Essays in Labour Macroeconomics

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I, Wongkot Similan Rujiwattanapong, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

This thesis consists of three chapters on the general equilibrium effects of unemployment insurance (UI) extensions on the macroeconomy. In Chapter 2, I quantify the effects of the increasing maximum UI duration during recessions on the drop in the correlation between output and labour productivity in the US since the early 1980's. Using a search and matching model with stochastic UI duration, heterogeneous match quality, variable search intensity and on-the-job search, I find that the model can explain over half of this drop.

In Chapter 3, I investigate the impact of UI extensions on the incidence of long-term unemployment and on the unemployment duration distribution in the US. I extend the model in Chapter 2 by allowing for further worker heterogeneity and for UI benefits to depend on match quality during employment. I demonstrate that eliminating all UI extensions during the Great Recession could lower the (long-term) unemployment rate by 0.9-3.4 (4) percentage points and the average unemployment duration by 27 weeks. Once UI statuses and benefit levels are accounted for, unobserved heterogeneity of workers does not account for much of the incidence of long-term unemployment.

In Chapter 4, I study the role of worker's UI history and the responses of unemployment and its duration structure to UI extensions. Building on the model in Chapter 3, I consider three unemployment statuses: insured, formerly insured and uninsured (who never received UI). To make the model empirically consistent, I introduce a drop in job search efficiency amongst the insured unemployed workers. This feature increases the persistence of unemployment, average unemployment duration and long-term unemployment, and moderates their responses to UI extensions. Comparing to Chapter 3, the effects of removing UI extensions during the Great Recession on the unemployment duration is revised downwards to a 24-week reduction. Finally, this extension removal improves welfare but the gain subsides as the economy recovers.

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Chapter 1

Introduction

The effects of unemployment insurance (UI) extensions on the aggregate labour market have long been studied from both theoretical and empirical perspectives. The generous UI extensions and the unprecedented rise in unemployment duration during the Great Recession in the US have sparked a greater interest in quantifying the effect of UI extensions on the macroeconomy, particularly unemployment and its duration structure. This question becomes more complicated since the extensions themselves were triggered by the state unemployment rate. Some studies find a limited role of UI extensions whilst others find a more substantial effect of the UI extensions.

The departure of unified results is mainly due to the methodology of these studies which focus either on the microeconomic or macroeconomic impact of UI extensions. This thesis develops a framework which helps reconcile these mixed outcomes by studying a general equilibrium search and matching model where the behaviour of workers and firms, and UI policies are realistically incorporated. This framework is able to distinguish between the microeconomic and macroeconomic effects of UI extensions. It allows me to study the mechanisms through which UI extensions affect the macroeconomy as well as the policy experiments and welfare analyses.

With this research agenda, this thesis consists of three chapters each of which studies the impact of UI extensions on the macroeconomy from both positive and normative aspects. In Chapter 2, I quantify the effects of the increasing maximum

UI duration during recessions on the drop in the correlation between output and labour productivity in the US since the early 1980's. One distinctive feature of the US UI system is the extension of the maximum UI duration that is triggered when the unemployment rate is above a certain threshold making the policy countercyclical. While the standard UI duration is 26 weeks, the extended UI duration has increased from the average of 52 weeks during 1948-1985 to 78 weeks after 1985. Using a search and matching model with stochastic UI duration, heterogeneous match quality, variable search intensity and on-the-job search, I demonstrate that the systematic change in the generosity of UI extensions can explain over half of the fall in the procyclicality of labour productivity.

The increase in the generosity of the UI duration during the times of high unemployment, often recessions, weakens the links between output and output per worker via two channels. First, the generous UI policy raises the worker's outside option, making the workers become more selective with respect to the quality of job offers. Second, the UI extensions lower job search effort of the unemployed causing a slower job-worker matching. The former channel raises the overall productivity in recessions. The latter prolongs the extensions as they depend on the unemployment rate. With the UI extensions being more generous in post-1985 periods, the upward pressure on the labour productivity is expected to be stronger in recent recessions than in earlier ones, and contributes to the fall in the procyclicality of labour productivity.

In Chapter 3, I investigate the impact of UI extensions on the incidence of long-term unemployment and on the unemployment duration distribution in the US. Using a search and matching model with endogenous separations, variable job search intensity, on-the-job search and worker heterogeneity, I allow for the maximum UI duration to depend on unemployment rate and for UI benefits to depend on match quality during employment. The model can account for a large fraction of the observed rise in the long-term unemployment and realistic dynamics of the unemployment duration distribution during the Great Recession. A benefit of using a general equilibrium model is that I can distinguish between the direct impact of UI extensions on the number of insured unemployed workers and the responses of job search behaviour, match formation and match separation. I show that eliminating all UI extensions during the Great Recession could potentially lower the unemployment rate by 0.9-3.4 percentage points primarily via the response of job separations. At the same time, it could drastically reduce the long-term unemployment rate by roughly 4 percentage points and the average unemployment duration by up to 27 weeks via the response of job search behaviour of insured unemployed workers. The microeconomic effect of UI extensions is consistent with the existing literature as its effect on the unemployment rate is minimal. I find that once the worker heterogeneity in UI statuses and benefit levels has been accounted for, unobserved heterogeneity of workers does not account for much of the incidence of long-term unemployment.

In Chapter 4, I study the role of worker's UI history and the responses of unemployment and its duration structure to UI extensions. Building on Chapter 3's general equilibrium search and matching model with endogenous job separation, variable search intensity with on-the-job search, worker heterogeneity and automatic UI extension, I consider three unemployment statuses: insured, formerly insured and uninsured (who never received UI). To make the model empirically consistent, I introduce a drop in job search efficiency amongst the insured unemployed workers. This feature allows the formerly insured, whose search efficiency has fallen, to exert similar search efforts to the uninsured, and at the same time find a job at a slower rate than do the uninsured. The fall in the formerly insured workers' job finding rate increases the persistence of unemployment duration and long-term unemployment. Furthermore, the drop in job search efficiency lowers the value of being insured unemployed which has two implications. First, it lowers the job separations of employed workers who are on the margin of returning to unemployment. Second, it increases the job search intensity of the insured (to avoid losing the search efficiency), and thereby shortens the unemployment spells. This means that the response of insured unemployment to UI extensions is expected to be more moderated. Comparing to results from Chapter 3 where the search efficiency is constant throughout an unemployment spell, UI extensions during the Great Recession still account for a 0.9-3.4 percentage point increase in the unemployment rate but its effect on the average unemployment duration is revised downwards to an increase of 24 weeks (instead of 27 weeks). Finally, I find that on average there is a welfare gain from eliminating all UI extensions during the Great Recession of 0.14 percent, which is a combination of 0.27 percent welfare increase for the employed and 1.27 percent welfare drop for the unemployed, and that the total welfare gain subsides as the economy recovers.

Chapter 2

Unemployment Insurance and Labour Productivity over the Business Cycle

2.1 Introduction/Motivation

The labour productivity has become significantly less procyclical in the U.S. since the early 1980's. In particular, the cross correlation between output and labour productivity has fallen from 70 percent in the 1948-1985 period to only around 30 percent thereafter.[1] This change in the procyclicality of the labour productivity is usually coined "the labour productivity puzzle".

This paper explores the hypothesis that the fall in the procyclicality of labour productivity is related to the systematic change in the generosity of the U.S. unemployment insurance (UI) system. One distinctive feature of the U.S. UI system is the extension of the maximum UI duration that is triggered when the unemployment rate is above a certain threshold making the policy countercyclical. While the standard UI duration is 26 weeks, the extended UI duration has increased from the average of 52 weeks during 1948-1985 to 78 weeks after 1985.[2] This increase in the generosity of the UI duration during the times of high unemployment, often recessions, weakens the links between output and output per worker via two

[1] This change in the correlation is depicted in Figure 2.1.
[2] Figure 2.2 summarises this increasing generosity of the UI duration policy in the U.S.

channels. First, the generous UI policy raises the worker's outside option, making the workers become more selective with respect to the quality of job offers. Second, the UI extensions lower job search effort of the unemployed causing a slower job-worker matching. With the UI extensions being more generous in post-1985 periods, the upward pressure on the labour productivity is expected to be stronger in recent recessions than in earlier ones, and contributes to the fall in the procyclicality of labour productivity.

I extend the Mortensen-Pissarides search and matching model to incorporate stochastic UI duration, match-specific productivity, variable search intensity and on-the-job search. The cyclical behaviour of the average match productivity is key in explaining the correlation between output and output per worker in the model. By allowing for variable search intensity, I can separate the contributions of the two proposed channels, namely, match formations and job search effort, on the fluctuations in labour productivity over the business cycle. Lastly, searching on the job is allowed so that the model can produce a realistic correlation between unemployment and vacancies.

I find that the countercyclical UI policy can account for 50 percent of the drop in the contemporaneous correlation between output and labour productivity observed in the data. By isolating the contributions of the two channels, I find that both match formations and job search effort have a significant explanatory power over the correlation between output and labour productivity. By shutting down one channel, the other can explain around half of the drop in the correlation that the model can produce. The model also generates realistic moments of key labour market variables in the U.S., including the ratio of insured to total unemployment rates over the business cycle. Lastly, I show that the model can generate the downward-sloping duration-dependent job finding probability that is qualitatively similar to the data due to different job finding rates among the unemployed.

I am not the first to investigate the source of the decline in the correlation between output and labour productivity. Galí and van Rens (2014) suggest that decreasing employment adjustment costs have generated a substantial fall in the procyclicality of the labour productivity. Berger (2015) explains the puzzle using a competitive industry model with the countercyclical restructuring of firms where lower-quality workers are more likely to be shed during recessions, and this occurs more often in recent times due to the decreasing labour union power. Garin, Pries and Sims (2016) use a model with aggregate and island-specific shocks as well as complete markets, and show that the falling correlation between output and labour productivity is from the relatively lower importance of aggregate shocks. McGrattan and Prescott (2012) also study the sources of the labour productivity puzzle by considering intangible capital and sectoral productivity shocks.

There are a number of studies showing significant effects of changes in the UI policy on macroeconomic variables including the labour productivity and wages. From a theoretical perspective, Acemoglu and Shimer (2000) show that an increase in both the duration and the level of UI benefits can increase labour productivity and wages in a model with risk aversion and precautionary savings. Marimon and Zilibotti (1999), using a search and matching model with risk-neutral agents and two-sided heterogeneity, show that a positive replacement rate with unlimited UI duration also leads to a higher labour productivity when compared to the case without UI. Empirical results from Ehrenberg and Oaxaca (1976) suggest that a higher UI benefit level has a positive impact on re-employment wages. Caliendo, Tatsiramos and Uhlendorff (2013) find that a longer UI duration increases re-employment wages, match quality and match stability.

The paper is organised as follows. Section 2 describes the model. Section 3 discusses the calibration exercise. Section 4 analyses the results. Section 5 concludes.

2.2 Model

2.2.1 Setup

The model is based on the standard Mortensen-Pissarides search and matching model with the incorporation of aggregate productivity shocks, stochastic UI duration, heterogeneous match quality, variable search intensity and on-the-job search. Time is discrete and of monthly frequency. Search is assumed to be random. There are a continuum of workers of measure one and a larger continuum of firms each with either zero or one employee. They are infinitely-lived and risk-neutral, and discount future utility flows or profits each period by a constant factor $\beta \in (0,1)$.

2.2.1.1 Workers

Workers maximise the expected discounted lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[c_t - \nu(s_t) \right]$$

where $E_t(\cdot)$ is the expectation operator conditional on period t information, c_t is consumption and $\nu(s_t)$ is the disutility of job search effort which can be exerted during both unemployment and employment. There are three types of workers: employed (e), unemployed with UI (u^{UI}), and unemployed without UI (u^{UU}).

An employed worker in period t with match-specific quality m works and receives wage $w_{m,t}$ from her matched firm. She searches on the job with intensity $s^e_{m,t}$ that costs disutility of $\nu_e(s^e_{m,t}) = a_e(s^e_{m,t})^{1+d_e}$, where a_e and d_e are positive constants. At the end of the period: (i) her current match is exogenously destroyed with probability δ in which case she becomes unemployed immediately, (ii) her match-specific productivity for $t+1$ is to be redrawn from a time-invariant distribution $F(m)$ with probability λ, and (iii) she meets a new vacant firm with probability $p(s^e_{m,t}) \equiv p^e_{m,t}$, draws a new match quality m and decide whether to stay with the current firm. If becoming unemployed in $t+1$, an employed worker in period t is eligible for UI benefits in period $t+1$ with probability $(1-\psi) \in (0,1]$. $(1-\psi)$ can be less than 1 to reflect how some newly unemployed workers are ineligible for or do not claim UI benefits.[3] The employed can always exit employment if desired at the end of period t.

Given a set of state variables $\omega = \{z, u, u^{UI}, u^{UU}, e_m; \forall m\}$[4], an employed worker with match quality m and last period's employment status $j \in \{e, UI, UU\}$ has the

[3] In the U.S., the average ratio of the insured unemployed to the total unemployed is 36% between 1967-2014.

[4] The states variables $\{z, u, u^{UI}, u^{UU}, e_m; \forall m\}$ are respectively the total factor productivity, the unemployment rate, the insured unemployment rate, the uninsured unemployment rate, and the number of employed workers in every level of match quality.

following value function

$$\begin{aligned}
W^j(m;\omega) \;=\; \max_{s^e(m;\omega)} \;& w^j(m;\omega) - \nu_e(s^e(m;\omega)) + \beta E_{\omega'|\omega}\Big[\dots \\
& \underbrace{(1-\delta)(1-\lambda)}_{\text{Pr(match survives, same } m)}\Big(\underbrace{(1-p^e(m;\omega)(1-F(m)))}_{\text{Pr(no job-to-job transition)}}W^{e+}(m;\omega') \\
& + \underbrace{p^e(m;\omega)(1-F(m))}_{\text{Pr(make job-to-job transition)}}E_{m'|m'>m}[W^{e+}(m';\omega')]\Big) \\
& + \underbrace{(1-\delta)\lambda}_{\text{Pr(match survives, changing } m)} E_{m'}\Big[\underbrace{(1-p^e(m;\omega)(1-F(m')))}_{\text{Pr(no job-to-job transition)}}W^{e+}(m';\omega') \\
& + \underbrace{p^e(m;\omega)(1-F(m'))}_{\text{Pr(make job-to-job transition)}}E_{m''|m''>m'}[W^{e+}(m'';\omega')]\Big] \\
& + \underbrace{\delta}_{\text{Pr(match destroyed)}}\Big((1-\psi)U^{UI}(\omega') + \psi U^{UU}(\omega')\Big)\Big] \qquad (2.1)
\end{aligned}$$

where $W^{e+}(m;\omega') \equiv \max\{W^e(m;\omega'), (1-\psi)U^{UI}(\omega') + \psi U^{UU}(\omega')\}$. Last period's employment status matters for the workers as it represents the outside option they have when negotiating for wages. Given the recursive nature of the problem, the time scripts are dropped and variables with superscript $'$ are of the next period. Variables with subscripts m and/or ω depend on the match-specific productivity and/or the set of aggregate state variables. $E_{\omega'|\omega}[\cdot]$ is the mathematical expectation operator over the distribution of $\omega'|\omega$. $E_m[\cdot]$ is similarly defined but taken over the invariant distribution of m, $F(m)$. $U^{UI}(\omega)$ and $U^{UU}(\omega)$ are the values of being insured and uninsured unemployed respectively. The expression for the optimal search intensity can be found in Appendix 2.6.2.

An insured unemployed worker in period t receives UI benefits b and leisure flow h.[5] She also exerts job search effort s_t^{UI} that comes at the utility cost of $\nu_u(s_t^{UI}) = a_u(s_t^{UI})^{1+d_u}$, where a_u and d_u are positive constants. She meets a vacant firm with probability $p(s_t^{UI}) \equiv p_t^{UI}$. A new worker-firm match draws a match-specific productivity for their production in $t+1$ from the time-invariant distribution $F(m)$. They can dissolve the match and return to the unemployment/vacancy pool

[5]This flow h can be interpreted as the value of leisure, home production, food stamps, etc.

if the draw is not good enough. An insured unemployed worker in t who fails to be employed in $t+1$ loses her UI eligibility in $t+1$ with probability $\phi(u_t)$ where u_t is the unemployment rate at the beginning of t. Since the inverse of $\phi(u_t)$ is the expected duration of receiving UI, I use this function to control for the UI duration that changes with the unemployment rate in the U.S., and discuss its properties in more detail in the next subsection.[6] Insured unemployed workers that meet a firm but decide to remain unemployed and continue to search for a job may additionally lose UI eligibility with probability ξ.[7] This parameter can be greater than zero to reflect the job search monitoring in UI recipients.

For an uninsured unemployed worker, the setting is analogous except she does not receive the UI benefits b and when failing to become employed she simply remains unemployed without UI. She also exerts job search effort s_t^{UU} that comes at the utility cost of $\nu_u(s_t^{UU}) = a_u(s_t^{UU})^{1+d_u}$, and meets a vacant firm with probability $p(s_t^{UU}) \equiv p_t^{UU}$.

The Bellman equations for the insured and uninsured unemployed workers can be written as, respectively:

$$\begin{aligned} U^{UI}(\omega) &= \max_{s^{UI}(\omega)} \quad b+h-\nu_u(s^{UI}(\omega))+\beta p^{UI}(\omega)E_{m'\omega'|\omega}\Big[\max\Big\{W^{UI}(m';\omega'),\\ &\qquad \underbrace{(1-\phi(u))(1-\xi)}_{\text{Pr(UI eligible|turn down a firm)}}U^{UI}(\omega')+\underbrace{\Big(\phi(u)+(1-\phi(u))\xi\Big)}_{\text{Pr(UI ineligible|turn down a firm)}}U^{UU}(\omega')\Big\}\Big]\\ &\qquad +\beta(1-p^{UI}(\omega))E_{\omega'|\omega}\Big[\underbrace{(1-\phi(u))}_{\text{Pr(UI eligible|no meeting)}}U^{UI}(\omega')+\phi(u)U^{UU}(\omega')\Big] \end{aligned} \tag{2.2}$$

$$\begin{aligned} U^{UU}(\omega) &= \max_{s^{UU}(\omega)} \quad h-\nu_u(s^{UU}(\omega))\\ &\qquad +\beta p^{UU}(\omega)E_{m'\omega'|\omega}\Big[\max\Big\{W^{UU}(m';\omega'),U^{UU}(\omega')\Big\}\Big]\\ &\qquad +\beta(1-p^{UU}(\omega))E_{\omega'|\omega}[U^{UU}(\omega')] \end{aligned} \tag{2.3}$$

[6]This setting for the UI duration policy, first used in Fredriksson and Holmlund (2001), helps reduce the state space greatly.

[7]The effective probability of an insured unemployed worker being eligible for UI next period given she turns down a match formation is therefore $(1-\phi(u_t))(1-\xi)$.

The expressions for optimal search intensity for unemployed workers can be found in Appendix 2.6.2.

2.2.1.2 UI Duration Policy: $\phi(u_t)$

Empirically, there are three main types of UI duration policy in the U.S.: (i) the standard UI duration of 26 weeks (ii) the automatic extension programme that is triggered by the state unemployment rate (either total, insured or both) called "Extended Benefits (EB)" programme which extends UI further by 13-20 weeks, and (iii) the ad-hoc programmes that are often issued in the recessions and also triggered by the state unemployment rate providing additional UI ranging from 13 to 53 weeks. To capture these features, I combine the extensions in (ii) and (iii) together and make them a function of the unemployment rate u.[8] Specifically, $\phi(u)$ can assume two values: a low value (implying a longer UI duration) for the recessionary periods and a high value for the normal periods. There is a threshold unemployment rate $\bar{u}$ such that when $u \geq \bar{u}$, the maximum UI duration increases and is represented by ϕ_L, and when $u < \bar{u}$, the maximum UI duration remains standard at 26 weeks and is represented by ϕ_H, where $0 < \phi_L < \phi_H < 1$. In summary,

$$\phi(u_t) \quad = \quad \phi_L \mathbb{1}\{u_t \geq \bar{u}\} + \phi_H \mathbb{1}\{u_t < \bar{u}\};\ \forall t$$

I assume this UI duration policy $\phi(u)$ is known to all agents; therefore, they expect a longer UI duration when the unemployment rate is expected to exceed $\bar{u}$.[9] It is useful to compare the UI duration policy modelled in this paper with that in Mitman and Rabinovich (2014) who study the effects of maximum UI duration in the U.S. on jobless recoveries, and Faig, Zhang and Zhang (2012) who study the contribution of countercyclical UI duration policy on the labour market dynamics. Mitman and Rabinovich (2014) assume all UI extensions are unexpected and perceived to last forever by the agents. Although the model in this paper may not be able to replicate

[8] This is the reason why the unemployment rate is a state variable for the policy functions, and so is the composition of employed and unemployed workers due to the endogenous destruction margin.

[9] As explained in Appendix 2.6.1, some UI extensions are not anticipated per se but due to the fact that the U.S. government has always issued ad-hoc UI extensions during the recessions, it can be argued that in reality agents expect these additional ad-hoc UI extensions *around* recessionary periods (particularly with a high unemployment rate), just not exactly when the policy is implemented.

exactly the timing of UI extensions like in theirs, it can match quite well most of the characteristics in the labour markets usually associated with the UI duration policy, whilst preserving the agents' rational expectation. Faig et al (2012) let the UI duration policy vary with aggregate TFP shocks instead of unemployment rates like in this paper.

In order to finance these benefits, the government collects lump sum tax τ_t from all firms that are in production. The tax is set to satisfy the government budget constraint in each period. Namely,

$$\tau_t = \frac{bu_t^{UI}}{1-u_t}; \forall t$$

2.2.1.3 Production

Production Function The production technology of a worker-firm match in period t with match-specific quality m is

$$y_{m,t} = z_t m$$

where $y_{m,t}$ is the output the match produces and z_t is the total factor productivity (TFP). The price of $y_{m,t}$ is normalised to unity.

Match-specific Productivity By assumption, the variations in labour productivity in this model only come from the changes in the average match quality given the aggregate state. A match-specific productivity drawn at the start of any worker-firm relationship is distributed according to a Beta distribution with parameters $\{\beta_1, \beta_2\}$. The distribution function is

$$F(m) = \underline{m} + \text{Betacdf}(m - \underline{m}, \beta_1, \beta_2)$$

where $\underline{m} > 0$ is the lowest productivity level. This idiosyncratic productivity m will remain until the match is either destroyed (with probability δ) or hit by a shock that causes the match to redraw m from $F(m)$ (with probability λ) in each period.

Aggregate Productivity Shocks There is only one exogenous aggregate shock in the model which is the shock to the total factor productivity, z, whose natural logarithm has an AR(1) representation with ρ_z being its persistence. Specifically,

$$\ln z_t = \rho_z \ln z_{t-1} + \varepsilon_t$$

where ε_t is normally and independently distributed with mean zero and standard deviation $\sigma_z > 0, \forall t$.

2.2.1.4 Firms

Firms maximise the expected discounted profits. They are matched with either one or zero worker. A firm in operation (matched with a worker) in period t sells output $y_{m,t}$, and pays wage $w_{m,t}$ to the worker. It also pays lump sum tax τ_t. Analogous to an employed worker, it faces an exogenous match-destruction shock and a shock to redraw its match-specific productivity. Further, it becomes unmatched when its worker takes up a new job offer.[10] The producing firm can walk away from the match if desired at the end of period.

Let J^j denote the value of a filled job given its worker's employment status last period $j \in \{e, UI, UU\}$, and V the value of posting a vacancy. The Bellman equation for an operating firm is

$$\begin{aligned} J^j(m;\omega) &= y(m;\omega) - w^j(m;\omega) - \tau(\omega) + \beta E_{\omega'|\omega}\Big[\\ &\quad (1-\delta)(1-\lambda)\Big((1-p^e(m;\omega)(1-F(m)))J^{e+}(m;\omega')\Big) \\ &\quad +(1-\delta)\lambda E_{m'}\Big[(1-p^e(m;\omega)(1-F(m')))J^{e+}(m';\omega')\Big] \\ &\quad +\delta V(\omega')\Big] \end{aligned} \tag{2.4}$$

where $J^{e+}(m;\omega') \equiv \max\{J^e(m;\omega'), V(\omega')\}$.

A vacant firm pays a flow cost of κ each period to post a vacancy. It meets a worker with probability q_t, and together they draw a match-specific productivity

[10] The probability that this event happens depends on the match-specific productivity they will have at the start of next period.

for $t+1$ and decide whether to continue with the production. It cannot directly choose the type(s) of workers to meet and therefore needs to take into account the distribution of workers over the employment status and, if employed, match-specific productivity as well as their search effort.

The value of posting a vacancy is

$$\begin{aligned} V(\omega) &= -\kappa + \beta q(\omega) E_{\omega'|\omega}\Bigg[\sum_m \zeta^e(m;\omega)(1-F(m))E_{m'|m'>m}[J^{e+}(m';\omega')] \\ &\quad + \zeta^{UI}(\omega)E_{m'}[J^{UI+}(m';\omega')] + \zeta^{UU}(\omega)E_{m'}[J^{UU+}(m';\omega')]\Bigg] \end{aligned} \tag{2.5}$$

where

$$\begin{aligned} \zeta^e(m) &= \frac{(1-\lambda)s^e_m e_m + \lambda f(m) s^e e}{s^e e + s^{UI}u^{UI} + s^{UU}u^{UU}}; \quad s^e e = \sum_m s^e_m e_m \\ \zeta^{UI} &= \frac{s^{UI}u^{UI}}{s^e e + s^{UI}u^{UI} + s^{UU}u^{UU}}; \quad \zeta^{UU} = \frac{s^{UU}u^{UU}}{s^e e + s^{UI}u^{UI} + s^{UU}u^{UU}} \end{aligned}$$

Free entry condition implies $V(\omega) = 0, \forall \omega$.

2.2.1.5 Meeting Function

The meeting function $M(s_t, v_t)$ takes the aggregate search intensity s_t and the number of job vacancies v_t in period t as inputs, and gives a number of meetings between workers and firms as output.[11] The function has constant returns to scale, and is increasing and concave in its arguments. In particular, I assume:[12]

$$M(s_t, v_t) = \frac{s_t v_t}{\left(s_t^l + v_t^l\right)^{\frac{1}{l}}} \tag{2.6}$$

Let $\theta_t = v_t/s_t$ denote the market tightness. The worker's meeting rate per search unit is $M(s_t, v_t)/s_t = M(1, \theta_t)$ which I also call the 'conditional' job finding rate per search unit since a positive match surplus is required for a successful match. The conditional job finding rate for an unemployed worker of type $i \in \{UI, UU\}$ is thus

[11] s_t is the sum of aggregate search intensity of employed and unemployed workers in time t.

[12] This matching function is similar to the one introduced by den Haan, Ramey and Watson (2000) with an addition of the variable search intensity.

$s_t^i M(1,\theta_t) = p_t^i$. Analogously, it is $s_{m,t}^e M(1,\theta_t) = p_{m,t}^e$ for an employed worker with match quality m. The 'conditional' job filling rate for a vacant firm is $M(s_t, v_t)/v_t = M(1/\theta_t, 1) = q_t$.

2.2.2 Wage and Match Surplus

Wages are determined each period using a generalised Nash bargaining rule. The bargaining power of a worker is $\mu \in (0,1)$ and that of a firm is $1-\mu$. Given $(m;\omega)$, the generalised Nash bargaining rule implies three different wages depending on the worker's employment status last period $j \in \{e, UI, UU\}$ due to their different outside options. Namely,

$$w^j(m;\omega) \quad = \quad \text{argmax} \left(WS^j(m;\omega)\right)^{\mu} \left(J^j(m;\omega)\right)^{(1-\mu)} \tag{2.7}$$

where WS^j is the surplus from working of type-j employed workers. The worker's surpluses are as follows:

$$\begin{aligned}
WS^e(m;\omega) &= W^e(m;\omega) - (1-\psi)U^{UI}(\omega) - \psi U^{UU}(\omega) \\
WS^{UI}(m;\omega) &= W^{UI}(m;\omega) - (1-\phi(u))(1-\xi)U^{UI}(\omega) \\
&\quad -(\phi(u) + (1-\phi(u))\xi)U^{UU}(\omega) \\
WS^{UU}(m;\omega) &= W^{UU}(m;\omega) - U^{UU}(\omega)
\end{aligned}$$

Given the above definitions, the total match surplus of a worker-firm match given the worker's previous employment status j is

$$S^j(m;\omega) \quad = \quad WS^j(m;\omega) + J^j(m;\omega)$$

The expressions for these employment-history-dependent surpluses can be found in Appendix 2.6.2. With the Nash bargaining rule, we have $WS^j(m;\omega) = \mu S^j(m;\omega)$ and $J^j(m;\omega) = (1-\mu)S^j(m;\omega)$. Therefore, both the worker and firm always agree that it is profitable to form a match if and only if $S^j(m;\omega) > 0$.

