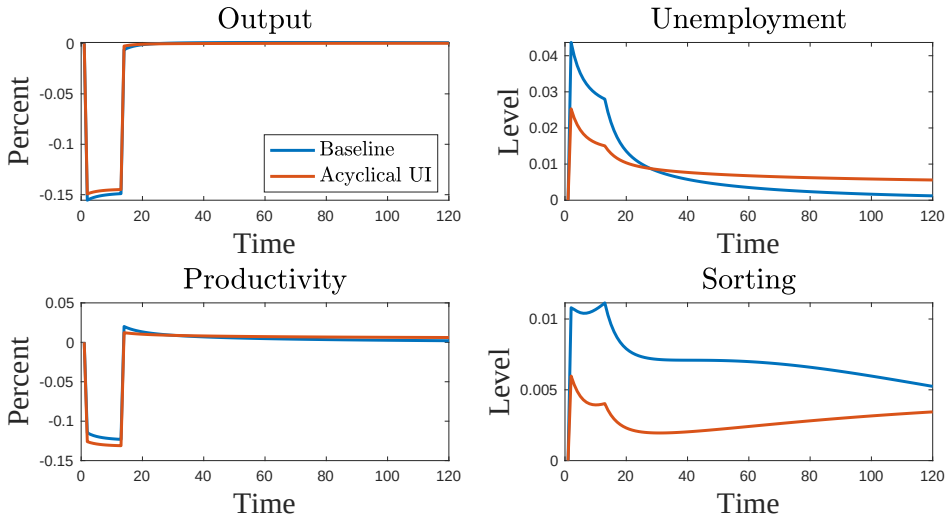


Figure 2.11. Recession under alternative UI policies

2.5.4 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 significant 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.

2.6 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.

2.6.1 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 2.12 plots the difference in social welfare ($\Delta\Omega$) relative to the acyclical case (i.e. $b_1 = 0$), normalized by steady state annual GDP.[34] 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.[35] 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

[34] 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.

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

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 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.[36]

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.

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

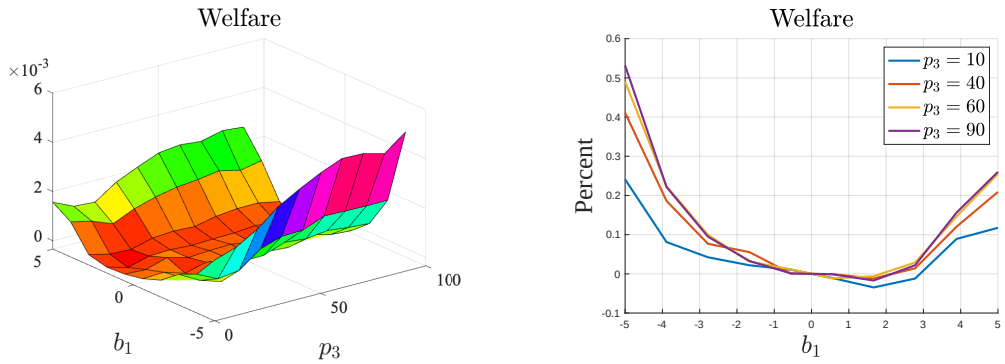


Figure 2.12. Social welfare under different $\{b_1, p_3\}$ combinations

2.6.2 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 2.13 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 2.13 that for workers the pattern of welfare gains follows that of the aggregate (Figure 2.12). 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.

2.6.3 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 2.14. 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.

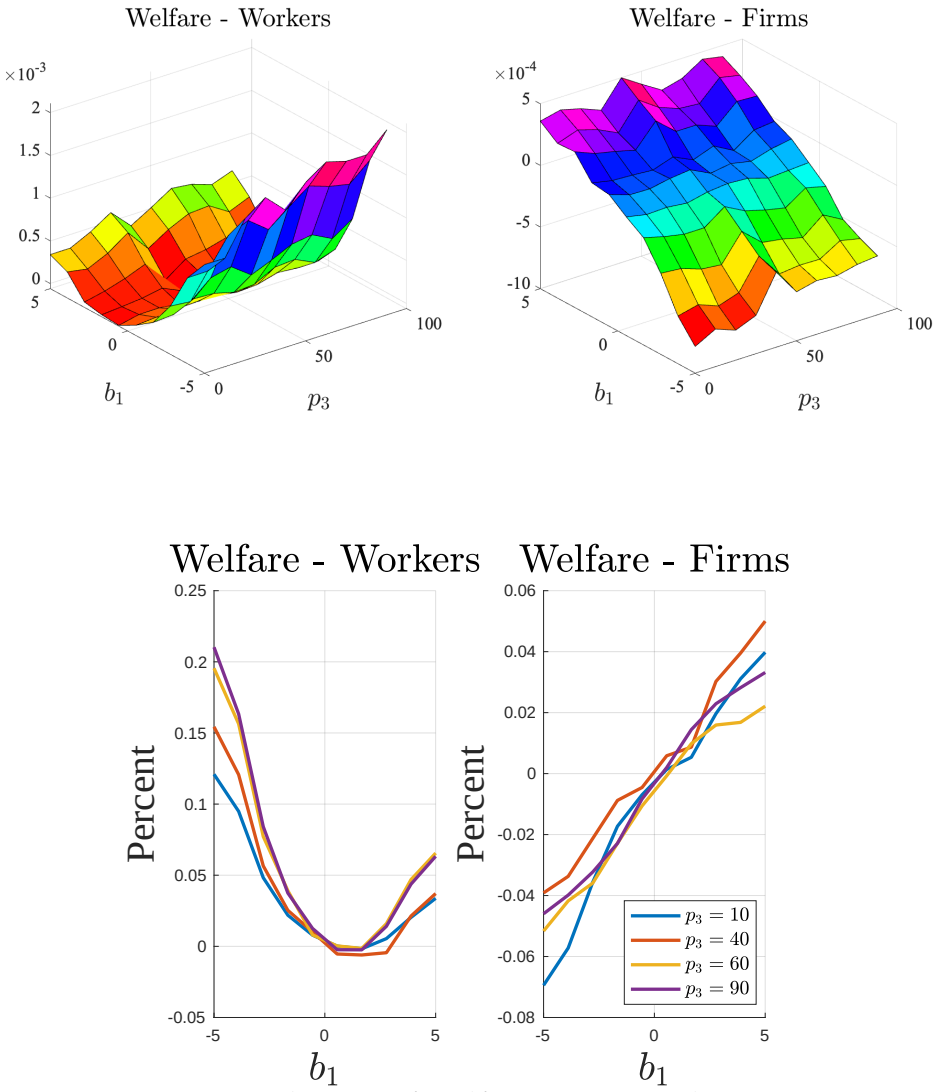


Figure 2.13. Distribution of welfare gains: Workers vs. Firms

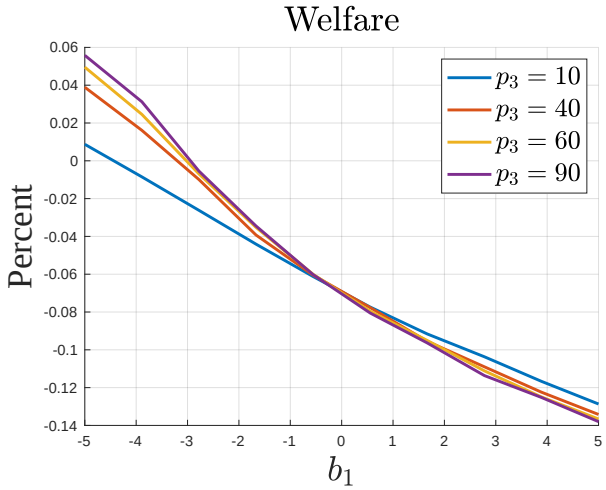


Figure 2.14. Social welfare in a recession under different UI policies

2.7 Conclusion

In this chapter, 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.

Chapter 2: Appendices

2.A Model Appendix

2.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.

2.A.2 Value Functions

Being unemployed with productivity x and aggregate productivity z has value

$$\begin{aligned} U_t(x) &= b_t(x) + \beta \mathbb{E}_t \left[(1 - f_{t+1}) U_{t+1}(x) + f_{t+1} \int E_{0,t}(x,y) \frac{v_{t+1}(y)}{V_{t+1}} dy \right] \\ &= b_t(x) + \beta \mathbb{E}_t U_{t+1}(x) \end{aligned} \tag{2.4}$$

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

$$\begin{aligned} P_t(x,y) &= p_t(x,y) \\ &\quad + \beta \mathbb{E}_t \Bigg[(1 - (1-\delta) \mathbb{1}\{P_{t+1}(x,y) \geq U_{t+1}(x)\} U_{t+1}(x) \\ &\quad + (1-\delta) \mathbb{1}\{P_{t+1}(x,y) \geq U_{t+1}(x)\} \Bigg((1 - s f_{t+1}) P_{t+1}(x,y) \\ &\quad + s f_{t+1} \int \max\{P_{t+1}(x,y), W_{1,t+1}(x,y',y)\} \frac{v_{t+1}(y')}{V_{t+1}} dy' \Bigg] \\ &= p_t(x,y) \\ &\quad + \beta \mathbb{E}_t \Bigg[(1 - (1-\delta) \mathbb{1}\{P_{t+1}(x,y) \geq U_{t+1}(x)\} U_{t+1}(x) \\ &\quad + (1-\delta) \mathbb{1}\{P_{t+1}(x,y) \geq U_{t+1}(x)\} P_{t+1}(x,y) \Bigg] \end{aligned} \tag{2.5}$$

where the second equality follows by imposing the sequential auction conditions.[37]

[37] 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.

Defining the match surplus as $S_t(x,y) = P_t(x,y) - U_t(x)$, and combining the values defined above, we have

$$S_t(x,y) = p_t(x,y) - b_t(x) + (1-\delta)\beta\mathbb{E}_t \max\{S_{t+1}(x,y), 0\} \tag{2.6}$$

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.

2.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.[38] 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

$$c'(v(y)) = q(\theta_t)J_t(y) \tag{2.7}$$

where the expected value of a contact is given as

$$\begin{aligned} J_t(y) \quad = \quad & \int \frac{u_{t+}(x)}{L_t} \max\{S_t(x,y), 0\}dx \\ & + \int\int \frac{se_{t+}(x,y)}{L_t} \max\{S_t(x,y) - S_t(x,y'), 0\}dxdy' \end{aligned} \tag{2.8}$$

2.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

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

matches who search on the job, a match with an alternative firm y' generates a renegotiation of σ to:

$$\sigma' = \begin{cases} S_{t+1}(x,y)/S_{t+1}(x,y') & \text{if } S_{t+1}(x,y') > S_{t+1}(x,y), \\ S_{t+1}(x,y')/S_{t+1}(x,y) & \text{if } \sigma S_{t+1}(x,y) < S_{t+1}(x,y') \leq S_{t+1}(x,y), \\ \sigma & \text{if } S_{t+1}(x,y') \leq \sigma S_{t+1}(x,y) \end{cases} \tag{2.9}$$

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:

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

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

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

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

$$\begin{aligned} w_t(\sigma,x,y) &= \sigma p_t(x,y) + (1-\sigma) b_t(x) \\ &\quad - (1-\delta)\beta \mathbb{E}_t \Bigg[\mathbb{1}\{S_{t+1}(x,y) \geq 0\} sp(\theta_{t+1}) \times \\ &\quad \int \Big[I_{t+1}(\sigma,x,y,y') - \sigma S_{t+1}(x,y) \Big] \frac{v_{t+1}(y')}{V_{t+1}} dy' \Bigg] \end{aligned} \tag{2.10}$$

2.A.5 Labour Market Flows

The law of motion for unemployment is

$$u_{t+1}(x) = u_{t+}(x)\left[1 - \int f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} dy\right] \tag{2.11}$$

and for employment

$$\begin{aligned} e_{t+1}(x,y) &= e_{t+}(x,y)\left[1 - \int s f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y') \geq S_t(x,y)\} dy'\right] \\ &\quad + \int e_{t+}(x,y') s f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq S_t(x,y')\} dy' \\ &\quad + u_{t+}(x) f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} \end{aligned} \tag{2.12}$$

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

$$\begin{aligned} \mathcal{W}_{t+1}(\sigma,x,y) &= \mathcal{W}_{t+}(\sigma,x,y)\left[1 - s f_t + \int s f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y') \leq \sigma S_t(x,y)\} dy'\right] \\ &\quad + \int e_{t+}(x,y') s f_t \frac{v_t(v)}{V_t} \mathbb{1}\{\sigma S_t(x,y) > S_t(x,y')\} \\ &\quad + u_{t+}(x) f_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} \end{aligned} \tag{2.13}$$

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

2.A.6 Equilibrium

Definition 2.2 (Equilibrium)**.** *Given a sequence of aggregate shocks $\{Z_t\}_{t=0}^T$ and initial distributions of employment $e_0(x,y)$ and unemployment $u_0(x)$, wage contracts $\mathcal{W}_0(\sigma,x,y)$, and the joint surplus function $S(x,y,z)$, an equilibrium is defined as a unique sequence*

for the distribution of vacancies $v_t(y)$, unemployed workers $u_t(x)$, worker-firm matches $e_t(x,y)$ and wage contracts $\mathcal{W}_t(\sigma,x,y)$ which is determined by: the job creation condition in 2.7, the definition of $J_t(y)$ in 2.8, the laws of motion for $u_t(x)$ and $e_t(x,y)$ in 2.11 and 2.12, the wage equation in 2.10 and the evolution of contracts $\mathcal{W}_t(\sigma,x,y)$ in 2.13.

2.B Data Appendix

2.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 (2013) 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.

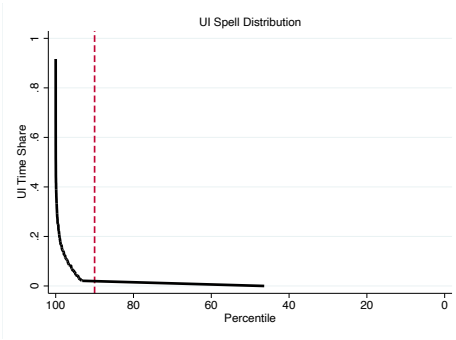
Occupation. The SIPP uses the Census of Population Occupational System to provide 3-digit occupation codes for individuals, which is closely related to the Standard Occupational Code (SOC) system for classifying worker occupations. One

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 and Dorn (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.

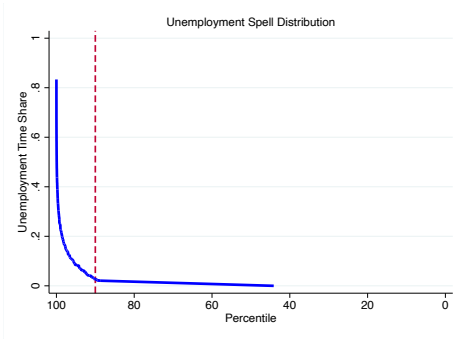
State-level aggregation. To estimate panel local projections using Chodorow-Reich et al. (2019) UI shocks, we generate state-level estimates for key variables. To obtain state-level measures of wages and UI income we simply use the weighted average across all individuals in the sample by state. We compute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

2.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 2.15. Labour force status: Distributions by time

	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.

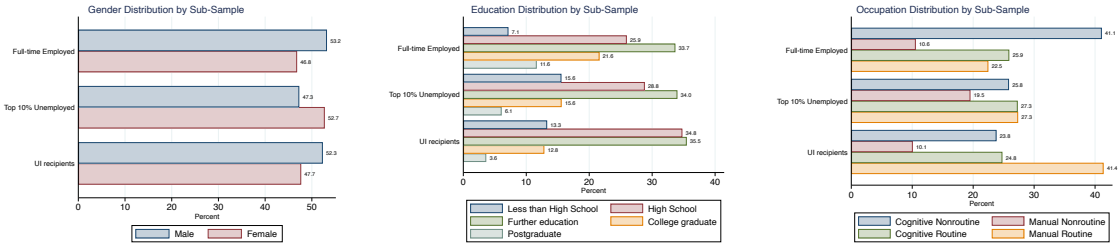
Table 2.9. US labour market experiences: SIPP 1996-2013

2.B.3 UI Claimants and the Unemployed in the Data

Incidence of UI claims. 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).[39] Figure 2.15 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 2.9 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.

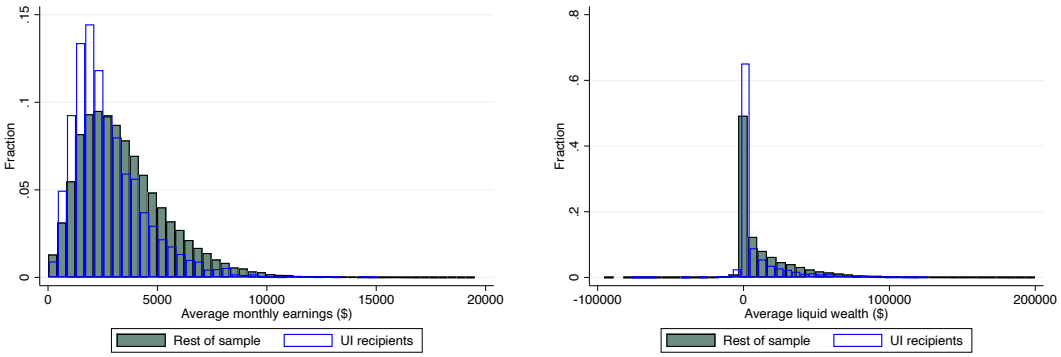
Characteristics of UI recipients. Figure 2.16 plots selected demographic characteristics by sub-sample, whilst Figure 2.17 plots earnings and wealth distributions.

[39] 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 2.16. Worker characteristics by sub-sample



(a) Earnings (b) Liquid wealth

Figure 2.17. Average earnings & wealth distributions: UI recipients vs. Rest of sample

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.

Table 2.10. Transition rates by group: SIPP 1996-2013

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

These patterns are reflected when we examine worker transition rates between employment and unemployment in the SIPP sample by worker characteristic. Table 2.10 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.

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.[40] The results are displayed in Table 2.11. The most strongly associated characteristic is the fraction of time spent a worker spends in unemployment. 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

[40]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.

	(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.

Table 2.11. Effects of worker-level observables on UI receipt status

wealth distributions appear to be much less strongly correlated with claiming UI when we account for other observables.

Finally, we quantify the relative importance of worker characteristics in accounting for cross-sectional variation in the duration of UI spells by estimating a simple cross-sectional regression on the fraction of time spent claiming UI (conditional on claiming UI). The results for various specifications are presented in Table 2.12. 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. We find a similar story when we look at time spent in unemployment in Table 2.13.

	(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 2.12. Accounting for fraction (%) time receiving UI

	(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.

Table 2.13. Accounting for share (%) time unemployed

Chapter 3

Participation, Job Search and Labour Force Attachment*

Abstract

This paper develops a tractable search & matching framework heterogeneous search intensity among the non-employed and endogenous job destruction that is consistent with the observed cyclical behaviour of both labour force flows and participation flows. Using UK flows data, we outline two key facts regarding the participation margin which motivate our model. Firstly, total inflows into the labour force are constant over the business cycle. Second, procyclicality in outflows from the unemployed is driven by a compositional shift in recessions towards workers with higher labour market attachment. In the model participation status depends on whether a non-employed worker's search intensity exceeds an arbitrary threshold, whilst labour market attachment depends on recent labour force experience. After calibrating the model to match key facts from the flows data, we illustrate that our tractable environment is able to generate the correct cyclical patterns for all labour force flows as we estimate in the data, as well as account for a sizeable amount of the labour market dynamics over the Great Recession period. Finally, we find that fluctuations in the composition of searchers amplifies unemployment volatility and is significant in accounting for the speed of the rise in unemployment at the onset of the Great Recession.

Keywords: *Participation, Search intensity, Labour force attachment*

JEL Codes: *E24, E32, J21, J64*

*This chapter is based on joint work with Tomas Key and Bradley Speigner, both Bank of England. The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees.

3.1 Introduction

Economists and policymakers have long been interested in accurately measuring the degree of economic slack over the business cycle. Until relatively recently, the dominant view was that fluctuations in labour market slack could be explained almost entirely by cyclical fluctuations in labour demand, whilst labour *supply* was viewed as acyclical and therefore unimportant for understanding cyclical labour market dynamics. Yet a distinguishing feature of the two most recent recessions for many advanced economies - the Great Recession in 2008, and the Covid-19 pandemic in 2020 - was a sizeable contraction in the size of the labour force. This led many researchers and policymakers alike to stress the importance of improving our knowledge regarding the role of cyclical changes in labour force participation rates for measuring labour market slack over the business cycle.[2]

Recent developments in the theoretical literature have reflected this pivot towards understanding the cyclicality of labour supply, where there has been a growth in the development of general equilibrium matching models featuring an endogenous participation margin. The goal of this literature has been to develop frameworks which jointly account for fluctuations in labour demand and supply, but has generally found that augmenting standard frameworks with a participation margin cannot easily account for the joint behaviour of labour market stocks and flows. These new 'puzzles' have not only been quantitative in nature (linked to other well-known puzzles such as the unemployment volatility puzzle), but rather *qualitative* in the sense that even generating the correct cyclicality of stocks is non-trivial. Moreover, most of this literature has taken a stock-based rather than *flow-based* approach. This has meant that often even when the cyclicality of stocks are correct, the underlying mechanisms are inconsistent with evidence from micro-data on labour market flows. Although there are some important recent exceptions to this - such as Krusell et al. (2017) and Cairo et al. (2022) - a standard general equilibrium matching framework featuring a labour force participation margin that is capable of matching empirically realistic labor force behavior consistent with micro-data on labour market flows has yet to emerge.

[2]For example see Bernanke (2012), Yellen (2014) and Bullard (2014).

This paper seeks to make a contribution by bridging a gap between the empirical and theoretical literature. Motivated by recent evidence emphasising the role of complex interactions between labour market flows for explaining cyclical labour supply (e.g. Elsby et al. 2015), we develop an equilibrium model of the labour market where labour force participation is determined by whether the search intensity e of a non-employed worker falls below some participation threshold $\underline{e}$. This contrasts with the standard approach where participation is a discontinuous decision made by an individual worker or household between 'active' job search (unemployment) or 'passive' job search (inactivity). As well as being analytically more convenient, this approach is also more consistent with the statistical definitions of unemployment and inactivity as based on 'active' job search, as well as studies which document a non-generate distribution of search intensity among the non-employed (e.g. Pizzinelli and Speigner 2017).[3]

The analysis in the paper proceeds in two steps. Firstly, we revisit evidence from micro-data regarding the cyclical behaviour of flows in order to motivate the key features of our theoretical framework. Then, we outline a model of equilibrium labour market dynamics featuring a participation margin which is able to replicate these salient facts about the behaviour of labour force flows over the business cycle, which is the main contribution of our paper.

The first part of the paper presents empirical analysis of labour market flows using data from the UK Labour Force Survey (LFS) between 1993Q1-2023Q1. Our main focus is to identify two key features of the participation margin in the data which motivate our theoretical framework. Firstly, we document that total inflows into the labour force from inactivity are roughly constant over the business cycle, where this steady flow of new workers are more likely to transition into employment (unemployment) during expansions (recessions). This suggests that the average search intensity among inactive workers is inelastic with respect to changes in aggregate labour market conditions. Secondly, procyclical outflows from the labour force are driven by compositional shifts among the non-employed towards workers with a higher degree of labour market attachment. Notably, we find that those who have recently separated from jobs or who have been long-term unemployed are less likely to withdraw from the labour market, whilst their share among the

[3]For instance, the International Labour Organization (ILO) defines unemployed workers as being: (i) "without a job, have been actively seeking work in the past four weeks and are available to start work in the next two weeks", or (ii) "out of work, have found a job and are waiting to start it in the next two weeks"

non-employed increases during recessions. These facts are difficult to reconcile with the standard theoretical approach to modelling labour supply, where workers make a discrete decision to participate or not determined by labour market conditions, as this so-called 'discouraged worker' channel typically generates strongly procyclical inflows and countercyclical outflows.[4]

Next, we develop a theoretical framework that attempts to capture jointly the cyclical behaviour of labour demand and supply in a way which is consistent with these facts about participation flows. Our approach extends the standard search & matching framework with variable search effort to allow for heterogeneous search intensity among the non-employed and an endogenous job destruction margin. The key innovation in our approach relative to the previous literature is to define labour force participation among the non-employed relative to an exogenous, time-invariant search intensity threshold $\bar{e}$ which is then straightforward to calibrate using the flows data. There are several notable features of the model which are important in allowing us to match the empirical behaviour of the participation margin. Firstly, workers' search intensity e is exogenous and redrawn from a distribution (with frequency depending on labour market status). Search intensity among the inactive is therefore perfectly inelastic with respect to aggregate conditions, whilst we still allow for fluctuations in aggregate search intensity to be driven exclusively by compositional shifts in the pool of non-employed workers. Endogenous changes in labour market tightness then determine how the composition of inflows into unemployment and employment varies over the cycle. Secondly, workers who are endogenously laid-off are assumed to have a higher degree of attachment (i.e. search intensity) than workers who separate for exogenous reasons, where this high-degree of attachment then gradually declines over time. This is crucial for allowing the model to generate the same compositional shifts among the unemployment pool that we observe in the data.

Our first main finding is that in addition to being flexible enough to match all labour market flow rates in steady state, our resulting framework is able to replicate the correct cyclicality of labour force flows we estimate in the data conditional on a shock to aggregate labour productivity, and moreover is able to broadly account for the dynamics of labour market stocks when fitted to the Great Recession period. We do not rely on other assumptions such as rigid wages or risk-aversion to generate this result, and although the framework still suffers with generating

[4]See, for example, Tripier (2004), Haefke and Reiter (2006) and Veracierto (2008).

sufficient volatility we show that adopting standard strategies to address this significantly improves the fit of the model. Secondly, we illustrate that incorporating the participation margin in this way actually *amplifies* unemployment volatility. Key to this result is that the overall impact from the distribution of unemployed shifting towards those who are more attached to the labour market dominates the fact that in equilibrium this dampens the decline in job creation by firms. Finally, we show that through the lens of the model this composition effect is important for capturing the initial rise in unemployment during the Great Recession.

Overall, the paper puts forward a parsimonious version of an equilibrium search & matching model with variable worker search effort, where the key mechanisms around changes in the composition of the unemployment pool are consistent with micro-evidence on labour force flows, and which is able to account for the joint cyclical behaviour of labour market flows and stocks. Exploring extensions to the model to allow for endogeneity in the choice of search effort to capture the movements in intensive margin search effort outlined in Mukoyama et al. (2018) which is also able to capture both the dispersion and persistence we see in the data is the next step in our research agenda.

Related literature. Our paper seeks to bridge the empirical literature emphasising the role of cyclical labour supply with a theoretical literature that seeks to incorporate a labour supply margin into models of equilibrium unemployment with search & matching frictions. Additionally, we also bridge two branches of the theoretical literature by allowing for heterogeneous search intensity among the non-employed and defining non-participation relative to some exogenously chosen threshold, rather than via a discontinuous participation decision.

The flows-based approach to analysing the cyclical properties of the labour market we adopt in this paper follows key contributions such as Elsby, Michaels and Solon (2009), Fujita and Ramey (2009), Shimer (2012) and Elsby et al. (2019) using US data from the Current Population Survey (CPS), and Petrongolo and Pissarides (2008), Gomes (2009) and Smith (2011) using UK data. Most of this literature has focused on the debate as to whether separations into unemployment (the EU rate) or transitions from unemployment to employment (the UE rate) are more important for explaining unemployment volatility in the data, and tended not to focus on the role of transitions into and out of the labour force. The relationship between cyclicality in labour market conditions and labour supply has been recognised at least since early work by Perry (1971) and Okun (1973), which documented a mild

procyclicality of aggregate labour supply.[5] The seminal contribution emphasising the importance of the participation margin for cyclical labour market fluctuations is Elsby et al. (2015). Our analysis shows that similar patterns hold for the UK labour market, including the apparent increase in attachment of recently unemployed workers during the Great Recession. More recent work by Hobijn and Sahin (2021) provides evidence that cyclical movements in participation are driven by the same forces as changes in unemployment, as on average unemployed workers are more likely to exit the labour force than employed workers.

With regards to the theoretical literature, there have been many attempts at integrating a labour supply margin into standard models of equilibrium unemployment based on search & matching frictions following Mortensen and Pissarides (1994). Notable early examples include Tripier (2004) and Veracierto (2008), however in the models developed in these papers the incentives to participate are strongly procyclical such that unemployment becomes counterfactually procyclical. Haefke and Reiter (2006) find that heterogeneity in the outside option can address this issue, whilst Shimer (2013) emphasises the role of wage rigidities in mitigating the rise in the value of participation during booms. A subset of the literature has also embedded similar environments into New Keynesian models to study the implications of the participation margin for monetary policy.[6] However none of these studies attempt to develop environments which are consistent with the cyclical behaviour of labour market flows we observe in the micro-data.

There are several important exception to this. Firstly, Krusell et al. (2017) develop a rich environment where workers face idiosyncratic risk, incomplete markets, search frictions in the labour market and make a participation decision. In this environment, the correct cyclicality of transition rates is accounted for by wealth heterogeneity and associated compositional effects. The most closely related paper to ours is Cairo et al. (2022) who similarly aim to develop a simpler environment that can account for the correct cyclcial behaviour of labour market flows. In the context of a standard discrete participation decision, they emphasise the importance of the participation margin *countercyclical* (i.e. booms are times when households decide to send fewer workers to the labour force). To achieve this, Cairo et al. (2022) rely on several model features including non-linear utility, substitutability

[5] A brief overview of this literature is provided in Hobijn and Sahin (2021).

[6] Examples include Galí et al. (2012), Speigner (2012) and Campolmi and Gnocchi (2016). Erceg and Levine (2014) also study the implications of the participation margin for monetary policy, but do not model equilibrium unemployment using search & matching frictions.

between home and market goods, rigid wages, as well as additional assumptions. Relative to their environment, we rely on much fewer assumptions in an even simpler environment to generate a model consistent with the observed cyclicality of labour market flows.

Finally, our model is closely related to the literature which has allowed for variable search intensity in the context of search & matching models. Key examples of this are Pissarides (2000, ch.5), Shimer (2004), Mitman and Rabinovich (2015), Mukoyama et al. (2018) and Faberman et al. (2022). Our contribution relative to these papers is to allow for search intensity among the non-employed to be heterogeneous, and then to define labour force participation based on an exogenously determined threshold for search intensity.

Layout. The rest of the paper is structured as follows. In Section 3.2 we present evidence on the participation using flows data which motivate our subsequent model. Section 3.3 outlines the theoretical framework we develop. Section 3.4 presents the calibration of the baseline model to match the flows data. Section 3.5 outlines the main quantitative results of the paper. Section 3.6 concludes.

3.2 Motivating Evidence

In this section we revisit a number of stylised facts regarding the cyclicality of labour force flows using UK flows data. We first provide unconditional and conditional evidence on the cyclical properties of labour force flows, before separately characterising the behaviour of flows into and out of the labour force which motivate how we model the participation margin.

3.2.1 Data

Sources. For labour force flows we use data from the two-quarter longitudinal UK Labour Force Survey (LFS). For each quarter, individual observations contain information on demographics, as well as labour force status for the current and previous quarter. The linked data allows us to construct measures of labour force flow rates for the UK. We apply the recommended survey weights in order to make the sample representative of the UK population. The full sample covers the period 1993Q1-2023Q4.

Constructing labour market flows. We construct labour market flows for those aged 16-64. In order to correct for inconsistencies between the flow and stock es-

	EU	EN	UE	UN	NE	NU
std(x)	0.091	0.066	0.061	0.065	0.070	0.051
corr(x, Y)	-0.605	0.172	0.535	0.219	0.496	-0.256
corr(x, x_{-1})	0.359	-0.194	0.489	0.238	0.307	0.106

Notes: Data cover the sample period 2001Q4-2019Q4. All series are in logs and filtered using a HP filter using smoothing parameter $\lambda = 1600$ as standard for quarterly data.

Table 3.1. Labour market flows: Cyclical properties

timates, possibly due to non-random attrition or entry to and exit from the age-range, we adjust the transition rates following the approach taken by Elsby et al. (2015). This approach solves for the set of stock-consistent transition probabilities that minimizes the weighted sum of squares of the 'margin-error adjustments'.[7]

3.2.2 Cyclical properties of labour market flows

To fix ideas, we revisit the cyclical properties of each of the labour force transition rates[8] We present both unconditional evidence from detrended data (which is standard in the literature), as well as conditional evidence based on a labour productivity shock identified from an estimated VAR. We also present flow decompositions of labour market stocks during the Great Recession as in Elsby et al. (2015) to emphasise the non-negligible role of the participation margin for labour market slack during this period.

Unconditional evidence. Table 3.1 presents the unconditional cyclical properties of UK labour market flow rates individually. The magnitudes of the cyclical fluctuations across all the flow rates are fairly similar. As is well documented elsewhere, separations into unemployment are strongly countercyclical (corr. with output -0.6) whilst the job finding rate among unemployed is strongly procyclical. We find that inflows into employment from inactivity are also strongly procyclical, whereas inflows into unemployment are countercyclical. Finally, outflows into inactivity from both employment and unemployment are mildly procyclical.

Table 3.2 also presents variance decompositions of UK labour market stocks into contributions from each flow rate based on the methodology in Elsby et al. (2015). For both employment and unemployment, the flows between these two states (the

[7] See Elsby et al. (2015) for further details of this approach.

[8] These have been documented elsewhere using primarily US data. See for example Elsby et al. (2015), Krusell et al. (2017). For the UK, see Smith (2011).

	EU	EN	UE	UN	NE	NU	initial value	residual
EPOP	0.27	0.12	0.38	-0.02	0.30	-0.06	0.01	0.01
UR	0.31	-0.01	0.40	0.21	0.04	0.03	0.00	0.02
LFPR	0.08	0.41	0.07	0.04	0.35	0.04	0.00	-0.01

Notes: The table reports the decomposition of labour market stocks according to contribution by each flow rate following Elsby et al. (2015). All data cover the sample period 2001Q4-2019Q4.

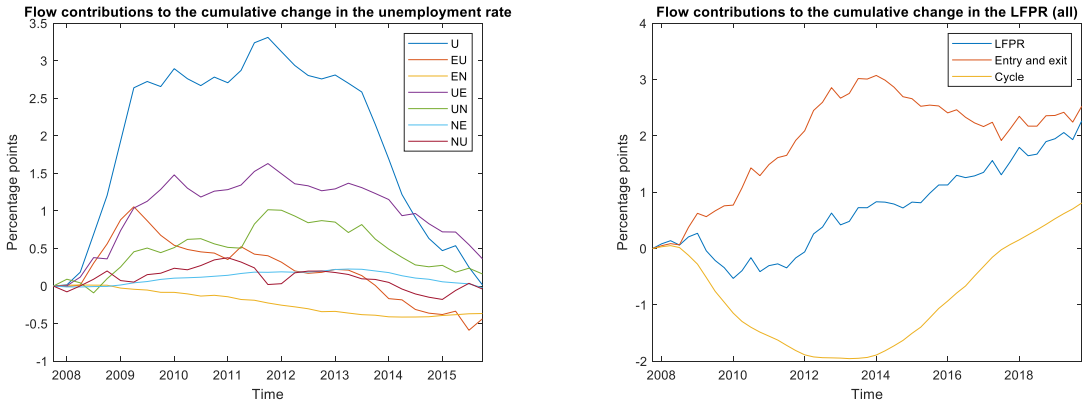
Table 3.2. Variance decomposition of changes in labour market stocks

EU and UE rates) account for the majority of fluctuations and has been the key focus of the empirical literature. However, participation flows also account for a non-negligible fraction of variation: for employment inflows from inactivity account for around 30% variance, whilst for unemployment changes in the withdrawal rate of unemployed workers (UN rate) accounts for around 20% unemployment variance.

Focusing in on the Great Recession period, Figure 3.1 illustrates visually how labour market flows contributed to changes in activity rates. For unemployment (left panel), the initial increase separations (EU rate) are important for driving unemployment at the onset of the recession whilst the decline in the job finding rate (UE rate) is the key driver overall. However the declining UN rate over this period plays a significant role in unemployment remaining persistently high. The right panel of Figure 3.1 does the same exercise for the participation rate, where we have grouped the flows rates into two groups: (i) within labour force transitions (labelled 'Cycle', the EU and UE rates), and (ii) transitions into and out of the labour force (the EN, UN, NE and NU rates). Perhaps counterintuitively, during the Great Recession the overall fall in participation is driven by the dynamics of *within* labour force transition rates, whilst the behaviour of the entry and exit flow rates actually pushed up on participation. This may seem like a puzzle, but in reality this is driven by the fact that unemployed workers are significantly more likely to leave the labour force (average EN rate is 0.02 compared to an average UN rate which is 0.2), so forces increasing unemployment during a recession also push down on participation.[9]

Conditional evidence. We also present evidence on the cyclicality of labour market flows conditional on an identified labour productivity shock, following the ap-

[9]This point is made in Hobijn and Sahin (2021), who argue that there is a 'participation' cycle in the data which lags the movements in cyclical unemployment precisely because of these compositional changes within the labour force.



(a) Unemployment rate

(b) Participation rate

Figure 3.1. Flow decomposition of labour market stocks during the Great Recession

proach Cairo et al. (2022) who use US flows data. More specifically, we estimate a VAR containing the six labour market flow rates, vacancies and real wages, as well as labour productivity (ordered first). Given the fairly short sample length for the UK flows data compared to the US, we instead estimate the VAR using Bayesian techniques following the approach outlined in Giannone et al. (2015). We also run the estimation using two different identification schemes for robustness: (i) a standard Cholesky approach, and (ii) a sign-restriction approach.[10]

Figure 3.2 presents the estimated IRFs to a positive productivity shock under both identification schemes. The overall story is consistent with unconditional evidence. In response to a positive labour productivity shock, separations into unemployment fall whilst job finding rates among the unemployed significantly increase. The outflow rate from employment (EN rate) is insensitive to the shock, whilst outflows from unemployment (UN rate) *increase*. Finally, inflows into employment increase whilst inflows into unemployment fall.

3.2.3 Participation margin in the data

In this section we emphasise the properties of the participation margin in the data which motivate the choices we make in our subsequent theoretical framework out-

[10]For the sign-restriction approach, the identifying assumptions are restrictions on the responses of the EU rate, the UE rate, the vacancy rate and productivity. The productivity response is restricted to be of a similar magnitude to the shock identified by the Cholesky decomposition; the UE and vacancy rate responses are restricted to be positive in response to this productivity shock; while the EU rate response is restricted to be negative.

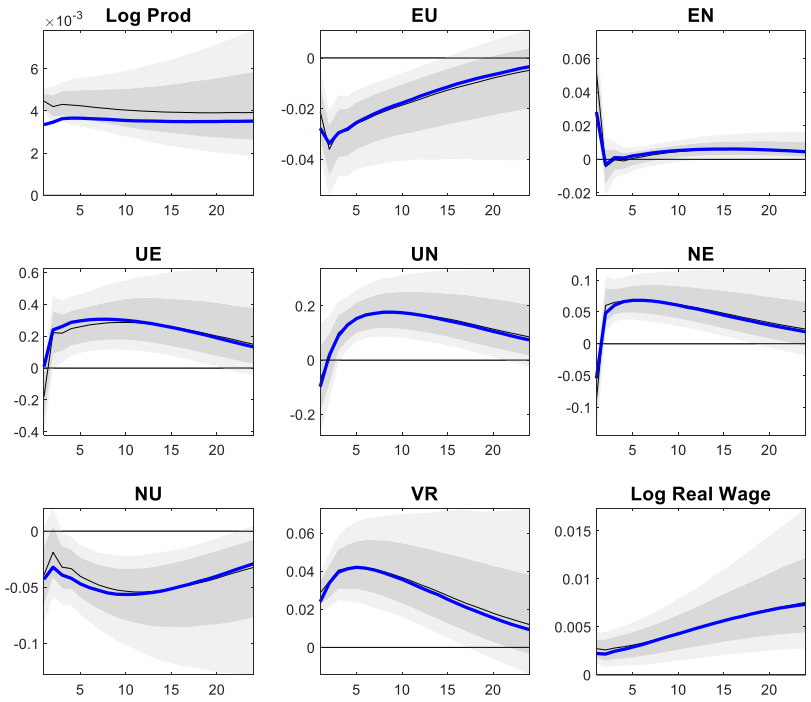


Figure 3.2. IRFs for a productivity shock identified by sign- and magnitude-restrictions (blue lines), alongside Cholesky IRFs (black lines, and shaded CIs)

lined in the next section. Specifically, we look separately at the cyclical behaviour of labour force inflows (i.e. NE and NU rates) and outflows (i.e. EN and UN rates).

Fact 1. Labour force inflows are acyclical. Figure 3.3 plots separately the raw labour force inflow rates (as well as their sum), and in the adjacent panel compares them to labour force outflow rates.[11] Immediately it can be seen that the aggregate labour force inflow rate was essentially flat during the Great Recession in the UK. Although the NE and NU rates are themselves cyclical, they move in opposite directions during the downturn such that the aggregate inflow rate remained roughly constant. What changes during the Great Recession is that the relatively constant inflow of new workers are more likely to enter unemployment rather than find a job straight away. In contrast, labour force outflows are strongly procyclical and are driven by the dynamics of the UN rate (see below).

From the perspective of the classic 'discouraged worker' channel, which predicts that labour force inflows should fall and outflows should increase during down-

[11] As stated previously these flow rates have been adjusted following the approach suggested in Elsby et al. (2015).

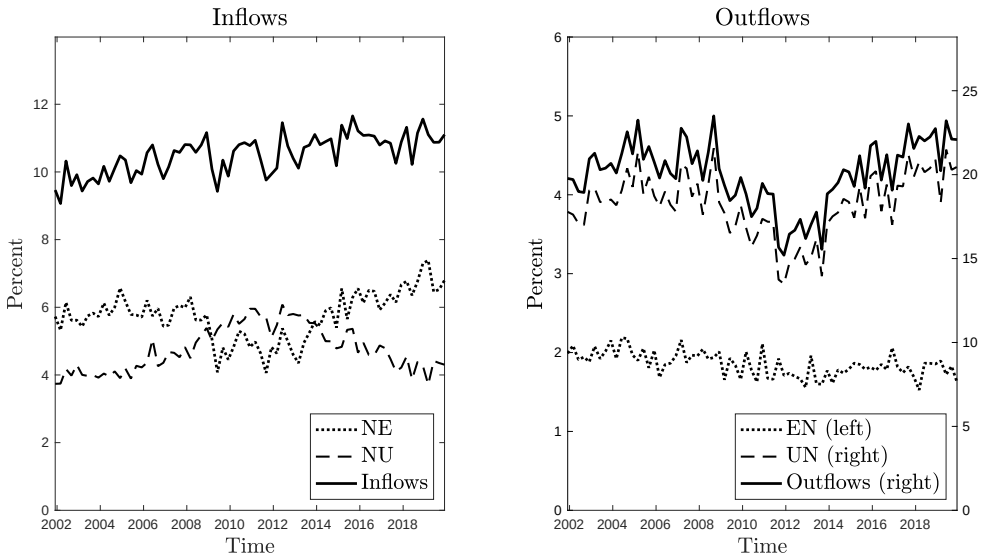


Figure 3.3. Participation margin in the data: Inflows vs. Outflows

turns as the value of employment falls and jobs are harder to find, this seems puzzling. Instead, we find that inflows are acyclical and outflows are procyclical. Taken together, this suggests that both labour force inflows and outflows are significantly inelastic to changes in aggregate conditions over the business cycle.

Fact 2. Procyclical outflows driven by composition effects among the non-employed. Similarly to Elsby et al. (2015) for the US, we find that an unemployed individual's prior labour force history is a key factor which determines their current probability of exiting the labour force (labour market 'attachment'). Overall, the aggregate withdrawal rate of unemployed fell during the Great Recession not because the existing unemployed started to search more, but rather because the composition of unemployed workers shifted towards workers with higher labour market attachment.

One characteristic which is important for determining attachment is prior labour market status (i.e. employment or inactivity). We refer to unemployed individuals whose previous labour market status was employment as 'Type 1' unemployment, with 'Type 2' referring to the unemployed who were previously inactive. Figure 3.4 illustrates that the share of Type 1 unemployed workers increases considerably when the labour market slackens, as is clearly visible in the aftermath of the 2008 financial crisis. This is driven by the wave of layoffs that occurs at the onset of recessions, resulting in a large flow of workers into the unemployment pool

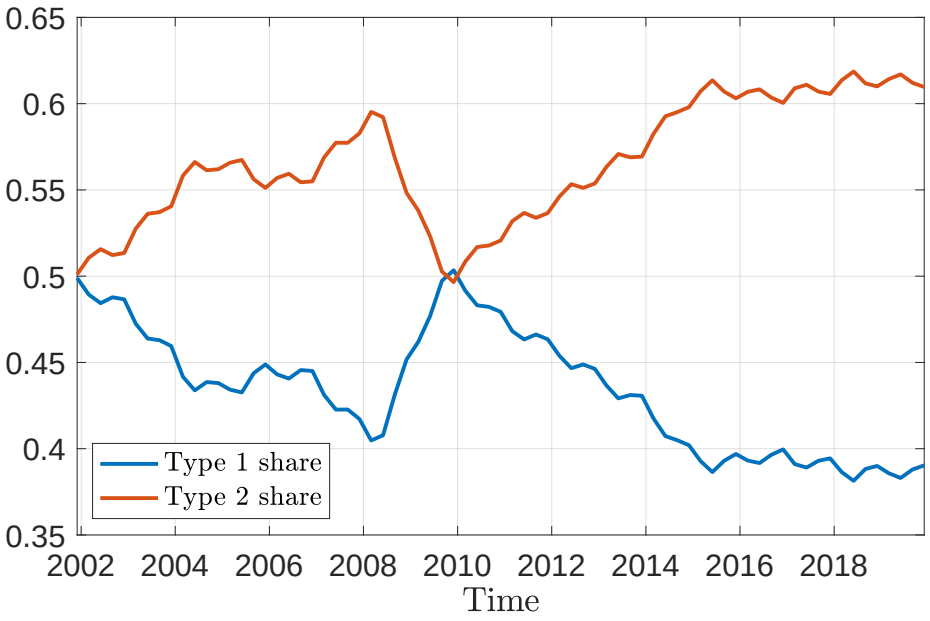


Figure 3.4. Unemployment composition in the UK: Type 1 vs Type 2

from employment. This compositional shift in the unemployment pool is part of what makes the aggregate probability of transitioning from unemployment to non-participation (UN) pro-cyclical.

Table 3.3 summarises in further detail how labour market attachment is determined by previous employment history. Over the full sample (1993Q1-2023Q1), the withdrawal rate of Type 2 unemployed is more than double that of Type 1 (24% and 11%, respectively). UN rates for both worker types fell significantly following the 2008 recession, slightly more so in percentage terms for Type 2 unemployed. Conversely, during the post-pandemic labour market recovery, withdrawal increased significantly for both groups, relatively more so for Type 1 unemployed. However, on average, even throughout business cycle fluctuations, it remains the case that the withdrawal rate of Type 2 unemployed is roughly double that of Type 1. This is illustrated visually in Figure 3.10.