2.2.3 Recursive Competitive Equilibrium

A recursive competitive equilibrium consists of value functions, $W^e(m;\omega)$, $W^{UI}(m;\omega)$, $W^{UU}(m;\omega)$, $U^{UI}(\omega)$, $U^{UU}(\omega)$, $J^e(m;\omega)$, $J^{UI}(m;\omega)$, $J^{UU}(m;\omega)$, and $V(\omega)$; market tightness $\theta(\omega)$; search policy $s^e(m;\omega)$, $s^{UI}(\omega)$ and $s^{UU}(\omega)$; and wage functions $w^e(m;\omega)$, $w^{UI}(m;\omega)$, and $w^{UU}(m;\omega)$, such that, given the initial distribution of workers over the employment status and match productivity, the government's policy $\tau(\omega)$ and $\phi(\omega)$, and the law of motion for z:

1. The value functions and the market tightness satisfy the Bellman equations for workers and firms, and the free entry condition, namely, equations (2.1), (2.2), (2.3), (2.4) and (2.5)

2. The search decisions satisfy the FOCs for optimal search intensity, which are equations (2.14), (2.15) and (2.16)

3. The wage functions satisfy the FOCs for the generalised Nash bargaining rule (equation (2.7))

4. The government's budget constraint is satisfied each period

5. The distribution of workers evolves according to the transition equations (2.17), (2.18) and (2.19), which can be found in Appendix 2.6.3, consistent with the maximising behaviour of agents

2.2.4 Solving the Model

In order to compute the market tightness (and, in effect, total match surpluses and search effort) in the model, the agents in the economy need to keep track of the distribution of workers over the employment status and match quality $\{e_m\ \forall m, u^{UI}, u^{UU}\}$ as they enter the vacancy creation condition (eq. 2.5). In order to predict next-period unemployment rate they need to know the inflow to and outflow from unemployment which are based on this distribution. I use the Krusell & Smith (1998) algorithm to predict the laws of motion for both the insured and total unemployment rates as a function of current unemployment rate (u) and TFP shock (z). As the distribution of employed workers by match quality does not vary much over time, I use the stochastic steady state distributions and adjust for the employment rate that can be inferred from the state variables. I report the performance of this approximation in Appendix 2.6.4.

2.3 Calibration

I estimate a subset of the parameters by matching key statistics of the U.S. economy, particularly its labour market. To obtain these statistics from the model, I solve for the policy functions, and simulate an economy for T periods where T is large and repeat for 1,000 times. In each simulation, I split the pre- and post-1985 periods at T_1 where $1 < T_1 < T$ and compute relevant statistics including the correlations between output and labour productivity for these two periods.[13]

In the simulation, the only difference between pre- and post-1985 periods is the UI duration policy $\phi(u)$. Specifically, I allow for an increase in its generosity during recessions from pre- to post-1985 periods. As a result, there are two UI duration regimes. When $u < \bar{u}$, the maximum UI duration is six months (standard) in both regimes; however, when $u \geq \bar{u}$, the maximum UI duration is extended to be in total:

1. Twelve months from period 1 to T_1 representing January 1948 to March 1985

2. Eighteen months from $T_1 + 1$ to T representing April 1985 to June 2014

Table 2.2 summarises all the pre-specified parameters while Table 2.3 describes the calibrated parameters in the model.

Discretisation I discretise the total factor productivity (z) using Rouwenhurst (1995)'s method to approximate an AR(1) process with a finite-state Markov chain. I use 51 nodes to solve the model and 5,100 nodes by linear interpolation in the simulations.

Similarly, I use 51 equidistant nodes to approximate the Beta distribution of the match-specific productivity $F(m)$ when solving the model and 5,100 nodes by

[13] Specifically, T is 5,320 and T_1 is 2,980 so that they are proportional to the data used in this paper. Additionally, I include 200 burn-in periods.

linear interpolation in the simulations. I define $f(m)$ to be $F'(m)/\sum_m F'(m)$ where $F'(m)$ is the probability density function of $F(m)$.

2.3.1 Pre-specified Parameters

The pre-specified parameters in the model are summarised in Table 2.2. For the discount factor β, I use the value of 0.9967 implying an annual interest rate of 4% which is the U.S. average. I follow Fujita and Ramey (2012) in pinning down the vacancy creation cost κ to be 0.0392 using survey evidence on vacancy durations and hours spent on vacancy posting.[14] I assign μ, the worker's bargaining power, to be 0.5 following den Haan, Ramey and Watson (2000).

ϕ_H and ϕ_L are respectively the UI exhaustion rates during normal periods and recessions. I set ϕ_H to be 1/6 which implies the standard maximum UI duration of 6 months given the monthly frequency. The UI exhaustion rates when $u \geq \bar{u}$ are set to be $\phi_{L,pre85} = 1/12$ for the pre-1985 periods and $\phi_{L,post85} = 1/18$ for the post-1985 periods implying the maximum UI duration of 12 months (pre-1985 average) and 18 months (post-1985 average) respectively. I set $\bar{u}$, the threshold unemployment rate that triggers UI extensions, to be 6% which is on the lower bound of the observed UI extension criteria.

To determine the flow values of unemployed workers, h and, if insured, b, I use the results in Gruber (1997). In particular, the drop in consumption for the newly unemployed workers is 10% when receiving UI and 24% when not receiving UI given the replacement rate of 50%.[15]

The slope of the search cost function for the unemployed a_u is normalised such that the search effort of the uninsured unemployed s^{UU} is unity when the economy is in the steady state, similar to Nagypál (2005). The power parameters in the search cost functions for both employed and unemployed workers (d_e and d_u) are set to

[14] Fujita and Ramey (2012) find the vacancy cost to be 17% of a 40-hour-work week. Normalising the mean productivity to unity, this gives the value of 0.17 per week or 0.0392 per month. The actual mean productivity may be higher than (but not greatly different from) unity due to truncation from below of the match-specific quality.

[15] To find the implied h and b given a set of parameters, I first guess the mean wage for the newly unemployed and solve the model to obtain the policy functions. I then simulate the model to check if the guess is close to its counterpart from the simulation. If it is not, I replace the guessed wage for the newly fired with the one from the simulation and repeat until the two are close enough.

unity in line with Christensen, Lentz and Mortensen (2005) and Yashiv (2000).

2.3.2 Calibrated Parameters

I use the simulated method of moment to assign values to the remaining eleven parameters $\{l, \delta, \lambda, \psi, \xi, a_e, \underline{m}, \beta_1, \beta_2, \rho_z, \sigma_z\}$ by matching twelve moments.[16] The values of these parameters are in Table 2.3. The targeted moments used in the calibration are the first and second moments of the unemployment rate, job destruction rate and job finding rate, the first moment of the job-to-job transtion rate, average unemployment duration, and insured unemployment rate, the second moment and autocorrelation of labour productivity, and the correlation between output and labour productivity. I describe the data source in this calibration exercise in Appendix 2.6.1. The model's generated moments are reported in Table 2.1 along with their empirical counterparts. Table 2.5 shows other related moments not targeted in the calibration.

2.4 Results

2.4.1 Performance

As shown in Table 2.4, the baseline model despite being over-identified matches the twelve targeted moments quite well overall including the first moments of unemployment rate, job finding rate, job destruction rate and job-to-job transition rate. It can also match the characteristics of the labour productivity quite well. The average job finding rate is somewhat higher than the data whilst unemployment and job findings exhibit slightly higher fluctuations than the data. The mean unemployment duration is lower than the data but this is mainly due to the Great Recession periods where there is an unprecedented spike in average duration of unemployment. With regards to related moments that are not targeted (shown in Table 2.5), it can match the dynamics of the employment rate and insured unemployment rate as well as the cyclicality of unemployment, job finding rate and job destruction rate quite well. The correlation between unemployment and vacancies is however moderately

[16] The calibrated parameters are to minimise the sum of squared residuals of percentage changes between the model-generated moments and their empirical counterparts.

negative (-0.27) while it is strongly negative in the data (-0.88).[17]

Additionally, I also find the path of TFP shocks that yields the detrended output series identical to the data (using the parameters in Table 2.2 and 2.3), and compare the resulting model series to the data. Figure 2.5 shows that the model produces similar dynamics of unemployment, job findings, and unemployment durations while job destructions fluctuate too little comparing to the data. It is expected that the detrended series from the model may be different from the data (Figure 2.6) since no low frequency changes is accounted for. However, the model's insured unemployment series is close to the data from both the cyclical and raw-data aspects, as shown in Figure 2.7 and 2.8, especially during recessions when the insured unemployment rate spikes.

2.4.2 The Correlation Between Output and Labour Productivity

With respect to the labour productivity puzzle, the model can explain a significant part of the drop in the procyclicality of the labour productivity. Particularly, it can generate half of the observed fall in the correlation between output and labour productivity from pre- to post-1985 periods (0.20 as compared to 0.40) as shown in Table 2.6. Note that a standard search and matching model without any change in UI duration does not have different policy functions over the business cycles and will therefore not be able to produce any shift in this correlation. The correlation produced by the model is also close to that in the data (0.67 as compared to 0.62). For the pre-1985 periods, the model-generated correlation is higher than that in the data (0.81 as compared to 0.70), and the difference is larger for the post-1985 periods (0.61 as compared to 0.30).

The success of the model in generating a sizeable fall in the correlation comes from the fall in the UI exhaustion rate during high unemployment (ϕ_L) from the pre-1985 to post-1985 periods which alters the policy functions in the model: (i) match surpluses and (ii) job search effort. A lower ϕ_L in post-1985 periods lowers the match surpluses and lifts up the average labour productivity during the recessions.

[17] Hagedorn and Manovskii (2011) show that a longer model period emphasises the time aggregation issues and lowers the correlation between unemployment and vacancies.

At the same time, a lower ϕ_L lowers the job search effort and, in effect, employment, thereby prolonging the UI extensions once triggered.

Match Surpluses The existence of the $\phi(u)$ creates a discontinuity in the match surpluses as a function of unemployment rate as shown in Figure 2.3. When $u \geq \bar{u}$, $\phi(u)$ falls from ϕ_H to ϕ_L. The fall in $\phi(u)$ increases the outside options and decreases the surpluses from working for most workers.[18] Therefore, it is less likely for matches to be formed, especially those with low match quality m. This puts an upward pressure on the average labour productivity against negative shocks to z, and results in a less-than-perfect correlation between output and labour productivity. Since $\phi_{L,post85} < \phi_{L,pre85}$, the post-1985 match surpluses fall even further when $u \geq \bar{u}$ comparing to those in pre-1985 periods. This means, in post-1985 periods, the positive response of labour productivity upon a negative shock is stronger, and results in a lower correlation between output and labour productivity comparing to the pre-1985 periods.

Job Search Effort Similar to the previous argument, the existence of $\phi(u)$ creates a drop in the job search effort and job finding rate for the insured unemployed around $\bar{u}$ where $\phi(u)$ falls from ϕ_H to ϕ_L as seen in Figure 2.4. When $u \geq \bar{u}$, there are fewer meetings and, as a result, higher unemployment which feeds back to the UI policy $\phi(u)$ to remain at ϕ_L for longer.[19] With $\phi_{L,post85} < \phi_{L,pre85}$, the post-1985 job search effort fall even further when $u \geq \bar{u}$ comparing to those in pre-1985 periods. Unemployment is thus more likely to remain high and lengthen the effects the UI extension has on the falling correlation between output and labour productivity in post-1985 periods.

[18] Specifically, the surpluses of workers with history $\{e, UI\}$ fall as shown in Figure 2.3. We can see that the surplus for workers with history UU, however, increases slightly with lower $\phi(u)$ because it is better for this type of workers to become re-employed and increase the likelihood of receiving UI in the event that they return to unemployment.

[19] In this model, the persistence of UI extensions interacts with the persistence of unemployment, which is in line with the hypothesis in Mitman and Rabinovich (2014) where a longer UI duration increases the persistence of unemployment.

2.4.3 Impulse Response Functions

The impulse response functions (IRFs) of key variables in the model are useful in demonstrating how the UI duration policy affects the correlation between output and labour productivity. Figure 2.9 and 2.10 show respectively the IRFs of output (y), labour productivity (LP) and average match quality ($E(m)$) to 1% and 2% negative TFP (z) shocks from its steady state for pre-1985 (solid lines) and post-1985 (dashed lines) periods.

In the case of 1% negative deviation, there is not much difference between the responses of variables in pre- and post-1985 periods because unemployment does not exceed $\bar{u}$ and trigger the UI extension. We can see the labour productivity recovers as soon as the shock subsides while output reaches its trough 6 months after the shock occurs for both eras. Therefore, the correlation between output and labour productivity is less than perfect during this time but there is hardly any difference between pre- and post-1985 periods.

On the contrary, the IRFs between pre- and post-1985 periods are very different when the size of the shock is instead 2% negative deviation from the steady state. This is mainly because the UI extension is triggered for the post-1985 periods (from the fifth month onwards) but not in the pre-1985 periods where the IRFs are almost identical to the 1% deviation case. As discussed in the previous subsection, a extension of UI tends to raise the overall match quality as can be seen in Figure 2.10. The average match quality in post 1985 stays positive throughout once the UI extension is triggered. Labour productivity also behaves similarly. Despite its negative response, it recovers at a faster rate than in pre-1985 periods once UI extension is in place. More starkly is the response of output that reaches its trough 15 months after the initial shock, almost one year later than the cases without UI extension (the pre-1985 period with 2% shock and both pre- and post-1985 periods with 1% shock). The quicker recovery of labour productivity combined with the highly persistent negative output response makes the correlation between output and labour productivity in post-1985 periods much smaller than that in pre-1985 periods.

2.4.4 Decomposition of Countercyclical UI Duration Effects

As a change in the UI duration policy affects the procyclicality of labour productivity through the change in match surpluses and job search effort, I decompose the effect of this policy change to measure the contribution of each channel to the business cycle properties of labour productivity.

In the first case, to see how much the change in job search effort after 1985 explains the fall in the labour productivity's procyclicality, I assume both workers and firms always use the pre-1985 match surpluses throughout the simulation to make decisions on match formation and dissolution (i.e., the policy functions for match surpluses are the same for pre- and post-1985 periods). In the second case, I fix the job search effort at the pre-1985 periods to estimate the impact of the change in match surpluses, that is due to the increase in the generosity of UI duration policy, on the procyclicality of the labour productivity.

It turns out that both match surpluses and job search effort explain a substantial part of the drop in the output-labour-productivity correlation and deliver a higher overall correlation of 0.76-0.77 as shown in Table 2.7. It is rather surprising that the search effort channel contributes as just much as the match surplus channel to the drop since it only affects insured unemployed workers whilst the change in match surpluses affects most workers. This finding shows that in order to obtain a sizeable shift in the correlation between output and labour productivity, the variable search intensity margin is just as important as the total match surpluses that workers and firms use to determine match formations and dissolutions. Assuming search effort to be constant can undermine the effect of UI duration policy on the behaviour of the labour productivity over the business cycles.

2.4.5 Hazard Rate of Exiting Unemployment

Modelling heterogeneity in unemployed workers also has an implication for the duration-dependent job finding probabilities. Contrary to a constant unemployment exit rate in a standard search and matching model (with no participation margins), the model in this paper can produce a realistic feature of the rate an unemployed worker finds a job by durations of unemployment. Empirically, this rate is decreasing and usually convex in the time spent in unemployment, the properties that the model can replicate as depicted by Figure 2.11. I present the hazard functions in two cases: (i) the insured unemployed workers remain insured throughout the unemployment spell, and (ii) the insured unemployed become uninsured with probability ϕ_H each period (implying the standard UI duration during normal times), as these are the lower and upper bounds for the realised maximum UI durations. The reason the hazard rate is decreasing in unemployment duration is due to the change in the composition of unemployed workers. Uninsured unemployed workers have a higher job finding rate and therefore exit unemployment faster than the insured type. With time, unemployed workers are more represented by the insured type, the exit rate therefore falls with the unemployment duration and only becomes constant when there is no uninsured type left in the unemployment pool.

When compared to the data, Kroft, Lange, Notowidigdo and Katz (2016) have estimated this hazard rate parametrically controlling for observable characteristics from the CPS data between 2002-2007. They find that the relative job finding rate (normalised to unity at zero duration) drops sharply during the first 8-10 months, after which the rate becomes stable around 0.4-0.5. This function drops slightly faster than what my model can produce given that the insured unemployed remain insured throughout the spell (case (i)). However, when the stochastic UI exhaustion rate is taken into account (case (ii)), the model can explain only partially the drop in the hazard function during the first months of unemployment. The model's true performance lies between these two functions as the maximum UI durations can vary between 6 months to almost 2 years.

2.5 Conclusion

This paper is set out to quantify how much the increasingly generous UI duration policy during recessionary periods in the U.S. contributes to the substantial fall in the procyclicality of its labour productivity over the business cycle. The results are obtained from a search and matching model with stochastic UI duration, heterogeneous match quality, variable search intensity and on-the-job search. This model can produce 50% of the empirical drop in the correlation between output and labour productivity. The countercyclical UI duration policy lowers the total match surpluses in bad times and therefore raises the average labour productivity while output is more negatively affected. At the same time, this policy lowers job search effort of the insured unemployed, contributing to a higher persistence in unemployment and thus the UI extension (since it is a function of the unemployment rate) and its effect on the correlation between output and labour productivity. Since the UI duration policy is more generous after 1985, its effect via these two channels is stronger than that in pre-1985 periods, which gives rise to the falling procyclicality of the labour productivity. Lastly, the model performs very well in producing key statistics in the labour markets especially the ratio of insured to total unemployment rates over the business cycles.

2.6 Appendix for Chapter 2

2.6.1 Data

Both empirical and simulated (logged) data in this paper are detrended by using the Hodrick-Prescott (HP) filter with a smoothing parameter of 1600 for quarterly data and of 129600 for monthly data following Ravn & Uhlig (2002). When necessary, monthly empirical series are converted to quarterly frequency by using a quarterly average except for the job finding rate and the job destruction rate whose quarterly series are obtained by iterating the law of motion for unemployment. The range of data (unless stated otherwise) is from January 1948 to June 2014. All series are seasonally adjusted.

2.6.1.1 Unemployment

Monthly data on unemployment level and labour force level are obtained from the Current Population Survey (CPS) provided by the Bureau of Labor Statistics (BLS), U.S. Department of Labor, from January 1948 to June 2014.[20] They do not include persons marginally attached to the labour force. The ratio of these two series forms the official definition of unemployment rate ('U3' as labelled by BLS).

2.6.1.2 Output and Labour Productivity

For output, I use the quarterly real GDP series provided by the Bureau of Economic Analysis (BEA), U.S. Department of Commerce, and I use the BLS quarterly series for non-farm output per job to represent the labour productivity.[21]

2.6.1.3 Transition Rates

I obtain the monthly job finding rates and job destruction rates as is done in Shimer (2005) without correcting for time aggregation bias.[22] As converting the monthly turnover rates to quarterly ones by simply computing a quarterly average would

[20] The series IDs are respectively LNS13000000 and LNS11000000.

[21] The series ID for labour productivity is PRS85006163.

[22] By correcting for the time aggregation bias, the destruction rates will be higher and closer to the BLS data. However, since Shimer (2005)'s correction means a newly unemployed worker has on average half a month to find a new job before being recorded as unemployed, one must also adjust the Bellman equations in a discrete-time model accordingly, otherwise the implied unemployment will be too high when the model period is longer than half a month.

overestimate the job finding rates and underestimate the job destruction rates, one should iterate the law of motion for monthly unemployment (u_t^{mo}) instead.

$$
\begin{aligned}
u_{t+1}^{mo} &= (1-\rho_{f,t}^{mo})u_t^{mo} + \rho_{x,t}^{mo}(1-u_t^{mo}) && (2.8)\\
u_{t+2}^{mo} &= (1-\rho_{f,t+1}^{mo})u_{t+1}^{mo} + \rho_{x,t+1}^{mo}(1-u_{t+1}^{mo}) && (2.9)\\
u_{t+3}^{mo} &= (1-\rho_{f,t+2}^{mo})u_{t+2}^{mo} + \rho_{x,t+2}^{mo}(1-u_{t+2}^{mo}) && (2.10)
\end{aligned}
$$

where $\rho_{f,t}^{mo}$ and $\rho_{x,t}^{mo}$ are respectively the monthly job finding and destruction rates at time t. Replacing u_{t+2}^{mo} in (2.10) with u_t^{mo} using (2.8) and (2.9) and setting $u_{t+1}^{q} \equiv u_{t+3}^{mo}$ and $u_t^q \equiv u_t^{mo}$, one can obtain[23]

$$
u_{t+1}^{q} = (1-\rho_{f,t}^{q})u_t^{q} + \rho_{x,t}^{q}(1-u_t^{q}) \qquad (2.11)
$$

where

$$
\begin{aligned}
\rho_{x,t}^{q} &= \rho_{x,t+2}^{mo} + \rho_{x,t+1}^{mo}(1-\rho_{x,t+2}^{mo}-\rho_{f,t+2}^{mo})\\
&\quad + \rho_{x,t}^{mo}(1-\rho_{x,t+1}^{mo}-\rho_{f,t+1}^{mo})(1-\rho_{x,t+2}^{mo}-\rho_{f,t+2}^{mo}) && (2.12)\\
\rho_{f,t}^{q} &= 1-\rho_{x,t}-\prod_{i=0}^{2}(1-\rho_{x,t+i}^{mo}-\rho_{f,t+i}^{mo}) && (2.13)
\end{aligned}
$$

2.6.1.4 UI Duration Policy

Data on UI extensions in the U.S. is provided by Employment and Training Administration (ETA), U.S. Department of Labor, which collects and summarises the Federal Unemployment Compensation Laws dating back to August 1935. There are 3 main types of UI durations: (i) the standard UI duration of 26 weeks (ii) the automatic extension programme that is triggered by the state unemployment rate (either total, insured or both) called "Extended Benefits (EB)" programme which extends UI further by 13-20 weeks, and (iii) the ad-hoc programmes that are often issued in the recessions and also triggered by the state unemployment rate providing addi-

[23] We could also obtain the quarterly series of unemployment rates by collecting the first monthly unemployment rate of every quarter as in Robin (2011) instead of averaging every 3 months. This does not change significantly the statistics reported in this paper.

tional UI ranging from 13 to 53 weeks.[24] The maximum duration of unemployment benefits in the U.S. are shown chronologically in Figure 2.2 where I sum together all types of UI durations. Apart from the early 1980's recessions, the extended UI duration has been steadily increasing throughout the 1948-2014 period with its highest level at 99 weeks during the Great Recession.

2.6.2 Expressions for Optimal Search Intensity and Match Surplus

Given the Bellman equations for the three types of workers $\{e, UI, UU\}$, we can take the first derivative to find the optimal search effort for these workers. The first order conditions are as follows

$$\begin{aligned} \nu_e'(s^e(m;\omega)) &= -\beta(1-\delta)M(1,\theta(\omega))E_{\omega'|\omega}\Big[\dots \qquad (2.14)\\ & (1-\lambda)(1-F(m))\Big(WS^{e+}(m;\omega') - E_{m'|m'>m}[WS^{e+}(m';\omega')]\Big)\\ &+ \lambda E_{m'}\Big[(1-F(m'))(WS^{e+}(m';\omega') - E_{m''|m''>m'}[WS^{e+}(m'';\omega')])\Big]\Big]\\ \nu_u'(s^{UI}(\omega)) &= \beta M(1,\theta(\omega)) \times \\ & E_{m'\omega'|\omega}\Big[\max\{WS^{UI}(m';\omega'),0\} - \xi(1-\phi)US(\omega')\Big] \qquad (2.15)\\ \nu_u'(s^{UU}(\omega)) &= \beta M(1,\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS^{UU}(m';\omega'),0\}\Big] \qquad (2.16) \end{aligned}$$

where $\nu_i'(s) = a_i(1+d_i)s^{d_i}; i \in \{e,u\}$.

The surplus from being insured (as opposed to uninsured) of unemployed workers is defined as

$$US(\omega) \equiv U^{UI}(\omega) - U^{UU}(\omega)$$

The expressions for the total surpluses of worker-firm matches given the workers' previous employment statuses (e, UI, UU) and the surplus of being insured unemployed are respectively:

[24] For a more detailed account, see the ETA website. Appendix B of Mitman and Rabinovich (2014) also provides a good summary.

$$\begin{aligned}
S^e(m;\omega) &= y_{mZ} - \nu_e(s^e(m;\omega)) - \tau - (1-\psi)(b+h-\nu_u(s^{UI}(\omega))) \\
&\quad -\psi(h-\nu_u(s^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
&\quad (1-\delta)(1-\lambda)\Big((1-p^e(m;\omega)(1-F(m)))S^{e+}(m;\omega')\ldots \\
&\quad +p^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S^{e+}(m';\omega')]\Big) \\
&\quad +(1-\delta)\lambda E_{m'}\Big[(1-p^e(m;\omega)(1-F(m')))S^{e+}(m';\omega')\ldots \\
&\quad +p^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S^{e+}(m'';\omega')]\Big] \\
&\quad -(1-\psi)p^{UI}(\omega)E_{m'}[\mu S^{UI+}(m';\omega')] \\
&\quad -\psi p^{UU}(\omega)E_{m'}[\mu S^{UU+}(m';\omega')] \\
&\quad +(1-\psi)\Big(\phi + p^{UI}(\omega)(1-\phi)\xi\Big)US(\omega')\Big]
\end{aligned}$$

$$\begin{aligned}
S^{UI}(m;\omega) &= y_{mZ} - \nu_e(s^e(m;\omega)) - \tau - (1-\phi)(1-\xi)(b+h\nu_u(s^{UI}(\omega))) \\
&\quad -(1-(1-\phi)(1-\xi))(h-\nu_u(s^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
&\quad (1-\delta)(1-\lambda)\Big((1-p^e(m;\omega)(1-F(m)))S^{e+}(m;\omega')\ldots \\
&\quad +p^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S^{e+}(m';\omega')]\Big) \\
&\quad +(1-\delta)\lambda E_{m'}\Big[(1-p^e(m;\omega)(1-F(m')))S^{e+}(m';\omega')\ldots \\
&\quad +p^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S^{e+}(m'';\omega')]\Big] \\
&\quad -(1-\phi)(1-\xi)p^{UI}(\omega)E_{m'}[\mu S^{UI+}(m';\omega')] \\
&\quad -\Big(1-(1-\phi)(1-\xi)\Big)p^{UU}(\omega)E_{m'}[\mu S^{UU+}(m';\omega')] \\
&\quad +\Big(1-\psi-(1-\phi)^2(1-\xi)(1-\xi p^{UI}(\omega))\Big)US(\omega')\Big]
\end{aligned}$$

$$
\begin{aligned}
S^{UU}(m;\omega) \quad = \quad & y_{mZ} - \nu_e(s^e(m;\omega)) - \tau - (h - \nu_u(s^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\dots \\
& (1-\delta)(1-\lambda)\Big((1-p^e(m;\omega)(1-F(m)))S^{e+}(m;\omega')\dots \\
& + p^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S^{e+}(m';\omega')]\Big) \\
& + (1-\delta)\lambda E_{m'}\Big[(1-p^e(m;\omega)(1-F(m')))S^{e+}(m';\omega')\dots \\
& + p^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S^{e+}(m'';\omega')]\Big] \\
& - p^{UU}(\omega)E_{m'}[\mu S^{UU+}(m';\omega')] \\
& + (1-\psi)US(\omega')\Big]
\end{aligned}
$$

$$
\begin{aligned}
US(\omega) \quad = \quad & b - \nu_u(s^{UI}(\omega)) + \nu_u(s^{UU}(\omega)) \\
& + \beta E_{\omega'|\omega}\Big[p^{UI}(\omega)\mu E_{m'}[S^{UI+}(m';\omega')] - p^{UU}(\omega)\mu E_{m'}[S^{UU+}(m';\omega')] \\
& (1-\phi)\Big(1-\xi p^{UI}(\omega)\Big)US(\omega')\Big]
\end{aligned}
$$

2.6.3 Transitions

Employment The mass of employed agents in t with match quality m, $e_{m,t}$, evolves as follows

$$
\begin{aligned}
e_{m,t+1} \quad = \quad & \Big((1-\delta)(1-\lambda)(1-p^e_{m,t}+p^e_{m,t}F(m))e_{m,t} \\
& + (1-\delta)(1-\lambda)f(m)\int_{m'<m} p^e_{m',t}e_{m',t}dm' \\
& + (1-\delta)\lambda f(m)\int_{m'}(1-p^e_{m',t}+p^e_{m',t}F(m))e_{m',t}dm' \\
& + (1-\delta)\lambda F(m)f(m)\int_{m'} p^e_{m',t}e_{m',t}dm'\Big)\mathbb{1}\{S^e_{m,t+1}>0\} \\
& + f(m)(u^{UI}_t p^{UI}_t)\mathbb{1}\{S^{UI}_{m,t+1}>0\} \\
& + f(m)(u^{UU}_t p^{UU}_t)\mathbb{1}\{S^{UU}_{m,t+1}>0\} \qquad (2.17)
\end{aligned}
$$

where $\mathbb{1}\{\cdot\}$ is an indicator function. The total employment is the sum of all employed workers over the match qualities $e_t = \int e_{m,t}\ dm$ and the aggregate output can be computed as $y_t = z_t \int m \cdot e_{m,t}\ dm$.