Another characteristic which correlates with attachment is unemployment duration.[12] As reported in the first column of Table 3.3, the withdrawal rate is actually

[12]For the US labour market, Krueger et al. (2014) document that the long-term unemployed have a significantly higher probability of exiting the labour force compared to the short-term unemployed. They also find that the labour force withdrawal rate of the long-term unemployed is also more sensitive to the business cycle, dropping by much more in recessions than for the short-term

Transition probabilities (per cent per quarter)	Full sample (1993q1-2023q1)	Pre-2008 high	Post-2008 low	Post-pandemic high (2022-2023)
Unemployment to non-participation flow				
Aggregate	18.2	19.7	14.5	24.0
By employment history				
Previously employed (Type 1 unemployed)	11.3	11.9	9.2	16.8
Previously inactive (Type 2 unemployed)	24.0	24.9	18.8	28.4
By unemployment duration				
Short-term unemployed	19.4	20.8	16.3	22.5
Long-term unemployed	16.9	18.1	12.9	26.5
By employment history and unemployment duration				
Type 1 STU	9.7	10.4	8.1	12.5
Type 1 LTU	13.2	14.2	9.9	23.1
Type 2 STU	26.9	27.8	22.9	29.0
Type 2 LTU	20.4	20.8	15.1	29.7

Table 3.3. UN rate by previous employment status and unemployment duration.

slightly lower for the long-term unemployed (LTU) compared to the short-term unemployed (STU). Withdrawal rates for both of these groups display the expected pattern over the business cycle, falling after the 2008 recession and rising during the tight labour market post-pandemic. Similar to what Krueger et al. (2014) document for the US, we also find that the withdrawal rate of the LTU is more sensitive to labour market fluctuations, falling by about a third in the aftermath of the 2008 recession compared to a quarter for the STU. The LTU withdrawal rate also increased by far more in percentage terms post-pandemic relative to the equivalent STU rate (an increase of almost 50% of the former compared to less than 10% for the latter). Given that the long-term unemployment share of total unemployment is highly counter-cyclical, as the long-term share rises during recessions this constitutes another channel through which the aggregate UN rate is lowered through a compositional effect during recessions.

It is a surprising result that LTU withdrawal rates are lower than for STU in the UK, given that Krueger et al. (2014) find different results for the US. To investigate this further, the bottom panel in Table 3.3 also reports withdrawal rates conditional on

unemployed. As outlined in the text, we find very different results for the UK.

unemployment duration and previous labour market status. Doing so reveals that attachment does fall with unemployment duration for Type 1 unemployed workers. What this suggests is that the 'detachment' hypothesis holds for individuals who have recently lost their jobs, gradually becoming less attached to the labour force as more time is spent in joblessness. In contrast, we essentially find evidence of 'reverse' duration dependence of labour force attachment for Type 2 workers in the UK, who become even less likely to quit the labour force as the duration of their unemployment spell goes on.

How much of the total cyclical variation in the aggregate UN rate can these two compositional channels, history dependence and unemployment duration (including their interactive effects) account for? We address this using a similar type of 'shift-share' exercise as in Elsby et al. (2015), though using more recent data allows us to capture the recovery period following the Covid-19 pandemic, featuring an unprecedented level of labour market tightness in the UK, which reveals some new insights about how labour force attachment evolves during an expansion as well as a contraction.[13]

The aggregate UN probability can be expressed as the weighted sum of the corresponding probabilities for each group i as:

$$UN_t = \sum_i \omega_{it} UN_{it}$$

where ω_{it} denotes the unemployment share of group i at time t. In our baseline exercise we group workers according both to their unemployment duration and their prior labour market status before an unemployment spell.[14]. The counterfactual path for UN_t is generated by holding fixed the unemployment weights at their 2008 value, ω_{i08}.

[13]This is a key difference from this analysis compared to Elsby et al. (2015), who concentrate solely on recessionary episodes. There are several other differences in our approach that merit comment. Elsby et al. (2015) calculate counterfactual, fixed-composition paths from the trough-to-peak rise in unemployment over several US recessionary periods, whilst instead calculate a counterfactual path for the entire sample period since 2008. The reason this is important is that there continue to be important dynamics in the UN rate that persist after the unemployment rate has peaked. Another point of difference relative to the empirical exercise of Elsby et al. (2015) is that we have fewer recessionary episodes available in the UK data, so we focus attention on the sample period following 2008.

[14]The unemployment duration bands we use are more finely disaggregated than the binary STU/LTU split reported in Table 3.3. They are: (i) less than 6 months, (ii) 6 months or over but less than 12 months, (iii) 1 year and over but less than 2 years and (iv) 2 years and over. Along with prior labour market status (employed or inactive) this gives 8 groups in total.

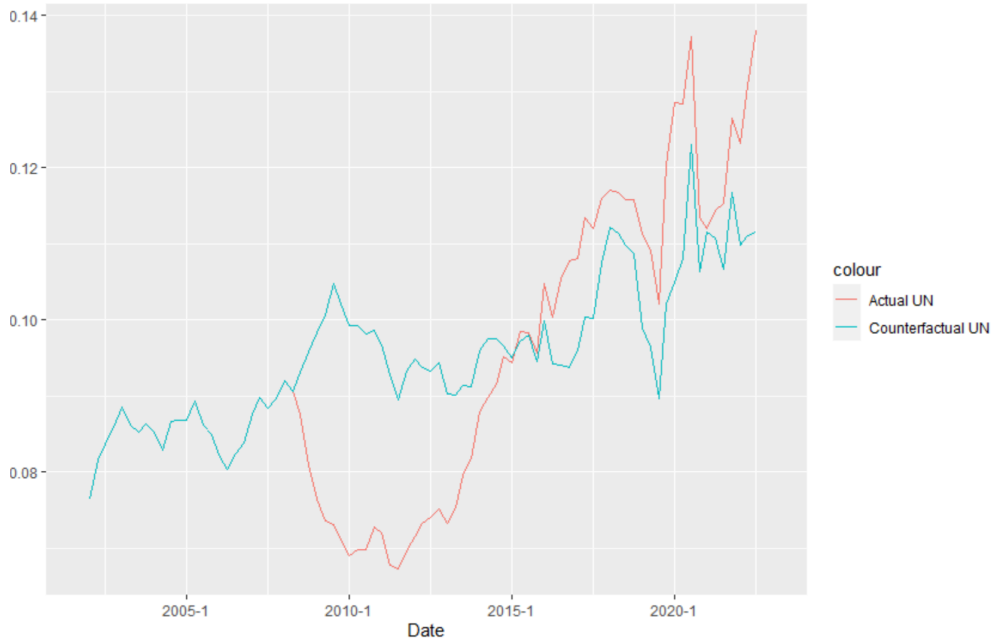


Figure 3.5. Actual and Counterfactual UN rate (holding unemployment distribution fixed)

In the baseline exercise (see Figure 3.11), we find that whilst these two compositional effects account for the majority of fluctuations in the UN rate over this period, there is still a substantial fraction unexplained which is robust to allowing for a more disaggregated set of controls.[15] Digging deeper, we find that this phenomenon appears to be driven by Type 2 unemployed workers receiving social security benefits in the sample (see Figure 3.12). When we exclude these workers we instead find that essentially all of the changes in the UN flow during this period be accounted for by these two compositional channels (see Figure 3.5).[16]

[15] We perform the same exercise but controlling for a much richer set of observable characteristics including age, gender, education and an indicator of whether the individual, if employed, was made redundant involuntarily. This results in a total of $i = 256$ groups, yet despite this larger set of controls most of the persistent fall, and eventual trough, in UN following the 2008 recession is still not explained, though they do effectively explain all of the increase in UN in the later period following the pandemic.

[16] Broadly defined, benefits claimants are workers claiming any of housing allowance, unemployment benefits, child support as well as other forms of assistance. We establish that there had been a large drop in the UN hazard in particular for people who had recently entered the labour force and were on benefits. Substantial reforms were made to the UK's out of work benefits regime with the introduction of the Employment and Support Allowance (ESA) programme in 2008 which replaced the previous incapacity benefits system. New ESA claimants were required to undertake a work capability assessment in order to claim incapacity benefits. According to a UK Government assessment, a significant proportion of ESA claimants were found to be fit for work. By raising the difficulty of successfully claiming inactivity benefits, the ESA reform is likely to have contributed

Given that our goal is not to study the effects of social benefit policies, we excludes benefit recipients from the data sample we use to calibrate the model.

3.2.4 Summary

In this section we have revisited the importance of the participation margin for cyclical labour market dynamics in the context of the UK, as well as providing conditional and unconditional evidence on the cyclicality of labour force flow rates. We emphasised two key facts regarding the participation margin in the data. Firstly, flows into the labour force are roughly constant over the business cycle, suggesting that search intensity of the non-employed is fairly inelastic to changes in aggregate conditions. Secondly, procyclical outflows from the labour force are driven by changes in the composition of the unemployment pool rather than existing unemployed increasing search intensity or more employed workers leaving jobs. More specifically, we find that during the Great Recession the composition of the unemployment pool in the UK shifted more towards workers who had recently been in employment, and towards LTU workers, both of whom are groups with lower withdrawal rates (higher labour market /attachment). In the next section we outline a search & matching model with participation flows which captures these salient features of the flows data.

3.3 Model

In this section we outline an equilibrium search & matching with heterogeneous search intensity among the non-employed. The key feature of the model is that participation among the non-employed is defined by search intensity relative to some exogenous, time-invariant threshold $\bar{e}$.

3.3.1 Environment

Time is discrete and runs for ever. The economy is populated by a constant mass of *ex ante* identical infinitely-lived workers and an infinite mass of potential single-worker firms. We normalize the size of the population to 1. All agents in the economy discount the future with factor $\beta \in (0,1)$.

to the reduction of the UN flow during the early 2010s as fewer people would have been able to claim benefits that were not tied to an obligation to actively search for work. We wish to thank Doug Rendle for this insight.

Workers. Workers are risk-neutral and derive linear utility from a single consumption good. At any point in time workers are either in employment or out of employment. All workers out of employment are characterised by an idiosyncratic value of search effort $e \in [0, \infty)$, which for simplicity we initially assume is exogenous and follows a stochastic process outlined below.[17] There exists an exogenous, time-invariant threshold $\underline{e}$ below which a worker is classified as inactive (n), otherwise a worker is classed as unemployed (u). In this environment all non-employed workers search but with different intensities, and the labour force status of the non-employed is determined by their search intensity relative to this threshold. Workers in employment earn a wage $w(a)$ which depends on an idiosyncratic value of job-specific productivity a (described below). Non-employed workers receive flow value $b(e)$, which in general will depend negatively on the level of search effort (i.e. $b'(e) \leq 0$).

Search intensity. Non-employed search intensity e is exogenous and drawn from a distribution $F(e)$. In order to capture the duration dependence in search effort we see in the data, we assume that workers re-draw from $F(e)$ at different frequencies depending on: (i) their current search intensity e, and (ii) how they entered non-employment. Inactive workers (i.e. $e < \underline{e}$) re-draw search intensity with probability λ_n each period. Workers who enter unemployment directly from employment due to separation ('Type 1' unemployed) re-draw with probability λ_{u_1}, after which point they become 'Type 2' unemployed who re-draw e in every period (conditional on not finding a job or drawing $e < \underline{e}$ and transitioning to inactivity). Finally, inactive workers who draw search intensity $e \geq \underline{e}$ become Type 2 unemployed.

Vacancies, wages & separations. New jobs are created by firms who can freely enter the market by posting vacancies v_t at period flow cost κ. Existing jobs are characterised by a job-specific productivity level a which is redrawn at the beginning of every period from a distribution $G(a)$. Wages are determined via Nash bargaining such that workers always receive a fixed fraction $\eta \in (0, 1)$ of the joint match surplus. As standard this implies the existence of a threshold value $\underline{a}$ below which both workers and firms will agree to terminate the match. Worker-firm pairs

[17] In practice we could extend the model to allow for an endogenous search intensity decision along the lines of Shimer (2004) or Mukoyama et al. (2018). To generate the heterogeneity in the choice of e that we need, we would need to assume some source of heterogeneity in this optimal choice, for example heterogeneous search disutility costs, such as in Christiano, Trabandt and Walentin (2022).

can also separate exogenously for reasons unrelated to productivity with probability $\delta^x \in (0,1)$. We assume that workers who separate endogenously due to job-specific productivity shocks have higher labour market attachment (i.e. draw a search intensity $e \geq \underline{e}$), whilst workers who separate exogenously have lower attachment (i.e. $e < \underline{e}$).[18]

Matching. A non-employed worker with search effort e finds a job with probability $p(e, \tilde{e}, \theta)$, where $\tilde{e}$ is aggregate search effort, θ is labour market tightness (i.e. the ratio of vacancies to searchers). This is assumed to derive from a matching function $M(\tilde{e}\tilde{s}, v) = \int p(e, \tilde{e}, \theta) dF(e) \cdot \tilde{s}$, where $\tilde{s}$ is the number of searchers. Among the unemployed the average job finding rate can be expressed as $p_u(\tilde{e}, \theta) = \int_{\underline{e}} p(e, \tilde{e}, \theta) \frac{dF(e)}{1-F(\underline{e})}$, whilst for the inactive the average job finding rate is: $p_n(\tilde{e}, \theta) = \int^{\underline{e}} p(e, \tilde{e}, \theta) \frac{dF(e)}{F(\underline{e})}$ Similarly, a vacant job meets with a worker with probability $q(\tilde{e}, \theta)$. Note that whilst average search intensity $\tilde{e}_t$ will fluctuate over the business cycle due to fluctuations in the pool of searchers (the extensive margin), the average *within-group* search intensity (i.e. the intensive margin) remains constant because the exogenous threshold $\underline{e}$ and the distribution $F(e)$ are assumed to be time-invariant. We later exploit this fact when calibrating the model together with a functional form for the matching function which ensures that the overall labour force inflow rate is constant over the business cycle.

Productivity. Each job produces $Z_t a_t$ units of the final good, where Z_t is the aggregate component of labour productivity and evolves stochastically according to the process:

$$\ln Z_t = (1 - \rho_z) \ln \bar{Z} + \rho_z \ln Z_{t-1} + \epsilon_t \tag{3.1}$$

where $\epsilon_t \sim \mathcal{N}(0, \sigma_z^2)$.

3.3.2 Labour market dynamics

Step 0: Stocks and productivity. At the beginning of period t aggregate labour productivity Z_t is revealed. The endogenous state variables are the beginning of period distribution of unemployed workers across both Type 1 and Type 2, and inactive workers $\{u_{1,t-1}, u_{2,t-1}, n_{t-1}\}$.

[18] This assumption the model to be consistent with the empirical behaviour of labour force outflows in two ways: (i) it ensures the EN flow rate in the model is constant over the business cycle, and (ii) that the composition of unemployed during recessions shifts towards workers with higher attachment.

Step 1: Separations. Matches are exposed to a job-specific productivity shock drawn from distribution $G(a)$. After observing the value of the shock firms and workers decide to continue the match based on whether the productivity draw is above the job destruction threshold, $a \geq \underline{a}_t$. Alongside this, a measure δ^x of existing matches separate for exogenous reasons unrelated to productivity. The overall separation rate is therefore $\delta_t = \delta^x + (1 - \delta^x)G(\underline{a}_t)$. Workers who separate join the current period pool of searchers in the matching process. We assume that workers who separate endogenously will search for new matches with higher search intensity (i.e. they have higher labour market attachment), whilst workers who separate exogenously are assumed to search with lower intensity. The resulting labour market stocks after separation shocks are given by:

$$\tilde{u}_{1,t} = u_{1,t-1} + (1 - \delta^x)G(\underline{a}_t)(1 - u_{t-1} - n_{t-1}) \tag{3.2}$$

$$\tilde{u}_t = \tilde{u}_{1,t} + u_{2,t-1} \tag{3.3}$$

$$\tilde{n}_t = n_{t-1} + \delta^x(1 - u_{t-1} - n_{t-1}) \tag{3.4}$$

Step 2: Production. Production takes place and wages are paid to workers in active matches. Aggregate output is given by:

$$Y_t = (1 - \tilde{u}_t - \tilde{n}_t) \cdot Z_t \frac{\int_{\underline{a}_t} a dG(a)}{1 - G(\underline{a}_t)} \tag{3.5}$$

Step 3: Search. Searchers and vacancies match together via a constant returns aggregate matching function. New matches do not become productive until the next period. The number of searchers in the current period is given by $\tilde{s} = \tilde{u}_t + \tilde{n}_t$, and labour market tightness is defined as $\theta_t = v_t/(\tilde{u}_t + \tilde{n}_t)$. Aggregate search intensity $\tilde{e}_t$ is given by:

$$\tilde{e}_t = \tilde{u}_t \cdot \frac{\int_{\underline{e}} eF'(e)de}{1 - F(\underline{e})} + \tilde{n}_t \cdot \frac{\int^{\underline{e}} eF'(e)de}{F(\underline{e})} \tag{3.6}$$

where fluctuations are driven solely by changes in the composition of the non-employed. After matching has occurred, workers who are unsuccessful face the possibility of drawing a new search intensity e. Post-matching labour market stocks are given by:

$$u_{1,t} = (1 - p_u(\tilde{e}_t, \theta_t))(1 - \lambda_{u_1})\tilde{u}_{1,t} \tag{3.7}$$

$$u_{2,t} = (1 - p_u(\tilde{e}_t, \theta_t))(1 - F(\underline{e}))[\lambda_{u_1}\tilde{u}_{1,t} + u_{2,t-1}] + (1 - p_n(\tilde{e}_t, \theta_t))(1 - F(\underline{e}))\lambda_n\tilde{n}_t \tag{3.8}$$

$$u_t = u_{1,t} + u_{2,t} \tag{3.9}$$

$$n_t = (1 - p_u(\tilde{e}_t, \theta_t))F(\underline{e})(\lambda_{u_1}\tilde{u}_{1,t} + u_{2,t-1}) + (1 - p_n(\tilde{e}_t, \theta_t))(1 - \lambda_n + \lambda_n F(\underline{e}))\tilde{n}_t \tag{3.10}$$

3.3.3 Equilibrium

In this section we outline the conditions determining equilibrium in this environment. The Bellman equations describing the asset values associated with workers and firms corresponding to the timing outlined above are detailed in Appendix 3.A.

Job creation. In equilibrium free entry implies that the value of an unfilled job is driven to zero in equilibrium:

$$V_t = 0$$

Imposing this condition in the Bellman equations for the firms yields the following job creation condition:

$$\frac{\kappa}{q(\tilde{e}_t, \theta_t)} = \beta \mathbb{E}_t \left[(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} J_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a}_{t+1})} \right] \tag{3.11}$$

Wages. Wages are determined via Nash bargaining, which ensures that workers receive a fixed fraction $\eta \in (0, 1)$ of the joint match surplus. The Nash wage satisfies the following equation:

$$\frac{\eta}{1 - \eta} J_t(a) = W_t(a) - \left\{ \int_{\underline{e}} U_{1,t}(e') dF(e') + \int^{\underline{e}} N_t(e') dF(e') \right\} \tag{3.12}$$

Separations. The separation threshold for job-specific productivity $\underline{a}$ is defined as:

$$J_t(\underline{a}) = 0$$

Using the definition $J_t(a)$ we can define a recursive equation for $\underline{a}_t$:

$$0 = Z_t \underline{a}_t - w_t(\underline{a}_t) + \frac{\kappa}{q(\tilde{e}_t, \theta_t)} \tag{3.13}$$

Definition 2.3 (Equilibrium)**.** *An equilibrium with Nash bargained wages for a given realization of* $\{Z_t\}_{t=0}^T$ *and initial labour market stocks* $\{u_{1,0}, u_{2,0}, n_0\}$ *is defined as a reservation productivity* $\underline{a}_t$*, a wage schedule* $w_t(a)$*, labour market tightness* θ_t*, aggregate search intensity* $\tilde{e}_t$*, aggregate labour market stocks* $\{u_{1,t}, u_{2,t}, n_t\}$*, and the value functions* $J_t(a)$*,* $W_t(a)$*,* $U_{1,t}(e)$*,* $U_{2,t}(e)$ *and* $N_t(e)$ *which satisfy (i) the laws of motion in (3.2)-(3.10), (ii) the value functions defined in (3.15)-(3.19), (iii) the job creation condition in (3.11), (iv) the Nash sharing rule in (3.12), and (v) the separation threshold condition in (3.13).*

3.4 Calibration

The model is parameterized at a quarterly frequency. Where possible, the model parameters are calibrated in a way that is consistent with standard parameter values that are routinely used in the wider literature on quantitative search & matching models. Otherwise parameters are set to match key observable moments in the data. The resulting parameter values are summarized in Table 3.4. The accompanying steady state fit of the model is reported in Table 3.5

Functional forms. We assume that the search intensity distribution $F(e)$ and job-specific productivity distribution $G(a)$ are both log-normal, with parameters $\{\mu_F, \sigma_F\}$ and $\{\mu_G, \sigma_G\}$ respectively. For the flow utility associated with non-employment $b(e)$, we assume two distinct values $\{b_U, b_N\}$ corresponding to unemployment and inactivity, where $b_U > b_N$. Finally, for matching we follow Pissarides (2000) and assume that the job finding probability for a non-employed worker with search intensity e is given by (we omit the t subscripts):

$$p(e, \tilde{e}, \theta) = e \cdot M \left(\frac{\theta}{\tilde{e}} \right)^{1-\alpha}$$

where M is a matching efficiency constant and $\alpha > 0$ is the elasticity of new matches with respect to searchers. The corresponding job filling probability for a firm posting a vacancy is given by:

$$q(\tilde{e}, \theta) = M \left(\frac{\tilde{e}}{\theta} \right)^{\alpha}$$

This choice of functional form, where the individual job finding probability is increasing proportionally in search effort e, i.e. $p(e, \tilde{e}, \theta) = e \cdot p(\tilde{e}, \theta)$, together with a time-invariant participation threshold $\underline{e}$ and search intensity distribution $F(e)$, ensures that the ratio of the NE and UE flows are constant (as in the data). To see this, note that the average job finding probabilities an inactive and unemployed workers (respectively) are given by:

$$p_n(\tilde{e}, \theta) = \frac{\int^{\underline{e}} eF'(e)de}{F(\underline{e})} \cdot M \left(\frac{\theta}{\tilde{e}} \right)^{1-\alpha}$$

$$p_u(\tilde{e}, \theta) = \frac{\int_{\underline{e}} eF'(e)de}{1 - F(\underline{e})} \cdot M \left(\frac{\theta}{\tilde{e}} \right)^{1-\alpha}$$

Hence the ratio of the employment inflow rates is constant in the model (denoted by χ):

$$\frac{p_n(\tilde{e},\theta)}{p_u(\tilde{e},\theta)} = \frac{\int_{\underline{e}}^{\bar{e}} eF'(e)de}{\int_{\underline{e}} eF'(e)de} \cdot \frac{1-F(\underline{e})}{F(\underline{e})} = \chi$$

Externally calibrated parameters. Beginning with the deep parameters that are treated as structural, we set the discount factor $\beta = 0.99$ and workers' relative bargaining strength $\eta = 0.5$ (implying symmetric Nash bargaining), values which are commonly used in the literature. The means of the idiosyncratic shock distributions G and F, as well as tightness θ and the steady state level of aggregate productivity A, are all normalised.[19] We set the values of the aggregate labour productivity process $\{\rho_z, \sigma_z\}$ to match the observed serial correlation and volatility of labour productivity in the data. We set the standard deviation of search intensity among the non-employed $\sigma_F =$ based on reported search intensity in the LFS.

The elasticity of the matching function α is obtained via estimation of a log-linear version of the matching function:

$$\log(h_t) = \log(M_t) + (1-\alpha)\log(\theta_t) + \epsilon_t \tag{3.14}$$

where h_t denote new hires in period t. In the absence of data on search effort $\tilde{e}_t$ we treat this as an unobserved state variable which is instead absorbed by allowing for time-varying matching efficiency M_t in the estimation.[20] We estimate the above specification using a Kalman filter as in Pizzinelli and Speigner (2017), which results in an estimated elasticity $\hat{\alpha} = 1 - \hat{\alpha} = 0.7$.[21]

Targets. We set several parameters in order to match the average flow rates in the LFS. We set the (constant) EN rate in the model δ^x directly to match the empirical counterpart. Given this, we then target the steady state share of jobs destroyed endogenously $G(\underline{a})$ to match the empirical separation rate into unemployment. We set the exogenous participation threshold value of search intensity $\underline{e}$ to match the

[19] This normalisation does not influence the model's equilibrium properties.

[20] Given that total hires in the model are given by $h_t = \tilde{s}_t \mu_F M \left(\frac{\theta_t}{\tilde{e}_t}\right)^{1-\alpha}$, the log-linear version of the matching function is:

$$\log(h_t) = \log(\tilde{s}_t) + \log\mu_F + \log M - (1-\alpha)\log(\tilde{e}_t) + (1-\alpha)\log(\theta_t)$$

In practice, in the estimation we are defining the unobserved state as $M_t = \frac{\tilde{s}_t \mu_F M}{\tilde{e}_t^{1-\alpha}}$, so M_t is really capturing fluctuations in the number of searchers $\tilde{s}_t$ and aggregate search intensity $\tilde{e}_t$.

[21] For more details on the matching function estimation methodology see Pizzinelli and Speigner (2017).

ratio of the NE and UE rates in the model, given by χ above. The arrival probabilities of idiosyncratic shocks to search intensity $\{\lambda_{u_1}, \lambda_n\}$ are set to match the observed flow rates between inactivity and unemployment (i.e. the UN and NU rates). The match efficiency constant M is set to target the average UE rate. Additionally, we set the probability of drawing a search intensity shock under the threshold $F(\underline{e})$ such that 57% unemployed workers on average are Type 2, as in the LFS data. The flow value b_u is set such that the average flow value of non-employment is equal to 0.71, following Hall and Milgrom (2008). Finally, to calibrate the standard deviations of the job-specific productivity distribution σ_G we target the observed volatility in the EU rate. The remaining parameters, the flow cost of posting a vacancy κ and the flow value of inactivity b_N, are then implied by the remaining steady state conditions of the model.[22]

Solution. We solve the model by log-linearly approximating around the steady state. For additional details see Appendix 3.A.

3.5 Main Results

In this section we present the main results of the paper. First, we examine the cyclical behaviour of the model and compare this to the data, both for the whole sample period and specifically during the Great Recession. Secondly, we examine the role of the participation margin in our model for unemployment volatility.

3.5.1 Model dynamics

IRFs. Figure 3.6 reports the model-generated IRFs for the same variables for which we estimated empirical IRFs in Figure 3.2, whilst Figure 3.7 reports the resulting IRFs for the labour market stocks in the model. All IRFs are reported in log deviations from the steady state levels. The overall takeaway is that our baseline model is able to qualitatively capture the joint behaviour of all 6 labour market transition rates consistent with what is reported in the data, though with some quantitative deficiencies owing to the simplicity of our model. Unlike the model in Cairo et al. (2022), our model does not require the presence of wage rigidities to achieve this. We first discuss how the model qualitatively matches the behaviour of the labour market transition rates. Table 3.5 also reports the definitions of flow rates in the model for reference.

[22] More details of how we solve for the parameters and steady state sequentially is provided in Appendix 3.A.

Parameter	Value	Description	Source/Target
Assigned:			
β	0.99	Discount factor	Standard
η	0.72	Worker bargaining power	Standard
μ_F	0	Mean of search intensity distribution	Normalization
μ_G	0	Mean of productivity distribution	Normalization
θ	1	Steady state tightness	Normalization
Z	1	Steady state aggregate productivity	Normalization
σ_F	1.0323	Std. dev. of search intensity distribution	ONS
ρ_z	0.7079	Persistence of aggregate productivity	ONS
σ_z	0.0051	Std. dev. of aggregate productivity	ONS
α	0.72	Matching function elasticity	Estimated
Calibrated:			
δ^x	0.019	Exogenous separation rate	$EN = 0.019$
$G(\underline{a})$	0.012	Share of destroyed matches	$EU = 0.012$
$\underline{e}$	0.999	Participation threshold	$\chi = 0.2127$
λ_{u_1}	0.1676	Type 1 unemp. persistence	$UN = 0.182$
λ_n	0.0902	Inactivity persistence	$NU = 0.047$
M	0.0690	Match efficiency	$UE = 0.268$
$F(\underline{e})$	0.4549	Inactivity draw probability	$\frac{u_2}{u} = 0.57$
b_u	5.1213	Unemployment flow value	$b_U \frac{\tilde{u}}{\tilde{u}+\tilde{n}} + b_N \frac{\tilde{n}}{\tilde{u}+\tilde{n}} = 0.7$
σ_G	0.1623	Std. dev. of productivity distribution	$\sigma_{EU} = 0.091$
Implied:			
κ	0.0021	Vacancy cost	
b_N	-0.0121	Inactive flow value	

Table 3.4. Summary of parameters

Empirical concept	Model concept	Data	Model
UR	$\frac{u}{1-n}$	0.059	0.041
LFPR	$1-n$	0.774	0.805
EU rate	$(1-\delta^x)G(\underline{a})$	0.012	0.012
EN rate	δ^x	0.019	0.019
UE rate	$p_u(\tilde{e},\theta)(1-\delta)$	0.268	0.268
UN rate	$(1-p_u(\tilde{e},\theta))F(\underline{e})\frac{\lambda_{u_1}\tilde{u}_1+u_2}{\tilde{u}} + p_u(\tilde{e},\theta)\delta^x$	0.057	0.057
NE rate	$p_n(\tilde{e},\theta)(1-\delta)$	0.182	0.182
NU rate	$p_n(\tilde{e},\theta)(1-\delta^x)G(\underline{a}) + (1-p_n(\tilde{e},\theta))\lambda_n(1-F(\underline{e}))$	0.047	0.047

Table 3.5. Steady state performance: Model vs. Data

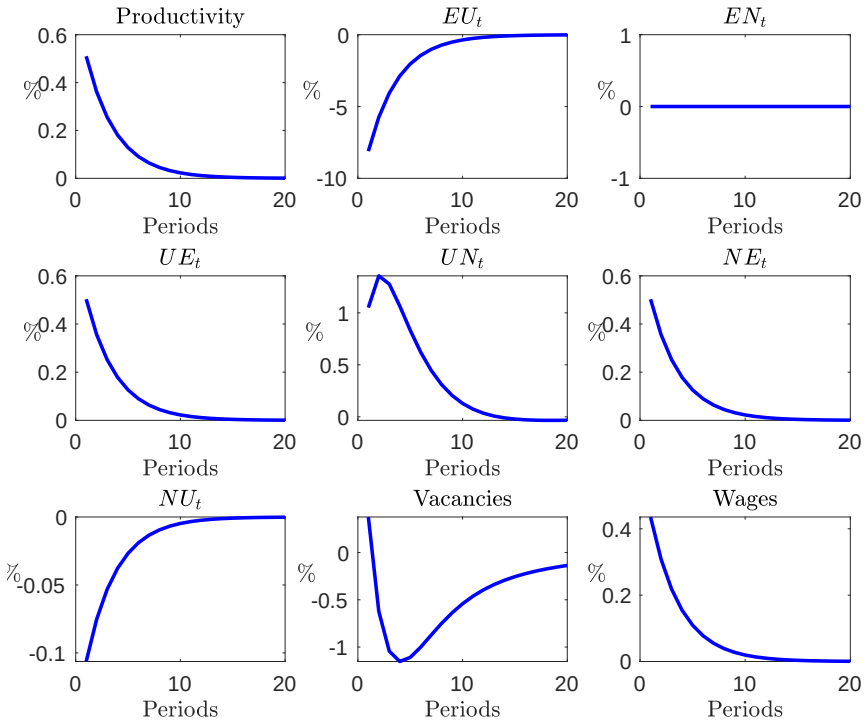


Figure 3.6. IRFs for a productivity shock in the calibrated model. Expressed as log deviations from steady state levels.

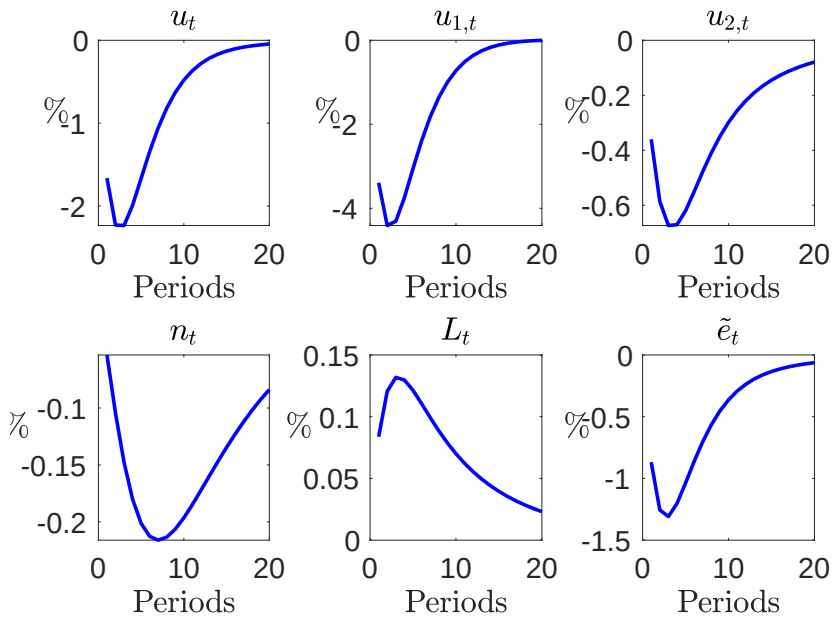


Figure 3.7. Response of stocks to a productivity shock in the calibrated model. Expressed as log deviations from steady state levels.

First considering separations from employment, countercyclicality in the EU rate is driven by the job destruction margin $\bar{a}_t$ (which declines in response to an increase in Z_t), whilst the EN rate is constant by assumption. Next, we consider inflows into employment. The procyclicality in these flow rates is driven by two channels: (i) an increase in the matching probabilities $p_u(\tilde{e}, \theta)$ and $p_n(\tilde{e}, \theta)$, and (ii) a fall in job destruction (which in the model is capturing a time aggregation effect, i.e. workers have to first find jobs then survive separation). Moreover, these flows are proportional to each other in the model given our assumptions regarding the matching function.

Finally, we consider the flows between unemployment and inactivity. Although unemployed workers find jobs faster (which puts countercyclical pressure on UN flow in the model), the distribution of the unemployment pool shifts *away* from Type 1 unemployed workers (who have persistently higher search effort) due to the decline in job destruction. Overall this latter effect dominates and the UN flow is procyclical (as in the data).[23] The countercyclical NU flow is the outcome of a reduction in the number of inactive workers entering unemployment either directly or via employment. As worker contact rates increase, workers are more likely to find a job and enter employment (and less likely to transition into unemployment). This is amplified by the falling job destruction margin $\bar{a}_t$, which reduces further the number of inactive entering unemployment via employment.

The remaining panels in Figure 3.6 display the corresponding responses of vacancies and wages, whilst the overall outcome on the aggregate stocks is displayed in Figure 3.7. Overall, participation increases and unemployment falls in response to the shock, whilst the pool of unemployed workers shifts towards Type 2 unemployed ($u_{1,t}$ declines by significantly more than $u_{2,t}$ due to the decline in job destruction). Aggregate search effort $\tilde{e}_t$ declines both because (i) the aggregate number of searchers declines, and (ii) the pool of searchers shifts away from workers who have greater attachment (higher search intensity). This latter effect is entirely driven by changes in composition, given that within-group search intensity is constant (as there is no intensive margin of adjustment for search effort in the model).

[23] There is also a time aggregation channel operating on the UN flow which contributes to procyclicality: unemployed workers find new jobs faster, and are then subject to a 'retirement' shock δ_x in the next period before commencing production.

The largest discrepancy between the model and the data is in the response of vacancies. Whilst initially job creation responds positively to the increase in aggregate productivity, after several periods job creation then declines persistently, driven by the strong and persistent decline in aggregate search effort which reduces the firm's contact rate $q(\theta)$. In contrast, Figure 3.2 illustrates in the data that job creation increases strongly and persistently.

Moments. Tables 3.6 report the cyclical properties of labour market flows and stocks from model simulations and compares them to the data. The results are broadly consistent with results from the model IRFs. Overall, the model under our baseline calibration is able to match qualitatively the same co-movements of flows and stocks that we see in the data, though quantitatively the fit of the model can be significantly improved. Notably, the baseline model overall still suffers somewhat from an inability to generate sufficient volatility relative to the data.

Additionally, we examine the implications of our calibration strategy for these results. More specifically, we repeat the quantitative exercise adopting standard approaches for generating additional volatility in matching models from the literature: (i) a small-surplus calibration as in Hagedorn and Manovskii (2008), and (ii) allowing for wage rigidity.[24] The results are reported in the bottom two panels of Table 3.6. We find that both a small-surplus calibration strategy and rigid wages help generates substantially more volatility on the separation margin, job finding margin and participation margin, whilst making overall co-movement of flows with output more significant, and leading to realistic volatility in the stocks.

Great Recession. Finally, we examine the fit of the model over the Great Recession period. This is instructive given that in the context of the UK flows data we use in this paper, the Great Recession is the only business cycle event. More specifically, we solve for the appropriate sequence of shocks to aggregate labour productivity ϵ_t that allow us to exactly match de-trended labour productivity in the data over this period. We then feed this series through our baseline model and compare the implied behaviour of labour market stocks with the data. The results from this exercise are plotted in Figure 3.8. Overall the model is able to account for a large fraction of the fall in employment (1.6 p.p. compared to 2.7 p.p.), and essentially all of the initial 2.5 p.p. increase in unemployment. However, consistent with the simulation results reflecting insufficient volatility reported in Table 3.6, in both cases our baseline model is unable to fully account for the decrease (increase)

[24] More details about these alternative calibration strategies can be found in Appendix 3.A.

	Flows						Stocks		
	EU	EN	UE	UN	NE	NU	E	U	LFPR
Panel A. Data									
std(x)	0.091	0.066	0.061	0.065	0.070	0.051	0.006	0.062	0.002
corr(x, Y)	-0.605	0.172	0.535	0.219	0.496	-0.256	0.737	-0.771	0.243
corr(x, x_{-1})	0.359	-0.194	0.489	0.238	0.307	0.106	0.855	0.884	0.651
Panel B. Baseline									
std(x)	0.092	0.00	0.006	0.019	0.006	0.001	0.002	0.032	0.001
corr(x, Y)	-0.970	0.00	0.970	0.949	0.970	-0.9701	0.827	-0.924	0.334
corr(x, x_{-1})	0.548	-	0.548	0.804	0.548	0.548	0.850	0.822	0.928
Panel C. Small surplus									
std(x)	0.199	0.00	0.010	0.042	0.010	0.003	0.004	0.069	0.001
corr(x, Y)	-0.955	0.00	0.955	0.967	0.955	-0.955	0.911	-0.969	0.442
corr(x, x_{-1})	0.548	-	0.548	0.801	0.548	0.548	0.849	0.822	0.930
Panel D. Rigid wages									
std(x)	0.110	0.00	0.0105	0.022	0.0105	0.002	0.002	0.040	0.001
corr(x, Y)	-0.945	0.00	0.945	0.956	0.945	-0.945	0.864	-0.950	0.458
corr(x, x_{-1})	0.548	-	0.548	0.814	0.548	0.548	0.853	0.822	0.924

Notes: Simulated data are logged and HP filtered using smoothing parameter $\lambda = 1600$. Each replication computes simulated statistics from a sample of 120 quarterly observations. Reported statistics are averages over 100 replications.

Table 3.6. Cyclical properties: Model vs. Data

in employment (unemployment). Looking at the model-implied flows relative to the data (see Figure 3.13) reveals that whilst the model is able to reasonably capture fluctuations in the EU rate (targeted) and UN rate (untargeted) over the Great Recession period, the shortfall in volatility can be accounted for by the fact that the model is only generates less than half of the decline in the UE rate.

3.5.2 Participation and the Unemployment Volatility Puzzle

In our calibrated model, fluctuations in labour force participation reflect changes in the composition of searchers in a manner consistent with observed cyclicality of labour force flows. In this section we isolate the role of this composition effect for unemployment volatility. To do this, we compare our baseline model to a version of the model where all non-employed workers search with the same intensity, i.e. where $\sigma_F = 0$ such that $e = 1$ for all non-employed workers (who are all classed as unemployed as standard).[25]

[25]For the purposes of the exercise we keep as many of the structural parameters of the model the same where possible. More details about this version of the model can be found in Appendix 3.A.

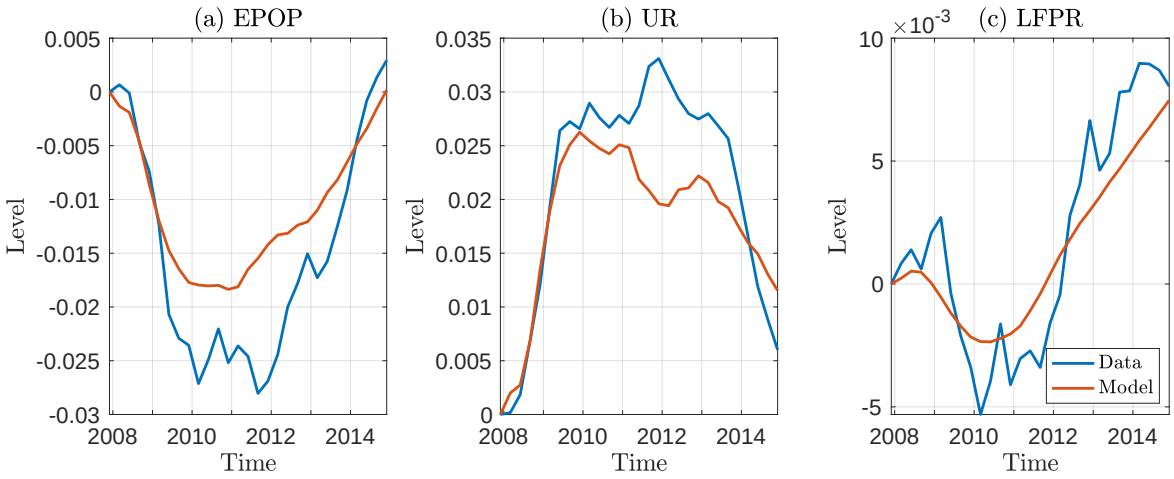


Figure 3.8. Labour market stocks in the Great Recession: Data vs Model. All series are normalized to zero at 2001Q1.

Table 3.7 reports the results from this quantitative exercise, as well as corresponding moments in the data. Consider first (in panel I) the basic DMP model with endogenous job destruction (i.e. $\sigma_F = 0$, $e = 1$). As expected, given the well-known issues with generating sufficient unemployment volatility under our calibration approach the model only generates around a 33% of the unemployment volatility we find in the data.[26] Next, we identify the role of endogenous changes in the composition of job searchers. The results from our baseline model are reported in panel II. We find that the presence of this composition effect actually *amplifies* unemployment volatility. In practice this is the outcome of two opposing forces: (i) changes in the composition of unemployed workers, and (ii) a GE effect on job creation by firms. Endogenous shifts in the composition of unemployment between Type 1 and Type 2 workers increases the persistence of unemployment fluctuations via the UN channel. During a recession, job separations increase which shifts the composition of unemployed workers towards Type 1, who have persistently higher search effort than Type 2 workers (who instead are more likely to reduce search effort and transition to inactivity). In general equilibrium, shifting the pool of searchers towards workers with persistently higher search intensity dampens the fall in job creation by firms, which accounts for the significant reduction in the UE rate volatility compared to the standard model. Overall, we find that the first

[26] We know from Fujita and Ramey (2012) that the presence of endogenous job destruction contributes somewhat to alleviating the severity of the unemployment volatility puzzle outlined in Shimer (2005) in the context of a model with constant separations.

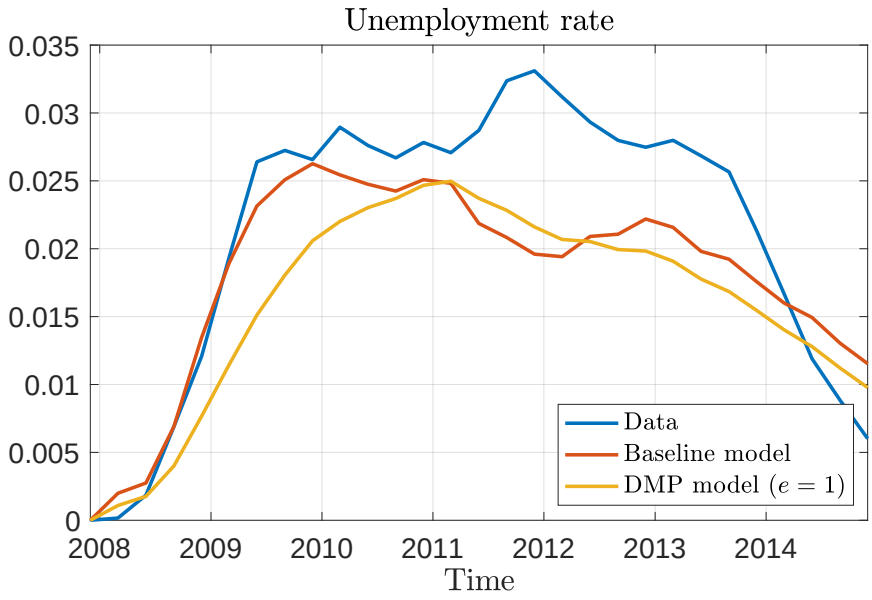


Figure 3.9. Contribution of composition effect among searchers in the model over the Great Recession period. All series are normalized to zero at 2008Q1.

channel dominates and shifts in the composition of searchers amplify unemployment fluctuations.

Further to this exercise, we can use the model to quantify the contribution of this composition effect for unemployment dynamics during the Great Recession. Figure 3.9 plots the model-implied paths of unemployment during the Great Recession period under both versions of the model (as well as the data for reference). Through the lens of our model, the participation margin is crucial for accounting for the speed of the rise in unemployment at the onset of the Great Recession, as well as amplifying the peak of the unemployment profile. Overall this suggests that it is the combination of the job destruction margin with the presence of composition effects at the participation margin which amplifies unemployment volatility in our model relative to a standard DMP model with endogenous job destruction.

These findings appear at first glance to contrast with those in Mukoyama et al. (2018), who conduct the same quantitative exercise as above using a DMP model with worker search effort and find the opposite conclusion, i.e. that endogenous fluctuations in search intensity *dampen* unemployment volatility. However in practice our analysis complements theirs. The model outlined in Mukoyama et al. (2018) on studies on the implications of fluctuations on the *intensive* margin of search effort (i.e. individual worker adjustments), and abstracts from composition

	std$(u) \times 100$	std$(EU) \times 100$	std$(UE) \times 100$
I. Data	6.12	9.12	6.07
II. DMP model ($e = 1$)	2.14	10.93	1.35
III. Baseline model	3.21	9.15	0.57

Notes: Simulated data are logged and HP filtered using smoothing parameter $\lambda = 1600$. Each replication computes simulated statistics from a sample of 120 quarterly observations. Reported statistics are averages over 100 replications.

Table 3.7. Unemployment volatility and participation

effects (all workers choose the same e). In contrast, our model essentially assumes the opposite by abstracting from movements on the intensive margin and focuses solely on the impact of composition effects within the pool of searchers.

3.6 Conclusion

In this paper we have developed a tractable search & matching framework with heterogeneous search intensity among the non-employed that is consistent with the cyclical behaviour of labour market flows in the data. Firstly, using micro-data from the UK LFS we documented the cyclical patterns of labour market flows, as well as two important features of the participation margin which motivated our modelling approach, namely that the inflows are broadly inelastic to aggregate conditions whilst procyclical outflows are driven by changes in the composition of unemployed workers during recessions. After outlining a tractable model consistent with these facts and calibrated to match UK flows data, we document that the model is able to broadly capture labour market dynamics during the Great Recession period, and that the presence of compositional changes among the non-employed in our model contribute to increased unemployment volatility.

Chapter 3: Appendices

3.A Model Appendix

3.A.1 Value functions

Below we outline the asset values associated with firms and workers that define the recursive structure of the labour market. For brevity of notation we indicate dependence on the aggregate state by the time subscript t.