Job Destructions The job destruction rate of employed workers of type m and the average job destruction rate are respectively

$$\rho_{x,t}(m) = \begin{cases} \delta & \text{if } S^e_{m,t+1} > 0, \\ 1 & \text{otherwise} \end{cases}$$

$$\rho_{x,t} = \frac{\delta \int_{\{m:S^e_{m,t+1}>0\}} e^{post}_{m,t} dm + \int_{\{m:S^e_{m,t+1}\leq 0\}} e^{post}_{m,t} dm}{e_t}$$

$$\begin{aligned} \text{where } e^{post}_{m,t} = & (1-\lambda)(1-p^e_{m,t}+p^e_{m,t}F(m))e_{m,t} \\ & +(1-\lambda)f(m)\int_{m'<m} p^e_{m',t}e_{m',t}dm' \\ & +\lambda f(m)\int_{m'}(1-p^e_{m',t}+p^e_{m',t}F(m))e_{m',t}dm' \\ & +\lambda F(m)f(m)\int_{m'} p^e_{m',t}e_{m',t}dm' \end{aligned}$$

denotes employed workers with match productivity m at the end of the period t.

Job Findings The job finding rate for an unemployed worker of type $i = \{UI, UU\}$ and the average job finding rate are respectively

$$\rho^i_{f,t} = \int \rho^i_{f,t}(m)f(m)dm$$

$$\rho_{f,t} = \frac{u^{UI}_t \rho^{UI}_{f,t} + u^{UU}_t \rho^{UU}_{f,t}}{u^{UI}_t + u^{UU}_t}$$

$$\text{where } \rho^i_{f,t}(m) = \begin{cases} p^i_t & \text{if } S^i_{m,t+1} > 0, \\ 0 & \text{otherwise} \end{cases}$$

Job-to-job Transitions The match-specific and the average job-to-job transition rates are respectively

$$\begin{aligned} \rho^{ee}_{m,t} = & (1-\delta)\Big((1-\lambda)p^e_{m,t}(1-F(m))E_{m'>m}[\mathbf{1}\{S^e_{m',t+1}>0\}] \\ & +\lambda\int_{m'} p^e_{m,t}f(m')(1-F(m'))E_{m''>m'}[\mathbf{1}\{S^e_{m'',t+1}>0\}]dm'\Big) \end{aligned}$$

$$\rho^{ee}_t = \frac{\int_m \rho^{ee}_{m,t}e_{m,t}dm}{e_t}$$

Unemployment The mass of unemployed workers with and without UI benefits as well as the total unemployment evolve respectively as follows

$$
\begin{aligned}
u_{t+1}^{UI} &= \underbrace{(1-\phi_t)(1-p_t^{UI})u_t^{UI}}_{\text{unmatched, not losing UI}} + \underbrace{\chi_t^{UI}(1-\phi_t)(1-\xi)p_t^{UI}u_t^{UI}}_{\text{bad match, not losing UI}} \\
&+ \underbrace{(1-\psi)\rho_{x,t}e_t}_{\text{destroyed match, not losing UI}} \qquad (2.18)
\end{aligned}
$$

$$
\begin{aligned}
u_{t+1}^{UU} &= \underbrace{\phi_t(1-p_t^{UI})u_t^{UI}}_{\text{unmatched, losing UI}} + \underbrace{\chi_t^{UI}\Big(\phi_t+(1-\phi_t)\xi\Big)p_t^{UI}u_t^{UI}}_{\text{bad match, losing UI}} \\
&+ (1-\rho_{f,t}^{UU})u_t^{UU} + \underbrace{\psi\rho_{x,t}e_t}_{\text{destroyed match, losing UI}} \qquad (2.19)
\end{aligned}
$$

$$
u_{t+1} = u_{t+1}^{UI} + u_{t+1}^{UU} \qquad (2.20)
$$

where $\chi_t^{UI} \equiv \int \mathbf{1}\{S_{m,t+1}^{UI} \leq 0\} f(m)dm$ denotes the rate the newly formed matches with u^{UI} are not viable.

2.6.4 Performance of the Approximation Method

Below I report the average percentage deviations (in absolute value) of the 1st, 2nd, 3rd and 4th moments of the approximated distribution of employed workers over match quality from the distributions obtained from the simulation. The method described in the Model section delivers distributions that are less than 1% different in terms of the 1st, 2nd and 4th moments from the actual distributions found in the simulation. However it generates the 3rd moment that is more than 3% different from its counterpart since the skewness is more sensitive to the cut-offs in the distributions coming from endogenous destructions.

Table 2.1: Performance of the Approximation Method

Percentage deviation (%)	Mean	Std
1st moment	0.4260	0.3499
2nd moment	0.3790	0.4621
3rd moment	3.7461	3.4375
4th moment	0.1809	0.2995

Table 2.2: Pre-specified Parameters For Baseline Model (Monthly)

Parameter	Description	Value	Source/Remarks
β	Discount factor	0.9967	Annual interest rate of 4%
κ	Vacancy posting cost	0.0392	Fujita & Ramey (2012)
μ	Worker's bargaining power	0.5	Den Haan, Ramey & Watson (2000)
ϕ_H	UI exhaustion rate	1/6	6 months max UI duration, ETA
$\phi_{L,I}$	UI exhaustion rate	1/12	12 months max UI duration, ETA
$\phi_{L,II}$	UI exhaustion rate	1/18	18 months max UI duration, ETA
b	UI benefit	0.1221	Gruber (1997) given $E(w) = 0.872$
h	Leisure flow	0.6627	Gruber (1997) given $E(w) = 0.872$
$\bar{u}$	UI policy threshold	0.06	ETA
a_u	Search cost function	0.1287	Normalisation
d_u, d_e	Search cost function	1	Christensen et al (2004), Yashiv (2000)

Table 2.3: Calibrated Parameters For Baseline Model (Monthly)

Parameter	Description	Value
l	Matching function	0.6010
δ	Exogenous destruction	0.0234
λ	Redrawing new m	0.5000
ψ	Losing UI after becoming unemp.	0.4900
ξ	Losing UI after meeting firm	0.4605
a_e	Search cost function	0.1100
$\underline{m}$	Lowest match-specific prod.	0.4689
β_1	Match-specific prod. distribution	2.8024
β_2	Match-specific prod. distribution	4.5101
ρ_z	Persistence of TFP	0.9715
σ_z	Standard deviation of TFP shocks	0.0056

Table 2.4: Targeted Moments

Moment	Data	Model
E(u)	0.0583	0.0603
E(ρ_f)	0.4194	0.4387
E(ρ_x)	0.0248	0.0258
E(ρ_{ee})	0.0320	0.0321
E(u_{dur}) (weeks)	15.4287	12.7217
E(u^{UI}/u)	0.0290	0.0384
std(u)	0.1454	0.1633
std(ρ_f)	0.0999	0.1203
std(ρ_x)	0.0890	0.0836
std(LP)	0.0131	0.0123
$corr(LP, LP_{-1})$	0.7612	0.7716
corr(y, LP)	0.6186	0.6663

Table 2.5: Moments Not Targeted

Moment	Data	Model
std(u_{dur}) (weeks)	6.9941	5.7471
std(u^{UI})	0.1657	0.2250
std(v)	0.1408	0.0611
std(u)/std(y)	8.8121	7.2951
std(e)/std(y)	0.9900	0.9795
std(w)/std(y)	0.3878	0.4959
corr(y,ρ_f)	0.8009	0.9118
corr(y,ρ_x)	-0.8414	-0.7973
corr(y,u)	-0.8825	-0.8971
corr(u, v)	-0.8786	-0.2675
corr(y, v)	0.8850	0.5353
$E(m)_{pre85}$	-	0.8814
$E(m)_{post85}$	-	0.8824

Table 2.6: Correlation Between Output (y) and Labour Productivity (LP)

	Data	Model
corr(y, LP)	0.6186	0.6663
corr$(y, LP)_{pre85}$	0.7015	0.8150
corr$(y, LP)_{post85}$	0.2954	0.6111
Δcorr(y, LP)	0.4061	0.2039

Table 2.7: Decomposition of UI Effects on $corr(y, LP)$

	Data	Baseline	S-fixed	s-fixed
corr(y, LP)	0.6186	0.6663	0.7617	0.7727
corr$(y, LP)_{pre85}$	0.7015	0.8150	0.8470	0.8490
corr$(y, LP)_{post85}$	0.2954	0.6111	0.7239	0.7390
Δcorr(y, LP)	0.4061	0.2039	0.1231	0.1100

Figure 2.1: Correlations between output and output per worker for 1948Q1-1985Q1 and 1985Q2-2014Q2 (both variables are of quarterly frequency and detrended using the HP filter with a smoothing parameter of 1,600) (the green lines are linear fitted trends) (Source: BEA and BLS)

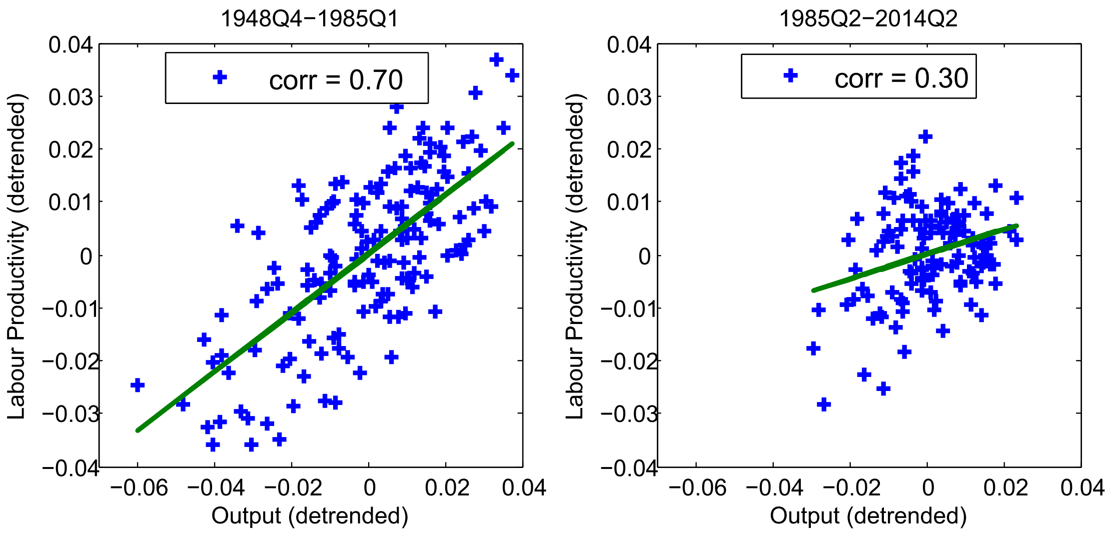


Figure 2.2: Maximum UI duration (in weeks) as plotted as against time periods from 1948Q1 to 2014Q2 (shaded areas denote recessions) (Source: ETA)

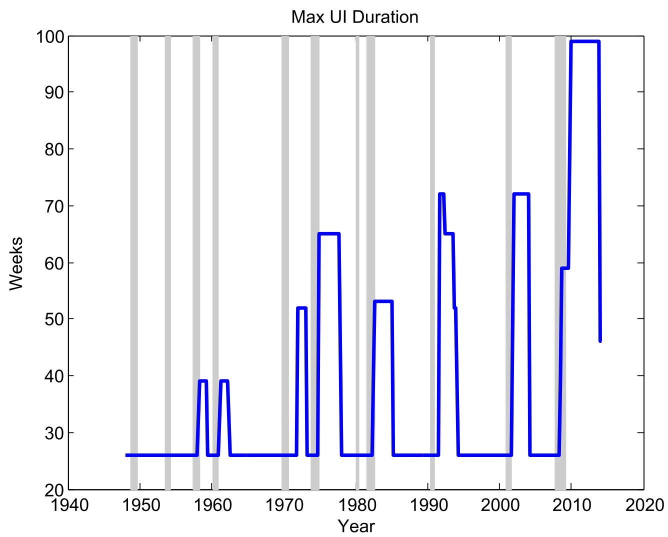


Figure 2.3: Total match surpluses $S^i; i \in \{e, UI, UU\}$ plotted against unemployment rate (u): For the match-specific and total factor productivities at the middle nodes

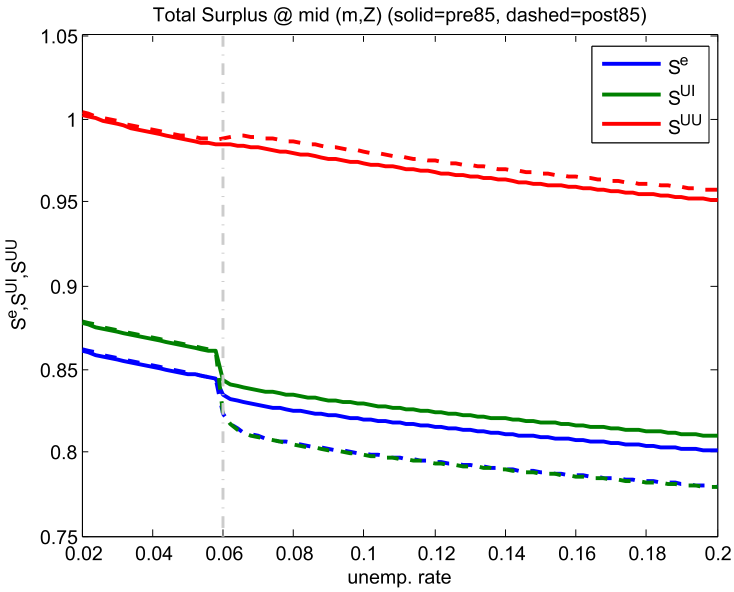


Figure 2.4: Conditional job finding rates (worker's meeting rates) by employment statuses plotted against unemployment rate: For the match-specific and total factor productivities at the middle nodes

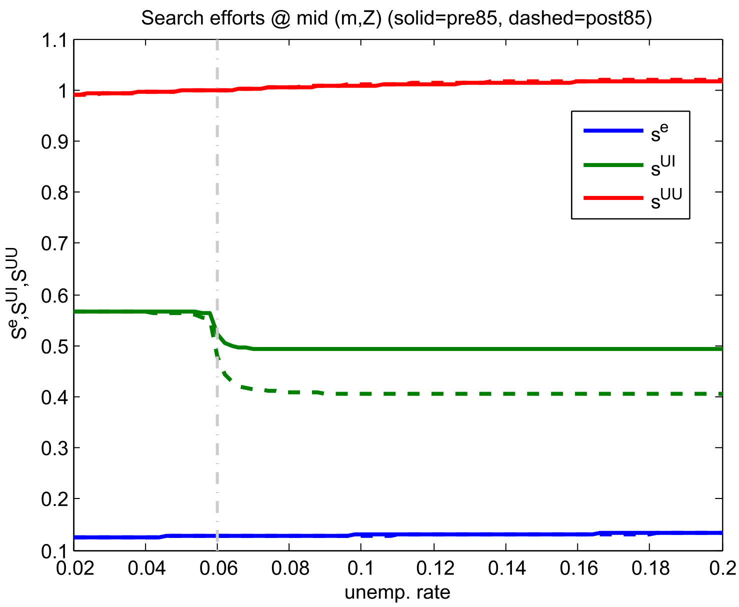


Figure 2.5: Model-generated (solid) and empirical (dashed) detrended series of main variables

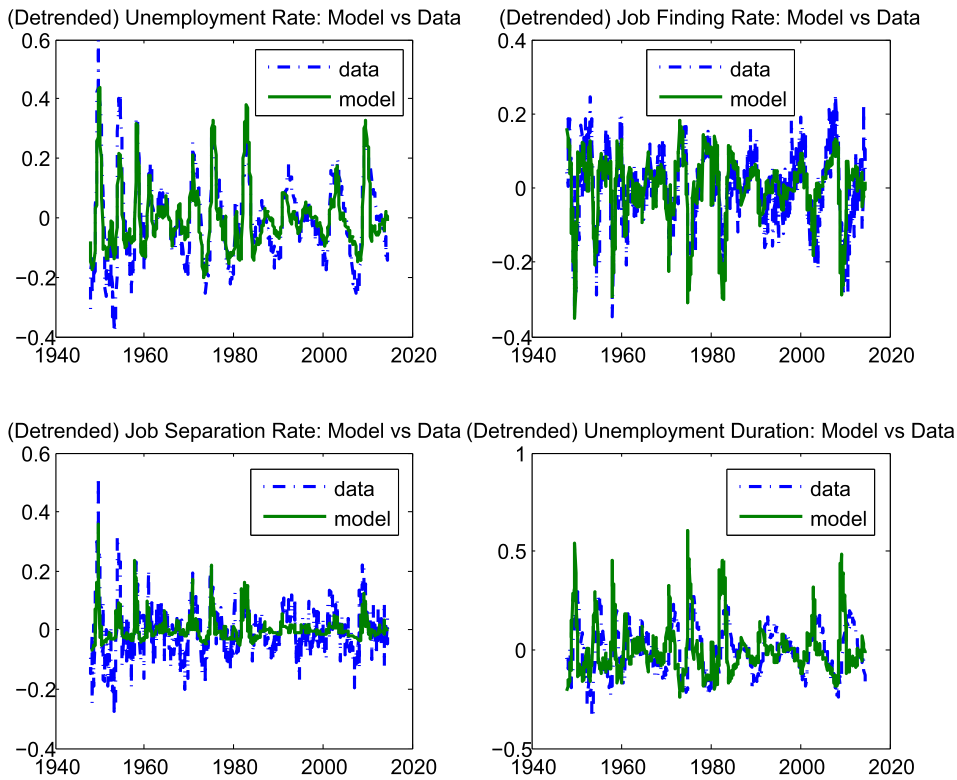


Figure 2.6: Model-generated (solid) and empirical (dashed) raw series of main variables

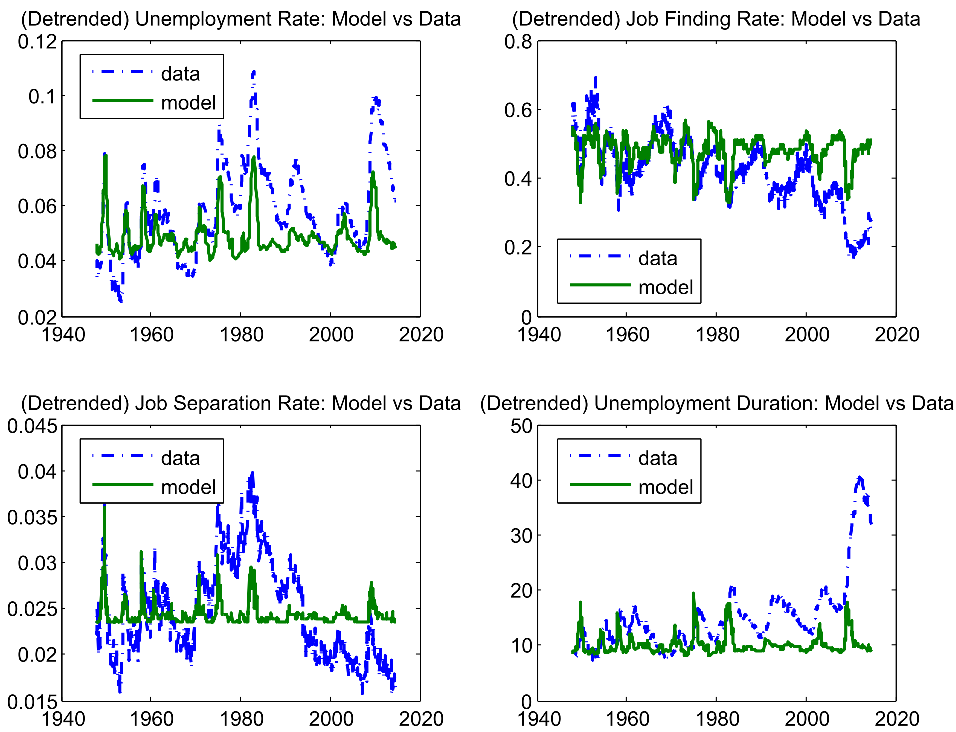


Figure 2.7: Model-generated (solid) and empirical (dashed) detrended series of insured unemployment rate

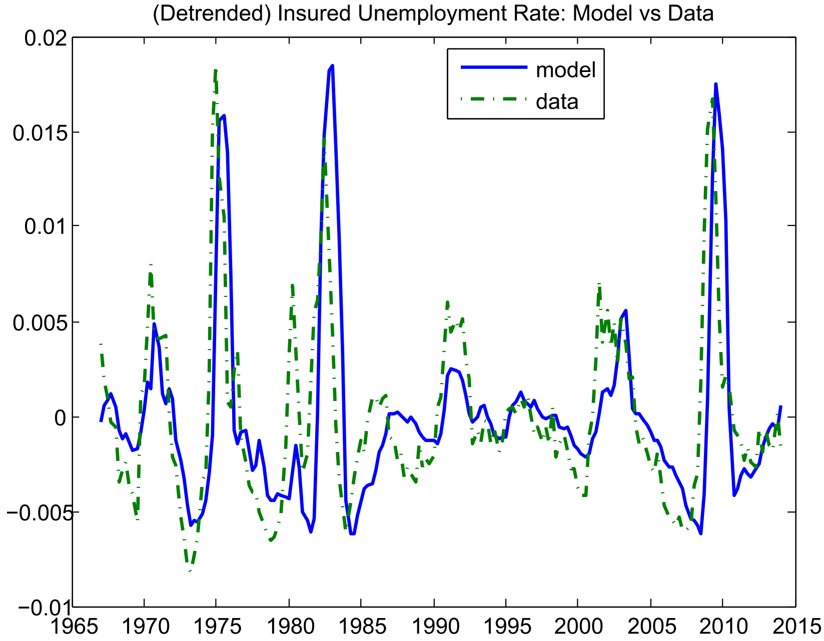


Figure 2.8: Model-generated (solid) and empirical (dashed) raw series of insured unemployment rate

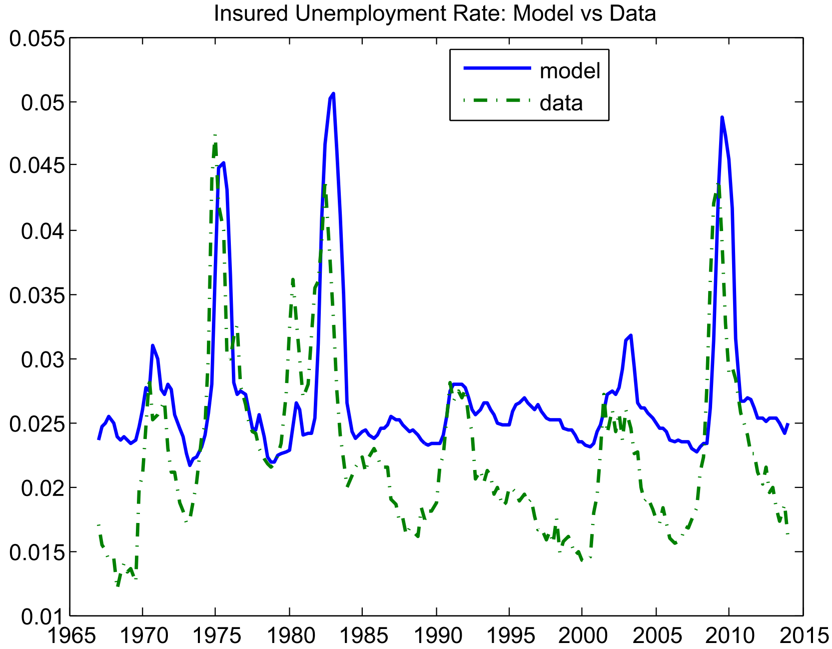


Figure 2.9: IRF of 1% Negative TFP Shock

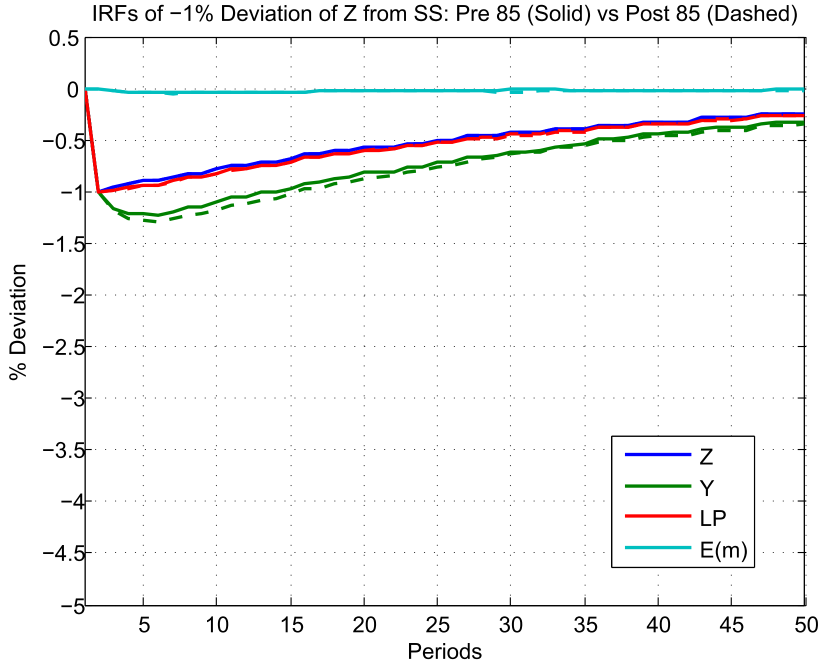


Figure 2.10: IRF of 2% Negative TFP Shock

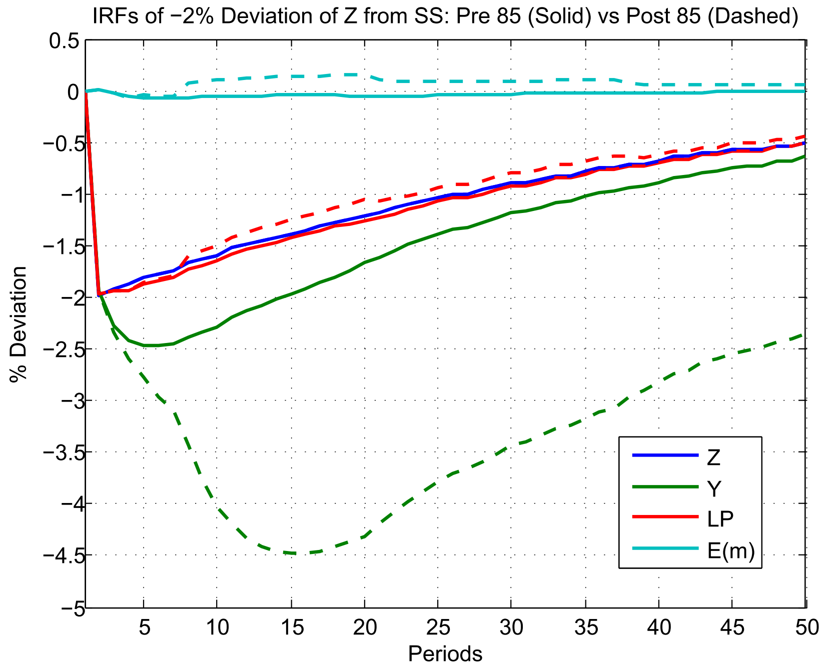
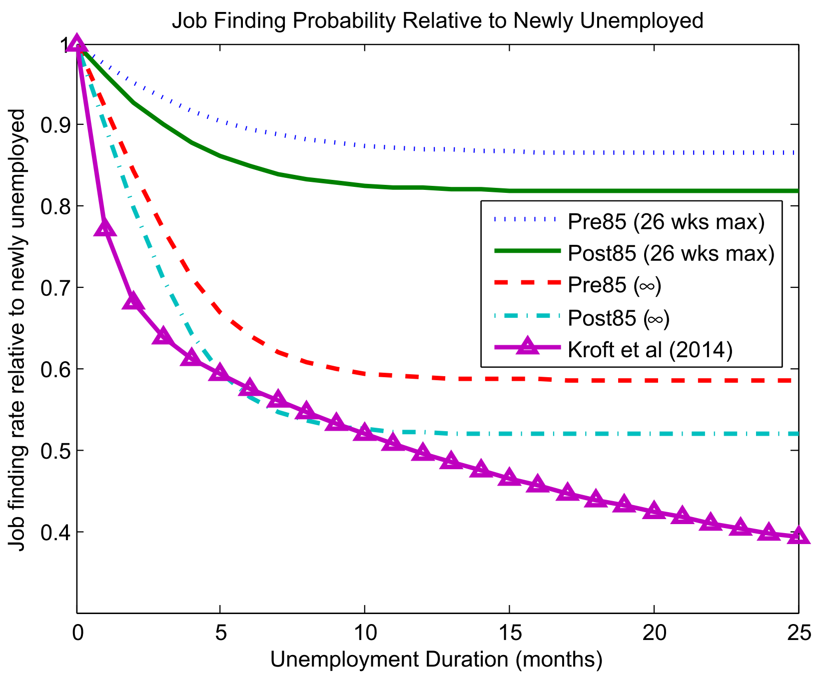


Figure 2.11: Duration-dependent Job Finding Probability (implied UI durations in brackets)



Chapter 3

Long-term Unemployment Dynamics and Unemployment Insurance Extensions

3.1 Introduction/Motivation

From the onset of the Great Recession, the US labour market exhibits dynamics never seen before in previous recessions. Underlying the persistently high unemployment is an unprecedented rise in the long-term unemployment (as represented by those whose unemployment duration is greater than 6 months) as seen in Figure 3.1. The long-term unemployment rate had never been above 2 percent apart from the early 1980s recession where it reached 2.5 percent. During the Great Recession, it went up to 4.4 percent representing 46 percent of the total unemployment population whilst its share was only 26 percent in the early 1980s recession.

This paper investigates the impact of unemployment insurance (UI) extensions on the long-term unemployment and the distribution of unemployment duration over the business cycles using a search and matching model in general equilibrium. While the analysis applies to the cyclical fluctuations in general, the focus of the paper is on the Great Recession, the period during which UI eligible unemployed workers could receive benefits for the maximum of 99 weeks (whereas the standard maximum UI duration is only 26 weeks) as depicted in Figure 3.2. From the same

Figure, it can be seen that the UI duration has been extended during recessionary periods since late 1950s and its generosity, as measured by weeks of maximum UI duration, has been increasing over time (apart from one extension in the early 1980s). In the US, there are primarily two types of UI extensions: (1) automatic UI extensions that are in the federal laws since 1970s and are triggered by the state (insured) unemployment rate, and (2) discretionary UI extensions that are issued specifically during the recessions.[1] Figure 3.3 shows that both the automatic and total UI extensions have been increasing in their generosity and that discretionary extensions are a feature of every recession since late 1950s.

Based on this countercyclical UI system, I extend the standard search and matching model to incorporate unemployment-dependent UI extensions, variable search intensity, endogenous separations, on-the-job search, and worker's heterogeneity in terms of productivity and benefit level. The job search decision of a worker depends not only on their UI status, benefit level, and individual productivity but also on the aggregate productivity and the unemployment rate which determine when and for how long UI extensions will occur.

Many empirical studies have documented how the labour market outcomes of unemployed workers can differ with respect to their UI status. These differences come in many forms including their unemployment duration and unemployment exit rate (Moffitt and Nicholson (1982), Moffitt (1985), Katz and Meyer (1990), Meyer (1990), Card and Levine (2000)), job search intensity (Krueger and Mueller (2010, 2011)) and consumption (Gruber (1997)). Katz and Meyer (1990) find a large fraction of UI recipients expect to be recalled and represent over half of the unemployment duration in the sample. This is related to a recent work by Fujita and Moscarini (2015) who show that the recall rate rises during the recession and that the negative duration dependence in unemployment exit rate only occurs among those who are eventually recalled. I provide further empirical evidence regarding the dif-

[1] The automatic extensions are called extended benefits (EB) whilst the ad-hoc extensions are under different names. For example, in 1958, the programme was called Temporary Unemployment Compensation Act (TUC) and in 1961, it was Temporary Unemployment Extended Compensation Act (TEUC). From 1991 onwards, the discretionary extensions have been under the name Emergency Unemployment Compensation (EUC).

ferences in labour market outcomes of unemployed workers with and without UI by studying their transition rates from unemployment and the stocks of unemployment durations. I find that the differences in the unemployment exit rates between insured and uninsured unemployed workers are more pronounced in 2010, when UI was extended up to 99 weeks, than in 2008 when no extensions was in place. As a result, in 2010, over half of the long-term unemployed workers were represented by the insured unemployed whilst in 2008 they represented only 15 percent of the long-term unemployed.

There is a large literature studying the effects of the recent UI extensions on the unemployment exit rate and total unemployment during the Great Recession. Empirical studies include (but not limited to) Farber and Valletta (2011), Fujita (2011), Valletta and Kuang (2010), Mazumder (2011), Rothstein (2011), Hagedorn, Karahan, Manovskii, and Mitman (2015), Barnichon and Figura (2014), and Hagedorn, Manovskii, and Mitman (2015). Most of these studies focus on the "micro" effect of the UI extensions, namely, the direct impact of increasing maximum UI duration on the probability of exiting unemployment or on the job search decisions of the unemployed. They have found a small but significant impact of UI extensions. A notable exception is Hagedorn, Karahan, Manovskii, and Mitman (2015). They take into account the response of job creation to benefit extensions and find a larger effect on unemployment.

A benefit of using a general equilibrium model is that I can distinguish between the direct impact of UI extensions on the number of insured unemployed workers and the responses of job search behaviour, match formation and match separation. Based on the direct UI effect and the response from job search (which I classify as the "micro" effect), I find that the peak of the unemployment rate would be 0.9-1.7 percentage points smaller if there was no extensions during the Great Recession. This is consistent with estimates from the existing empirical literature that are in the range of 0.1-1.8 percentage points.[2] With respect to the general equilibrium effect

[2] Fujita (2011) finds the UI extensions contribute to 0.8-1.8 percentage points increase in the unemployment rate during the Great Recession. Aaronson et al (2010)'s estimates are between 0.5-1.25 percentage points. Valetta and Kuang (2010)'s estimate is 0.4 percentage points. Rothstein (2011)'s estimates are between 0.1-0.5 percentage points.

where the response of match formation/separation decisions are also considered, I find a larger impact of the UI extensions similar to results from Hagedorn et al (2015). In this paper, however, the additional effect is from the match separation margin.

Quantitative studies on the effects of UI extensions are conducted by Mitman and Rabinovich (2014) on jobless recoveries, Faig, Zhang and Zhang (2012) on the volatility of unemployment and vacancies, and Nakajima (2012) whose focus is on the Great Recession. Nakajima (2012) studies an economy with transition dynamics and finds that the UI extensions can contribute to the rise of 1.4 percentage points in the unemployment rate. The model in this paper is most similar to that in Mitman and Rabinovich (2014). They use an equilibrium search and matching model to study the impact of UI extensions on jobless recoveries. In their model, the discretionary UI extensions are treated as unexpected and assumed to last forever by the agents in the economy (i.e., agents have adaptive expectations) such that the model's simulated UI extensions are exactly the same as the data. In this paper, I assume all the UI extensions are systematic and the agents have rational expectations regarding the timing and the length of these UI extensions which are driven solely by the aggregate productivity (via unemployment rate).[3] As a result, agents in my model would respond less strongly to UI extensions in comparison to theirs, in terms of both the job search intensity and the decision to form or dissolve a match. Additionally, workers in my model have control over their job search intensity whilst in their model workers do not make decisions on how hard to look for a job. Therefore, unemployed workers in my model have heterogeneous job finding rates according to their UI status and benefit level whilst there is a single job finding rate for all unemployed workers in their model. As previously mentioned, I show in the empirical section of the paper that insured and uninsured unemployed workers do have different labour market outcomes and that this gap widened during the Great Recession.

Heterogeneity in the job finding rates is crucial in explaining the unemploy-

[3] I show in the results section how consistent the model's generated UI extensions are with the data.

ment duration structure in the US labour market. As shown in Wiczer (2015), a single job finding rate implies the average unemployment duration and long-term unemployment that are just over half of what can be observed in the data.[4] This point regarding an inadequacy of a single job finding rate is key to the results in this paper. Not only unemployed workers in my model exit unemployment at different rates according to their UI status but even the insured workers themselves also have different exit rates due to different benefit levels.[5]

This paper also complements the literature on the incidence of the long-term unemployment and worker heterogeneity. Ahn and Hamilton (2016) use a state space model to uncover the unobserved heterogeneity of workers in terms of unemployment exit rate. Worker heterogeneity is also the focus in Hornstein (2012) in accounting for unemployment dynamics with different durations. Ravn and Sterk (2013) consider this difference in unemployment exit rates together with incomplete markets and price rigidities to study the amplification mechanism on unemployment. Carrillo-Tudela and Visschers (2014) offer an alternative explanation on the fluctuations of aggregate unemployment and its duration over business cycles by studying the role of unemployed workers' occupational mobility. Ahn (2016) extends Ahn and Hamilton (2016) to incorporate various observable characteristics of the workers (but not their UI statuses). My paper considers a degree of observed and unobserved worker heterogeneity where the former comes from the unemployment insurance status and the latter is from the worker's productivity which eventually affects the job finding rate.

To show how consistent the unemployment series at different durations from the model are with the empirical data, I estimate the same non-linear state space model in Ahn and Hamilton (2016) using Maximum Likelihood. I find the model's estimates are similar to the empirical values. This has implications on the sources of long-term unemployment. I show that their interpretation of unobserved heterogeneity is related to the UI statuses in my model since the insured unemployed

[4]Wiczer (2015) studies the rise of long-term unemployment using occupational mismatch.

[5]In Chapter 2, I show that a single job finding rate for insured unemployed workers hardly affects the distribution of unemployment durations. In this paper, I allow for the job finding rates of insured unemployed workers to vary with the benefit level and individual-specific productivity.

workers have a lower unemployment exit rate. I find that the worker's productivity does not matter much once different UI statuses are taken into account.

The heterogeneity in unemployment exit rates results in the negative duration dependence that is purely compositional. At longer durations, the pool of unemployed workers is more represented by those with lower exit rates. The duration-dependent unemployment exit rate is a featured result in several studies including Clark and Summers (1979), Machin and Manning (1999) and Elsby, Hobijn, and Şahin (2008). Kroft, Lange, Notowidigdo and Katz (2016) analyse the impact of a genuine duration dependence in unemployment exit rate along with the labour force participation margin on the rise of long-term unemployment. They also find little account for the observable characteristics of the workers (but they do not include UI statuses in their analysis). Elsby, Hobijn, Şahin and Valetta (2011) study the flows between non-participation and unemployment at different unemployment durations. Aaronson, Mazumder, and Schechter (2010) analyse the impact of the transition rates between employment, unemployment and non-participation as well as the labour force demographics on the long-term unemployment. While the labour force participation margin is undoubtedly important in accounting for unemployment, the model in this paper abstracts from it. I show in the empirical section that the labour force exit rate varied only little during the Great Recession even when conditioned on the UI status and several observable characteristics of workers. Barnichon and Figura (2014) also find similar results that UI extensions did not affect the labour force participation rate in the past 35 years.

To preview the results, the model can account for a large fraction of the observed rise in the long-term unemployment and realistic dynamics of the unemployment duration distribution during the Great Recession. The main driver of the long-term unemployment is the response of job search behaviour to UI extensions whilst the job separation margin is more important in accounting for the observed rise in total unemployment. In a counterfactual exercise, I show that eliminating all UI extensions during the Great Recession could potentially lower the unemployment rate by 0.9-3.4 percentage points. At the same time, it could drastically reduce the long-term unemployment rate by roughly 4 percentage points and the average unemployment duration by up to 27 weeks. The micro effect of UI extensions is consistent with the existing literature as its effect on the unemployment rate is minimal. I also analyse the impact of Reachback provision, a programme that provides UI eligility to unemployed workers who have already exhausted their benefits prior to the extensions of UI and have found a small impact on unemployment.

The main contribution of this paper is to quantify the impact of UI extensions on the incidence of long-term unemployment and on the unemployment duration distribution in a general equilibrium model, taking into account the responses of job search, match formation and job separation under rational expectation regarding the maximum UI duration. The framework is useful for policy experiments to study the mechanisms through which the UI extensions affect the aggregate labour market.

The paper is organised as follows. Section 2 discusses some motivating data on UI extensions and long-term unemployment during the Great Recession. Section 3 describes the model. Section 4 discusses the calibration exercise. Section 5 analyses the results under the baseline model and counterfactual experiments, and it also discusses welfare implications. Section 6 measures how consistent the model's results are with the empirical data. Section 7 concludes.

3.2 Empirical Evidence

I first examine the empirical evidence that (1) workers currently receiving UI benefits tend to find a job at a slower rate than those without UI and that (2) this gap between insured and uninsured workers' job finding rates was more pronounced during the Great Recession. These findings are important for explaining the surge in the long-term unemployment. I study the transition rates from unemployment to employment, unemployment and out-of-labour-force (OLF) (namely UE, UU and UOLF rates respectively) as well as the distributions of unemployment duration between 2006 and 2014 according to the UI statuses and several other observable characteristics of unemployed workers including age, education, gender, industry, occupation, reasons for unemployment and recall expectation. They are constructed from the CPS Basic Monthly Data and CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplement. I consider workers whose age is 16 years or older. Since the workers' UI history is only surveyed when the supplement takes place (every two years), I obtain the transition rates by merging the January supplement data with the basic monthly data for the following February. Transition rates are calculated as a fraction of unemployed workers conditioned on their UI status (i.e., whether they are currently receiving UI benefits or not) and possibly other characteristics moving into either employment, unemployment or OLF in the following month.

I focus on the changes in the transition rates in January 2008, when UI extensions were not in place, relative to January 2010, conveniently when the UI duration was just extended to 99 weeks in most states. Tables 3.2, 3.3 and 3.4 summarise respectively the UE, UU and UOLF rates in 2008 and 2010. I subsequently show that as a result of the increase in UE rate and the drop in UU rate, the share of long-term unemployed workers who were receiving UI benefits became larger in 2010 and 2012. The shares during 2006-2014 are summarised in Table 3.5. I contrast them with the shares of newly unemployed workers (with duration less than 5 weeks) who were receiving UI benefits in Table 3.6.

Job findings Table 3.2 shows that the job finding rate of current UI recipients is generally smaller than that of non-UI recipients and this gap became larger during the Great Recession. In January 2008, when there was no UI extensions, unemployed workers with and without UI found a job at rate 21 percent and 28 percent respectively, whilst in January 2010, when the maximum UI duration was 99 weeks, the job finding rate of insured unemployed workers fell dramatically to 7 percent, 11 percentage points smaller than that of the uninsured unemployed. The UE rate by UI status for 2006-2014 periods is plotted in Figure 3.4.

These findings are still consistent when I control for other observable characteristics of the workers. Insured workers had a lower job finding rate than uninsured workers in most subgroups in 2008 and in all subgroups in 2010.[6] The job finding

[6]Current UI recipients in the following subgroups find a job at a faster rate than non-UI recipients: professional/business services, those on temporary layoff, those who are expecting a recall. How-

rates from 2008 to 2010 for current UI recipients in most subgroups fell by a larger maginitude than for non-UI recipients.

To stay unemployed or to exit the labour force? Accompanying the drop in job findings during the Great Recession are an increase in the UU rate and a small change in the UOLF rate. This is the case regardless of the workers' UI statuses. Table 3.3 shows that from 2008 to 2010 the UU rate increased by 16 percentage points for workers with UI and by 12 percentage points for workers without UI. At the same time, Table 3.4 shows that the fall in the UOLF rate was only 2(3) percentage points for the (un)insured unemployed. This finding suggests that UI extensions do not significantly affect the labour force exit rate.[7] The same results apply when I condition on other observable characteristics of workers. I plot the UU and UOLF rates by UI status during 2006-2014 in Figures 3.5 and 3.6 respectively.

Distribution of unemployment duration I now shift the focus to the stocks of unemployment by durations. Figure 3.7 shows that the unemployment duration distribution shifted towards longer duration bins in 2010 and 2012. This is expected since the average job finding rate fell substantially during these periods, but what is interesting is that the shares of insured unemployed workers in longer duration bins also increased dramatically as depicted in Figure 3.8.

In fact, the share of long-term unemployed workers who were current UI recipients rose substantially from 15 percent to 51 percent between 2008 and 2010 as shown in Figure 3.9. This large increase in the share of current UI recipients during the Great Recession is a prominent feature in all subgroups considered as shown in Table 3.5.[8] In Figure 3.9, I contrast this with the shares of insured workers amongst the newly unemployed that did not increase as much.

---

ever, workers in professional/business services have a much lower job finding rate in 2010 (at 4.3 percent) than in 2008 (at 46 percent). It is not surprising that insured workers knowing or expecting to be back at work have a job finding rate similar to uninsured workers in the same subgroups.

[7]For simplicity, the model I present in the following section will therefore not feature the labour force participation margin.

[8]In most subgroups, there is at least a 30 percentage point increase in the share of current UI recipients from 2008 to 2010. This finding does not apply to two subgroups: workers with less than high school degree and workers with low-skilled occupations.

In summary, insured unemployed workers tend to find a job at a slower rate than those without UI and this gap was more pronounced when the maximum UI duration was extended during the Great Recession. These results largely apply when I condition on several other observable characteristics of the workers. Accompanying the drop in the job finding rate was a substantial rise in the UU rate whilst the UOLF rate remained rather stable. Following the change in these transition rates, the long-term unemployment rose dramatically during the Great Recession and were mainly represented by insured unemployed workers.

3.3 Model

I present in this section a random search and matching model à la Pissarides (2000) with endogenous separations, variable job search intensity and on-the-job search. On top of this, I allow for the maximum UI duration to depend on the unemployment rate. Workers may differ in terms of UI status, benefit level and labour productivity. Only the last attribute is permanent. These differences not only affect how hard workers search for jobs but also how likely worker-firm matches are formed and dissolved. Workers with higher outside options, e.g. those with higher (potential) UI benefits, tend to exit unemployment more slowly and are more likely to quit.

I begin this section by specifying technology and preferences of workers and firms as well as the UI duration policy and UI eligibility. I then discuss wage determination, and finally present the equilibrium conditions.

3.3.1 Technology and Preferences

Time is discrete and runs forever. There are two types of agents in the economy: a continuum of workers of measure one and a large measure of firms. Workers have either high or low productivity (type H or L). A match consists of one worker and one firm whose output depends on the aggregate productivity (z), its match-specific productivity (m), and type-i worker's productivity (η_i). Specifically,

$$y_{it}(m) \quad = \quad z_t \times m \times \eta_i \quad ; i \in \{H, L\}$$

The price of output $y_{it}(m)$ is normalised to one. The aggregate productivity z has the following AR(1) representation

$$\ln z_t = \rho_z \ln z_{t-1} + \varepsilon_t$$

where the only exogenous shock in the model ε_t is normally and independently distributed with mean zero and standard deviation σ_z. The match-specific productivity m is drawn at the start of every new worker-firm match from a distribution $F(m)$. At the rate $1-\lambda$, a given match keeps its match quality m to the next period, otherwise it has to redraw a new m from the same distribution $F(m)$ for its production next period. η_i is type-i worker's productivity where $\eta_L < \eta_H$ and η_H is normalised to 1. A worker's productivity is permanent.

With respect to preferences, both workers and firms are infinitely-lived and risk-neutral. They discount future flows by the same factor $\beta \in (0,1)$. Workers are either employed (e), insured unemployed (UI) or uninsured unemployed (UU). They exert job search effort s at the cost of $\nu_e(s)$ when employed, and at the cost $\nu_u(s)$ when unemployed regardless of their UI status. These search cost functions $\nu_e(.)$ and $\nu_u(.)$ are strictly increasing and convex. During unemployment, workers' job search intensity may vary depending on their UI status, benefit level and productivity, whilst during employment, it depends on their match quality and productivity. For employment status $j \in \{e,u\}$, a worker's period utility flow is $c_i - \nu_j(s)$ where c_i is type-i worker's consumption:

$$c_{it} = \begin{cases} w_{it}(m,\tilde{m}) & \text{if employed at match quality } m \\ h + b_i(\tilde{m}) & \text{if insured unemployed} \\ h & \text{if uninsured unemployed} \end{cases}$$

where $w_i(m,\tilde{m})$ is the wage of type-i worker that depends on m, the current match quality, and $\tilde{m}$, the match quality in her most recent employment. h can be interpreted as home production or leisure flow during unemployment. $b_i(\tilde{m})$ is the UI benefit of type-i worker with match quality $\tilde{m}$ in her most recent employment. I describe the UI system in the next subsection.

On the firm side, they are either matched with a worker or unmatched. Matched firms sell output, pay negotiated wage to their workers and pay lump-sum tax τ to finance the UI payment. A match is exogenously separated at rate δ and an endogenous separation can occur when either the value of a worker or firm is negative. When firms are unmatched with a worker, they post a vacancy at cost κ and cannot direct their posting to a specific type of workers.

3.3.1.1 UI Duration Policy and UI Eligibility

UI Duration The maximum UI duration is captured by the variable $\phi(u_t)$. Namely, insured unemployed workers exhaust their UI benefits at the rate

$$\phi(u_t) \equiv \phi_L \mathbb{1}\{u_t \geq \bar{u}\} + \phi_H \mathbb{1}\{u_t < \bar{u}\}$$

where $\phi_L < \phi_H$ implying the rate is a decreasing function of the unemployment rate u_t in the economy.[9] Since the inverse of $\phi(u_t)$ is the expected duration of receiving UI benefits, a fall in the rate implies an unemployment insurance extension. This UI duration policy is set to mimic the rules for the UI extensions in the US where these extensions are dependent on the state unemployment rate (above which the extensions are triggered). During normal times when $u_t < \bar{u}$, the UI exhaustion rate is ϕ_H which is set to imply a standard UI duration of 26 weeks. When the unemployment rate is high and above $\bar{u}$ (often in recessions), insured unemployed workers exhaust the benefits at a slower rate ϕ_L. I can capture the observed increase in the duration of UI extensions in the US by lowering in the value that ϕ_L takes.

UI Eligibility Upon losing a job, employed workers become uninsured at the rate $1-\psi$. This is to reflect how some unemployed workers do not take up their UI benefits. On top of this, insured unemployed workers lose UI eligibility after an unproductive meeting with a firm at rate ξ to reflect how UI recipients' job search are being monitored.

[9] This stochastic UI exhaustion is first used in Fredericksson and Holmlund (2001). Mitman and Rabinovich (2014), Faig, Zhang and Zhang (2012), and also the model in Chapter 2 of this thesis treat this rate to be state-dependent.

UI payment is financed each period by lump-sum tax payment (τ) from matched firms:

$$\tau(1-u) = \sum_{i\in\{H,L\}} \sum_{\tilde{m}} u_i^{UI}(\tilde{m}) b_i(\tilde{m})$$

where $u_i^{UI}(\tilde{m})$ is the number of type-i insured unemployed workers whose UI benefit is $b_i(\tilde{m})$.

3.3.1.2 Search and Matching

Workers and unmatched firms meet via a meeting function $M(s,v)$ where s is the aggregate search intensity and v is the number of job vacancies. The meeting function $M(.,.)$ has constant returns to scale, and is strictly increasing and concave in its arguments. Market tightness can be defined as $\theta \equiv v/s$. The conditional job finding probability per unit of search is $\frac{M}{s} = M(1,\theta)$; therefore, the conditional job finding probability of type-i worker with employment status j is $s_i^j M(1,\theta) \equiv p_i^j(\theta)$.[10] Analogously, the probability that a firm meets a worker is $\frac{M}{v} \equiv q(\theta)$.

3.3.1.3 Timing

1. Given (u_t, z_t), production takes place and UI duration policy $\phi(u_t)$ is set
2. Workers choose job search effort
3. Current matches draw a new m at rate λ
4. Workers and unmatched firms meet
5. Aggregate productivity z_{t+1} next period is realised
6. Matches/meetings dissolve
7. u^{UI} lose UI eligibility at rate $\phi(u_t)$ if not meeting a firm, or at rate $\phi(u_t) + \big(1-\phi(u_t)\big)\xi$ if a meeting has occurred
8. Unemployment u_{t+1} for next period is realised

[10]The conditional job finding probability is essentially the probability that a worker meets a firm. The true job finding rate dependes on whether such a meeting leads to a successful match formation.

3.3.1.4 Workers' Value Functions

I first define the set of state variables as $\omega \equiv \{z, u, u_i, u_i^{UI}(\tilde{m}), u_i^{UU}, e_i(m); \forall m, \tilde{m} \text{ and } i \in \{H, L\}\}$ where u_i is the number of type-i unemployed workers, $u_i^{UI}(\tilde{m})$ is the number of type-i insured unemployed workers whose match quality in their most recent employment was $\tilde{m}$, u_i^{UU} is the number of type-i uninsured unemployed workers and $e_i(m)$ is the number of type-i employed workers with current match quality m.

Employed workers The value of a type-i employed worker with last period's employment status and associated benefit level $j \in \{e(\tilde{m}), UI(\tilde{m}), UU\}$ is

$$\begin{aligned}
W_i^j(m;\omega) = \max_{s_i^e(m;\omega)} \; & w_i^j(m;\omega) - \nu_e(s_i^e(m;\omega)) + \beta E_{\omega'|\omega}\Bigg[\\
& \underbrace{(1-\delta)(1-\lambda)}_{\text{Pr(stay matched, keep } m)} \Big[\underbrace{(1-p_i^e(m;\omega)(1-F(m)))}_{\text{Pr(stay with current firm)}} W_i^{e(m)+}(m;\omega') \\
& + \underbrace{p_i^e(m;\omega)(1-F(m))}_{\text{Pr(move to new firm)}} E_{m'|m'>m}[W_i^{e(m)+}(m';\omega')] \Big] \\
& + \underbrace{(1-\delta)\lambda}_{\text{Pr(stay matched, new } m)} E_{m'} \Big[\underbrace{(1-p_i^e(m;\omega)(1-F(m')))}_{\text{Pr(stay with current firm)}} W_i^{e(m)+}(m';\omega') \\
& + \underbrace{p_i^e(m;\omega)(1-F(m'))}_{\text{Pr(move to new firm)}} E_{m''|m''>m'}[W_i^{e(m)+}(m'';\omega')] \Big] \\
& + \underbrace{\delta}_{\text{Pr(match exogenously separated)}} \Big((1-\psi)U_i^{UI}(m,\omega') + \psi U_i^{UU}(\omega') \Big) \Bigg]
\end{aligned} \tag{3.1}$$

where $W_i^{e(m)+}(m';\omega') \equiv \max\{W_i^{e(m)}(m';\omega'), (1-\psi)U_i^{UI}(m,\omega') + \psi U_i^{UU}(\omega')\}$ showing that employed workers can always become unemployed (and get unemployment insurance at rate $1-\psi$).[11] $U_i^{UI}(m)$ and U_i^{UU} are respectively the value of the insured unemployed with benefit $b_i(m)$ and the value of the uninsured unemployed. The expressions for optimal search intensity of employed workers can be found in Appendix 3.8.1.

[11] Similar to the argument made in Krause and Lubik (2010), the current wage affects neither the decision of the employed worker to quit nor their job search effort due to the timing of the model and the bargaining structure. As a result, the bargaining set is still convex and Nash bargaining is still applicable for the determination of wage. Shimer (2006) discusses the implications of having a non-convex payoff set.