Worker Bellmans. The value of an employed worker is given by

$$\begin{aligned} W_t(a) &= w_t(a) + \beta \mathbb{E}_t \Bigg[(1-\delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1-G(\underline{a}_{t+1})} \\ &\quad + \delta^x \int^{\underline{e}} N_{t+1}(e') \frac{dF(e')}{F(\underline{e})} + (1-\delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1-F(\underline{e})} \Bigg] \end{aligned} \tag{3.15}$$

The above equation states that with probability $(1-\delta_{t+1})$ the employment relationship continues to be productive in the next period. With probability δ^x, the worker will instead separate into inactivity in $t+1$ and upon doing so draws a new value of e from the conditional distribution $F(e|e < \underline{e})$. With probability $(1-\delta^x)G(\underline{a}_{t+1})$ the match separates endogenously due to the job-specific productivity shock and the individual becomes Type 1 unemployed next period, drawing a value from the conditional distribution $F(e|e \geq \underline{e})$.

The values associated with Type 1 and Type 2 unemployment are given by

$$\begin{aligned} U_{1,t}(e) &= b(e) + \beta \mathbb{E}_t \Bigg[p(e, \tilde{e}_t, \theta_t)(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a})} \\ &\quad + \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big)(1 - \lambda_{u_1}) U_{1,t+1}(e) \\ &\quad + p(e, \tilde{e}_t, \theta_t)(1 - \delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1 - F(\underline{e})} \\ &\quad + \lambda_{u_1} \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big) \int_{\underline{e}} U_{2,t+1}(e') dF(e') \\ &\quad + \Big(\lambda_{u_1}(1 - p(e, \tilde{e}_t, \theta_t)) + p(e, \tilde{e}_t, \theta_t)\delta^x \frac{1}{F(\underline{e})}\Big) \int^{\underline{e}} N_{t+1}(e') dF(e') \Bigg] \end{aligned} \tag{3.16}$$

$$\begin{aligned} U_{2,t}(e) &= b(e) + \beta \mathbb{E}_t \Bigg[p(e, \tilde{e}_t, \theta_t)(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a})} \\ &\quad + p(e, \tilde{e}_t, \theta_t)(1 - \delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1 - F(\underline{e})} \\ &\quad + \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big) \int_{\underline{e}} U_{2,t+1}(e') dF(e') \\ &\quad + \Big(1 - p(e, \tilde{e}_t, \theta_t) + p(e, \tilde{e}_t, \theta_t)\delta^x \frac{1}{F(\underline{e})}\Big) \int^{\underline{e}} N_{t+1}(e') dF(e') \Bigg] \end{aligned} \tag{3.17}$$

and the value of inactivity is given by

$$\begin{aligned} N_t(e) &= b(e) + \beta \mathbb{E}_t \Bigg[p(e, \tilde{e}_t, \theta_t)(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} W_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a})} \\ &\quad + p(e, \tilde{e}_t, \theta_t)(1 - \delta^x) G(\underline{a}_{t+1}) \int_{\underline{e}} U_{1,t+1}(e') \frac{dF(e')}{1 - F(\underline{e})} \\ &\quad + \lambda_n \Big(1 - p(e, \tilde{e}_t, \theta_t)\Big) \int_{\underline{e}} U_{2,t+1}(e') dF(e') \\ &\quad + (1 - \lambda_n)(1 - p(e, \tilde{e}_t, \theta_t)) N_{t+1}(e) \\ &\quad + \Big(\lambda_n(1 - p(e, \tilde{e}_t, \theta_t)) + p(e, \tilde{e}_t, \theta_t)\delta^x \frac{1}{F(\underline{e})}\Big) \int^{\underline{e}} N_{t+1}(e') dF(e') \Bigg] \end{aligned} \tag{3.18}$$

Firm Bellmans. The asset value of a filled job is given by

$$J_t(a) = Z_t a - w_t(a) + \beta \mathbb{E}_t \Bigg[(1 - \delta_{t+1}) \int_{\underline{a}_{t+1}} J_{t+1}(a') \frac{dG(a')}{1 - G(\underline{a}_{t+1})} + \delta_{t+1} V_{t+1} \Bigg] \tag{3.19}$$

and the value associated with an unfilled vacancy is given by:

$$\begin{aligned} V_t &= -\kappa + \beta \mathbb{E}_t q(\tilde{e}_t, \theta_t)(1-\delta_{t+1}) \int_{\underline{a}_{t+1}} J_{t+1}(a') \frac{dG(a')}{1-G(\underline{a}_{t+1})} \\ &\quad + \beta \mathbb{E}_t (1 - q(\tilde{e}_t, \theta_t)(1-\delta_{t+1})) V_{t+1} \end{aligned} \tag{3.20}$$

where $q(\tilde{e}_t, \theta_t)$ denotes the probability of filling a vacancy.

3.A.2 Model solution

Linear approximations. When obtaining a linearized solution to the model, we need to keep track of several integrals that do not have closed form expressions, namely $\int_{\bar{a}_t} a dG(a)$, $\int_{\bar{e}} eU_{1,t}(e)dF(e)$ and $\int^{\bar{e}} eN_t(e)dF(e)$. To overcome this issue we take local approximations to these integrals.

A first-order Taylor expansion of $\tilde{a}_t = \int_{\bar{a}_t} a dG(a)$ gives:

$$\tilde{a}_t \approx \tilde{a} - \bar{a} g(\bar{a})(\bar{a}_t - \bar{a})$$

The remaining integrals are a little more tricky. Taking a Taylor approximation we can re-write:

$$\int^{\bar{e}} eN_t(e)dF(e) \approx \int^{\bar{e}} eN(e)dF(e) + \int^{\bar{e}} edF(e) \cdot \Big[N_t(e) - N(e) \Big]$$

Integrating again between $[0, \bar{e}]$ and rearranging allows us to write:

$$\int^{\bar{e}} eN_t(e)dF(e) \approx \int^{\bar{e}} eN(e)dF(e) + \frac{\int^{\bar{e}} edF(e)}{F(\bar{e})} \Big[\tilde{N}_t - \tilde{N} \Big]$$

where $\tilde{N}_t = \int^{\bar{e}} N_t(e)dF(e)$. By exactly the same argument we can also write:

$$\int_{\bar{e}} eU_{1,t}(e)dF(e) \approx \int_{\bar{e}} eU_1(e)dF(e) + \frac{\int_{\bar{e}} edF(e)}{1-F(\bar{e})} \Big[\tilde{U}_{1,t} - \tilde{U}_1 \Big]$$

where $\tilde{U}_{1,t} = \int_{\bar{e}} U_{1,t}(e)dF(e)$.

3.A.3 Calibration approaches

Baseline. Our baseline calibration strategy proceeds sequentially as follows. The sample period used to estimate average flow rates is 2001Q4 to 2019Q4, so excluding the Covid-19 pandemic and its repercussions. We first fix the externally calibrated parameters to their chosen values and as impose normalizations.

The (constant) flow probability from employment to inactivity δ^x is equated to the sample average of the empirical employment-to-inactivity flow (P^{ni}). We can then solve for the steady state value of $G(\underline{a}) = P^{nu}/(1-\delta)$ which simply follows from the model-equivalent definition of the transition probability from employment to unemployment (see Table 3.5. For a given value of σ_G critical value $\underline{a}$ is then obtained through the inversion $G^{-1}(\underline{a})$. We then solve jointly for $\{F(\underline{e}), \lambda_{u_1}, \lambda_n\}$ as well as steady state stocks which are consistent with the remaining flow rate targets, as well as the target unemployment distribution, using the laws of motion governing labour market dynamics. This comprises a system of 10 equations in 10 unknowns: $\{u_1, u_2, u, n, \tilde{u}_1, \tilde{u}, \tilde{n}, F(\underline{e}), \lambda_{u_1}, \lambda_n\}$.

Given a solution for $F(\underline{e}$ consistent with observed participation flows, we can then solve for participation threshold $\underline{e}$ which is consistent with the empirically observed relative job finding rates of unemployed and inactive workers:

$$\frac{P^{in}}{P_{un}} = \frac{\int_{\underline{e}}^{\bar{e}} eF'(e)de}{\int_{\underline{e}} eF'(e)de} \cdot \frac{F(\underline{e})}{1-F(\underline{e})}$$

as well as the value for match efficiency M.

Since no closed form solution for the wage is possible, the remaining parameters $\{\kappa, b_U, b_N\}$ are obtained by solving the system of equations consisting of the all Bellman equations outlined above, together with the definition of the separation threshold (equation 3.13), the Nash sharing rule (equation 3.12), the marginal worker's wage, the job creation condition (equation 3.11), and finally the Hall and Milgrom (2008) target for the average flow value of non-employment to equal 0.71. This comprises a system of 11 equations in as many unknowns:

$$\{U_1, U_2, N, W, J, W(\underline{a}), \kappa, b_U, b_N, \tilde{w}, w(\underline{a})\}$$

Finally, to calibrate σ_G we loop over this procedure to find the value consistent with the empirical volatility in the EU flow observed in the data.

Small surplus. The small surplus calibration strategy we use follows essentially the same sequence as above, but with two key differences following Hagedorn and Manovskii (2008): (i) we set the worker bargaining power $\eta = 0.052$, and (ii) we target an average flow value of non-employment equal to 0.955. We also recalibrate the value of σ_G to still be consistent with σ_{EU}, which requires $\sigma_G = 0.7126$.

Rigid wages. Again the calibration procedure follows the same process as above. We allow for wage rigidity by specifying an ad hoc rule which ensures worker

bargaining power is countercyclical, following the approach taken in Jung and Kuester (2015). This is convenient in an environment with endogenous job destruction and Nash wages, as this allows the separation margin to still be tractable whilst ensuring all separations are efficient (in the private sense). More specifically, we impose that worker bargaining power η_t evolves according to:

$$(1-\eta_t) = (1-\eta)\cdot \exp\{\gamma_w Z_{t-1}\}$$

We then jointly set $\sigma_G, \gamma_w\}$ to target the $\{\sigma_{EU}, \sigma_{UE}\}$. This results in values $\sigma_G = 0.4543$, $\gamma_w = 2.4850$, though overall the model in this case has difficulty matching both the separation and job finding margins.

DMP model with no search intensity. In Section 3.5 we utilise a version of our baseline model with heterogeneity in search intensity among the non-employed shut down, i.e. $\sigma_F = 0$ and $e = 1$. For the purposes of this exercise we try to keep as many of the parameters the same as possible. Specifically, we maintain the same values for the externally calibrated parameters $\{\beta, \eta, \alpha, \rho_z, \sigma_z\}$, as well as the the standard deviation of job-specific productivity σ_G and the share of matches which separate $G(\underline{a})$. We then choose values for $\{M, b_U, \kappa\}$ which are consistent with the steady state levels of employment and the vacancy filling rate from our baseline calibration.

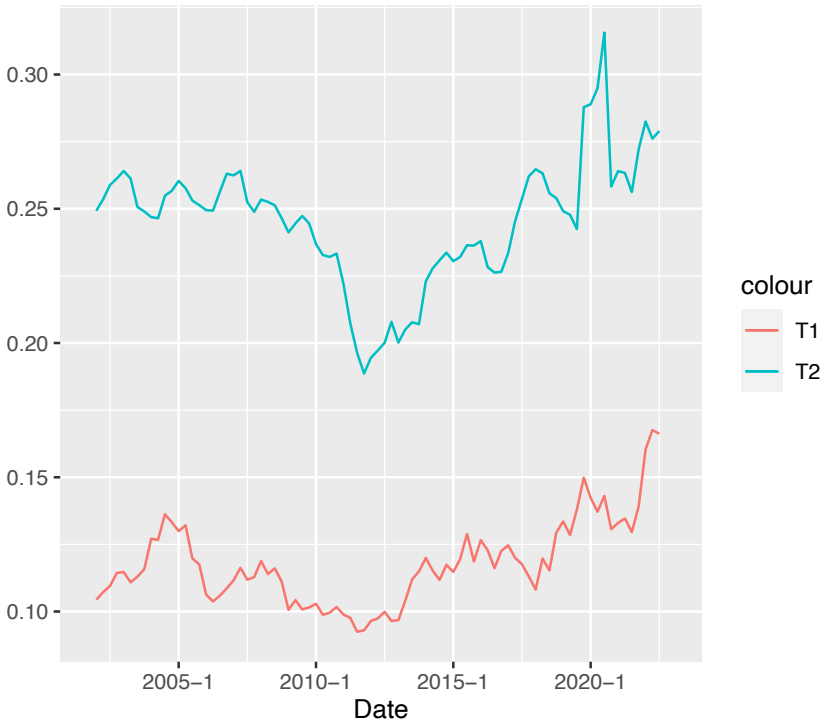


Figure 3.10. UN rate: Type 1 vs Type 2

3.B Additional Tables and Figures

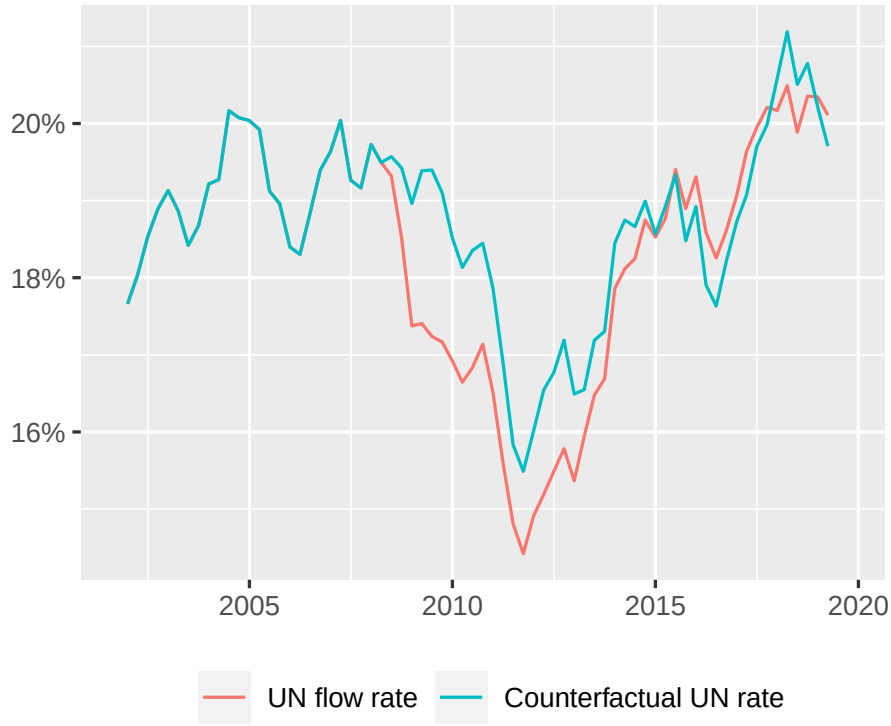


Figure 3.11. Actual and Counterfactual UN rate (incl. social welfare recipients)

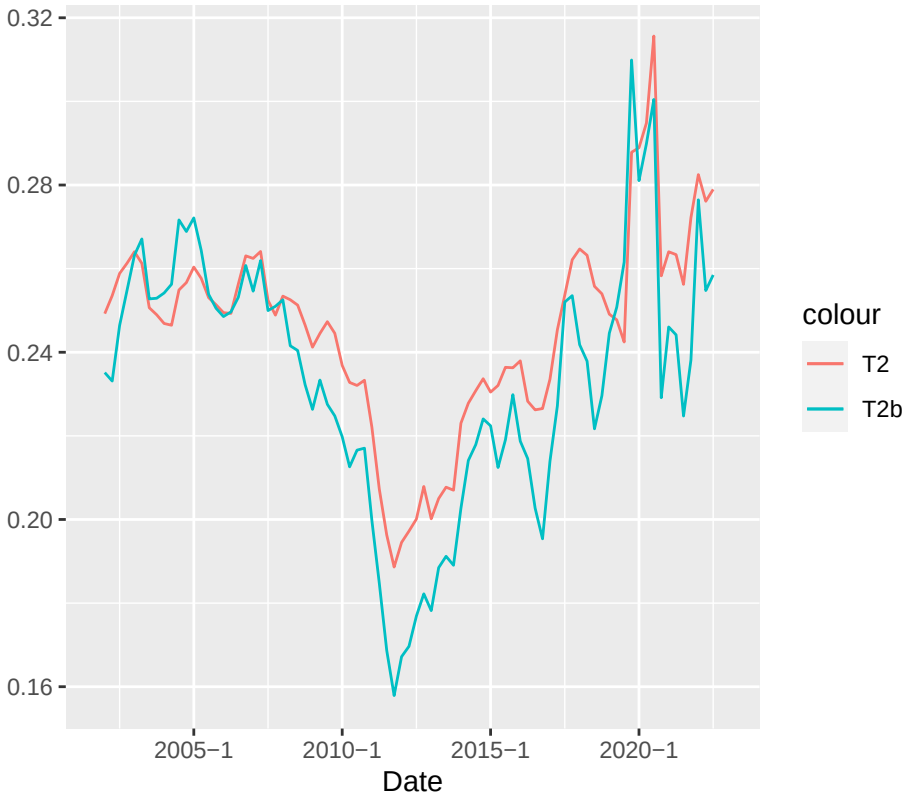


Figure 3.12. UN rate for Type 2: Role of benefit recipients

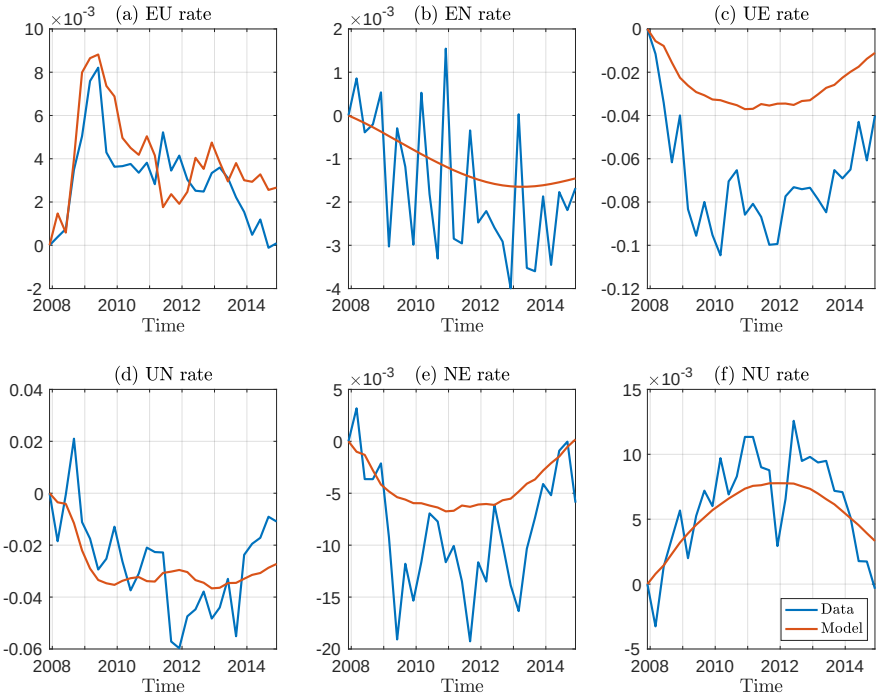


Figure 3.13. Labour market flows in the Great Recession: Data vs Model

State in t	Transition Probability	State in $t+1$
l	$1-\delta_{t+1}$	l
l	$(1-\delta^x)G(\underline{a}_{t+1})$	u_1
l	0	u_2
l	δ^x	n
u_1	$p_u(\theta_t)(1-\delta_{t+1})$	l
u_1	$(1-p_u(\theta_t))(1-\lambda_{u_1})+p_u(\theta_t)(1-\delta^x)G(\underline{a}_{t+1})$	u_1
u_1	$(1-p_u(\theta_t))\lambda_{u_1}(1-F(\underline{e}))$	u_2
u_1	$(1-p_u(\theta_t))\lambda_{u_1}F(\underline{e})+p_u(\theta_t)\delta^x$	n
u_2	$p_u(\theta_t)(1-\delta_{t+1})$	l
u_2	$p_u(\theta_t)(1-\delta^x)G(\underline{a}_{t+1})$	u_1
u_2	$(1-p_u(\theta_t))(1-F(\underline{e}))$	u_2
u_2	$(1-p_u(\theta_t))F(\underline{e})+p_u(\theta_t)\delta^x$	n
n	$p_n(\theta_t)(1-\delta_{t+1})$	l
n	$p_n(\theta_t)(1-\delta^x)G(\underline{a}_{t+1})$	u_1
n	$(1-p_n(\theta_t))\lambda_n(1-F(\underline{e}))$	u_2
n	$(1-p_n(\theta_t))(1-\lambda_n+\lambda_n F(\underline{e}))+p_n(\theta_t)\delta^x$	n

Table 3.8. Transition Rates: Model

Chapter 4

Heterogeneous Discounting and Unemployment

Abstract

We propose a novel channel of amplification in the labour market via heterogeneity in discounting of future values between workers and firms. If workers and firms discount the continuation of matches differently in response to aggregate shocks, we illustrate in a stylised environment that the degree of *dispersion* between the discount factors of different households introduces an additional amplification channel via its effect on the job creation margin. We characterise this mechanism in the context of a standard TANK model extended to allow for search frictions in the labour market. In the TANK model discount factor dispersion is driven by the relative response of profit income to labour income in response to shocks. We use the model to quantify the strength of this novel amplification channel, finding under a standard calibration that this channel amplifies both demand and supply shocks. Quantitatively we find that the amplification is significant for demand shocks due to the higher sensitivity of profit income, whilst irrelevant for the transmission of supply shocks owing to the well-known insensitivity of profits to changes in productivity in this environment.

Keywords: *Search & matching; TANK models; Household heterogeneity; Stochastic discount factors*

JEL Codes: *E24, E30, E32, E44, J23*

4.1 Introduction

In this paper we study of novel channel of amplification for the transmission of shocks to the labour market which operates through heterogeneity in stochastic discount factors across households. In the presence of labour market frictions employment matches have an asset value. In an environment where households are heterogeneous in their stochastic discount factors this implies that some workers will value the continuation of matches differently to the firms they are matched with. Firstly, in a stylised two-agent environment with search frictions and heterogeneity in stochastic discount factors, we illustrate that in the presence of SDF heterogeneity, the dispersion in SDFs matters for the response of the joint match surplus to shocks and ultimately for the transmission of these shocks to the labour market via the job creation channel. In principle this channel can either amplify or dampen the effect of aggregate shocks depending on the direction of dispersion, which itself is driven by the underlying differences in household income sources and their relative responses to shocks.

We embed this mechanism into an otherwise standard two-agent New Keynesian model ('TANK') based on Bilbiie (2008) extended to allow for search frictions in the labour market frictions in order investigate the determinants of discount factor dispersion. We use this environment for two main reasons. Firstly, by definition TANK models adopt a tractable two-agent structure of household heterogeneity. Secondly, the presence of the NK block allows the presence of firms with market power who earn profits in equilibrium which are typically only remunerated to one type of household. In equilibrium this implies that consumption heterogeneity is driven by differences in income sources which generates heterogeneity in SDFs. Moreover, the presence of nominal rigidities allows us to study the implications of discount factor dispersion for the transmission of demand shocks (as well as more commonly studied supply shocks). Through the lens of the resulting framework, we illustrate that fluctuations in discount factor dispersion is entirely driven by differences in the response of labour income relative to profit income to shocks.

Next, we utilise the model under a fairly standard calibration to quantify the direction and size of this novel amplification channel in response to both demand and supply shocks. In both cases we find that this channel amplifies the effects of aggregate shocks, though to very different degrees. In the first instance, we find that this channel delivers significant amplification in the case of a demand shock. This

is for two key reasons. Firstly, profits in the NK model are highly sensitive to demand shocks. Secondly, as is well-known, profits are countercyclical with respect to demand shocks in the TANK model. This means that profit and labour income are pushed in opposite directions in the case of a demand shock. Taken together, this generates sizeable volatility in discount factor dispersion and quantitatively significant amplification of the demand shock. This contrasts starkly to the case of a supply (productivity) shock. In this case the model has the well-known feature that profits are relatively insensitive to productivity shocks, whilst labour and profit incomes co-move positively in this case. Overall the amplification generated under supply shocks is quantitatively negligible.