Unemployed worker The difference between insured and uninsured workers stems from the period utility flow during unemployment. Amongst insured unemployed workers, their period utility flow can differ according to $\tilde{m}$, their match quality in the most recent employment, since the UI benefits are attached to this variable. Therefore, the values of type-i uninsured unemployed workers and insured unemployed workers with benefit $b_i(\tilde{m})$ are respectively

$$\begin{aligned} U_i^{UU}(\omega) = \max_{s_i^{UU}(\omega)} \; & h - \nu_u(s_i^{UU}(\omega)) + \beta E_{m'\omega'|\omega}\Big[\ldots \\ & p_i^{UU}(\omega)\max\{W_i^{UU}(m';\omega'), U_i^{UU}(\omega')\} + (1-p_i^{UU}(\omega))U_i^{UU}(\omega')\Big] \end{aligned} \tag{3.2}$$

and

$$\begin{aligned} U_i^{UI}(\tilde{m},\omega) = \max_{s_i^{UI}(\tilde{m},\omega)} \; & b_i(\tilde{m}) + h - \nu_u(s_i^{UI}(\tilde{m},\omega)) \\ & +\beta E_{m'\omega'|\omega}\Big[p_i^{UI}(\tilde{m},\omega)\max\Big\{W_i^{UI(\tilde{m})}(m';\omega'),\ldots \\ & \underbrace{(1-\phi_u)(1-\xi)}_{\text{Pr(keep UI | meeting a firm)}}U_i^{UI}(\tilde{m},\omega') + \underbrace{(\phi_u+(1-\phi_u)\xi)}_{\text{Pr(lose UI | meeting a firm)}}U_i^{UU}(\omega')\Big\} \\ & +(1-p_i^{UI}(\tilde{m},\omega))\Big((1-\phi_u)U_i^{UI}(\tilde{m},\omega') + \phi_u U_i^{UU}(\omega')\Big)\Big] \end{aligned} \tag{3.3}$$

The expressions for optimal search intensity of insured and uninsured unemployed workers are shown in Appendix 3.8.1.

3.3.1.5 Firms

Matched firms Similar to the setup of employed workers, the value of a matched firm with type-i worker whose work history is $j \in \{e(\tilde{m}), UI(\tilde{m}), UU\}$ is

$$\begin{aligned} J_i^j(m;\omega) = \; & y_i(m;\omega) - w_i^j(m;\omega) - \tau(\omega) + \beta E_{\omega'|\omega}\Big[\ldots \\ & (1-\delta)(1-\lambda)\Big[(1-p_i^e(m;\omega)(1-F(m)))J_i^{e(m)+}(m;\omega')\Big] \\ & +(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))J_i^{e(m)+}(m';\omega')\Big]\Big] \end{aligned} \tag{3.4}$$

where $J_i^{e(m)+}(m';\omega') \equiv \max\{J_i^{e(m)}(m';\omega'),0\}$. Note that I have already imposed the free entry condition which implies the value of an unmatched firm is zero, i.e. $V(\omega)=0, \forall\omega$.

Unmatched firms Since unmatched firms cannot direct their search to a particular type of worker, the distribution of workers' search intensity over employment status, UI status, benefit level, productivity type and match quality of on-the-job searchers (as denoted by ζ's in the following equation) enters the unmatched firm's problem and, therefore, becomes a part of the state variables. The value of an unmatched firm is

$$\begin{aligned} V(\omega) &= -\kappa + \beta q(\omega) E_{\omega'|\omega}\Bigg[\sum_{i\in\{H,L\}}\Big(\sum_m \zeta_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[J_i^{e(m)+}(m';\omega')] \\ &\quad + \sum_m \zeta_i^{UI}(m,\omega)E_{m'}[J_i^{UI(m)+}(m';\omega')] + \zeta_i^{UU}(\omega)E_{m'}[J_i^{UU+}(m';\omega')]\Big)\Bigg] \end{aligned} \tag{3.5}$$

$$\begin{aligned} \text{where}\quad \zeta_i^e(m) &= \frac{(1-\lambda)s_i^e(m)e_i(m)+\lambda f(m)\sum_m s_i^e(m)e_i(m)}{s} \\ \zeta_i^{UI}(m) &= \frac{s_i^{UI}(m)u_i^{UI}(m)}{s};\quad \zeta_i^{UU} = \frac{s_i^{UU}u_i^{UU}}{s} \\ s &= \sum_{i\in\{H,L\}}\Big(\sum_m\big(s_i^e(m)e_i(m)+s_i^{UI}(m)u_i^{UI}(m)\big)+s_i^{UU}u_i^{UU}\Big) \end{aligned}$$

3.3.2 Wage and Surplus

Wages are negotiated bilaterally using a generalised Nash bargaining rule. For $i\in\{H,L\}$, type-i workers with previous employment status $j\in\{e(\tilde{m}),UI(\tilde{m}),UU\}$ and match quality m receive

$$w_i^j(m;\omega) = \text{argmax}\Big(WS_i^j(m;\omega)\Big)^{\mu}\Big(J_i^j(m;\omega)\Big)^{(1-\mu)} \tag{3.6}$$

where μ is the worker's bargaining power. WS_i^j is the surplus of type-i employed workers with history j and it is the difference between the value of working and the corresponding outside option. We can define the total match surplus $S_i^j \equiv WS_i^j + J_i^j$. As a result, $WS_i^j = \mu S_i^j$ and $J_i^j = (1-\mu)S_i^j$. The surpluses of employed workers are as follows

$$
\begin{aligned}
WS_i^{e(\tilde{m})}(m;\omega) &\equiv W_i^{e(\tilde{m})}(m;\omega) - (1-\psi)U_i^{UI}(\tilde{m},\omega) - \psi U_i^{UU}(\omega) \\
WS_i^{UI(\tilde{m})}(m;\omega) &\equiv W_i^{UI(\tilde{m})}(m;\omega) - (1-\phi(u))(1-\xi)U_i^{UI}(\tilde{m},\omega) \\
&\quad -(\phi(u)+(1-\phi(u))\xi)U_i^{UU}(\omega) \\
WS_i^{UU}(m;\omega) &\equiv W_i^{UU}(m;\omega) - U_i^{UU}(\omega)
\end{aligned}
$$

The expressions for total match surpluses can be found in Appendix 3.8.1.

3.3.3 Recursive Competitive Equilibrium

A recursive competitive equilibrium is characterised by value functions, $W_i^{e(\tilde{m})}(m;\omega)$, $W_i^{UI(\tilde{m})}(m;\omega)$, $W_i^{UU}(m;\omega)$, $U_i^{UI}(\tilde{m},\omega)$, $U_i^{UU}(\omega)$, $J_i^{e(\tilde{m})}(m;\omega)$, $J_i^{UI(\tilde{m})}(m;\omega)$, $J_i^{UU}(m;\omega)$, and $V(\omega)$; market tightness $\theta(\omega)$; search policy $s_i^e(m;\omega)$, $s_i^{UI}(m,\omega)$ and $s_i^{UU}(\omega)$; and wage functions $w_i^{e(\tilde{m})}(m;\omega)$, $w_i^{UI(\tilde{m})}(m;\omega)$, and $w_i^{UU}(m;\omega)$, such that, given the initial distribution of workers over productivity level, employment status, UI status, benefit level and match productivity, the government's policy $\tau(\omega)$ and $\phi(\omega)$, and the law of motion for z:

1. The value functions and the market tightness satisfy the Bellman equations for workers and firms, and the free entry condition, namely, equations (3.1), (3.2), (3.3), (3.4) and (3.5)

2. The search decisions satisfy the FOCs for optimal search intensity, which are equations (3.7), (3.8) and (3.9)

3. The wage functions satisfy the FOCs for the generalised Nash bargaining rule (equation (3.6))

4. The government's budget constraint is satisfied each period

5. The distribution of workers evolves according to the transition equations (3.10), (3.12) and (3.13), which can be found in Appendix 3.8.2, consistent with the maximising behaviour of agents

3.3.4 Solving the Model

In order to compute the market tightness (and, in effect, total match surpluses and search effort) in the model, the agents in the economy need to keep track of the distribution of workers over the productivity level, employment status, UI status, benefit level and match quality $\{e_i(m), u_i^{UI}(\tilde{m}), u_i^{UU}; i \in \{H, L\}, \forall m, \tilde{m}\}$ as they enter the vacancy creation condition (equation 3.5). In order to predict next period's unemployment rate they need to know the inflow into and outflow from unemployment which are based on this distribution. I use the Krusell & Smith (1998) algorithm to predict the laws of motion for both the insured and total unemployment rates as a function of current unemployment rate (u) and aggregate productivity (z). As the distributions of employed workers by match quality and insured unemployed workers by benefit level do not vary much over time, I use the stochastic steady state distributions (also separating between high and low unemployment states for the distribution of the insured unemployed), and adjust for the employment rate that can be inferred from the state variables. I report the performance of this approximation in Appendix 3.8.3.

3.4 Calibration

Before I calibrate the model to match the US economy, I specify the functional forms for the search cost functions, the distribution function of the match-specific productivity and the meeting function between workers and firms. I obtain a subset of the parameters using the simulated method of moments. The rest of the parameters are taken from the empirical data and the literature. Table 3.8 summarises the pre-specified parameters while table 3.10 describes the calibrated ones.

Functional forms I assume the search cost function takes the following power function

$$\nu_j(s) \quad = \quad a_j s^{1+d_j} \; ; \;\; j \in \{e, u\}$$

where a_j and d_j are strictly positive scalars. I distinguish the search cost only between employment (e) and unemployment (u) to control for the relation between job-to-job transition rate and the job finding rate. Workers of type-H and type-L face the same cost of search and so do unemployed workers with and without UI.

With respect to the distribution of match quality, a worker-firm match draws a new m from the following Beta distribution

$$F(m) = \underline{m} + \text{betacdf}(m - \underline{m}, \beta_1, \beta_2)$$

where β_1 and β_2 are strictly positive scalars, and $\underline{m} > 0$ is the lowest productivity level.

The meeting function between unmatched firms and workers is similar to that in den Haan, Ramey and Watson (2000) with the introduction of search intensity

$$M(s,v) = \frac{sv}{\left(s^l + v^l\right)^{\frac{1}{l}}}; l > 0$$

Discretisation I discretise the aggregate productivity (z) using Rouwenhurst (1995)'s method to approximate an AR(1) process with a finite-state Markov chain. I use 51 nodes to solve the model and 5,100 nodes by linear interpolation in the simulations. Similarly, I use 51 equidistant nodes to approximate the Beta distribution of the match-specific productivity $F(m)$ when solving the model and 5,100 nodes by linear interpolation in the simulations. I define $f(m)$ to be $F'(m)/\sum_m F'(m)$ where $F'(m)$ is the probability density function of $F(m)$. Finally, I use 101 equidistant nodes to approximate the unemployment rate between 0.02 to 0.2.

Simulation I apply the calibrated model to the U.S. economy by feeding in the productivity shocks that match the deviations of output (GDP per capita) from HP trend as well as the observed maximum UI durations during each recession. It is useful to note that the timing of each UI extension and how long it lasts are not predetermined. They are purely the result of the model's simulated unemployment rate which can be used to measure how well the model can replicate the US labour market.

Additionally, from May 2007, the Emergency Unemployment Compensation law has included the "Reachback Provision" providing UI eligility to unemployed workers who have already exhausted their benefits prior to the extensions of UI. I also simulate the model accordingly and study the impact of this programme in the results section.

3.4.1 Pre-specified Parameters

The pre-specified parameters in the model are summarised in Tables 3.8 and 3.9. The model is monthly and I use the value 0.9967 for the discount factor β, implying an annual interest rate of 4% which is the U.S. average. I follow Fujita and Ramey (2012) in pinning down the vacancy creation cost κ to be 0.0392 using survey evidence on vacancy durations and hours spent on vacancy posting.[12] I assign μ, the worker's bargaining power, to be 0.5 following den Haan, Ramey and Watson (2000).

ϕ_H and ϕ_L are respectively the UI exhaustion rates during normal periods and recessions. I set ϕ_H to be 1/6 which implies the standard maximum UI duration of 26 weeks given the monthly frequency. With regards to the UI extensions during recessions, I can sort them into four main UI duration groups:

1. 39 weeks (9 months) for January 1948 - December 1971
2. 52 weeks (1 year) for January 1972 - December 1974 and July 1982 - September 1991
3. 68 weeks (16 months) for January 1975 - June 1982 and October 1991 - July 2008
4. 90 weeks (21 months) for August 2008 - June 2014

The above durations are obtained by averaging the observed maximum UI durations over the respective periods when UI were extended. The value ϕ_L changes and implies the maximum UI duraitons according to the above UI duration regimes.

[12] Fujita and Ramey (2012) find the vacancy cost to be 17% of a 40-hour-work week. Normalising the mean productivity to unity, this gives the value of 0.17 per week or 0.0392 per month. The actual mean productivity may be higher than (but not greatly different from) unity due to truncation from below of the match-specific quality.

Note that these are the maximum UI durations used only when the unemployment rate is above the threshold $\bar{u}$. For example, in the simulation, the UI extension in the Great Recession is not triggered until April 2009. I set $\bar{u}$ to be 6.5 percent which has been historically used as a criterion in most of the UI extensions.

To determine the utility flow of type-i unemployed workers, h and, if insured, $b_i(m)$, I use the results in Gruber (1997). In particular, the drop in consumption for the newly unemployed workers is 10 percent when receiving UI and 24 percent when not receiving UI given the replacement rate of 50 percent.[13] To find the implied h and $b_i(m)$ given a set of parameters, I first guess the mean wages for the (type-i) unemployed with different match qualities $\{w^0(m), w_i^0(m); \forall m\}$ and set h such that the average ratio of h to $w^0(m)$ is 0.76 (where I use the steady state distribution of unemployed workers by match qualities to compute the weighted average). For $b_i(m)$, it is set such that the ratio of $h + b_i(m)$ over $w_i^0(m)$ is 0.9 for each match quality m. I then solve and simulate the model to check if the guess is close to its counterpart from the simulation. If it is not, I replace the guessed wages with the simulated ones and repeat until they are close enough.

The slope of the search cost function for the unemployed a_u is normalised such that the search effort of the uninsured unemployed s^{UU} is unity when the economy is in the steady state, similar to Nagypál (2005). The power parameters in the search cost functions for both employed and unemployed workers (d_e and d_u) are set to unity in line with Christensen, Lentz and Mortensen (2005) and Yashiv (2000) implying a quadratic search cost function.

3.4.2 Calibrated Parameters

I use the simulated method of moments to assign values to the remaining twelve parameters $\{l, \delta, \lambda, \psi, \xi, a_e, \underline{m}, \beta_1, \beta_2, \rho_z, \sigma_z, \eta_L\}$ by matching main statistics in the U.S. labour market as well as the labour productivity process during 1948-2007.[14]

[13]Aguiar and Hurst (2005) report the drop in food consumption of workers upon becoming unemployed to be 5 percent and the drop in food expenditure to be 19 percent. However, in their study, unemployed workers are not distinguished by their UI status which makes it impossible separately identify h and $b_i(m)$'s under the present calibration strategy.

[14]The calibrated parameters are to minimise the sum of squared residuals of percentage changes between the model-generated moments and their empirical counterparts.

The twelve moments I try to match are the following:

- First and second moments of unemployment rate, job finding rate, job separation rate, and average unemployment duration
- First moment of job-to-job transition rate and insured unemployment rate
- Second moment and autocorrelation of labour productivity[15]

The model's generated moments are reported in Table 3.7 along with their empirical counterparts. Table 3.11 shows other related moments not targeted in the calibration. The values of calibrated parameters are in Table 3.10.

In terms of the targeted moments, the baseline model matches the twelve targeted moments quite well overall. However, the insured unemployment rate is slightly higher and the job finding rate is more volatile than in the data. With regards to related moments that are not targeted, it can match the dynamics of unemployment grouped in four duration bins quite well in terms of the first and second moments. However, the model could further improve on the volatility of vacancies and the correlation between unemployment and vacancies.[16]

3.5 Results

In this section, I first discuss the model's performance in generating realistic dynamics of the US labour market with the focus on the long-term unemployment and the unemployment duration structure. The results are based on the aggregate productivity series that matches the deviations of output from its HP trend as depicted in Figure 3.10.[17] Next, I study the mechanisms of the model in generating such dynamics, particularly how the three following channels respond to UI extensions:

[15]The transition rates are author's own calculations based on the CPS data. For output, I use the quarterly real GDP series provided by the Bureau of Economic Analysis (BEA), and I use the BLS quarterly series for non-farm output per job to represent the labour productivity.

[16]The main reason why vacancies are not as volatile as they are in the data is due to the endogenous separation margin. In recessions, unemployment increases at a faster rate from endogenous match separations which makes vacancy posting less costly, and this counteracts with the effect of negative aggregate shocks.

[17]We can see that the drop in aggregate productivity during the Great Recession is neither of larger magnitude nor does it exhibit more persistence than in previous recessions.

job search behaviour, match formation and match separation. Then I conduct policy experiments to measure the impact of UI extensions (via these channels) and the Reachback Provision programme on the labour market during the Great Recession. Lastly, I study the duration dependence in the unemployment exit rate.

3.5.1 Performance

UI Extensions I show in Figure 3.11 that the model is successful in generating realistic UI extensions both in terms of when they are triggered and how long each extension lasts. This is due to how well the model can replicate the unemployment rate in the US (of which UI extensions are a function) as shown in Figure 3.12. The model produces 95 percent of the observed unemployment rate between October 2009 and June 2014 as shown in Table 3.12.[18]

Long-term Unemployment The model can account for a large fraction of the observed rise in long-term unemployment in the Great Recession as depicted in Figure 3.13. Specifically, between October 2009 and June 2014, it generates 87 percent of the observed long-term unemployment rate (reported in Table 3.12). Despite this success, the model tends to overshoot the long-term unemployment and does not produce enough persistence in some of the previous recessions. The main reason for this comes from the sudden change in optimal job search behaviour of insured unemployed workers when the maximum UI duration returns to the standard duration, the mechanism that I will discuss in the next subsection.

Distribution of Unemployment Duration Figure 3.14 shows that the model can produce a substantial rise in the average unemployment duration in the Great Recession.[19] However, the model's series drops quickly as the economy recovers whilst it is more persistent in the data. The model also does very well in producing a realistic shift in the distribution of unemployment duration towards longer duration bins as previously discussed in the empirical section. In Figure 3.15 I plot the distributions

[18] This number is calculated by averaging the absolute percentage deviations of the model's unemployment series from the empirical counterpart. I choose October 2009 as the starting period as it was when the US unemployment rate reached its peak at 9.98 percent during the Great Recession.

[19] To be specific, the model can generate 77 percent of the empirical average unemployment duration series as reported in Table 3.12.

in December 2007 and June 2010, where UI was only extended in the latter case.[20] With respect to the entire 1948-2014 period, I show in Figure 3.16 the shares of unemployment by four duration bins (less than 1 month, 2-3 months, 4-6 months and longer than 6 months). These figures provide an evidence that the model is suitable for studying the dynamics of the entire distribution of unemployment durations and not just for the long-term unemployment dynamics.

Job Findings In the left panel of Figure 3.17, I compare the model's job finding rate with the empirical series. Despite a clear negative trend that the model does not take into account, it produces a fall in the job finding rate during the Great Recession similar in magnitude to that in the data. When I further condition on the UI status of workers as displayed in the left panel of Figure 3.18, we can see that (1) the job finding rate of the insured unemployed workers are on average lower than that of the uninsured, and (2) the job finding rate of the insured falls more dramatically than that of the uninsured. Both features are consistent with findings from the empirical section.

3.5.2 Mechanisms

Job Search Behaviour The endogenous UI extensions affect the optimal search behaviour of workers in the following ways: (1) only the search intensity of insured unemployed workers varies with the maximum UI duration and (2) the higher the UI benefits the lower the search effort is being exerted, and such behaviour is more noticeable when the extended UI duration is longer.

I show in Figure 3.19 that the conditional job finding rate of the insured unemployed workers drops whenever UI is extended (implied by $u \geq \bar{u}$) whilst the rates for the employed and uninsured unemployed are largely constant. Further, amongst the insured unemployed, their job search effort decreases in the amount of benefit they receive as shown in the left panel of Figure 3.20. With regards to the worker heterogeneity, higher productivity workers exert more search effort as their value during employment is relatively higher than the lower productivity type (right panel

[20] I choose June 2010 because it is when the model's long-term unemployment rate reaches its peak. Additionally, the model generates a hump in the distribution in 2010 similar to the empirical distribution owing to the endogenous separation margin.

of Figure 3.20). Mapping this to the simulation of the US economy in Figure 3.18, the job finding rates between the two productivity types during 1948-2014 are quite similar. However, when I separate the job finding rates by UI statuses instead, they are very different. Specifically, the unemployment exit rate of the insured unemployed is smaller and exhibits higher volatility which is consistent with the empirical evidence. This suggests that once we condition on the UI status, the workers' productivity types contribute little to the rise of the long-term unemployment.

It is useful to note that the job finding rates in Figure 3.18 are driven not only by the job search behaviour but also by the decision between a worker and a firm to form a match once they meet. Such decisions as well as match separation decisions are also affected by the endogenous UI extensions as I discuss next.

Match Formation/Dissolution From the model section, we learn that the worker's surplus from being employed and the value of producing firms ($WS_i^j(m;\omega)$ and $J_i^j(m;\omega); j \in \{e(\tilde{m}), UI(\tilde{m}), UU\}$) are simply a constant fraction of the total match surplus ($\mu S_i^j(m;\omega)$ and $(1-\mu)S_i^j(m;\omega)$ respectively). This means both workers and firms always agree when a match should be formed (when the total surplus is positive) and when it should be dissolved (when the total surplus is negative). The match surplus when the worker is currently employed ($S_i^{e(\tilde{m})}(m;\omega)$) determines the endogenous match separations whereas the match surplus when the worker is currently unemployed ($S_i^{UI(\tilde{m})}(m;\omega)$ or $S_i^{UU}(m;\omega)$) determines how many matches will be formed, given that unemployed workers and firm have met.

Figure 3.21 shows that total match surpluses for employed and insured unemployed workers ($S_i^{e(\tilde{m})}(m;\omega)$ and $S_i^{UI(\tilde{m})}(m;\omega)$) decrease in unemployment and that they decrease at a faster rate when UI is extended ($u \geq \bar{u}$).[21] Similar to the optimal job search policy, The longer the extended duration, the more drastic is the drop in the surplus. Further, I show that $S_i^{UI(\tilde{m})}(m;\omega)$ increases in m and decreases in $\tilde{m}$ in Figures 3.22. m increases the surplus because a higher match quality in the production raises the firm's profit, the worker's wage and also the worker's potential UI

[21] It can be seen that the match surplus for the uninsured unemployed workers is higher when the UI extension is longer. This is because it is actually better for the uninsured unemployed to regain employment and potentially qualify for UI benefits.

benefit after being employed at m; on the other hand, a higher $\tilde{m}$ implies a higher outside option of the insured unemployed $(h + b_i(\tilde{m}))$ which means it is less likely for a match to be formed. A similar argument applies to $S_i^{e(\tilde{m})}(m;\omega)$ but instead on the job separation margin where $(h + b_i(\tilde{m}))$ is the outside option of the employed worker if she quits and is eligible for UI.

From the model's simulation, Figure 3.23 shows that the success rate of worker-firm meetings is procyclical and always close to one. The reasons are (1) for insured workers, those likely to have an unproductive meeting are those with currently high UI benefits and it is unlikely for them to meet a firm in the first place, and (2) for uninsured workers, the surplus from working is very high due to their lower outside option which means the meetings are likely to lead to viable matches. With respect to job separation, we can see from the right panel of Figure 3.17 that the separation rate is countercyclical which is a result of $S_i^{e(\tilde{m})}(m;\omega)$ becoming negative during recessions.

What Drives the Long-term Unemployment? In this exercise, I study the contribution of the three UI channels (job search behaviour, match formation and job separation) on the long-term unemployment during the Great Recession. By fixing one channel at a time I study the evolution of the long-term unemployment given the same path of aggregate shock (z) as in the baseline model (Figure 3.10).[22]

I find that the long-term unemployment is largely unaffected by the response of match formation and dissolution but it would fall drastically (over 3 percentage points) when the job search behaviour is fixed as shown in Figure 3.24. Despite a small impact on the long-term unemployment, the job separation margin has a sizeable contribution to the average unemployment duration and is more important than the job search response in accounting for the total unemployment as displayed in 3.25.

[22] Specifically, I set the unemployment rate used in the respective policy functions to be at the pre-Great Recession level which is less than $\bar{u}$ implying that UI is not extended.

3.5.3 Policy Experiment

To quantify the effects of UI extensions on the aggregate labour market during the Great Recession, I conduct a counterfactual experiment by eliminating all UI extensions, i.e. the maximum UI duration is 26 weeks instead of 90 weeks. I then study how unemployment, long-term unemployment and average unemployment duration respond under this scenario. Just like the previous decomposition exercise, I use the same path of aggregate productivity (z) as in the baseline model (Figure 3.10). The benefit of using a general equilibrium model is that I can isolate the effects of UI extensions according to the factors that respond to the maximum UI duration. I will study three scenarios:

1. The direct impact of changing the maximum UI duration from 90 weeks to 26 weeks
   - Only the number of insured unemployed workers is affected by this change
2. The direct impact of UI extensions + the response of job search intensity
   - I allow the optimal search intensity to adjust to when there is no UI extensions. Specifically, workers exert job search effort as if the unemployment rate was at its historical mean at 5.83 percent (below $\bar{u}$)
3. The direct impact of UI extensions + the responses of job search intensity and match surpluses:
   - I allow both the optimal search intensity and the decisions on match formation and match dissolution to correspond to when there is no UI extensions (setting the unemployment rate at 5.83 percent in the policy functions)

As most of the literature studying the effects of UI extensions mainly focus on the "micro" effect, the first two scenarios are most comparable whilst the last scenario can be considered as the "general equilibrium" effect where firms and workers take into account the effect of UI extensions on match separations.[23] Table 3.13 summarises the results from this experiment.

Long-term unemployment Figure 3.26 shows the evolution of the maximum UI durations under the counterfactual experiment where in the Great Recession it is 26 instead of 90 weeks. The response of long-term unemployment to the change in maximum UI duratiom is shown in Figure 3.27. It can be seen that UI extension has a huge impact on long-term unemployment even when the behaviour of workers and firms do not react to this change. This is however not surprising since with the standard UI duration (of 26 weeks) all long-term unemployed workers are uninsured by definition, and we also know that uninsured unemployed workers have a much higher unemployment exit rate than do insured unemployed workers. As a result, by removing all UI extensions during the Great Recession, the peak of the long-term unemployment rate falls drastically from 4.9 percent in the baseline model to 1.2 percent in the first scenario where workers and firms do not react to the cut in maximum UI duration (as shown in Table 3.13). It falls to 0.6 percent when job search behaviour responds to the change in UI duration and just slightly further to 0.5 percent when both job search and job separations respond to this change.

Unemployment Figure 3.28 shows the responses of unemployment rate (top panel). Comparing to the long-term unemployment, the unemployment rate is much less affected by the cut in UI duration. The direct impact of removing UI extensions is a slight fall of less than one percentage point in the unemployment rate (measured at its peak) as can be seen in Table 3.13. When job search behaviour responds to the extension removal, the peak of the unemployment rate falls by 1.7 percentage points. It is only within the general equilibrium context, where the decisions on match separations also react to the UI duration cut, that the peak of the unemployment rate substantially falls by 3.4 percentage points to 6.8 percent.

The reason that under the first two scenarios the impact on the unemployment rate is more subdued is because they are relevant for only a subgroup of unemployment population whilst in the last scenario the job separation margin applies to

[23] It is clear from the previous decomposition exercise that the response of match formation to UI extensions is negligible.

all employed workers and determines the inflow of (insured) unemployed workers. Using the same argument, we can explain why under the first two scenarios the UI extensions have a large impact on the long-term unemployment.

This result is consistent with the existing literature that studies the impact of UI extensions on the unemployment rate in the Great Recession. Most of the studies focus on the micro effect where the worker-firm relationships are not taken into account, and find that the unemployment rate would have been 0.1 to 1.8 percentage points lower had there been no UI extensions. My "micro effect" of around 0.9-1.7 percentage points is within the range of the empirical estimates (0.1-1.8 percentage points) albeit on the higher side. Moreover, the larger "general equilibrium" effect of UI extensions in this model is similar to findings in Hagedorn et al (2015) but they focus the impact on vacancy creation whilst mine comes from match separations. Lastly, the unemployment rate is much less persistent when there is no UI extensions, i.e. there would be no jobless recoveries. This result is consistent with the findings in Mitman and Rabinovich (2014).

Average unemployment duration In contrast to the response of the unemployment rate, eliminating UI extensions significantly affects the average unemployment duration during the Great Recession as depicted in the bottom panel of Figure 3.28. The direct effect of eliminating (64 weeks of) UI extensions alone accounts for a 24-week drop in the average duration of unemployment (measured at the peak of the series) as shown in Table 3.13. When job search behaviour adjusts to the UI duration cut, the duration drops by 2 weeks further. The additional impact from the general equilibrium effect is minimal.

To summarise, I find a large impact of UI extensions on the long-term unemployment and the average unemployment duration which mainly comes from the direct effect of changing maximum UI duration and to a smaller extent from the response of job search behaviour (where I label these two channels the micro effect) with a small role from the job separation margins. However, the story is the opposite for the unemployment rate. The micro effect of UI extensions is small relative to the general equilibrium effect when match formation/dissolution decisions respond to the change in the maximum UI duration. Overall, the impact of UI extensions on the unemployment rate is consistent with results from the existing literature.

3.5.4 Reachback Provision Programme

From May 2007, the Emergency Unemployment Compensation law has included the "Reachback Provision" providing UI eligility to unemployed workers who have already exhausted their benefits prior to the extensions of UI. This programme can potentially affect the long-term unemployment since the programme is targeted directly at this group of workers. As the programme is already incorporated when I simulate the model and present the results, I will in this exercise remove the programme and leave everything else the same including the paths of aggregate productivity and UI extensions in the baseline model. The results from this exercise are summaried in Table 3.14. Figure 3.29 shows how the long-term unemployment, unemployment and average unemployment duration are impacted by the removal of the programme.

I find that the programme does not have a significant impact on the aggregate labour market. The (long-term) unemployment rate is only (0.2) 0.3 percentage points smaller than in the baseline model when measured at its peak. The small impact of the programme is due to the fact that the subgroup of workers who are affected by the programme represents just 3.5 percent of the unemployment population. However, from the CPS data, the true effect of this programme could be non-trivial since unemployed workers who already exhausted UI represented a substantial 44 percent of the long-term unemployment population in January 2008. The model produces a much smaller number for this group of workers because once the insured unemployed exhaust their benefits, they adopt the job search behaviour of the uninsured which implies a much higher unemployment exit rate than the insured.

3.5.5 On-the-job Search

In this exercise I show how on-the-job search contributes to unemployment and its duration distribution during the Great Recession. Its effect could go in either direction. On one hand, on-the-job search allows employed workers to improve their match qualities by searching for other vacant firms and drawing new match qualities. Having higher match qualities implies higher associated UI benefit levels if they become insured unemployed. Since the job search intensities and job finding rates are decreasing in the benefit level, this would increase unemployment duration and total unemployment. On the other hand, on-the-job search also increases the value of being employed. Therefore, more unemployed workers would be induced to take up job offers even when the first match quality draws are not great (since they can conduct on-the-job search and leave the first matches with not so great match qualities), and spend less time in unemployment. I plot the evolution of long-term unemployment, unemployment and average unemployment duration during the Great Recession in Figure 3.30

On-the-job search has little impact on all three labour market variables outside recessionary periods, but it becomes clear that there is a positive impact when the maximum UI duration is extended during the Great Recession. I find that on-the-job search contributes to a small but significant increase in (long-term) unemployment of up to (0.4) 0.5 percentage points from the baseline model as well as a 1.1-week increase in the average unemployment duration.

3.5.6 Hazard Rate of Exiting Unemployment

Due to the heterogeneity in job finding rates amongst unemployed workers, the model generates the negative duration dependence in unemployment exit rate that comes purely from the changing composition in the stocks of unemployment. At longer unemployment durations, the stocks of unemployment are more represented by those with lower exit rates, and they are the insured unemployed workers with higher UI benefits in this case. Moreover, the strength of the duration dependence is positively correlated with the state of the economy as pointed out in Wiczer (2015).

In Figure 3.31, I plot the hazard rates of exiting unemployment by duration for December 2007 (maximum 26 weeks of UI) and June 2010 (maximum 90 weeks of UI) to show how the recession and UI extensions affect this hazard rate. The negative duration dependence is more severe with UI extensions and persists as long as the maximum UI duration itself. In the same figure, I also plot the empirical estimate by Kroft et al (2016) over 2002-2007 period and the model's counterpart. Empirical results based on Kroft et al (2016) and Wiczer (2015) suggest that the hazard rate is rather stable after 6 months of being unemployed. In the model, however, since the uninsured unemployed workers exit unemployment at a faster rate than do the insured, the hazard rate rises upon the exhaustion of UI benefits.

The heterogeneous worker productivity could potentially help explain the negative duration dependence after the UI exhaustion since type-H workers exit unemployment at a faster rate. However, despite this heterogeneity, the exit rates of both types (H and L) when uninsured are quite similar and much higher than when they are insured leaving the average exit rate after UI exhaustion rather stable. In order to fit the empirical results better, other heterogeneity amongst uninsured unemployed workers could be introduced such as different values of home production, or even a larger degree of heterogeneity in productivity.

3.6 On the Sources of Long-term Unemployment

In this section I first show how consistent the model's unemployment series are with the empirical data by estimating a non-linear state space model in Ahn & Hamilton (2016) using the model's generated data. Then I study the implications on the sources of long-term unemployment. They explore the roles of worker's unobserved heterogeneity on unemployment dynamics. Their interpretation is that there are two types of workers: type-H workers have an ex-ante higher rate of exiting unemployment than do type-L workers. They also allow for genuine duration dependence that could be positive (motivational effect) and negative (scarring effect). The measurements or observables in their model are unemployment series by 5 duration bins $\{u_t^1, u_t^{2.3}, u_t^{4.6}, u_t^{7.12}, u_t^{13+}\}$ which are, respectively, unemployed workers with duration less than 1 month, 2-3 months, 4-6 months, 7-12 months, and more than 12 months. The latent or hidden states are also time varying. They are the number of newly unemployed workers for each type and a factor governing the unemployment continuation probability for each type. I summarise their state space model in Appendix 3.8.4.

I obtain 50 different series of $\{u_t^1, u_t^{2.3}, u_t^{4.6}, u_t^{7.12}, u_t^{13+}\}$ using the Monte Carlo simulations from the baseline model. For each set of the simulated unemployment series, I use Maximum Likelihood to obtain a set of (twelve) estimates from the state space model as described in Appendix 3.8.4. The extended Kalman fiter is used to construct the likelihood function since some latent variables enter the equations for unemployment series non-linearly. Table 3.15 reports these estimates and their standard errors.

Overall, the model's estimates are consistent with the empirical ones in Ahn and Hamilton (2016). Based on these estimated parameters, I construct the series for (1) the probability that newly unemployed workers of each type stay unemployed the following month, (2) the number of newly unemployed workers of each type, and (3) the share of unemployment by each type. Comparisons between these series and their empirical counterparts from Ahn and Hamilton (2016) are shown in Figures 3.32, 3.33 and 3.34 respectively.

The probabilities that the newly unemployed workers stay unemployed in the following month from the model's estimates (Figure 3.32) exhibit more volatility over the business cycles especially for type-L workers. Nonetheless, during the Great Recession, the model's data implies the rise of this probability for type-L workers and a small drop for type-H workers similar to its empirical counterpart. Going back to the model's results, we can see from the left panel of Figure 3.18 that they complement well with the results from this estimation where the insured unemployed workers (the type with "lower" exit rate) has a much more volatile unemployment exit rate than the uninsured (the type with "higher" exit rate).

With respect to the number of newly unemployed during the Great Recession (Figure 3.33), the model's estimates also imply a spike of the inflow of type-L workers (and a much smaller rise for type-H) with similar magnitude to the empirical counterpart. However, since the UI status of newly unemployed workers in the model is governed solely by the poisson rate ψ, the series for the newly unemployed workers who are insured and uninsured are perfectly correlated and therefore do not complement the results in Figure 3.33. The series only differ as the workers remain unemployed which is related to Figure 3.34, showing the shares of total unemployment by unobserved types. The model's implied share has very similar dynamics to the data throughout the observed periods. However, the share of type-L workers does not show a clear negative trend like in Ahn and Hamilton (2016), but this is expected since the model does not account for any low frequency changes or a trend e.g. in the unemployment rate or the job finding rate. Figure 3.35 shows the model's shares of total unemployment by UI status and worker's productivity. It can be seen that the rise in the share of type-L workers from the estimation (Figure 3.34) has more similar dynamics to the share of the insured unemployed workers in the model (rather than the share of the low productivity workers which exhibits smaller fluctuations).

Figure 3.36 shows the implied unemployment continuation probabilities from the true duration dependence component which are similar to the empirical estimates. This probability is rather constant in the first 6 months of duration, and then increases during 6-12 months of unemployment implying a scarring effect. After 12 months of unemployment, it is more likely that a worker exits unemployment the longer she stays unemployed . These estimates are somewhat consistent with the model's hazard rate of exiting unemployment (Figure 3.31) discussed in the previous subsection. As the UI benefits run out, workers search harder for jobs and exit unemployment more quickly. The change in the job search behaviour (and therefore the hazard rate) depends on the maximum UI duration but we can observe that in the 1976-2014 periods (upon which the observations are based) the maximum UI duration during recessions is at least 12 months which is consistent with a fall in the probability of remaining unemployed after 12 months.

In summary, the model's unemployment series are consistent with the empirical data as estimated using a state space model. I can relate Ahn and Hamilton (2016)'s interpretation of worker unobserved heterogeneity to the UI statuses of unemployed workers in my model since the insured unemployed have lower unemployment exit rate than do the uninsured. They have similar dynamics in terms of the unemployment exit rate as well as the shares of total unemployment. Moreover, some feature of the genuine duration dependence in the job finding rate can also be related to the UI exhaustion in the model.

3.7 Conclusion

The long-term unemployment dynamics has an important implication on the recovery of the aggregate labour market. This paper quantifies the impact of countercyclical UI extensions on the long-term unemployment and the unemployment duration distribution.

I develop a general equilibrium search and matching model where the maximum UI duration depends on the unemployment rate and the UI benefits depend on the match quality during employment. Unemployed workers' job search behaviour differs according to their UI status, benefit level and productivity, and is affected by the maximum UI duration.

The main result is that UI extensions have a significant impact on the long-term unemployment and the average unemployment duration but the impact on the unemployment rate is more limited. By studying the mechanisms through which the UI extensions affect the labour market, the response of job search behaviour plays a crucial role on the long-term unemployment dynamics whereas the response of job separation decisions is more important in accounting for the total unemployment.

The model is also used to assess the impact of UI extensions during the Great Recession distinguishing between the micro effect (the direct impact on the number of insured workers and the response of job search) and the general equilibrium effect (micro effect plus the response of job separation decisions). The micro effect on unemployment is small and consistent with existing studies whilst the general equilibrium effect is somewhat larger. This is because the micro effect is relevant for a subgroup of unemployment population but the job separation margin applies to all employed workers determining the inflow of (insured) unemployed workers.

The result that the model produces little persistence in the long-term unemployment outside the extended UI periods could be altered by using an empirical fact that the majority of long-term unemployed workers outside recessionary periods are those who have already exhausted UI. A distinction between uninsured workers who never receive UI and those who have exhausted UI could help create the persistence needed to match the data. Specifically, the unemployment exit rate of the formerly-insured unemployed workers can be smaller than the rest of the uninsured unemployment population. This could come from selection whereby workers with high non-UI outside options are more likely to stay unemployed (e.g. heterogeneous values of home production, leisure, or a larger degree of individual productivity). Persistence or habits in job search behaviour during unemployment could potentially help explain not only the persistence of long-term unemployment but also its trend. The introduction of savings in the model could be useful in studying the interaction between private and public insurance as well as in the welfare analyses. These extensions would provide a more complete framework to study the impact of UI extensions.

3.8 Appendix for Chapter 3

3.8.1 Expressions for Optimal Search Intensity and Match Surplus

Given the worker's value functions when employed, insured unemployed and uninsured unemployed, we can take the first derivative to find the optimal search effort. The first order conditions for type-i workers are as follows

$$\begin{aligned} \nu_e'(s_i^e(m;\omega)) &= -\beta(1-\delta)M(\theta(\omega))E_{\omega'|\omega}\Big[\ldots \\ &\quad (1-\lambda)(1-F(m))\Big(WS_i^{e(m)+}(m;\omega') - E_{m'|m'>m}[WS_i^{e(m)+}(m';\omega')]\Big) \\ &+ \lambda E_{m'}\Big[(1-F(m'))(WS_i^{e(m)+}(m';\omega') - E_{m''|m''>m'}[WS_i^{e(m)+}(m'';\omega')])\Big]\Big] \end{aligned} \tag{3.7}$$

$$\nu_u'(s_i^{UI}(m,\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UI(m)}(m';\omega'),0\} - \xi(1-\phi(u))US_i(m,\omega')\Big] \tag{3.8}$$

$$\nu_u'(s_i^{UU}(\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UU}(m';\omega'),0\}\Big] \tag{3.9}$$

Total match surpluses and unemployed worker's surplus are as follows

$$\begin{aligned} S_i^{e(\tilde{m})}(m;\omega) &= y_i(m,\omega) - \nu_e(s_i^e(m;\omega)) - \tau(\omega) - (1-\psi)(b_i(\tilde{m}) + h - \nu_u(s_i^{UI(\tilde{m})}(\omega))) \\ &\quad -\psi(h - \nu_u(s_i^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\ &\quad (1-\delta)(1-\lambda)\Big((1-p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \\ &\quad +p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big) \\ &\quad +(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')\ldots \\ &\quad +p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big] \\ &\quad -(1-\psi)p_i^{UI(\tilde{m})}(\omega)E_{m'}[\mu S_i^{UI(\tilde{m})+}(m';\omega')] \\ &\quad -\psi p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')] \\ &\quad +(1-\psi)\Big(US_i(m,\omega') - US_i(\tilde{m},\omega')\ldots \\ &\quad +(\phi(u) + p_i^{UI(\tilde{m})}(\omega)\xi(1-\phi(u)))US_i(\tilde{m},\omega')\Big)\Big] \end{aligned}$$

$$
\begin{aligned}
S_i^{UI(\tilde{m})}(m;\omega) \;=\;& y_i(m,\omega) - \nu_e(s_i^e(m;\omega)) - \tau \\
& -(1-\phi)(1-\xi)(b(\tilde{m}) + h - \nu_u(s_i^{UI(\tilde{m})}(\omega))) \\
& -(1-(1-\phi)(1-\xi))(h - \nu_u(s_i^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
& (1-\delta)(1-\lambda)\Big((1-p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big) \\
& +(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big] \\
& -(1-\phi)(1-\xi)p_i^{UI(\tilde{m})}(\omega)E_{m'}[\mu S_i^{UI(\tilde{m})+}(m';\omega')] \\
& -\Big(1-(1-\phi)(1-\xi)\Big)p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')] \\
& +(1-\psi)US_i(m,\omega') \\
& -\Big((1-\phi)^2(1-\xi)(1-\xi p_i^{UI(\tilde{m})}(\omega))\Big)US_i(\tilde{m},\omega')\Big]
\end{aligned}
$$

$$
\begin{aligned}
S_i^{UU}(m;\omega) \;=\;& y_i(m,\omega) - \nu_e(s_i^e(m;\omega)) - \tau - (h - \nu_u(s_i^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
& (1-\delta)(1-\lambda)\Big((1-p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big) \\
& +(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big] \\
& -p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')] \\
& +(1-\psi)US_i(m,\omega')\Big]
\end{aligned}
$$

$$
\begin{aligned}
US_i(m,\omega) \;=\;& b(m) - \nu_u(s_i^{UI(m)}(\omega)) + \nu_u(s_i^{UU}(\omega)) \\
& +\beta E_{\omega'|\omega}\Big[p_i^{UI(m)}(\omega)E_{m'}[\mu S_i^{UI(m)+}(m';\omega')]\ldots \\
& -p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')] \\
& +(1-\phi)\Big(1-\xi p_i^{UI(m)}(\omega)\Big)US_i(m,\omega')\Big]
\end{aligned}
$$

3.8.2 Transitions

Employment The mass of type-i employed agents in t with match quality m, $e_{i,t}(m)$, evolves as follows

$$\begin{aligned} e_{i,t+1}(m) &= (1-\delta)(1-\lambda)(1-p^e_{i,t}(m)+p^e_{i,t}(m)F(m))e_{i,t}(m)\mathbb{1}\{S^{e(m)}_{i,t+1}(m)>0\} \\ &+(1-\delta)(1-\lambda)f(m)\int_{m'<m} p^e_{i,t}(m')e_{i,t}(m')\mathbb{1}\{S^{e(m')}_{i,t+1}(m)>0\}dm' \\ &+(1-\delta)\lambda f(m)\int_{m'}(1-p^e_{i,t}(m')+p^e_{i,t}(m')F(m))e_{i,t}(m')\mathbb{1}\{S^{e(m')}_{i,t+1}(m)>0\}dm' \\ &+(1-\delta)\lambda F(m)f(m)\int_{m'} p^e_{i,t}(m')e_{i,t}(m')\mathbb{1}\{S^{e(m')}_{i,t+1}(m)>0\}dm' \\ &+f(m)\int_{\tilde{m}} u^{UI}_{i,t}(\tilde{m})p^{UI}_{i,t}(\tilde{m})\mathbb{1}\{S^{UI(\tilde{m})}_{i,t+1}(m)>0\}d\tilde{m} \\ &+f(m)u^{UU}_{i,t}p^{UU}_{i,t}\mathbb{1}\{S^{UU}_{i,t+1}(m)>0\} \end{aligned} \tag{3.10}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function. The total employment is the sum of all employed workers over productviity types and match qualities $e_t=\sum_{i=H,L}\int e_{i,t}(m)\,dm$ and the aggregate output can be computed as $y_t=z_t\sum_{i=H,L}\int m\cdot e_{i,t}(m)\,dm$.

Job Destructions The job destruction rate of type-i employed workers with match quality m at the beginning of period t and m' at the end of period t, and the average job destruction rate are respectively

$$\begin{aligned} \rho_{x,it}(m,m') &= \begin{cases} \delta & \text{if } S^{e(m)}_{i,t+1}(m')>0, \\ 1 & \text{otherwise} \end{cases} \\ \rho_{x,it} &= \Bigg(\delta\int\int_{\{(m,m'):S^{e(m)}_{i,t+1}(m')>0\}} e^{post}_{i,t}(m,m')dm\,dm' \\ &\quad +\int\int_{\{(m,m'):S^{e(m)}_{i,t+1}(m')\le 0\}} e^{post}_{i,t}(m,m')dm\,dm'\Bigg)/e_t \end{aligned} \tag{3.11}$$

$$\begin{aligned} \text{where } e^{post}_{i,t}(m,m') &= (1-\lambda)(1-p^e_{i,t}(m')+p^e_{i,t}(m')F(m'))e_{i,t}(m') \\ &+(1-\lambda)f(m')p^e_{i,t}(m)e_{i,t}(m)\mathbb{1}\{m<m'\} \\ &+\lambda f(m')(1-p^e_{i,t}(m)+p^e_{i,t}(m)F(m'))e_{i,t}(m) \\ &+\lambda F(m')f(m')p^e_{i,t}(m)e_{i,t}(m) \end{aligned}$$

denotes employed workers with match productivity m at the beginning of period t and m' at the end of the period t.

Job Findings The job finding rate for a type-i unemployed worker of status $j = \{UI(\tilde{m}), UU\}$ and the average job finding rate are respectively

$$\begin{aligned}
\rho^{j}_{f,it} &= \int \rho^{j}_{f,it}(m) f(m) dm \\
\rho_{f,t} &= \frac{\int_{\tilde{m}} u^{UI}_{i,t}(\tilde{m}) \rho^{UI(\tilde{m})}_{f,it} d\tilde{m} + u^{UU}_{i,t} \rho^{UU}_{f,it}}{\int_{\tilde{m}} u^{UI}_{t}(\tilde{m}) d\tilde{m} + u^{UU}_{t}} \\
\text{where } \rho^{j}_{f,it}(m) &= \begin{cases} p^{j}_{i,t} & \text{if } S^{j}_{i,t+1}(m) > 0, \\ 0 & \text{otherwise} \end{cases}
\end{aligned}$$

Job-to-job Transitions The match-specific and the average job-to-job transition rates are respectively

$$\begin{aligned}
\rho^{ee}_{i,t}(m) &= (1-\delta)\Big((1-\lambda) p^{e}_{i,t}(m)(1-F(m)) E_{m'>m}[\mathbf{1}\{S^{e}_{i,t+1}(m,m') > 0\}] \\
&\quad + \lambda \int_{m'} p^{e}_{i,t}(m) f(m')(1-F(m')) E_{m''>m'}[\mathbf{1}\{S^{e}_{i,t+1}(m,m'') > 0\}] dm'\Big) \\
\rho^{ee}_{i,t} &= \frac{\int_m \rho^{ee}_{i,t}(m) e_{i,t}(m) dm}{e_t}
\end{aligned}$$

Unemployment The mass of type-i unemployed workers with and without UI benefits as well as the total unemployment evolve respectively as follows

$$\begin{aligned}
u^{UI}_{i,t+1}(\tilde{m}) &= \underbrace{(1-\phi_t)(1-p^{UI}_{i,t}(\tilde{m})) u^{UI}_{i,t}(\tilde{m})}_{\text{unmatched, not losing UI}} + \underbrace{\chi^{UI}_{i,t}(\tilde{m})(1-\phi_t)(1-\xi) p^{UI}_{i,t}(\tilde{m}) u^{UI}_{i,t}(\tilde{m})}_{\text{bad match, not losing UI}} \\
&\quad + \underbrace{(1-\psi) \int_{m'} \rho_{x,it}(\tilde{m}, m') e_{i,t}(\tilde{m}, m') dm'}_{\text{destroyed match, not losing UI}} \qquad (3.12) \\
u^{UU}_{i,t+1} &= \int_{\tilde{m}} \Big(\underbrace{\phi_t (1-p^{UI}_{i,t}(\tilde{m})) u^{UI}_{i,t}(\tilde{m})}_{\text{unmatched, losing UI}} + \underbrace{\chi^{UI}_{i,t}(\tilde{m}) \Big(\phi_t + (1-\phi_t)\xi\Big) p^{UI}_{i,t}(\tilde{m}) u^{UI}_{i,t}(\tilde{m})}_{\text{bad match, losing UI}} \Big) d\tilde{m} \\
&\quad + (1-\rho^{UU}_{f,it}) u^{UU}_{i,t} + \underbrace{\psi \rho_{x,it} e_{i,t}}_{\text{destroyed match, losing UI}} \qquad (3.13) \\
u_{t+1} &= \sum_{i=H,L} \left(\int_{\tilde{m}} u^{UI}_{i,t+1}(\tilde{m}) d\tilde{m} + u^{UU}_{i,t+1} \right) \qquad (3.14)
\end{aligned}$$

where $\chi_{i,t}^{UI}(\tilde{m}) \equiv \int \mathbf{1}\{S_{i,t+1}^{UI}(\tilde{m},m) \leq 0\} f(m)dm$ denotes the rate the newly formed matches with $u_i^{UI}(\tilde{m})$ are not viable.

3.8.3 Performance of the Approximation Method

Below I report the average percentage deviations (in absolute value) of the 1st, 2nd, 3rd and 4th moments of the approximated distribution of employed workers over match quality from the distributions obtained from the simulation. The method described in the Model section delivers distributions that are less than 1% different in terms of the 1st, 2nd and 4th moments from the actual distributions found in the simulation. However it generates the 3rd moment that is more than 3% different from its counterpart since the skewness is more sensitive to the cut-offs in the distributions coming from endogenous destructions.

Table 3.1: Performance of the Approximation Method

	Percentage deviations (%)	
	Mean	SE
1st moment	0.5650	0.3953
2nd moment	0.4670	0.4499
3rd moment	3.6819	3.4767
4th moment	0.2009	0.2936

3.8.4 Ahn and Hamilton (2016)'s State Space Model

To summarise briefly, Ahn and Hamilton (2016)'s state space model contains the latent variables which are the number of each type entering unemployment in each time period ($w_{H,t}$,$w_{L,t}$) and the time-varying factors governing their outflow rates ($x_{H,t}$,$x_{L,t}$). These four variables follow a random walk process. For example,

$$w_{H,t} = w_{H,t-1} + \varepsilon_{H,t}^{w}$$

The errors are independently and normally distributed with mean zero and standard deviation $\{\sigma_H^w, \sigma_L^w, \sigma_H^x, \sigma_L^x\}$ respectively. They assume the true duration dependence of unemployment exit rate is time invariant and summarised by $\{\delta_1, \delta_2, \delta_3\}$. The measurements or observables in their model are unemployment series by 5 duration bins $\{u_t^1, u_t^{2.3}, u_t^{4.6}, u_t^{7.12}, u_t^{13+}\}$. They are, respectively, unemployed workers with duration less than 1 month, 2-3 months, 4-6 months, 7-12 months, and more than 12 months. All five unemployment series can contain measurement errors $\{r_t^1, r_t^{2.3}, r_t^{4.6}, r_t^{7.12}, r_t^{13+}\}$ which are independently and normally distributed with mean zero and standard deviation $\{R1, R2.3, R4.6, R7.12, R13+\}$. The evolution of these series are as follows

$$
\begin{aligned}
u_t^1 &= \sum_{i=H,L} w_{it} + r_t^1 \\
u_t^{2.3} &= \sum_{i=H,L} [w_{i,t-1}P_{it}(1) + w_{i,t-2}P_{it}(2)] + r_t^{2.3} \\
u_t^{4.6} &= \sum_{i=H,L}\sum_{k=3}^{5} [w_{i,t-k}P_{it}(k)] + r_t^{4.6} \\
u_t^{7.12} &= \sum_{i=H,L}\sum_{k=6}^{11} [w_{i,t-k}P_{it}(k)] + r_t^{7.12} \\
u_t^{13+} &= \sum_{i=H,L}\sum_{k=12}^{47} [w_{i,t-k}P_{it}(k)] + r_t^{13+}
\end{aligned}
$$

$$
\begin{aligned}
\text{where } P_{it}(j) &= p_{i,t-j+1}(1) \times p_{i,t-j+2}(2) \times \ldots \times p_{i,t}(j) \\
p_{it}(\tau) &= \exp[-\exp(x_{it} + d_\tau)] \\
d_\tau &= \begin{cases} \delta_1(\tau - 1) & \text{for } \tau < 6 \\ \delta_1[(6-1)-1] + \delta_2[\tau - (6-1)] & \text{for } 6 \le \tau < 12 \\ \delta_1[(6-1)-1] + \delta_2[(12-1)-(6-1)] + \delta_3[\tau - (12-1)] & \text{for } 12 \le \tau \end{cases}
\end{aligned}
$$

The parameters to be estimated are the standard deviations of the errors $\{\sigma_H^w, \sigma_L^w, \sigma_H^x, \sigma_L^x, R1, R2.3, R4.6, R7.12, R13+\}$ and the parameters for true duration dependence $\{\delta_1, \delta_2, \delta_3\}$. I obtain 50 different series of $\{u_t^1, u_t^{2.3}, u_t^{4.6}, u_t^{7.12}, u_t^{13+}\}$ by using the Monte Carlo simulations. For each set of the simulated unemployment series, I obtain a set of twelve estimates from the same non-linear state space model using Maximum Likelihood. The extended Kalman fiter is used to construct the likelihood function since $\{x_{H,t}, x_{L,t}\}$ enter the equations for unemployment series non-linearly. Table 3.15 reports these estimates and their standard errors.