Finally, we investigate the sensitivity of these findings to several key parameters, notably those governing the SDF sensitivity relating to household preferences and worker bargaining power. Using non-recursive preferences allows us to examine separately the implications of increasing household intertemporal elasticity of substitution (IES) compared to the degree of risk aversion. Overall we illustrate that attitudes towards inter temporal substitution are more important for determining SDF volatility, and that lower levels of IES amplify the impact of heterogeneous discounting.

Related literature: This paper is chiefly related to several broad strands of the literature bridging household heterogeneity, labour market frictions, and the role of discounting for labour market fluctuations.

Firstly, the paper is related to the vast literature studying the role of household heterogeneity for the transmission of aggregate shocks. This covers both an earlier literature which utilised more tractable two-agent structures (as we do in this paper) such as contributions (e.g. Bilbiie 2008), and the more recent literature using richer models of household heterogeneity based on Kaplan et al. (2018) who embed a standard incomplete markets model based on Huggett (1993) into a New Keynesian framework. This literature has tended to emphasise the role of heterogeneity in household marginal propensities to consume (MPCs), both for the transmission of shocks and for the appropriate designs of monetary and fiscal policy.[1] Whilst in these environments there is heterogeneity in the stochastic discount

[1]Notable more recent examples using TANK models are: Galí et al. (2007), Nisticò (2016), Ascari et al. (2017), Broer et al. (2020), Cantore and Freund (2021), Bilbiie (2023), and Debortoli and Galí (2024). For HANK models see: McKay et al. (2016), Acharya and Dogra (2020), Auclert (2019), Auclert et al. (2020), Nuno and Thomas (2020), Werning (2015), Bayer et al. (2020), and Luetticke (2021).

factors between households, in the vast majority of this literature there is typically no role for those of constrained households as these households are off their Euler equation. Moreover, there are usually no frictions in the labour market which would otherwise give employment matches an asset value.

Secondly, there is a small but growing literature examining the interaction between household heterogeneity, incomplete markets and labour market frictions. A key contribution is the framework developed by Ravn and Sterk (2017, 2021), who embed search & matching frictions into a tractable incomplete markets model in Broer et al. (2020) and illustrate how the link between endogenous unemployment risk and precautionary savings can significantly amplify aggregate shocks. Broer et al. (2023) use a similar environment augmented to allow for a more empirically consistent job creation margin and use the environment to quantify the role of unemployment risk over the business cycle. Gornemann et al. (2021) build and solve a rich quantitative model featuring incomplete markets, search & matching frictions, and allowing for heterogeneity in preferences and worker skills. They use the model to study the distributional consequences of monetary policy. All these papers rely on the same mechanism for amplification - the interaction between aggregate demand, precautionary saving under incomplete markets and endogenous income risk from frictions in the labour market. In contrast, we emphasise a very different channel of amplification which does not rely on endogenous unemployment risk. We show that even when there is perfect risk-sharing within the family, household heterogeneity can still generate amplification in the labour market when there is heterogeneity in the discounting of match continuation values.

Finally, this paper also contributes to a small literature studying the relationship between discount rates and the labour market. This literature views job creation as another form of financial investment which should be subject to the same rate of discount as financial assets. The key contribution here is Hall (2017), who finds that feeding an estimated process for discount factors on US stock market data into a standard search & matching model leads to empirically plausible fluctuations in unemployment and overcomes the volatility puzzle. Kehoe et al. (2023) develop a standard search & matching model where household preferences are consistent with time-varying risk over the business cycle (via recursive preferences) and find quantitatively that the model is able to replicate US unemployment fluctuations without generating further empirical puzzles. Finally, a recent contribution by Martellini et al. (2021) builds a rich search framework with heterogeneous match

quality, and instead find that shocks to financial discount rates on their own do not generate sufficient volatility in labour market transition probabilities to induce large unemployment fluctuations. Relative to these papers, our contribution is to highlight that heterogeneity in the rates of financial discounting, induced by heterogeneity in income sources and the ability to smooth consumption, endogenously generates additional volatility in the labour market via its effect on the job creation margin.

Layout. The rest of the paper is organised as follows. Section 4.2 outlines the core mechanism in a stylised environment. Section 4.3 embeds the mechanism into a standard TANK model extended to allow for search frictions in the labour market and outlines the determinants of heterogeneous discounting. Section 4.4 details the main results of the paper where we quantify the role of heterogeneous discounting in amplifying demand and supply shocks. Section 4.5 concludes.

4.2 A Stylised Example

In this section we illustrate how the presence of heterogeneity in discounting between workers and firms affects job creation incentives in an otherwise standard environment with search & matching frictions. We derive the implications of discount factor heterogeneity for the key equation in this model - to job creation condition.

Environment. Time is discrete and runs forever. The economy is populated by a continuum of infinitely-lived households and is subject to fluctuations due to aggregate shocks. Households are risk-averse, derive utility from consuming a final consumption good, and discount the future according to $\beta \in (0,1)$. Households are heterogeneous in their ability to smooth consumption and are indexed by $i = \{C, U\}$ to be one of two types: (i) constrained households who only receive income from working, and (ii) unconstrained households who trade assets (including shares in firm profits). The composition of household types is fixed, where the fraction of constrained households is given by $\lambda \in (0,1)$. We assume there is perfect risk-sharing within the two types of household, but not *across* households. The consumption of different households will therefore respond differently to aggregate shocks, generating dispersion in stochastic discount factors $\beta^i_{t,t+\tau}$ where:

$$\beta^i_{t,t+\tau} = \beta \frac{u'(C^i_{t+\tau})}{u'(C^i_t)}$$

where $u'(\cdot) \geq 0$ and $u''(\cdot) \leq 0$.

Households inelastically supply labour to the market but face search frictions such that not all household members successfully find jobs. If matched, worker-firm pairs produce output $A > 0$ and the worker is paid a wage w^i, where wages are bargained such that the worker receives fraction $\eta \in (0,1)$ of the joint surplus of the match. If unemployed workers instead receive flow value $b > 0$. Matches separate exogenously with probability $\rho \in (0,1)$. Firms post vacancies v at per period cost $\chi > 0$. Matches are formed according to a constant returns matching function $M(V,U)$, where U is the number of job searchers. Contact rates for workers and vacancies $\{p(\theta), q(\theta)\}$ depend on the ratio of vacancies-to-searchers, i.e. $\theta = V/U$, which is endogenously determined by job creation.

Match surplus. Workers from different households discount the continuation of a match at different rates in the presence of aggregate shocks (i.e. out of steady state). This implies heterogeneity in the match surplus and therefore in wages w^i across households. To see this, define the total surplus of a match with worker from household i as $\mathbb{S}_i$, and the worker and firm surpluses as $\{\mathbb{S}_i^w, \mathbb{S}_i^f\}$. Given the assumptions made above can write:

$$\mathbb{S}_{U,t} = A - b + (1-\rho)\mathbb{E}_t \beta_{t,t+1}^U \mathbb{S}_{U,t+1}$$

$$\mathbb{S}_{C,t} = A - b + (1-\rho)\mathbb{E}_t \left[\beta_{t,t+1}^C \mathbb{S}_{C,t+1}^w + \beta_{t,t+1}^U \mathbb{S}_{C,t+1}^f\right]$$

For matches where workers are members of unconstrained households, both members of the match discount its continuation using the same discount factor. Otherwise, the continuation value of the match is discounted differently by either side.

Job creation. The implications for the job creation will determine whether the presence of heterogeneous discounting amplifies or dampens the response of the labour market to aggregate shocks. Imposing the free entry condition implies:

$$\chi = q(\theta)(1-\eta) \int \mathbb{S}_{i,t} di = q(\theta)(1-\eta) \cdot [(1-\lambda)\mathbb{S}_{U,t} + \lambda \mathbb{S}_{C,t}]$$

where $q(\theta)$ is the job filling rate and $q'(\cdot) \leq 0$. Job creation is driven by fluctuations in the weighted average of the joint surpluses, which somewhat complicates further derivations. To get around this we make a simplifying assumption that for the purposes of wage bargaining all workers use the *average* discount factor, defined as:

$$\beta_{t,t+1} = \lambda \beta_{t,t+1}^C + (1-\lambda)\beta_{t,t+1}^U$$

which also ensure that all workers are paid a single wage which we can characterise analytically.[2]

Proposition 4.1. *The Nash wage is given by the usual weighted average between worker & firm reservation wages:*

$$w_t = (1-\eta)b + \eta\bar{w}_t$$

where the firm's reservation wage $\bar{w}_t$ is now given by:

$$\bar{w}_t = A_t + \mathbb{E}_t\beta^U_{t,t+1}\chi\theta_{t+1} + \underbrace{\lambda\left[\frac{\chi}{q(\theta_{t+1})}(1-\rho-p(\theta_{t+1}))(\beta^U_{t,t+1}-\beta^C_{t,t+1})\right]}_{\text{SDF heterogeneity}}$$

Proof. See Appendix 4.A. □

In this environment, heterogeneous discounting affects labour market volatility via its effect on the firm's reservation wage and therefore job creation (as illustrated in Corollary 4.2).

Corollary 4.2. *The job creation condition in this environment can be written as:*

$$\frac{\chi}{q(\theta_t)} = (1-\eta)(A-b) + \mathbb{E}_t\frac{\chi}{q(\theta_{t+1})}\cdot\left[(1-\rho)\beta^U_{t,t+1} - \eta\lambda(1-\rho-p(\theta_{t+1}))(\beta^U_{t,t+1}-\beta^C_{t,t+1})\right]$$

where in the absence of household heterogeneity (i.e. $\lambda = 0$ and $\beta^C_{t,t+1} = \beta^U_{t,t+1}$) this channel disappears.

Whether this novel channel amplifies or dampens the response of the labour market to aggregate shocks ultimately depends on how the dispersion in discount factors itself responds to the shock, or more specifically on the direction of the inequality:

$$\beta^U_{t,t+1} - \beta^C_{t,t+1} \lessgtr 0$$

Overall the modified job creation in Corollary 4.2 suggests that the quantitative importance of this amplification channel will depend on (i) the sensitivity of SDFs to shocks, (ii) the fraction of constrained households λ, and (iii) worker bargaining power η. Without further structure we cannot characterise what forces determine fluctuations in discount factor dispersion. In the following section, we embed this stylised environment into a TANK model with search frictions in order to explore the implications of this channel in an otherwise well-understood environment.

[2] One rationalization for this could be that workers are represented by a third party in the wage bargain (e.g. a union) who bargains with firms on behalf of all workers, rather than just the worker in the match, in order to prevent wage differentials.

4.3 Quantification: Insights from a TANK Model

In this section we quantify the contribution of heterogeneous discounting to labour market volatility. To do this, we first embed the environment outlined above into a relatively standard two-agent New Keynesian model ('TANK') based on Bilbiie (2008). We then briefly discuss what drives heterogeneity in discount factor fluctuations in the model, before outlining a standard calibration of the model. The main results from simulating the responses to demand and supply shocks are presented in the following section.

4.3.1 A Simple TANK Model

We utilise a TANK model to quantify the role of heterogeneous discounting for two main reasons: (i) we maintain the tractable two-agent approach to capturing heterogeneity in consumption smoothing, and (ii) allowing for a New Keynesian block allows firms to make excess profits from market power which are typically remunerated to unconstrained households such that households have different income sources. Moreover, the NK block allows us to study the implications of heterogeneous discounting for demand shocks (as well as supply shocks). Below we briefly outline the key additional features of the model relative to our previous stylised environment. Further details about the TANK model can be found in Appendix 4.B.

Households. We broadly retain the same assumptions as in Section 4.2. A fraction $1-\lambda$ of "unconstrained" (U) households smooth income using riskless one-period bonds B_t yielding the gross nominal return R_t, and shares in an equity fund which owns firm profits S_t which can be purchased at (real) price Q_t. Optimization yields Euler equations for these two assets. The remaining fraction λ of "constrained" (C) households consume their labour income in every period. Households consume a continuum of differentiated goods sold by monopolistically competitive firms indexed by $k \in [0,1]$ at price $P_{k,t}$. Total consumption of household i is given by $C_t^i \equiv \left(\int_0^1 {C_{k,t}^i}^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}}$, where $\nu > 0$ is the elasticity of substitution across goods.[3]

[3]The overall demand for each good variety in the economy is standard:

$$C_{k,t} = \left(\frac{P_{k,t}}{P_t} \right)^{-\nu} C_t$$

Labour market. Again we retain the same assumptions about the labour market as in Section 4.2. It follows that aggregate employment denoted by N_t obeys the following law of motion:

$$N_t = (1-\rho)N_{t+1} + M_t \tag{4.1}$$

where M_t are newly formed matches.

Firms. There are a continuum of monopolistically competitive firms indexed by k who produce a differentiated good which they then sell to consumers at price $P_{k,t}$. All firms employ a fraction of total workers $N_{k,t}$ who produce output according to $Y_{k,t} = A_t N_{k,t}$ and are each paid a real wage $w_{k,t}$. In addition to per period vacancy costs $\chi > 0$, firms also face quadratic price adjustment costs governed by $\Psi > 0$.[4] Firm k chooses employment and vacancy postings to maximise present discounted profits subject to a law of motion for firm employment, the production function, and the standard demand curve for their output. Standard optimization techniques yield a standard job creation condition and a non-linear Phillips curve:

$$\frac{\chi}{q(\theta_t)} = \varepsilon A_t - w_t + (1-\rho)\mathbb{E}_t\left[\beta^U_{t,t+1}\frac{\chi}{q(\theta_{t+1})}\right] \tag{4.2}$$

$$1 - \Psi(\pi_t - \pi)\pi_t + \mathbb{E}_t[\beta^U_{t,t+1}\Psi(\pi_{t+1}-\pi)\pi_{t+1}\frac{Y_{t+1}}{Y_t}] = \nu(1-\varepsilon_t) \tag{4.3}$$

where π_t is the (gross) inflation rate and ε_t are real marginal costs. The fact that firms are identical ensures that optimal choices are symmetric across firms, which allows us to drop the k subscripts.

Wages. The determination of wages is identical to that described in Section 4.2, where we maintain the assumptions ensure a single equilibrium wage across all workers.[5] The only difference is that now (real) marginal costs ε_t also enter the firm's reservation wage.

Closing the model. Markets for goods, bonds and shares must clear. Goods market clearing requires that the total supply of goods (net of the costs of posting

where $P_t \equiv \left(\int_0^1 P_{k,t}^{1-\nu}\right)^{\frac{1}{1-\nu}}$ is the relevant price index.

[4] We assume Rotemberg (1982) price rigidities in order to stay closer to the TANK/HANK literature.

[5] Throughout the paper we maintain Nash bargaining for simplicity and tractability, but is just one possible way in which wages could be determined in relation to the worker's surplus that would preserve pass-through from heterogeneity in discount factors to the job creation margin, which is key for our main channel to operate.

vacancies and changing prices) must equal the total demand of households, given by $C_t \equiv \int_0^1 C_{k,t} dk = (1-\lambda)C_t^U + \lambda C_t^C$. This implies the following goods market clearing condition:

$$C_t = Y_t \left(1 - \frac{\Psi}{2}(\pi_t - \pi)\right) - \chi V_t \tag{4.4}$$

Bonds are in zero net supply and the market for shares must also clear, i.e. $B_t^U = 0, S_t^U = \frac{1}{1-\lambda}$. Lump-sum taxes are levied on each type of household to finance their unemployment benefits. Overall this implies the following equilibrium consumption allocation across households:

$$C_t^U = w_t N_t + \frac{1}{1=\lambda} D_t,\ C_t^C = w_t N_t \tag{4.5}$$

In this environment, consumption differences across the two types of households are due to the additional financial income unconstrained households obtain from holding firm shares.[6] Finally, we assume the presence of a central bank who determine R_t via a standard Taylor-type rule.

4.3.2 What Drives Heterogeneity in Discount Factors?

Through the lens of the TANK model, heterogeneity in discount factors is driven by the relative responses of different sources of income to aggregate shocks. Given the consumption allocation in equation (4.5), it follows that fluctuations in $\beta_{t,t+1}^C$ are entirely determined by fluctuations in labour income whereas $\beta_{t,t+1}^U$ captures changes to *both* labour and profit income in response to shocks. Hence factor dispersion in the model is driven by the response of profits *relative* to labour income.[7] We prove this formally below.

Proposition 4.3. *Suppose the utility function is a standard CRRA: $u'(C) = C^{-\sigma}$ It can be shown that to a first-order approximation discount factor dispersion can be expressed as:*

$$\beta_{t,t+1}^U - \beta_{t,t+1}^C \approx \frac{\beta\sigma}{1 + (1-\lambda)\gamma WN} \left[\mathbb{E}_t \Delta(w_{t+1} N_{t+1)} - \gamma \mathbb{E}_t \Delta D_{t+1} \right] \tag{4.6}$$

where $\gamma \equiv \frac{wN}{D}$ is the steady state ratio of labour income to profits.

[6] The importance of how firm profits are distributed across households in models of limited asset market participation models was first highlighted in Bilbiie (2008).

[7] This reflects another dimension of the importance of firm profits in New Keynesian models with limited asset market participation, a point originally raised in Bilbiie (2008) relating to how firm profits are distributed. Here we take the simple case of no redistribution of firm profits.

Proof. See Appendix 4.A. □

In response to an aggregate shock, whether the response of labour or profit income dominates depends on their relative direction and volatility, the size of labour income relative to profits in steady state (γ), as well as other factors anticipated in Section 4.2 such as λ (which controls the share of profits unconstrained households hold) and the preference parameters characterising the sensitivity of SDFs (here captured by σ). In the next section we outline a standard calibration of the model which we can then use to characterise this amplification channel quantitatively.

4.3.3 Parameterization

We outline a standard parameterization of the model at a quarterly frequency. For several values we calibrate them externally by setting them equal to standard values used in the literature on business cycles and search & matching models. Additionally we determine some parameters relating to the labour market by imposing external restrictions on steady state values such that the model matches key features of the US labour market. The parameterization is summarised in Table 4.2.

Functional forms. We use a more general non-recursive household utility function popularised by Epstein and Zin (1989), in order to allow for a richer parameterization of household stochastic discount factors. The expected discounted lifetime utility of household i is given by J_t^i, which is defined as:

$$J_t^i = \left[(1-\beta) {C_t^i}^{1-\frac{1}{\varphi}} + \beta \left(\mathbb{E}_t \left[{J_{t+1}^i}^{1-\sigma} \right] \right)^{\frac{1-\frac{1}{\varphi}}{1-\sigma}} \right]^{\frac{1}{1-\frac{1}{\varphi}}}$$

where $\sigma > 0$ measures the degree of household risk aversion, and $\varphi > 0$ captures the household's intertemporal elasticity of substitution (IES).[8] The corresponding expression for the stochastic discount factor of household i is given by:

$$\beta_{t,t+1}^i = \beta \left(\frac{C_{t+1}^i}{C_t^i} \right)^{-\frac{1}{\varphi}} \left(\frac{J_{t+1}^i}{\mathbb{E}_t \left[{J_{t+1}^i}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}} \right)^{\frac{1}{\varphi}-\sigma}$$

For matching we assume a standard Cobb-Douglas specification:

$$M(V_t, U_t) = \bar{m} V_t^{1-\xi} U_t^{\xi}$$

[8] Imposing the restriction $\sigma = \frac{1}{\varphi}$ recovers the standard power utility (CRRA) specification.

where ξ is the elasticity of new matches with respect to the stock of job searchers and $\bar{m}$ is a match efficiency constant.

Externally calibrated parameters. We calibrate several model parameters using standard values. The household discount factor β is set to 0.9926 to target a 3% annual average real interest rate. The intertemporal elasticity of substitution (IES) φ is set to 1.5. We initially set $\sigma = 1/\varphi$ such that preferences are CRRA. The elasticity of substitution across varieties is set to $\nu = 6$ to generate a 20% steady state markup. The price adjustment costs parameter Ψ is chosen to match an average price duration of 1 year. We choose a value of the match elasticity $\xi = 0.5$ which is standard in the context of the survey by Petrongolo and Pissarides (2001) and then set $\eta = \xi$ such that the Hosios' (1990) condition is satisfied. We choose a Taylor rule coefficient that is standard. Finally, the fraction of hand-to-mouth households λ is set t0 21% based on Debortoli and Galí (2024).

Steady state targets. Several parameters relating to the labour market are set to match standard quarterly targets for the US labour market. Specifically we set the values of $\rho, \chi, \bar{m}, b$ to match: (i) a 5.5% average unemployment rate, (ii) an average job filling rate equal to 0.7 as in Den Haan et al. (2000), (iii) an average quarterly job finding rate equal to 0.45 as in Shimer (2012), and (iv) a 40% replacement ratio as in Shimer (2005). Note that under this calibration of the replacement rate the standard Shimer (2005) critique will apply.

Model solution. The model is solved using standard perturbation techniques around a steady state with zero inflation.[9] A full description of the non-linear equilibrium conditions used to solve the model is given in Table 4.1 in Appendix 4.B.

4.4 Main Results

In this section we present the main quantitative findings. We use the calibrated TANK model to quantify the contribution of heterogeneous discounting by simulating the response to two different types of aggregate shocks - a demand (monetary policy) shock and a supply (productivity) shock - and comparing against the counterfactual where there is no heterogeneity in discounting (i.e. $\lambda = 0$).

[9]The model is initially solved using first-order perturbation, but later solved using higher order perturbation to allow the degree of risk aversion to influence the stochastic solution to the model when we deviate from using a power utility specification.

4.4.1 Demand shock

We first study the response of the model to a 1% contractionary shock to the monetary policy rate in the model. The responses of key variables in the model are presented in Figure 4.5. Declining demand is associated with a fall in output and inflation as standard, driven by downward pressure on labour demand by firms leading to falling wages and vacancies, lower labour market tightness and higher unemployment. As is well-known, a decline in the policy rate is also associated with an *increase* in firm profits in the NK environment.[10] Profits and labour income therefore move in different directions, inducing dispersion in the discount factors across households. Moreover, we find that profits are significantly more sensitive to demand shocks than labour income in our model. This induces the dispersion in discount factors to be positive, i.e. $\beta^U_{t,t+1} - \beta^C_{t,t+1} > 0$. As discussed above, this amplifies the effect of a contractionary shock via its effect on job creation.

The size of this additional amplification channel can be seen be examining the counterfactual response when $\lambda = 0$ in Figure 4.1. Our first main result is that discount factor heterogeneity amplifies the effect of the demand shock quite substantially. The greater fall in vacancies induces an additional 20% increase in the unemployment response, and leads to output falling by around an additional 1%. Note that because the discount factor heterogeneity channel is inherently forward-looking, its effect is entirely concentrated in the impact of the shock. Heterogeneity in discounting does not affect the persistence of the economy's response to the shock.

4.4.2 Technology shock

Secondly we study the response of the model to a 1% positive (labour) productivity shock. The responses of key variables in the model are presented in Figure 4.6. Job creation responds positively to the shock because the value of a worker to a firm increases, leading to falling unemployment and lower labour market tightness as standard. However the rise in real wages acts to dampens firms' incentives to hire more workers. In this case profits and labour income now move in the *same* direction. As the consumption level of constrained households increases by more (relative to steady state), the model predicts that $\beta^U_{t,t+1} - \beta_{t,t+1} < 0$, which acts to stimulate job creation.

[10] For a discussion of this channel, see Broer et al. (2020).

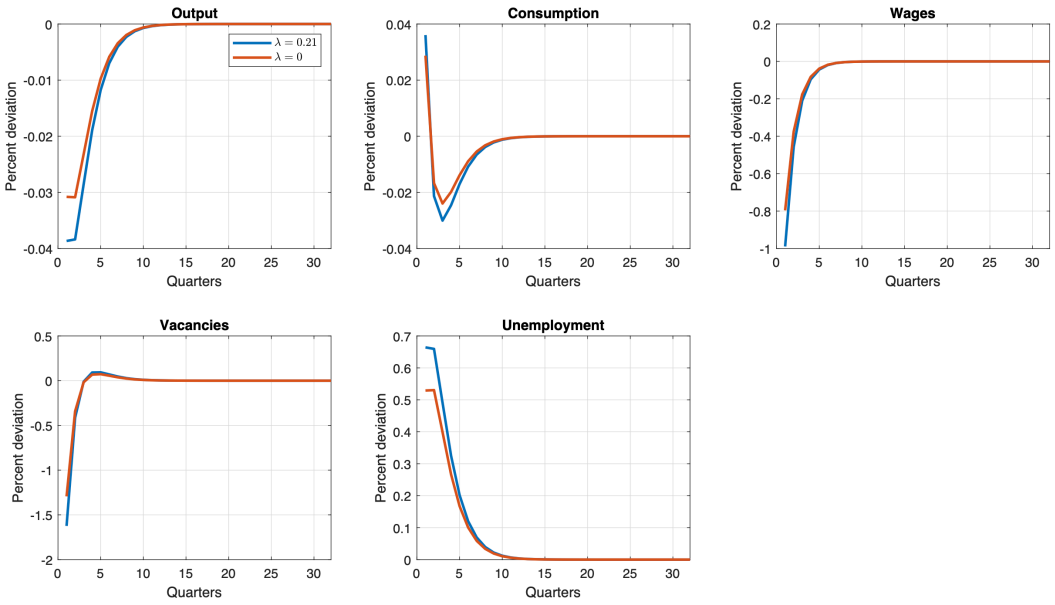


Figure 4.1. Amplification from SDF heterogeneity: Demand shock

Our second main result is that amplification of productivity shocks from our heterogeneous discounting channel is quantitatively insignificant. This is illustrated in Figure 4.2 where again we plot the responses relative to the counterfactual. This result is mainly driven by the fact that profits are not very sensitive to supply shocks, which is a well-known issue of our standard calibration approach (i.e. the unemployment volatility puzzle outlined in Shimer 2005). As a result, dispersion is SDFs is an order of magnitude smaller compared to the case of a monetary policy shock. Overall we see that the additional amplification from the heterogeneous discounting channel is vanishingly small.

Summary. We find that our heterogeneous discounting channel amplifies the response of the economy to standard demand and supply shocks. However, the quantitative significance of this channel is shown to depend on how firm profits respond to the aggregate shock relative to aggregate labour income, as well as their relative volatilities. A demand shock in the model moves labour and profit income in opposite directions and firm profits are roughly 4 times more volatile than labour income, so we find that heterogeneous discounting induces a fairly large amplification. In contrast, for a productivity shock labour income and profit income move in the same direction and have roughly equal volatilities in response to the shock, such that amplification in this case is quantitatively irrelevant.

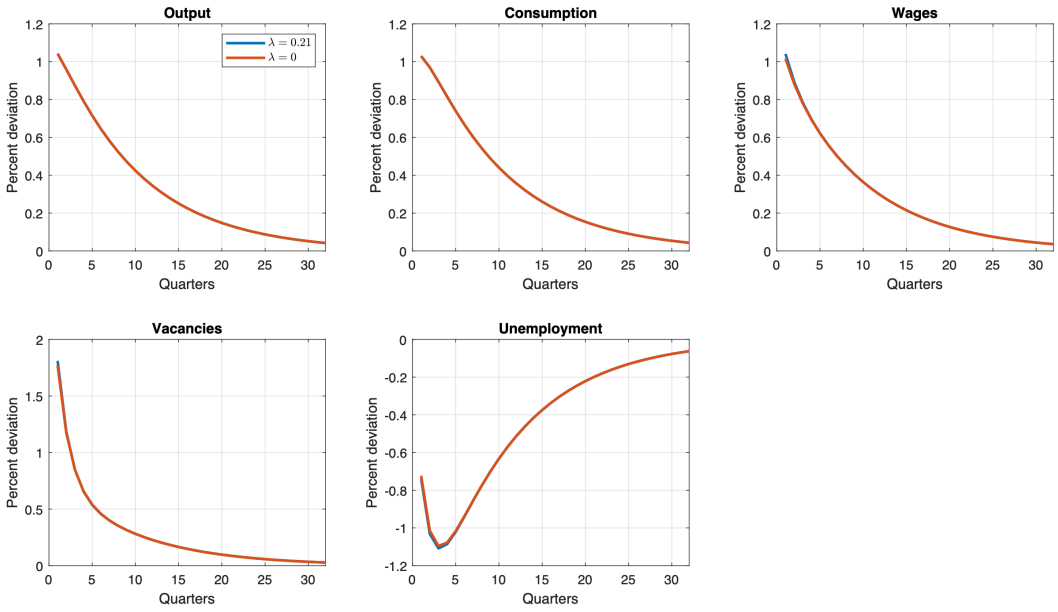


Figure 4.2. Amplification from SDF heterogeneity: Supply shock

4.4.3 Robustness

Finally, we investigate the sensitivity of amplification via this channel to changes in several key parameters outlined in Section 4.2, notably the parameters governing household preferences and the degree of worker bargaining power.

Household preferences. Epstein-Zin preferences feature two parameters: the IES parameter φ and degree of risk aversion σ. Under our baseline parameterization we set the former to a standard value and determine the latter by imposing the CRRA restriction, $\sigma = 1/\varphi$. We recompute the responses of the model to a contractionary demand shock under two alternative calibrations of these parameters. Firstly, we maintain the CRRA restriction but increase the value of φ from 1.5 to 3. Under the CRRA restriction this both simultaneously reduces household risk aversion and increases the appetite of households to engage in intertemporal substitution. Secondly, we move away from the CRRA restriction by fixing $\varphi = 1.5$ but increasing the degree of risk aversion σ to 5. This will allow us to identify whether risk aversion or intertemporal substitution appear to be more important for this amplification channel.

The IRFs are plotted in Figure 4.3. Firstly, we find that simultaneously increasing the degree of substitution elasticity whilst reducing risk aversion dampens ampli-

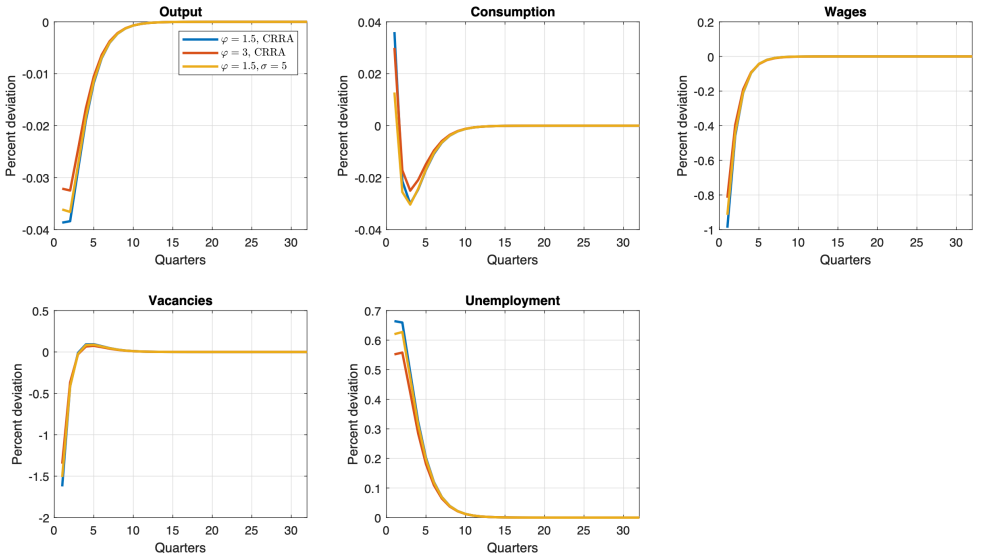


Figure 4.3. Robustness: Impact of IES φ and risk aversion σ.

fication. Quantitatively the effect on the amplification on impact is quite strong - with higher IES, the response now looks quantitatively similar to the baseline parameterization when we shut down heterogeneity ($\lambda = 0$) in Figure 2. Secondly, when we fix the IES parameter φ but increase the degree of risk aversion σ to a higher but plausible value (yellow line), we find that increasing household risk aversion without also changing attitudes towards intertemporal substitution dampens amplification. Taken together, these results suggest that household attitudes towards intertemporal substitution are more influential in determining volatility in stochastic discount factors (and therefore discount factor dispersion) than attitudes towards risk.

Bargaining power. Worker bargaining power η determines the influence of discount factor dispersion on job creation. We recompute the model responses for lower value of worker bargaining power $\eta = 0.4$. The results are plotted in Figure 4.4. Unsurprisingly, this significantly reduces amplification from the discount factor dispersion channel. Again quantitatively this is similar to maintaining the baseline calibration, but shutting down this channel altogether by eliminating household heterogeneity.

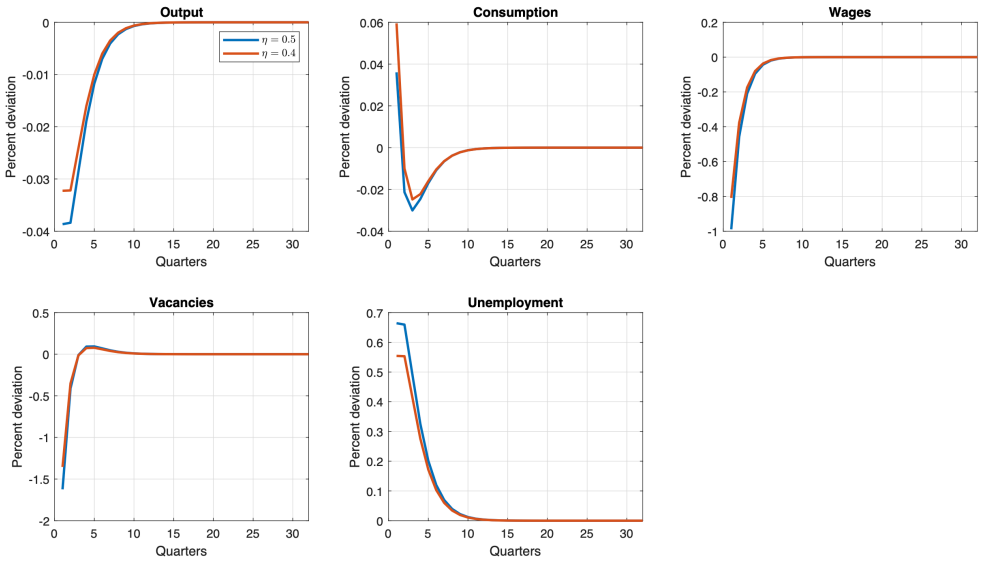


Figure 4.4. Robustness: Worker bargaining power.

4.5 Conclusion

This paper studies a novel channel of labour market amplification through heterogeneity in discounting. We show that when households are heterogeneous in their ability to smooth income and have different income sources, aggregate shocks generate heterogeneity in how households discount the continuation value of matches in the labour market, and that this matters for the transmission of aggregate shocks via the job creation margin. We illustrate this mechanism in the context of a standard TANK model extended to allow for search frictions in the labour market. We use a standard calibration of the model to quantify the effect of our heterogeneous discounting channel on the amplification of demand and supply shocks to the labour market. We find in the model that heterogeneous discounting amplifies both demand and supply shocks, though quantitatively the channel is only significant for demand shocks.

Chapter 4: Appendices

4.A Proofs

4.A.1 Proof of Proposition 4.1

Under Nash bargaining the wage satisfies the Nash sharing rule:

$$\mathbb{S}_t^w = \eta(\mathbb{S}_t^w + \mathbb{S}_t^f)$$

which states that the worker receive fraction η of the total match surplus, defined as the sum of the worker and firm surpluses. There in turn are defined as:

$$\mathbb{S}_t^w = w_t - b + \mathbb{E}_t\left[\beta_{t,t+1}(1-\rho-p(\theta_{t+1}))\mathbb{S}_{t+1}^w\right]$$

$$\mathbb{S}_t^f = A_t - w_t + (1-\rho)\mathbb{E}_t\left[\beta_{t,t+1}^U \mathbb{S}_{t+1}^f\right]$$

Substituting these expressions in the Nash sharing rule and rearranging gives:

$$w_t = (1-\eta)b + \eta A_t + \eta(1-\rho)\mathbb{E}_t\beta_{t,t+1}^U\mathbb{S}_{t+1}^f - (1-\eta)\mathbb{E}_t\beta_{t,t+1}(1-\rho-p(\theta_{t+1}))\mathbb{S}_{t+1}^w$$

Using $\mathbb{S}_{t+1}^w = \frac{\eta}{1-\eta}\mathbb{S}_{t+1}^f$:

$$w_t = (1-\eta)b + \eta\left[A_t + (1-\rho)\mathbb{E}_t\mathbb{S}_{t+1}^f(\beta_{t,t+1}^U - \beta_{t,t+1}) + \mathbb{E}_t\beta_{t,t+1}p(\theta_{t+1})\mathbb{S}_{t+1}^f\right]$$

then using the free entry condition $\frac{\chi}{q(\theta_t)} = \mathbb{S}_t^f$ yields:

$$w_t = (1-\eta)b + \eta\left[A_t + (1-\rho)\mathbb{E}_t\frac{\chi}{q(\theta_{t+1})}(\beta_{t,t+1}^U - \beta_{t,t+1}) + \mathbb{E}_t\beta_{t,t+1}\chi\theta_{t+1}\right]$$

Finally, using $\beta^U_{t,t+1} - \beta_{t,t+1} = \lambda(\beta^U_{t,t+1} - \beta^C_{t,t+1})$ and rearranging gives the final expression in Proposition 4.1:

$$w_t = (1-\eta)b + \eta\left[A_t + \mathbb{E}_t\left[\beta^U_{t,t+1}\chi\theta_{t+1}\right] + \lambda\mathbb{E}_t\left[\frac{\chi}{q(\theta_{t+1})}(1-\rho-p(\theta_{t+1}))(\beta^U_{t,t+1} - \beta^C_{t,t+1})\right]\right]$$

which has the standard interpretation of being a linear combination of the workers' and firms' reservation wages.

4.A.2 Proof of Proposition 4.3

The stochastic discount factor of some household i can be expressed as:

$$\beta^i_{t,t+1} = \beta\Big(\frac{u'(C^i_{t+1})}{u'(C^i_t)}\Big)$$

Assuming a standard CRRA utility function with parameter $\sigma > 0$ and taking a first-order Taylor expansion around the steady state gives:

$$\beta^i_{t,t+1} \approx \beta - \frac{\sigma\beta}{C^i}(C^i_{t+1} - C^i_t)$$

Using this, we can approximate discount factor dispersion by:

$$\beta^U_{t,t+1} - \beta^C_{t,t+1} \approx -\frac{\sigma\beta}{C^U}(C^U_{t+1} - C^U_t) + \frac{\sigma\beta}{C^C}(C^C_{t+1} - C^C_t)$$

$$= \frac{\sigma\beta}{C^U C^C}\left[(C^U - C^C)\mathbb{E}_t\Delta W_{t+1}N_{t+1} - \frac{C^C}{1-\lambda}\mathbb{E}_t D_{t+1}\right]$$

where the second equality follows from substituting in the (linear) equilibrium expressions for each type of household's consumption. Substituting out for the steady state consumption levels and rearranging gives the expression in Proposition 4.3:

$$= \frac{\sigma\beta}{1 + \frac{(1-\lambda)(WN)^2}{D}}\left[\mathbb{E}_t\Delta W_{t+1}N_{t+1} - \frac{WN}{D}\mathbb{E}_t\Delta D_{t+1}\right]$$

$$= \frac{\sigma\beta}{1 + (1-\lambda)WN\gamma}\left[\mathbb{E}_t\Delta W_{t+1}N_{t+1} - \gamma\mathbb{E}_t\Delta D_{t+1}\right]$$

where the final equality follows from defining $\gamma \equiv \frac{WN}{D}$ as the ratio of steady state aggregate labour income to firm profits.

4.B Model Appendix

Budget constraints. The period budget constraint for the representative unconstrained household is therefore given by:

$$C_t^U + \frac{B_t}{P_t} + Q_t S_t \leq R_{t-1}\frac{B_{t-1}}{P_t} + \int_0^1 w_{k,t} N_{k,t}^U dk + u_t b + [Q_t + D_t]S_{t-1} + T_t^U$$

where T_t^U denotes the transfers received by the unconstrained households, $N_{k,t}$ is the employment rate of agents in the household at firm k who earn the real wage $w_{k,t} \equiv \frac{W_{k,t}}{P_t}$, u_t is the fraction of household members who are unemployed, and b denotes unemployment benefits received by each unemployed member of the household.[11] Constrained households are excluded from asset markets. They consume their income in every period in a 'hand-to-mouth' fashion:

$$C_t^C = \int_0^1 w_{k,t} N_{k,t}^C dk + u_t b + T_t^C$$

where T_t^C are transfers received by constrained households. Hand-to-mouth behaviour implies perfect pass-through of labour income fluctuations to consumption for these households.

Euler equations: Unconstrained households choose consumption and asset holdings to maximise utility subject to their period budget constraint. This gives rise to the standard Euler equations for bonds and shares:

$$\frac{1}{R_t} = \mathbb{E}_t\left[\beta_{t,t+1}^U \frac{1}{\pi_{t+1}}\right] \tag{4.7}$$

$$Q_t = \mathbb{E}_t\left[\beta_{t,t+1}^U (Q_{t+1} + D_{t+1})\right] \tag{4.8}$$

where $\pi_{t+1} = P_{t+1}/P_t$ is the gross rate of price inflation in the economy. Note that the stochastic dis- count factor which matters for pricing assets belongs to unconstrained households due to the fact that constrained households are excluded from financial markets.

Labour market. The labour force is assumed to be constant and normalized to 1 such that $0 \leq N_t \leq 1$. The relevant stock of job searchers at the beginning of the period is given by:

$$U_t = 1 - N_{t-1} + \rho N_{t-1} = 1 - (1-\rho)N_{t-1} \tag{4.9}$$

[11] Note that the real wage is assumed to be common across workers from different household types. This assumption will be discussed in detail below.

where the job filling and job finding rates are defined as functions of tightness as standard:

$$\theta_t = \frac{V_t}{U_t}, \;\; q(\theta_t) = \frac{M_t}{V_t}, \;\; p(\theta_t) = \theta_t q(\theta_t) \tag{4.10}$$

Firms. Overall, firm k will choose employment, vacancies and prices to maximise the present discounted value of their profits:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^U_{t,t+1} \left[\frac{P_{k,t}}{P_t} Y_{k,t} - \chi V_{k,t} - w_{k,t} N_{k,t} - \frac{\Psi}{2} \left(\frac{P_{k,t}}{P_{k,t-1}} - \pi \right)^2 Y_{k,t} \right]$$

where the parameter Ψ controls the severity of the adjustment costs and π is the steady state gross inflation rate. Profits are discounted using the discount factor of unconstrained households, as only these households trade shares in firm profits.

$$N_{k,t} = (1-\rho) N_{k,t-1} + q(\theta_t) V_{k,t}$$

$$Y_{k,t} = \left(\frac{P_{k,t}}{P_t} \right)^{-\nu} Y_t$$

Standard optimization techniques and re-arrangement of first-order conditions yield the job creation condition and optimal pricing condition reported in the main body.

Value functions: The marginal value to the firm of a filled vacancies $\mathbb{S}^f_t$ is given by:

$$\mathbb{S}^f_t = \varepsilon_t A_t - w_t + (1-\rho) \mathbb{E}_t \left[\beta^U_{t,t+1} \mathbb{S}^f_{t+1} \right]$$

where the assumption of free entry implies that the firm's surplus from a match is equal to the expected cost of posted a vacancy. The worker's surplus is given by:

$$\mathbb{S}^w_t = w_t - b + \mathbb{E}_t \left[\beta_{t,t+1} (1 - \rho - p(\theta_{t+1})) \mathbb{S}^w_{t+1} \right]$$

where discounting is with respect to the union's discount factor, which captures heterogeneity in discounting across the two types of households.

Monetary policy. The return on bonds is determined by a monetary authority who follow a simple Taylor-type rule:

$$R_t = R_{ss} \pi_t^{\phi_\pi} \zeta_t \tag{4.11}$$

where ζ_t is the monetary policy (demand) shock we use in our simulations.

$J_t^i = \left[(1-\beta)C_t^{i\,1-\frac{1}{\varphi}} + \beta\left(\mathbb{E}_t\left[J_{t+1}^{i\,1-\sigma}\right]\right)^{\frac{1-\frac{1}{\varphi}}{1-\sigma}}\right]^{\frac{1}{1-\frac{1}{\varphi}}}$	(Household values)
$\beta_{t,t+1}^i = \beta\left(\frac{C_{t+1}^i}{C_t^i}\right)^{-\frac{1}{\varphi}}\left(\frac{J_{t+1}^i}{\mathbb{E}_t\left[J_{t+1}^{i\,1-\sigma}\right]^{\frac{1}{1-\sigma}}}\right)^{\frac{1}{\varphi}-\sigma}$	(Stochastic discount factors)
$\frac{1}{R_t} = \mathbb{E}_t\left[\beta_{t,t+1}^U \frac{1}{\pi_{t+1}}\right]$	(Bond Euler equation)
$Q_t = \mathbb{E}_t\left[\beta_{t,t+1}^U (Q_{t+1} + D_{t+1})\right]$	(Firm share Euler equation)
$N_t = (1-\rho)N_{t-1} + p(\theta_t)U_t$	(Employment law of motion)
$U_t = 1 - (1-\rho)N_{t-1}$	(Definition of job searchers)
$u_t = 1 - N_t$	(Unemployment rate)
$\theta_t = \frac{V_t}{U_t}$	(Labour market tightness)
$q(\theta_t) = \tilde{m}\theta_t^{-\xi}$	(Job filling rate)
$p(\theta_t) = \theta_t q(\theta_t)$	(Job finding rate)
$Y_t = A_t N_t$	(Aggregate production)
$\frac{\chi}{q(\theta_t)} = \varepsilon A_t - w_t + (1-\rho)\mathbb{E}_t\left[\beta_{t,t+1}^U \frac{\chi}{q(\theta_{t+1})}\right]$	(Job creation condition)
$1 - \Psi(\pi_t - \pi)\pi_t + \mathbb{E}_t[\beta_{t,t+1}^U \Psi(\pi_{t+1} - \pi)\pi_{t+1}\frac{Y_{t+1}}{Y_t}] = \nu(1-\varepsilon_t)$	(Optimal pricing condition)
$w_t = (1-\eta)b + \eta\left[\varepsilon_t A_t + \mathbb{E}_t\beta_{t,t+1}^U \chi\theta_{t+1} + \lambda\left[\frac{\chi}{q(\theta_{t+1})}(1-\rho-p(\theta_{t+1}))(\beta_{t,t+1}^U - \beta_{t,t+1}^C)\right]\right]$	(Nash wage)
$C_t^U = w_t N_t + \frac{1}{1=\lambda} D_t$	(Unconstrained consumption)
$C_t^C = w_t N_t$	(Constrained consumption)
$C_t = Y_t\left(1 - \frac{\Psi}{2}(\pi_t - \pi)\right) - \chi V_t$	(Market clearing)
$D_t = Y_t\left(1 - \frac{\Psi}{2}(\pi_t - \pi)^2\right) - w_t N_t - \chi V_t$	(Firm profits)
$R_t = R_{ss}\pi_t^{\varphi_\pi}\zeta_t$	(Taylor rule)

Table 4.1. Model equilibrium conditions

4.B.1 List of Model Equilibrium Conditions

A summary of the equilibrium conditions used to solve and simulate the model is presented in Table 4.1.

4.B.2 Parameterization

A summary of the parameter values which result from our calibration strategy outlined in Section 4.3 is provided in Table 4.2.