Figure 3.1: Unemployment and Long-term Unemployment (those unemployed > 6 months) in the U.S. (Source: CPS)

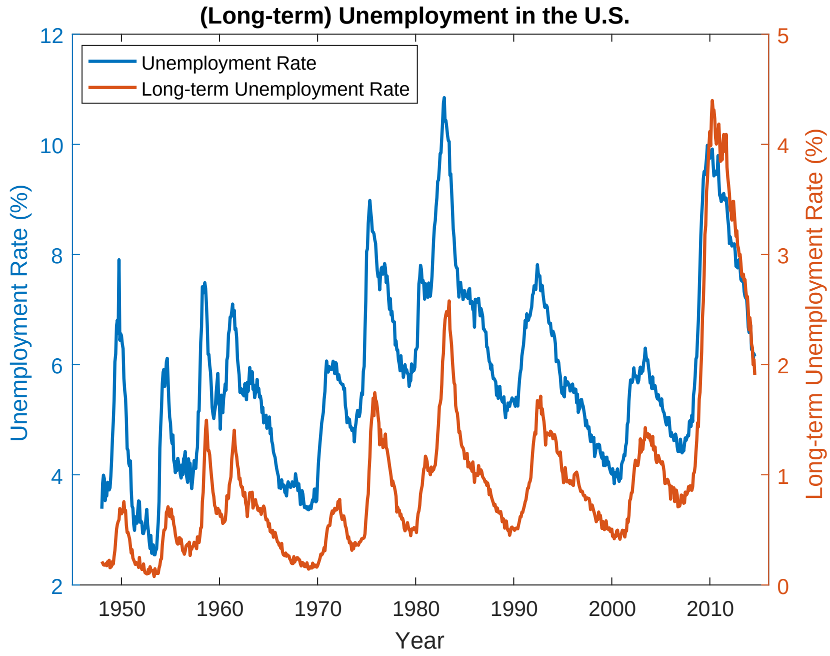


Figure 3.2: Maximum Unemployment Insurance Duration (weeks) in the U.S. (Source: ETA. Shaded areas denote the recessions)

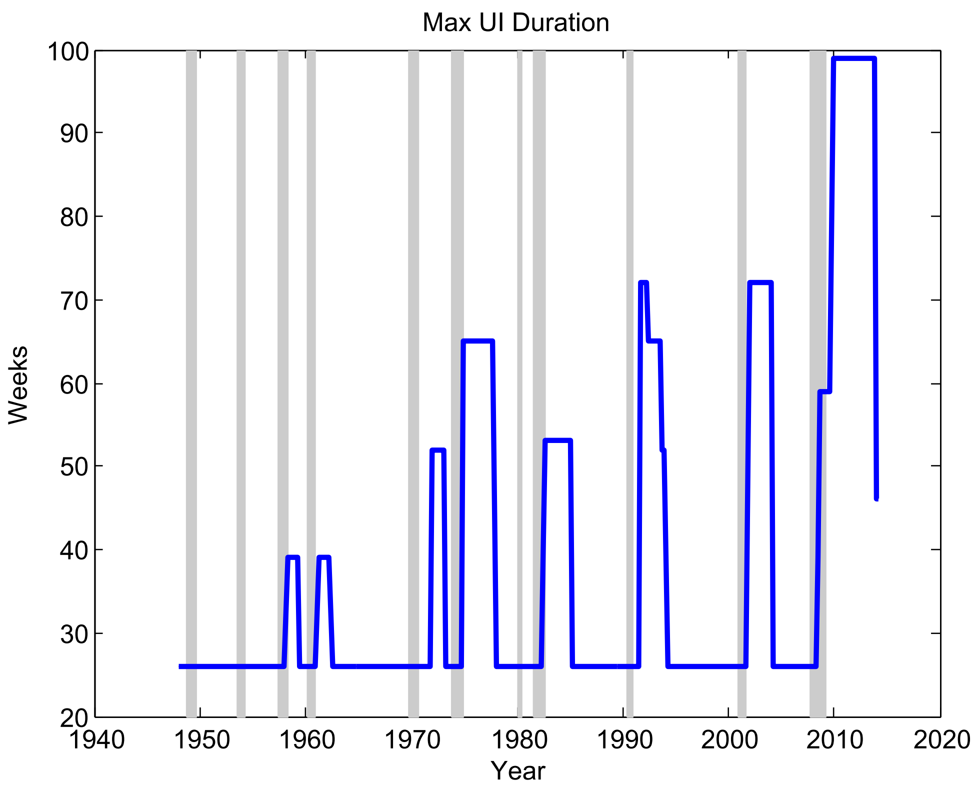


Figure 3.3: Maximum Unemployment Insurance Duration (weeks) in the U.S. with Automatic Extensions (Source: ETA. Shaded areas denote the recessions. Dashed green line denotes the automatic extensions)

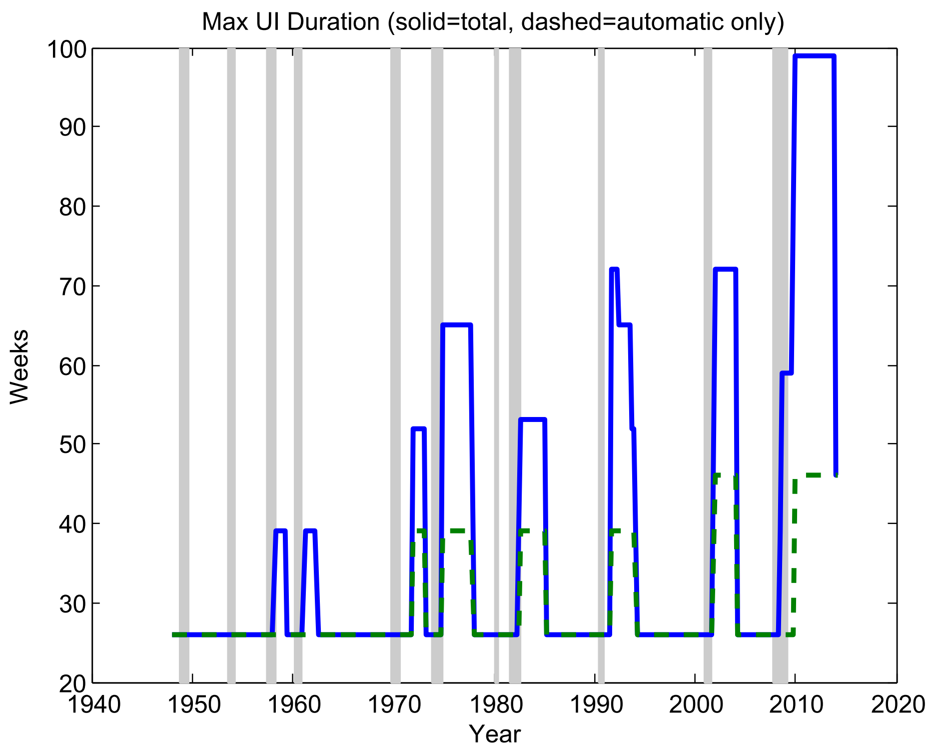


Figure 3.4: Unemployment-to-Employment Transition Rate (%) by UI status (Source: CPS)

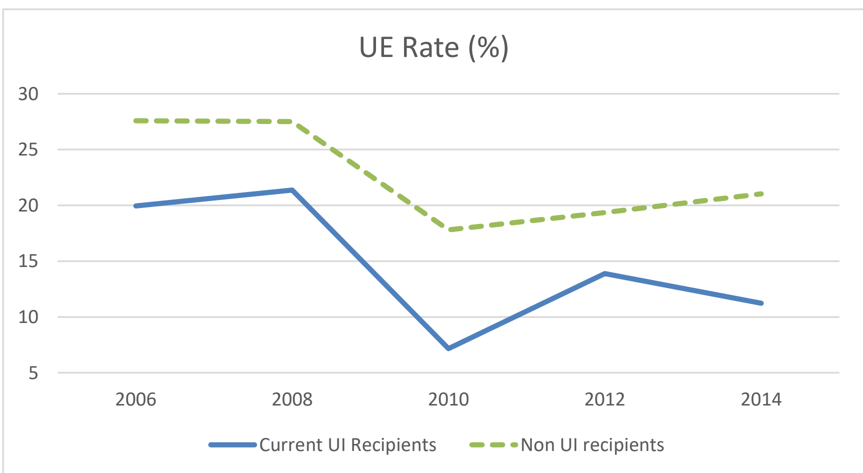


Figure 3.5: Unemployment-to-Unemployment Transition Rate (%) by UI status (Source: CPS)

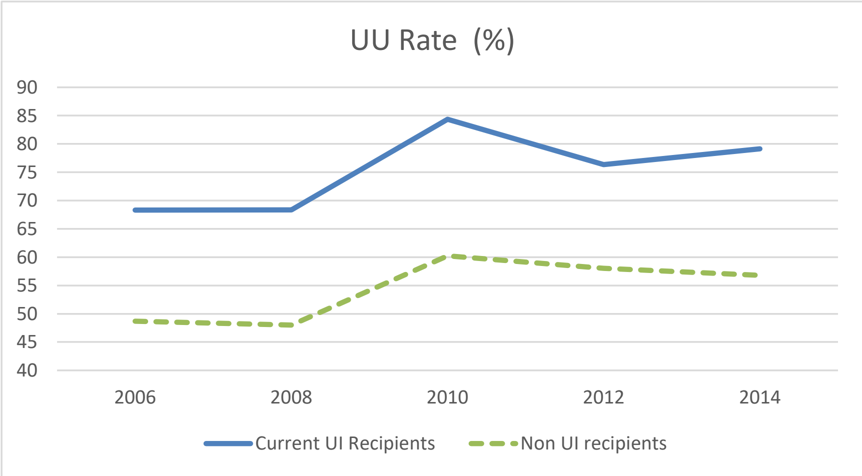


Figure 3.6: Unemployment-to-Out-of-Labour-Force Transition Rate (%) by UI status (Source: CPS)

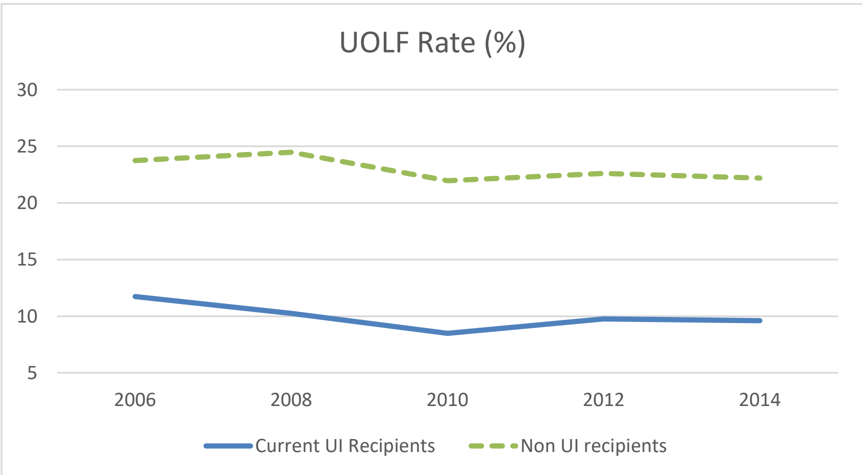


Figure 3.7: Distributions of unemployment durations and fractions represented by current UI recipients (Source: CPS)

Figure 3.8: Shares (%) of current UI recipients over total unemployment in each monthly duration bins (Source: CPS)

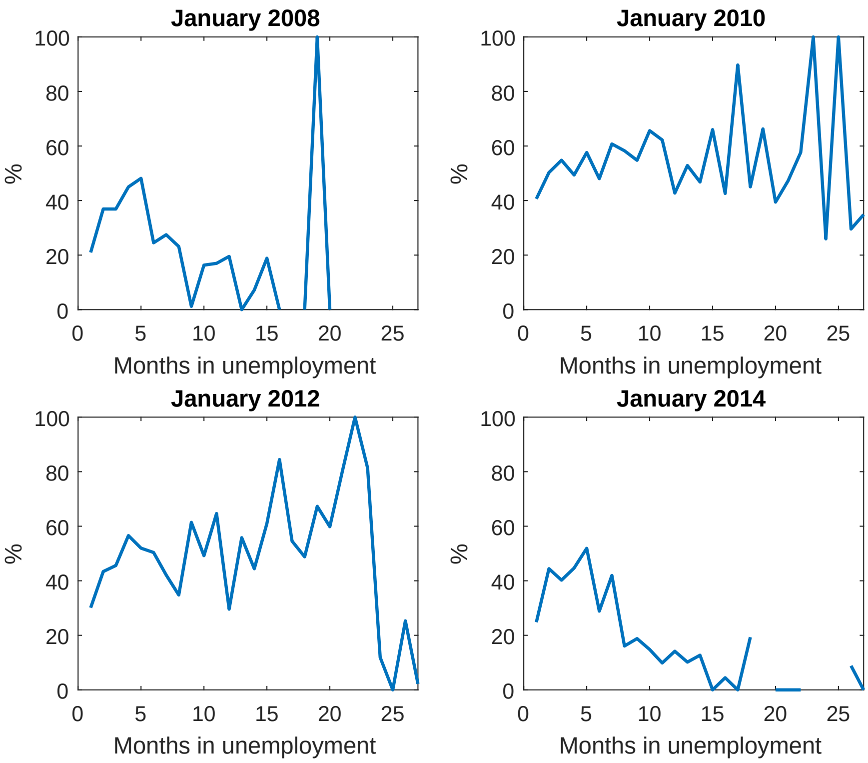


Figure 3.9: Shares (%) of Current UI Recepients in 2 Subgroups: Long-term Unemployment and Newly Unemployed Workers (Source: CPS)

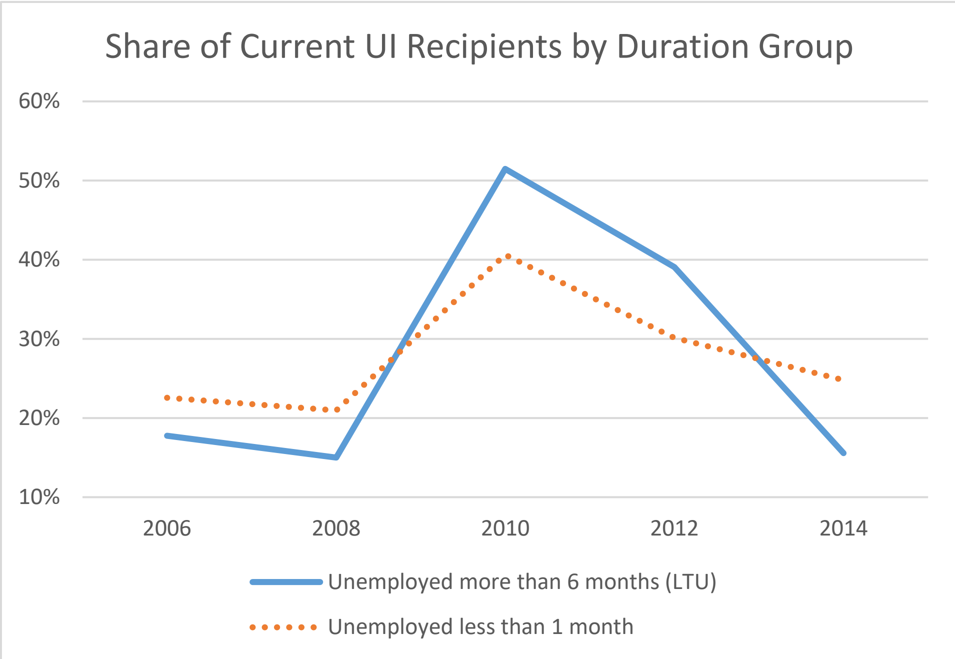


Figure 3.10: Aggregate Productivity Series (z) as Constructed to Match Output Deviations from HP Trend

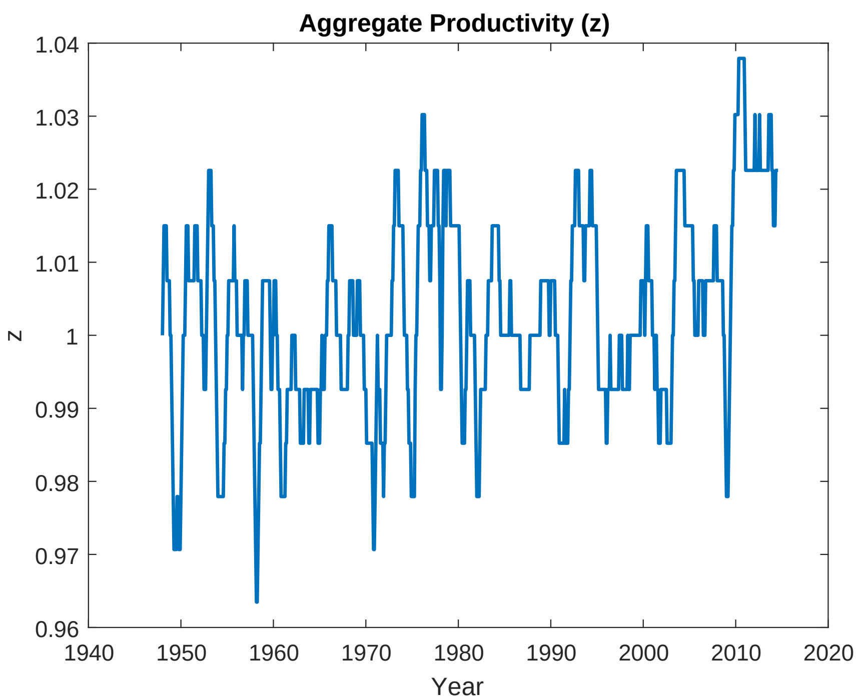


Figure 3.11: UI Extensions from the Model and the Data (Data source: ETA)

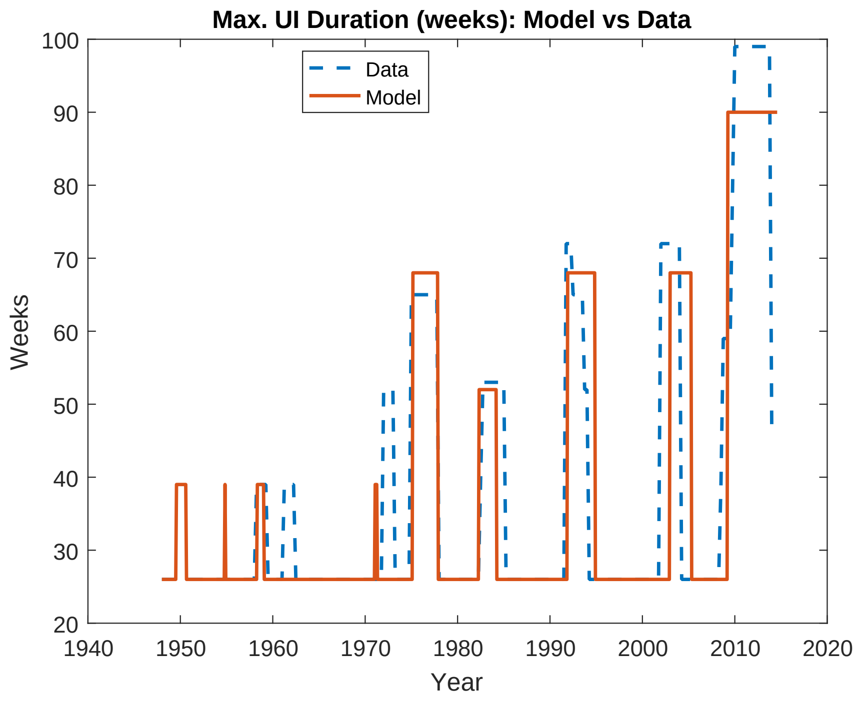


Figure 3.12: Unemployment Rate (%) from the Model and the Data (Data source: CPS)

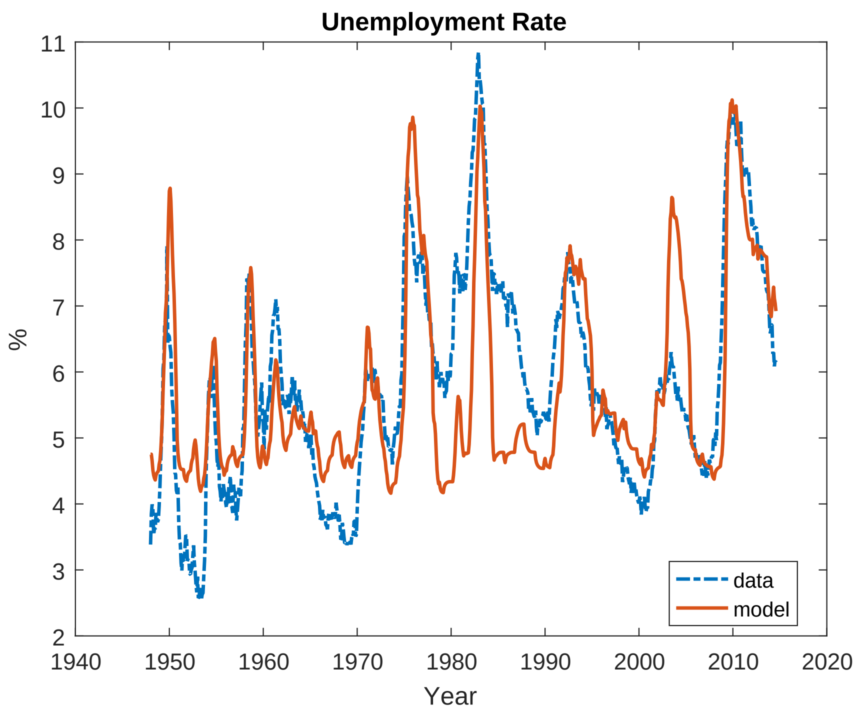


Figure 3.13: Long-term Unemployment Rate (%) from the Model and the Data (Data source: CPS)

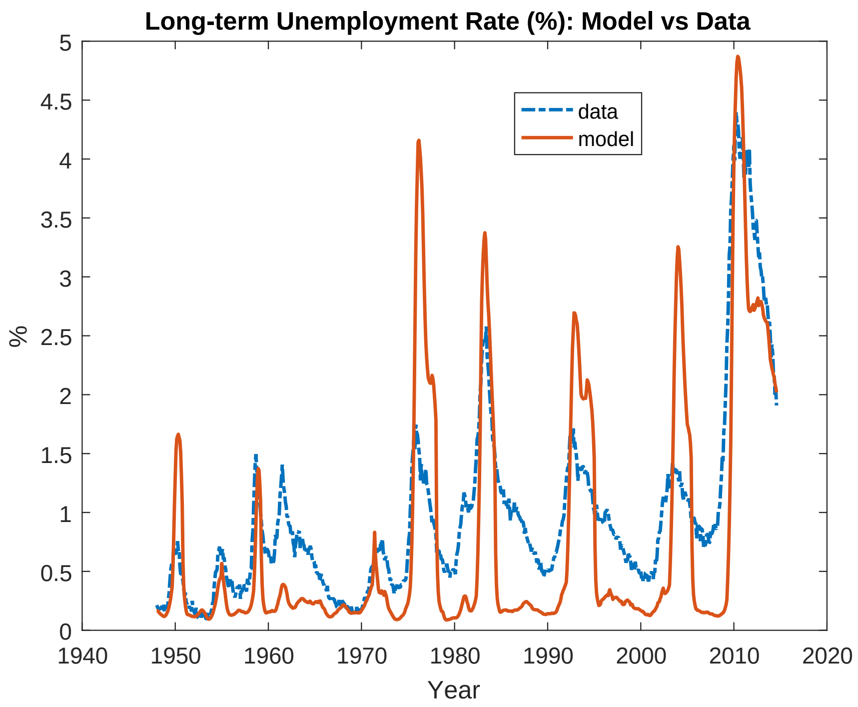


Figure 3.14: Average Unemployment Duration from the Model and the Data (Data source: CPS)

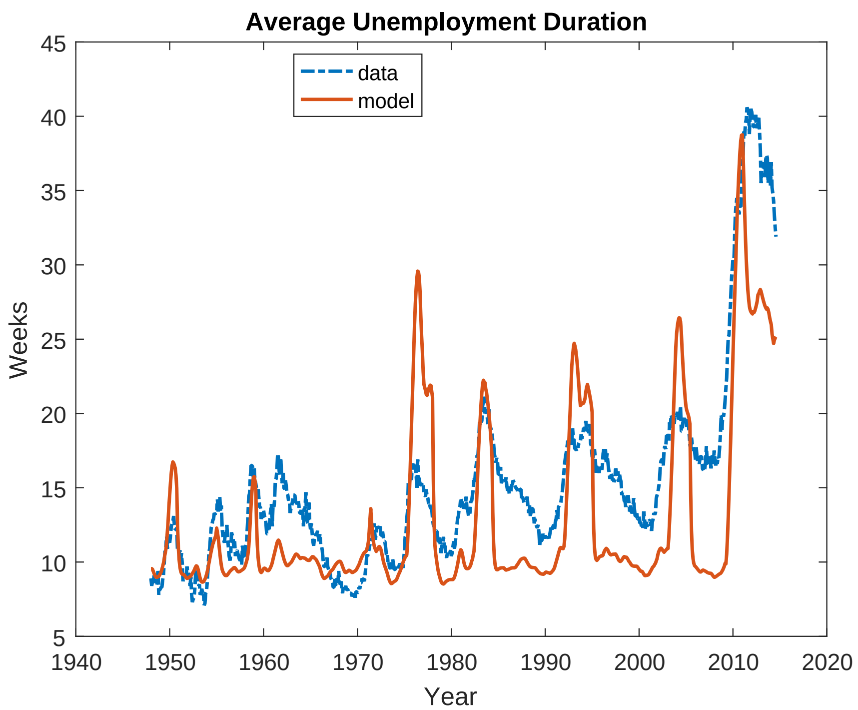


Figure 3.15: Distribution of Unemployment Durations during the Great Recession (Data source: CPS)

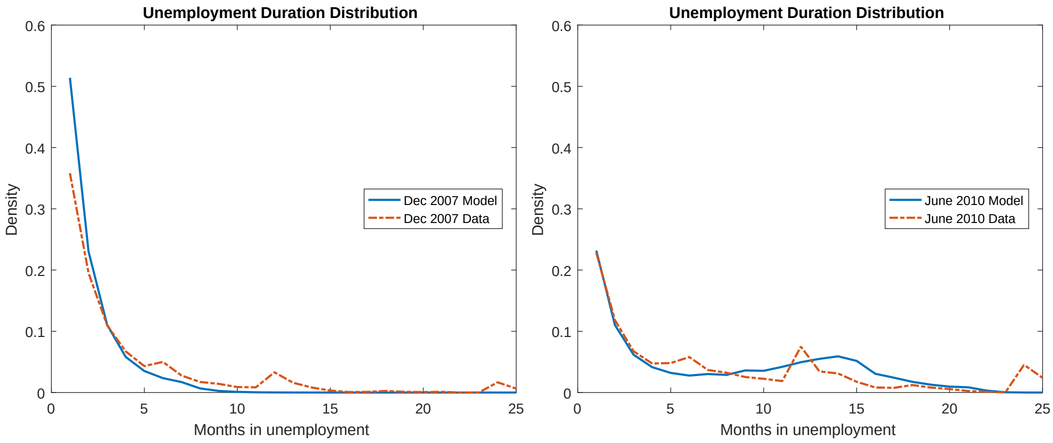


Figure 3.16: Unemployment Shares (%) by Durations (Data source: CPS)

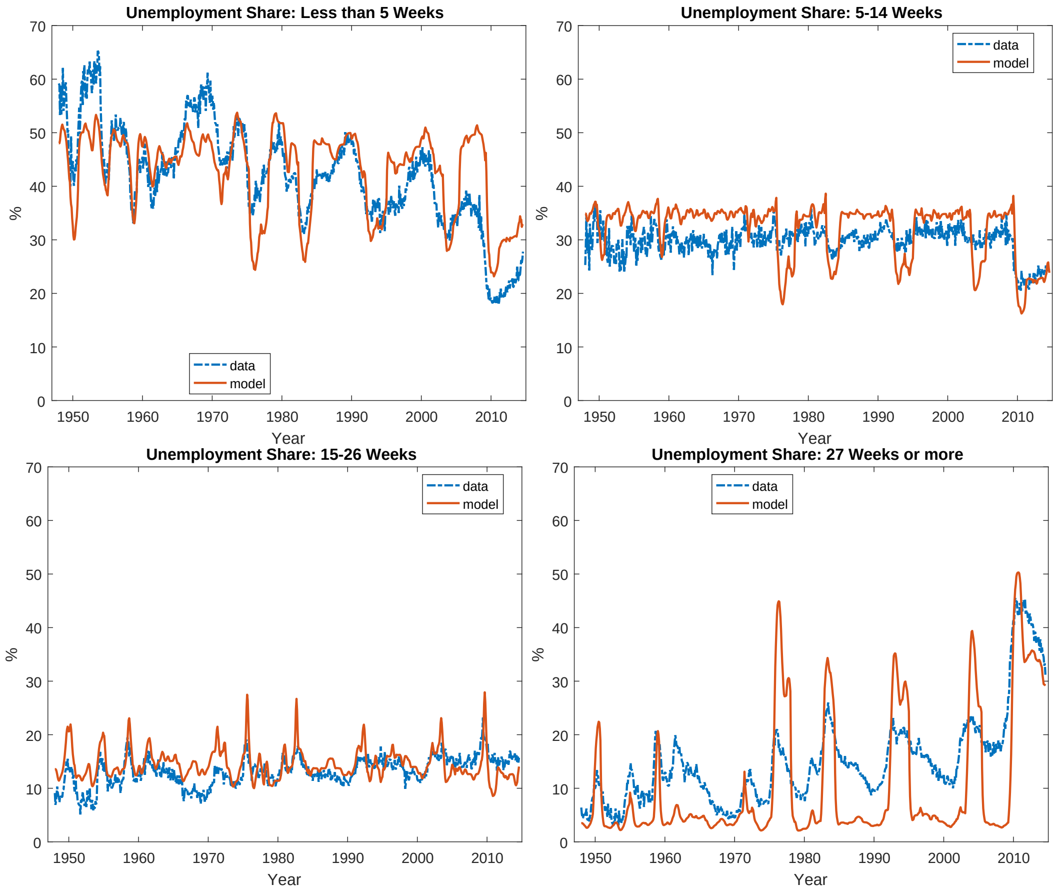


Figure 3.17: Job Finding (left panel) and Job Separation Rates (right panel) (%) as Observed in the Data and as Generated by the Model (Data source: CPS)