4.C Additional Figures

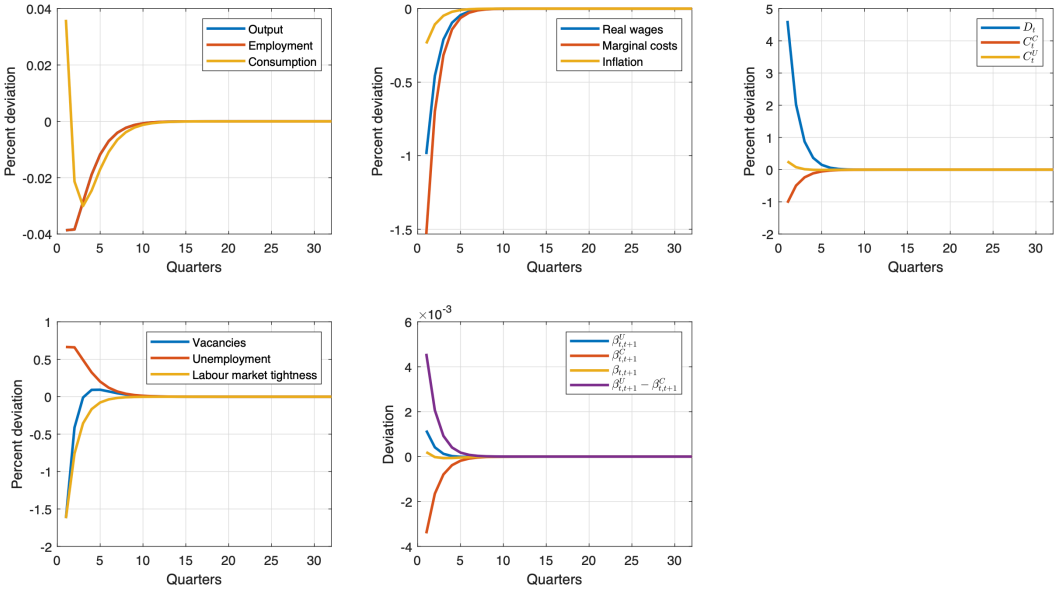


Figure 4.5. IRFs in response to a 1% contraction in monetary policy.

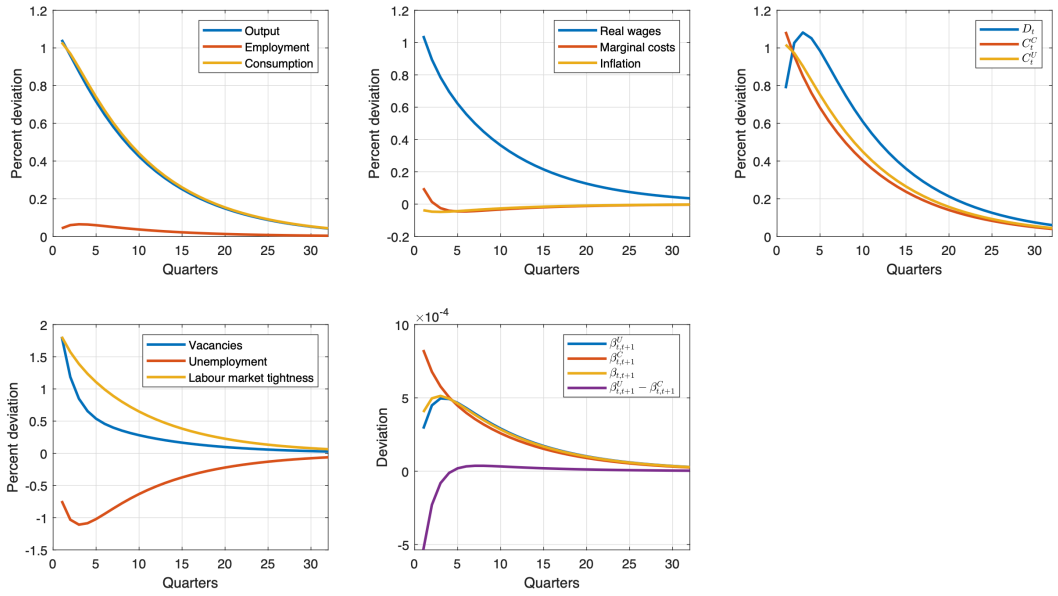


Figure 4.6. IRFs in response to a 1% increase in productivity.

Parameter	Description	Value	Source
Externally calibrated parameters:			
β	Discount factor	0.9926	3% avg.real interest rate
φ	IES	1.5	Standard
σ	Risk aversion	$1/\varphi$	CRRA utility
ν	Substitution elasticity	6	Standard
ξ	Match elasticity	0.5	Petrongolo and Pissarides (2001)
η	Workers' bargaining power	0.5	Hosios' condition
Ψ	Price adjustment cost	58.6969	avg. price duration of 1 year (Calvo)
ϕ_π	Taylor coefficient	2	Standard
A	Steady state productivity	1	Normalization
Internally calibrated parameters:			
ρ	Separation rate	0.0476	$u = 0.055$
χ	Vacancy posting costs	0.6553	$q(\theta) = 0.7$
$\bar{m}$	Match efficiency constant	0.5612	$p(\theta) = 0.45$
b	Unemployment benefits	0.3129	40% replacement rate
λ	Share of constrained households	0.21	Debortoli and Galí (2018)
Exogenous processes:			
ρ_a	Persistence of tech. shock	0.9	Standard
ρ_ξ	Persistence of mon. pol. shock	0.5	Standard

Table 4.2. Parameter Values

References

Acharya, S., & Dogra, K. (2020). Understanding HANK: Insights from a PRANK. *Econometrica*, *88*(3), 1113–1158.

Acosta, M., Mueller, A. I., Nakamura, E., & Steinsson, J. (2023). Macroeconomic effects of UI extensions at short and long durations.

Ascari, G., Colciago, A., & Rossi, L. (2017). Limited asset market participation, sticky wages, and monetary policy. *Economic Inquiry*, *55*(2), 878–897.

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review*, *109*(6), 2333–2367.

Auclert, A., Rognlie, M., & Straub, L. (2020). Micro jumps, macro humps: Monetary policy and business cycles in an estimated HANK model.

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, *103*(5), 1553–1597.

Bagger, J., & Lentz, R. (2019). An empirical model of wage dispersion with sorting. *The Review of Economic Studies*, *86*(1), 153–190.

Baily, M. N. (1978). Some aspects of optimal unemployment insurance. *Journal of Public Economics*, *10*(3), 379–402.

Baley, I., Figueiredo, A., & Ulbricht, R. (2022). Mismatch cycles. *Journal of Political Economy*, *130*(11), 2943–2984.

Balleer, A., Gehrke, B., Lechthaler, W., & Merkl, C. (2016). Does short-time work save jobs? A business cycle analysis. *European Economic Review*, *84*, 99–122.

Bayer, C., Born, B., & Luetticke, R. (2020). Shocks, frictions, and inequality in us business cycles.

Bernanke, B. S. (2012). Recent developments in the labor market: A speech at the National Association for Business Economics Annual Conference, Arlington, Virginia, March 26, 2012. *Board of Governors of the Federal Reserve System (US) Speech*, (636).

Bilbiie, F. O. (2008). Limited asset markets participation, monetary policy and (inverted) aggregate demand logic. *Journal of economic theory*, *140*(1), 162–196.

Bilbiie, F. O. (forthcoming). Monetary policy and heterogeneity: An analytical framework. *Review of Economic Studies*.

Birinci, S., Karahan, F., Mercan, Y., & See, K. (2021). Labor market policies during an epidemic. *Journal of Public Economics*, *194*, 104348.

Birinci, S., & See, K. (2023). Labor market responses to unemployment insurance: The role of heterogeneity. *American Economic Journal: Macroeconomics*, *15*(3), 388–430.

Blanchard, O. J., & Tirole, J. (2008). The joint design of unemployment insurance and employment protection: A first pass. *Journal of the European Economic Association*, *6*(1), 45–77.

Boeri, T. (2010). Institutional reforms in european labour markets. *Handbook of Labor Economics*, *4*, 1173–1236.

Broer, T., Druedahl, J., Harmenberg, K., & Öberg, E. (2023). The unemployment-risk channel in business-cycle fluctuations.

Broer, T., Harbo Hansen, N.-J., Krusell, P., & Öberg, E. (2020). The new keynesian transmission mechanism: A heterogeneous-agent perspective. *The Review of Economic Studies*, *87*(1), 77–101.

Bullard, J., et al. (2014). The rise and fall of labor force participation in the united states. *Federal Reserve Bank of St. Louis Review, First Quarter*, *96*(1), 1–12.

Cahuc, P., Kramarz, F., & Nevoux, S. (2021). The heterogeneous impact of short-time work: From saved jobs to windfall effects.

Cahuc, P., & Zylberberg, A. (2008). Optimum income taxation and layoff taxes. *Journal of Public Economics*, *92*(10-11), 2003–2019.

Cairó, I., Fujita, S., & Morales-Jiménez, C. (2022). The cyclicality of labor force participation flows: The role of labor supply elasticities and wage rigidity. *Review of Economic Dynamics*, *43*, 197–216.

Campolmi, A., & Gnocchi, S. (2016). Labor market participation, unemployment and monetary policy. *Journal of Monetary Economics*, *79*, 17–29.

Cantore, C., & Freund, L. B. (2021). Workers, capitalists, and the government: Fiscal policy and income (re) distribution. *Journal of Monetary Economics*, *119*, 58–74.

Carrillo-Tudela, C., Visschers, L., & Wiczer, D. (2022). Cyclical earnings, career and employment transitions.

Chetty, R. (2006). A general formula for the optimal level of social insurance. *Journal of Public Economics*, *90*(10-11), 1879–1901.

Chodorow-Reich, G., Coglianese, J., & Karabarbounis, L. (2019). The macro effects of unemployment benefit extensions: A measurement error approach. *The Quarterly Journal of Economics*, *134*(1), 227–279.

Christiano, L. J., Trabandt, M., & Walentin, K. (2021). Involuntary unemployment and the business cycle. *Review of Economic Dynamics*, *39*, 26–54.

Christoffel, K., Kuester, K., & Linzert, T. (2009). The role of labor markets for euro area monetary policy. *European Economic Review*, *53*(8), 908–936.

Coles, M. (2008). Optimal unemployment policy in a matching equilibrium. *Labour Economics*, *15*(4), 537–559.

Cooper, R., Meyer, M., & Schott, I. (2017). The employment and output effects of short-time work in Germany.

Crane, L. D., Hyatt, H. R., & Murray, S. M. (2023). Cyclical labor market sorting. *Journal of Econometrics*, *233*(2), 524–543.

Debortoli, D., & Galí, J. (2024). Heterogeneity and aggregate fluctuations: Insights from TANK models. *mimeo*.

Den Haan, W. J., Ramey, G., & Watson, J. (2000). Job destruction and propagation of shocks. *American Economic Review*, *90*(3), 482–498.

Dorn, D. (2009). Essays on inequality, spatial interaction, and the demand for skills. https://www.e-helvetica.nb.admin.ch/api/download/urn%3Anbn%3Ach%3Abel-152672%3Adis3613.pdf/dis3613.pdf

Elsby, M., Hobijn, B., Karahan, F., Kosar, G., & Şahin, A. (2019). Flow origins of labor force participation fluctuations. *AEA Papers and Proceedings*, *109*, 461–464.

Elsby, M. W., Michaels, R., & Solon, G. (2009). The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics*, *1*(1), 84–110.

Engen, E. M., & Gruber, J. (2001). Unemployment insurance and precautionary saving. *Journal of Monetary Economics*, *47*(3), 545–579.

Epstein, L. G., & Zin, S. E. (1989). Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework. *Econometrica*, *57*(4), 937–969.

Erceg, C. J., & Levin, A. T. (2014). Labor force participation and monetary policy in the wake of the Great Recession. *Journal of Money, Credit and Banking*, *46*(S2), 3–49.

Faberman, R. J., Mueller, A. I., Şahin, A., & Topa, G. (2022). Job search behavior among the employed and non-employed. *Econometrica*, *90*(4), 1743–1779.

Farber, H. S., & Valletta, R. G. (2015). Do extended unemployment benefits lengthen unemployment spells?: Evidence from recent cycles in the us labor market. *Journal of Human Resources*, *50*(4), 873–909.

Fujita, S., & Ramey, G. (2009). The cyclicality of separation and job finding rates. *International Economic Review*, *50*(2), 415–430.

Fujita, S., & Ramey, G. (2012). Exogenous versus endogenous separation. *American Economic Journal: Macroeconomics*, *4*(4), 68–93.

Galı, J., López-Salido, J. D., & Vallés, J. (2007). Understanding the effects of government spending on consumption. *Journal of the European Economic Essociation*, *5*(1), 227–270.

Galı, J., Smets, F., & Wouters, R. (2012). Unemployment in an estimated new keynesian model. *NBER Macroeconomics Annual*, *26*, 329–360. https://doi.org/10.1086/663994

Garcia-Cabo, J., Lipińska, A., & Navarro, G. (2023). Sectoral shocks, reallocation, and labor market policies. *European Economic Review*, *156*, 104494.

Giannone, D., Lenza, M., & Primiceri, G. E. (2015). Prior Selection for Vector Autoregressions. *The Review of Economics and Statistics*, *97*(2), 436–451.

Giersch, H. (1985). *Eurosclerosis* (tech. rep.). Kieler Diskussionsbeitr‰ ge.

Giupponi, G., & Landais, C. (2018). Subsidizing labor hoarding in recessions: The employment & welfare effects of short time work. *Available at SSRN 3287057*.

Giupponi, G., Landais, C., & Lapeyre, A. (2022). Should we insure workers or jobs during recessions? *Journal of Economic Perspectives*, *36*(2), 29–54.

Gomes, P. (2009). Labour market flows: Facts from the united kingdom.

Gornemann, N., Kuester, K., & Nakajima, M. (2021). Doves for the rich, hawks for the poor? distributional consequences of systematic monetary policy.

Haefke, C., & Reiter, M. (2006). Endogenous labor market participation and the business cycle.

Hagedorn, M., Karahan, F., Manovskii, I., & Mitman, K. (2019). Unemployment benefits and unemployment in the Great Recession: The role of equilibrium effects.

Hagedorn, M., Law, T. H., & Manovskii, I. (2017). Identifying equilibrium models of labor market sorting. *Econometrica*, *85*(1), 29–65.

Hagedorn, M., & Manovskii, I. (2008). The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review*, *98*(4), 1692–1706.

Hagedorn, M., Manovskii, I., & Mitman, K. (2016). Interpreting recent quasi-experimental evidence on the effects of unemployment benefit extensions.

Hall, R. E. (2017). High discounts and high unemployment. *American Economic Review*, *107*(2), 305–330.

Hall, R. E., & Milgrom, P. R. (2008). The limited influence of unemployment on the wage bargain. *American economic review*, *98*(4), 1653–1674.

Haltiwanger, J. C., Hyatt, H. R., McEntarfer, E., & Staiger, M. (2021). Cyclical worker flows: Cleansing vs. sullying.

Hobijn, B., & Şahin, A. (2021). Maximum employment and the participation cycle.

Hopenhayn, H., & Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy*, *101*(5), 915–938.

Hopenhayn, H. A., & Nicolini, J. P. (1997). Optimal unemployment insurance. *Journal of Political Economy*, *105*(2), 412–438.

Hosios, A. J. (1990). On the efficiency of matching and related models of search and unemployment. *The Review of Economic Studies*, *57*(2), 279–298.

Huggett, M. (1993). The risk-free rate in heterogeneous-agent incomplete-insurance economies. *Journal of Economic Dynamics and Control*, *17*(5-6), 953–969.

Ignaszak, M., Jung, P., & Keuster, K. (2020). Federal unemployment reinsurance and local labor-market policies. *Available at SSRN 3737598*.

Jäger, S., Schoefer, B., Young, S., & Zweimüller, J. (2020). Wages and the value of nonemployment. *The Quarterly Journal of Economics*, *135*(4), 1905–1963.

Jarosch, G. (2021). Searching for job security and the consequences of job loss.

Johnston, A. C., & Mas, A. (2018). Potential unemployment insurance duration and labor supply: The individual and market-level response to a benefit cut. *Journal of Political Economy*, *126*(6), 2480–2522.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182.

Jung, P., Korfmann, P., & Preugschat, E. (2021). Optimal regional labor market policies.

Jung, P., & Kuester, K. (2015). Optimal labor-market policy in recessions. *American Economic Journal: Macroeconomics*, *7*(2), 124–56.

Jung, P., & Kuhn, M. (2014). Labour market institutions and worker flows: Comparing Germany and the US. *The Economic Journal*, *124*(581), 1317–1342.

Kaplan, G., Moll, B., & Violante, G. L. (2018). Monetary policy according to hank. *American Economic Review*, *108*(3), 697–743.

Katz, L. F., & Meyer, B. D. (1990). The impact of the potential duration of unemployment benefits on the duration of unemployment. *Journal of Public Economics*, *41*(1), 45–72.

Kehoe, P. J., Lopez, P., Midrigan, V., & Pastorino, E. (2023). Asset prices and unemployment fluctuations: A resolution of the unemployment volatility puzzle. *The Review of Economic Studies*, *90*(3), 1304–1357.

Krueger, A. B., & Meyer, B. D. (2002). Labor supply effects of social insurance. *Handbook of public economics*, *4*, 2327–2392.

Krusell, P., Mukoyama, T., Rogerson, R., & Şahin, A. (2017). Gross worker flows over the business cycle. *American Economic Review*, *107*(11), 3447–76. https://doi.org/10.1257/aer.20121662

Landais, C., Michaillat, P., & Saez, E. (2018). A macroeconomic approach to optimal unemployment insurance: Applications. *American Economic Journal: Economic Policy*, *10*(2), 182–216.

Lazear, E. P. (1990). Job security provisions and employment. *The Quarterly Journal of Economics*, *105*(3), 699–726.

Lise, J. (2013). On-the-job search and precautionary savings. *Review of Economic Studies*, *80*(3), 1086–1113.

Lise, J., Meghir, C., & Robin, J.-M. (2016). Matching, sorting and wages. *Review of Economic Dynamics*, *19*, 63–87.

Lise, J., & Robin, J.-M. (2017). The macrodynamics of sorting between workers and firms. *American Economic Review*, *107*(4), 1104–1135.

Ljungqvist, L. (2002). How do lay-off costs affect employment? *The Economic Journal*, *112*(482), 829–853.

Luetticke, R. (2021). Transmission of monetary policy with heterogeneity in household portfolios. *American Economic Journal: Macroeconomics*, *13*(2), 1–25.

Marimon, R., & Zilibotti, F. (1999). Unemployment vs. mismatch of talents: Reconsidering unemployment benefits. *The Economic Journal*, *109*(455), 266–291.

Marinescu, I. (2017). The general equilibrium impacts of unemployment insurance: Evidence from a large online job board. *Journal of Public Economics*, *150*, 14–29. https://doi.org/10.1016/j.jpubeco.2017.02.012

Marinescu, I., & Skandalis, D. (2021). Unemployment insurance and job search behavior*. *The Quarterly Journal of Economics*, *136*(2), 887–931. https://doi.org/10.1093/qje/qjaa037

Martellini, P., Menzio, G., & Visschers, L. (2021). Revisiting the hypothesis of high discounts and high unemployment. *The Economic Journal*, *131*(637), 2203–2232.

McKay, A., Nakamura, E., & Steinsson, J. (2016). The power of forward guidance revisited. *American Economic Review*, *106*(10), 3133–3158.

Menzio, G., & Shi, S. (2010). Block recursive equilibria for stochastic models of search on the job. *Journal of Economic Theory*, *145*(4), 1453–1494.

Meyer, B. D. (1990). Unemployment insurance and unemployment spells. *Econometrica*, *58*(4), 757–782.

Michaillat, P., & Saez, E. (2021). Beveridgean unemployment gap. *Journal of Public Economics Plus*, *2*, 100009.

Michau, J.-B. (2015). Optimal labor market policy with search frictions and risk-averse workers. *Labour Economics*, *35*, 93–107.

Millard, S. (1995). The unemployment and welfare effects of employment protection legislation.

Millard, S., & Mortensen, D. (1997). The unemployment and welfare effects of labour market policy: A comparison of the usa and the uk. *Unemployment policy: government options for the labour market*, 545–571.

Mitman, K., Karahan, F., & Moore, B. (2022). Micro and macro effects of UI policies: Evidence from missouri.

Mitman, K., & Rabinovich, S. (2015). Optimal unemployment insurance in an equilibrium business-cycle model. *Journal of Monetary Economics*, *71*, 99–118.

Mortensen, D., & Pissarides, C. (2002). *Taxes, subsidies and equilibrium labor market outcomes* (CEP Discussion Papers). Centre for Economic Performance, LSE.

Mortensen, D. T., & Pissarides, C. A. (1994). Job creation and job destruction in the theory of unemployment. *The Review of Economic Studies*, *61*(3), 397–415.

Mukoyama, T., Patterson, C., & Şahin, A. (2018). Job search behavior over the business cycle. *American Economic Journal: Macroeconomics*, *10*(1), 190–215.

Nistico, S. (2016). Optimal monetary policy and financial stability in a non-ricardian economy. *Journal of the European Economic Association*, *14*(5), 1225–1252.

Nuño, G., & Thomas, C. (2022). Optimal redistributive inflation. *Annals of Economics and Statistics*, (146), 3–64.

Okun, A. M. (1973). Upward mobility in a high-pressure economy. *Brookings Papers on Economic Activity*, *1973*(1), 207–261.

Perry, G. L. (1971). Labor force structure, potential output, and productivity. *Brookings Papers on Economic Activity*, *1971*(3), 533–578.

Petrongolo, B., & Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic literature*, *39*(2), 390–431.

Petrongolo, B., & Pissarides, C. A. (2008). The ins and outs of european unemployment. *American Economic Review*, *98*(2), 256–62.

Pissarides, C. A. (2000). *Equilibrium unemployment theory*. MIT press.

Pizzinelli, C., & Speigner, B. (2017). Matching efficiency and labour market heterogeneity in the united kingdom.

Postel-Vinay, F., & Robin, J.-M. (2002). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica*, *70*(6), 2295–2350.

Ravn, M. O., & Sterk, V. (2017). Job uncertainty and deep recessions. *Journal of Monetary Economics*, *90*, 125–141.

Ravn, M. O., & Sterk, V. (2021). Macroeconomic fluctuations with HANK & SAM: An analytical approach. *Journal of the European Economic Association*, *19*(2), 1162–1202.

Rotemberg, J. J. (1982). Sticky prices in the United States. *Journal of Political Economy*, *90*(6), 1187–1211.

Rothstein, J. (2011). Unemployment insurance and job search in the Great Recession.

Schmieder, J. F., & Von Wachter, T. (2016). The effects of unemployment insurance benefits: New evidence and interpretation. *Annual Review of Economics*, *8*, 547–581.

Shimer, R. (2004). Search intensity.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, *95*(1), 25–49.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics*, *15*(2), 127–148.

Shimer, R. (2013). Search, labor force participation, and wage rigidities. *Advances in Economics and Econometrics: Volume 2, Applied Economics: Tenth World Congress*, *50*, 197.

Shimer, R., & Werning, I. (2007). Reservation wages and unemployment insurance. *The Quarterly Journal of Economics*, *122*(3), 1145–1185.

Shimer, R., & Werning, I. (2008). Liquidity and insurance for the unemployed. *American Economic Review*, *98*(5), 1922–42.

Smith, J. C. (2011). The ins and outs of UK unemployment. *The Economic Journal*, *121*(552), 402–444.

Speigner, B. J. (2012). *Essays on equilibrium unemployment dynamics* (Doctoral dissertation). The University of Edinburgh.

Tripier, F. (2004). Can the labor market search model explain the fluctuations of allocations of time? *Economic Modelling*, *21*(1), 131–146.

Veracierto, M. (2008a). Firing costs and business cycle fluctuations. *International Economic Review*, *49*(1), 1–39.

Veracierto, M. (2008b). On the cyclical behavior of employment, unemployment and labor force participation. *Journal of Monetary Economics*, *55*(6), 1143–1157. https://doi.org/https://doi.org/10.1016/j.jmoneco.2008.07.008

Werning, I. (2015). Incomplete markets and aggregate demand.

Yellen, J. L. (2014). *Labor market dynamics and monetary policy: A speech at the federal reserve bank of kansas city economic symposium, jackson hole, wyoming, august 22, 2014* (tech. rep.).