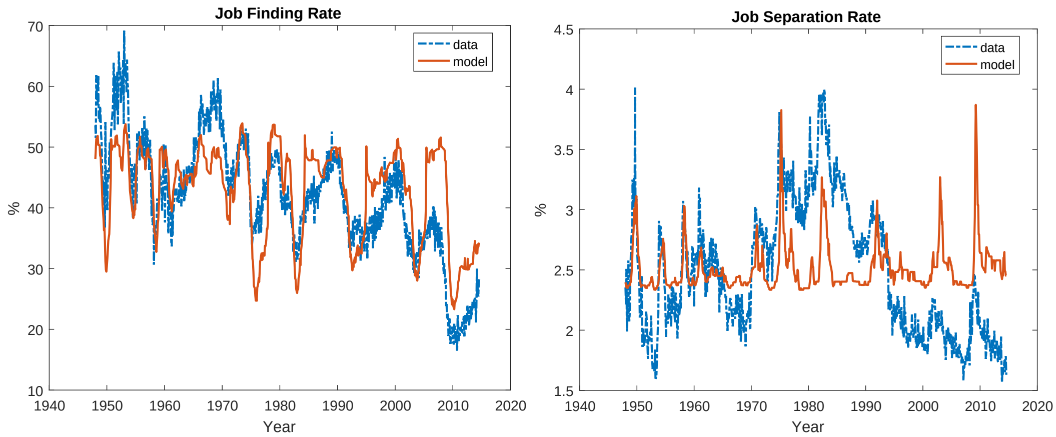


Figure 3.18: Unemployment Exit Rate (%) by UI Status (left panel) and Worker's Productivity (right panel)

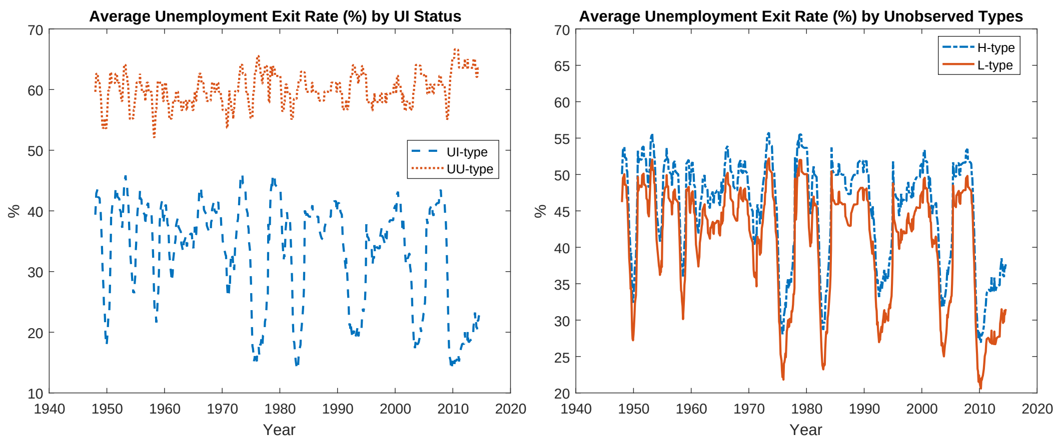


Figure 3.19: Conditional Job finding rate (%) as a function of unemployment by UI status $(p^e_H(\tilde{m}), p^{UI}_H(\tilde{m}), p^{UU}_H)$: For solid (dashed) lines, maximum UI duration is 39 (90) weeks

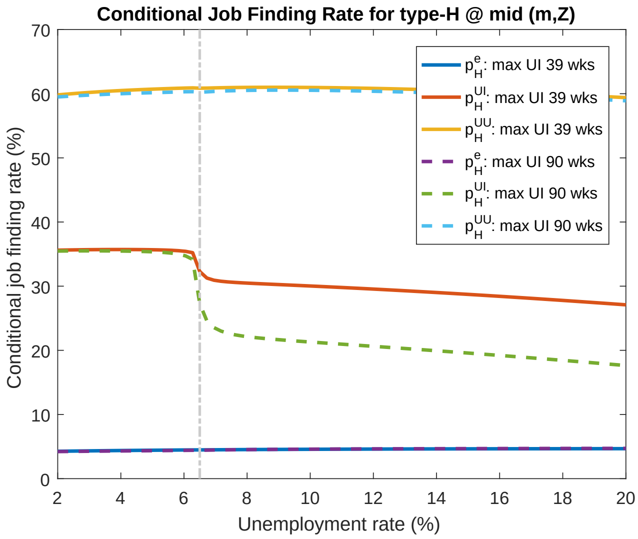


Figure 3.20: Conditional Job finding rate (%) as a function of unemployment by UI benefit levels ($p^{UI}_H(\tilde{m})$ by $\tilde{m}$) (left panel) and by Worker's Productivity $(p^{UI}_H(\tilde{m}), p^{UI}_L(\tilde{m}))$ (right panel): For solid (dashed) lines, maximum UI duration is 39 (90) weeks

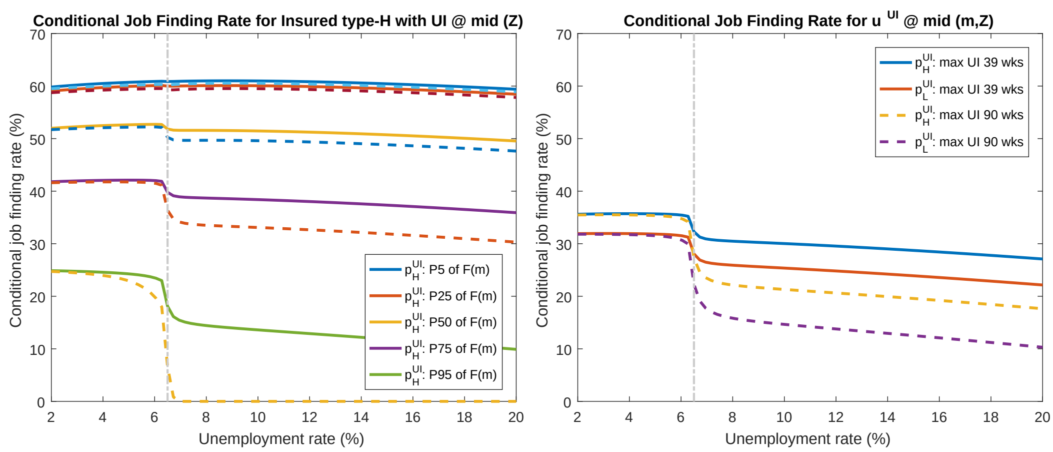


Figure 3.21: Total Match Surplus as a function of unemployment by UI status $(S_H^{e(\tilde{m})}(m), S_H^{UI(\tilde{m})}(m), S_H^{UU}(m))$ (left panel) and by worker's productivity $(S_H^{UI(\tilde{m})}(m), S_L^{UI(\tilde{m})}(m))$ (right panel): For solid (dashed) lines, maximum UI duration is 39 (90) weeks

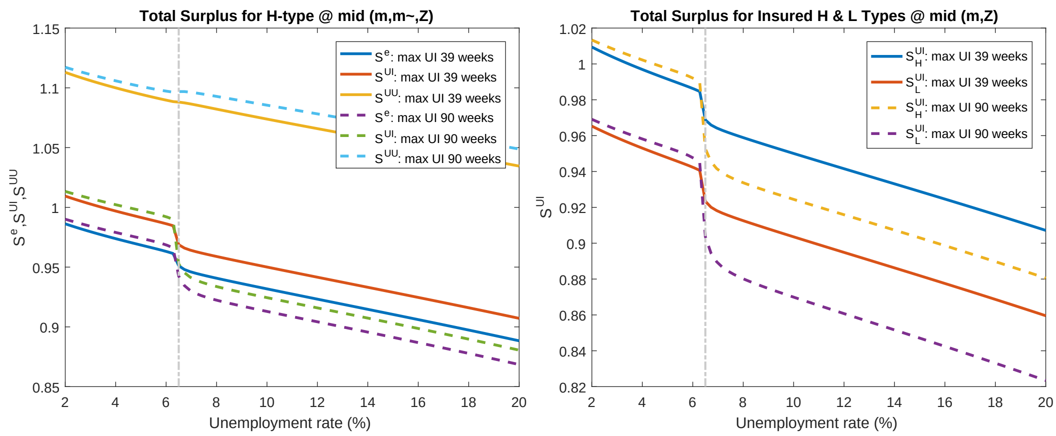


Figure 3.22: Total Match Surplus as a function of unemployment for the insured unemployed by future match quality ($S_H^{UI(\tilde{m})}(m)$ by m) (left panel) and by benefit level ($S_H^{UI(\tilde{m})}(m)$ by $\tilde{m}$) (right panel): For solid (dashed) lines, maximum UI duration is 39 (90) weeks

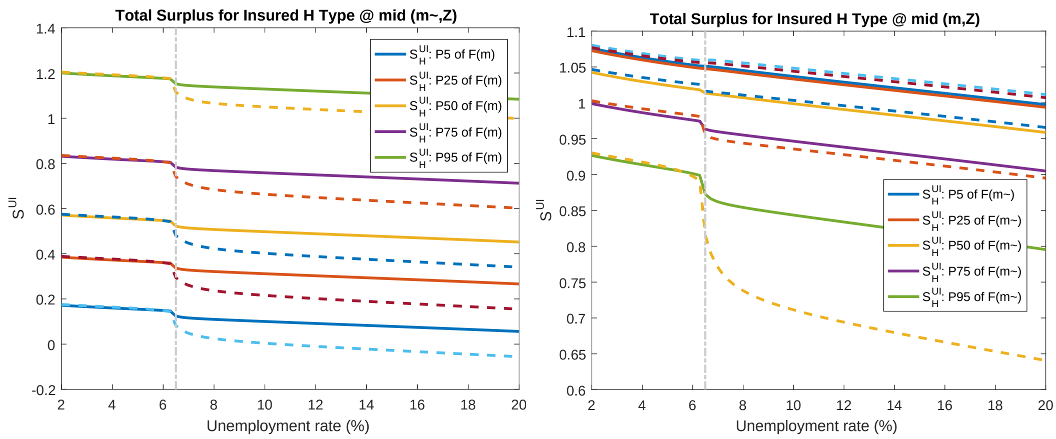


Figure 3.23: Success rate of meetings between unemployed workers and firms (fractions of meetings that lead to viable matches)

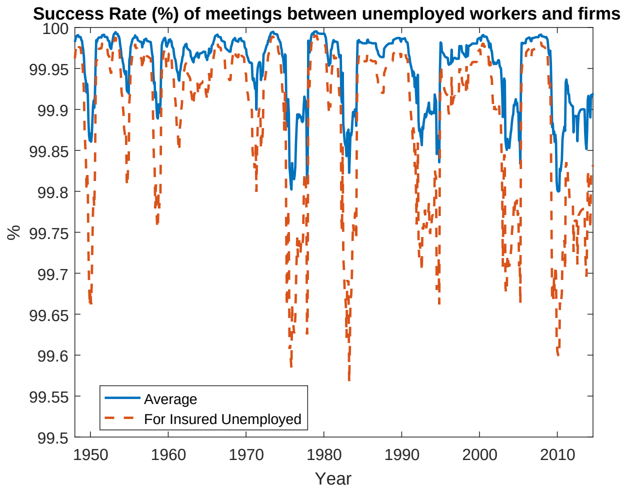
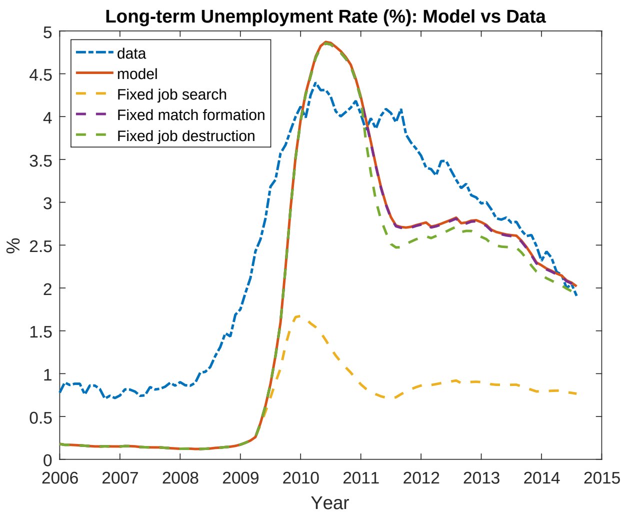
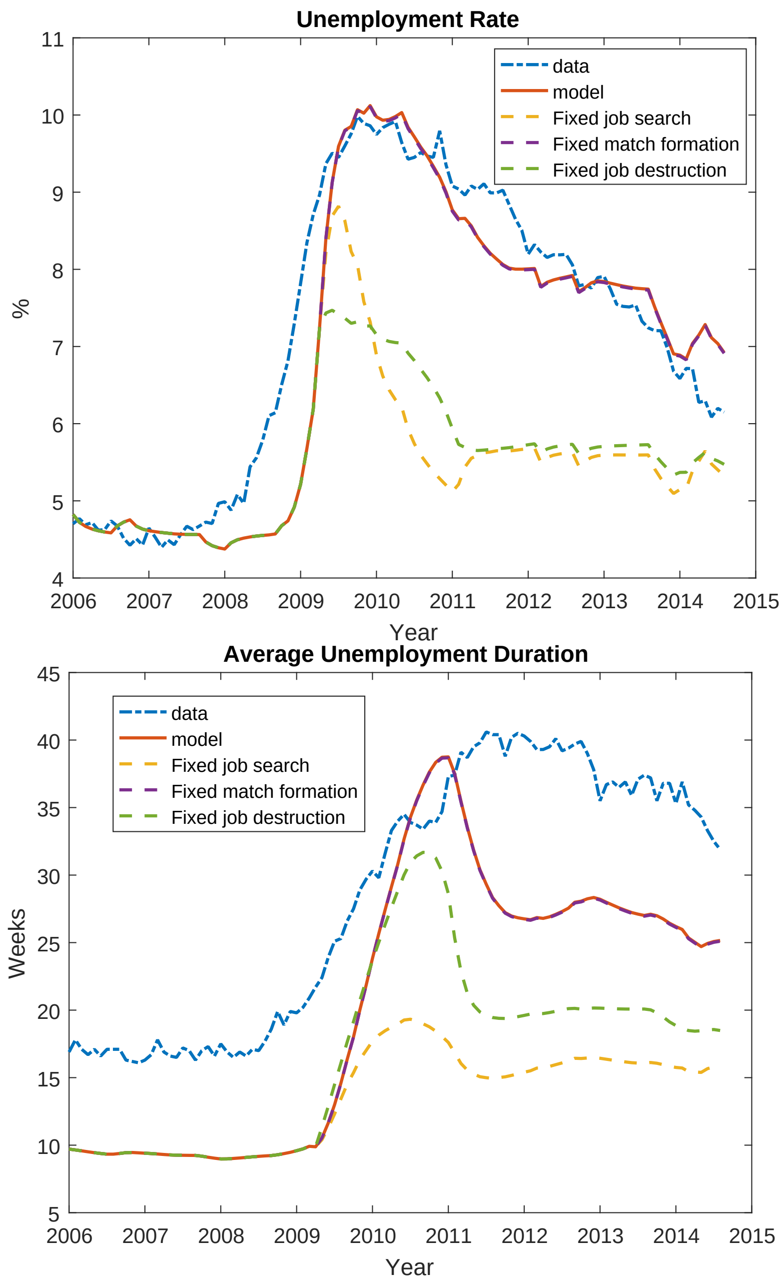


Figure 3.24: Decomposition of the Effect of UI Extensions on Long-term Unemployment (%): Data, Baseline Model and Counterfactual (each of the following channels is fixed: job search behavior, match formation and job destruction) (Data source: CPS)



Fixed job search: job search intensity ($s_i^e(\tilde{m}), s_i^{UI}(\tilde{m}), s_i^{UU}$) does not respond to UI extensions
Fixed match formation: match formation decisions ($S_i^{UI(\tilde{m})}(m), S_i^{UU}(m)$) do not respond to UI extensions
Fixed job destruction: match separation decisions ($S_i^{e(\tilde{m})}(m)$) do not respond to UI extensions

Figure 3.25: Decomposition of the Effect of UI Extensions on Unemployment (%) (top panel) and Average Unemployment Duration (weeks) (bottom panel): Data, Baseline Model and Counterfactual (each of the following channels is fixed: job search behavior, match formation and job destruction) (Data source: CPS)



Fixed job search: job search intensity ($s_i^e(\tilde{m}), s_i^{UI}(\tilde{m}), s_i^{UU}$) does not respond to UI extensions

Fixed match formation: match formation decisions ($S_i^{UI(\tilde{m})}(m), S_i^{UU}(m)$) do not respond to UI extensions

Fixed job destruction: match separation decisions ($S_i^{e(\tilde{m})}(m)$) do not respond to UI extensions

Figure 3.26: UI Extensions: Data, Baseline Model and Counterfactual (with no UI extensions) (Data source: ETA)

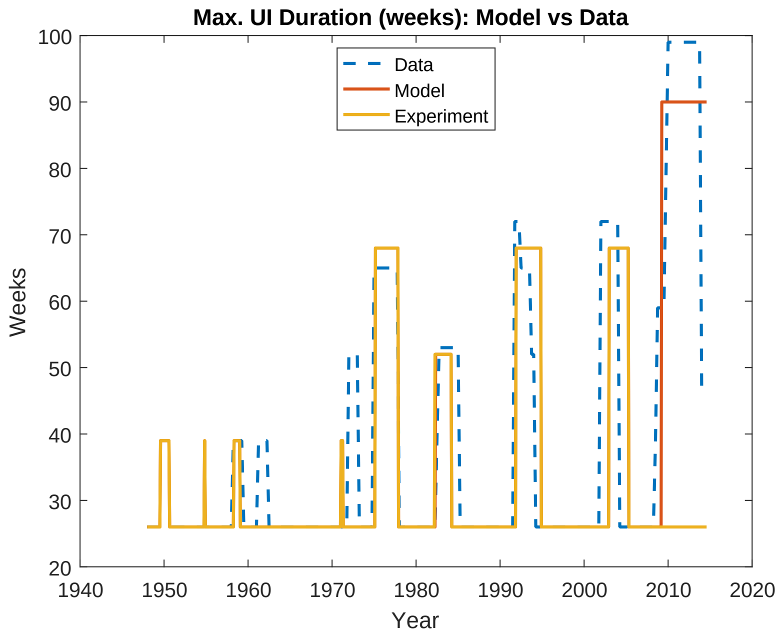
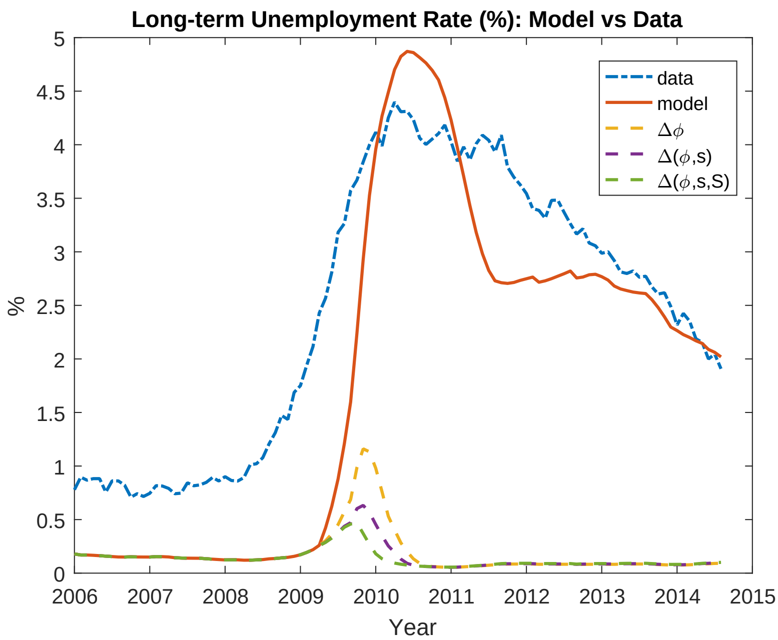
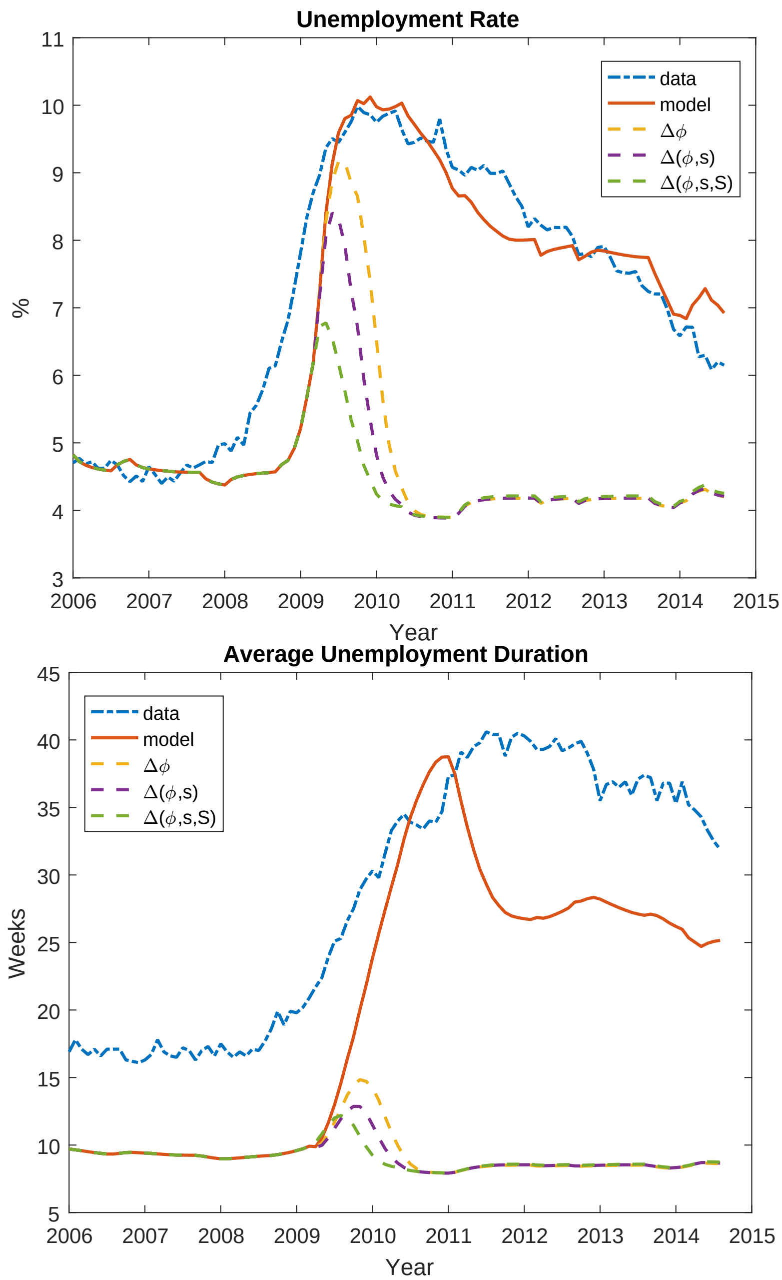


Figure 3.27: The Effect of Removing UI Extension on the Long-term Unemployment (%): Data, Baseline Model and Counterfactual (with no UI extensions) (Data source: CPS)



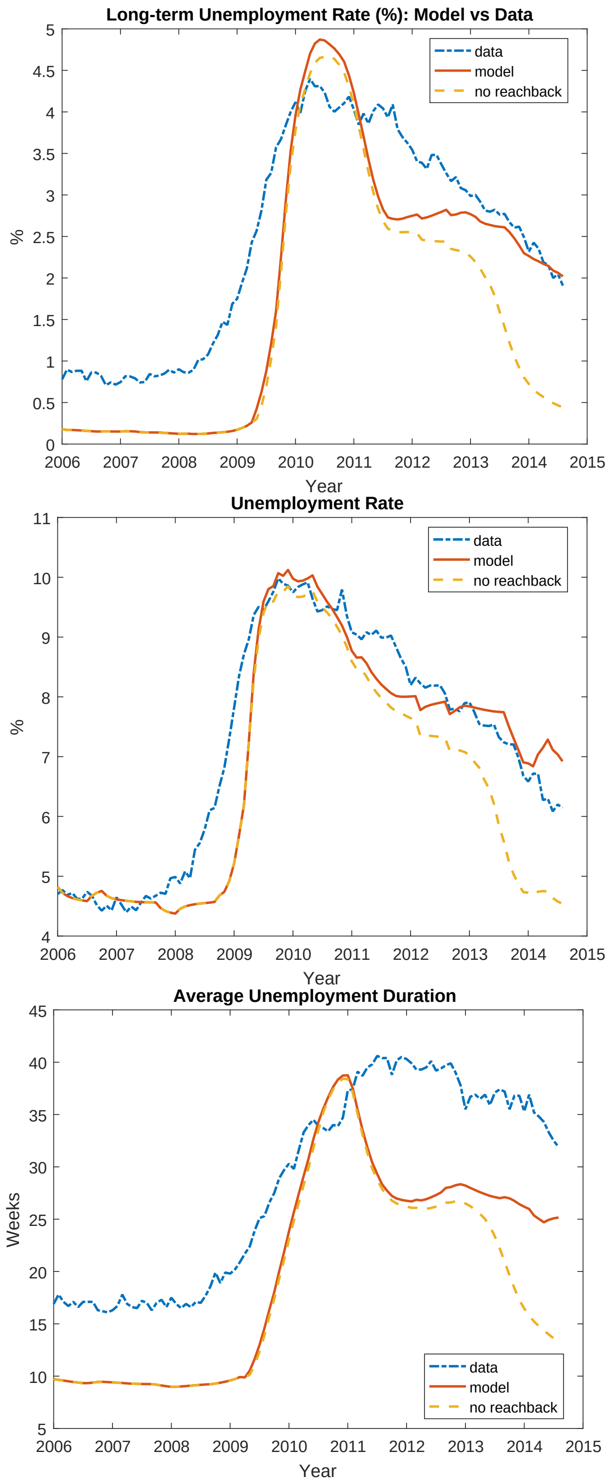
$\Delta\phi$: only maximum UI duration changes
$\Delta(\phi, s)$: maximum UI duration and job search effort change
$\Delta(\phi, s, S)$: maximum UI duration, job search effort and match surplus change

Figure 3.28: The Effect of Removing UI Extension on Unemployment (%) (top panel) and Average Unemployment Durations (bottom panel): Data, Baseline Model and Counterfactual (with no UI extensions) (Data source: CPS)



$\Delta\phi$: only maximum UI duration changes
$\Delta(\phi, s)$: maximum UI duration and job search effort change
$\Delta(\phi, s, S)$: maximum UI duration, job search effort and match surplus change

Figure 3.29: The Effect of Removing Reachback Provision Programme on Long-term Unemployment (%) (top panel), Unemployment (%) (middle panel) and Average Unemployment Durations (bottom panel): Data, Baseline Model and Model without Reachback Provision (Data source: CPS)



From May 2007, the Emergency Unemployment Compensation law has included the "Reachback Provision" providing UI eligility to unemployed workers who have already exhausted their benefits prior to the extensions of UI. This programme is featured in the baseline model whilst it is not in the counterfactual experiment.

Figure 3.30: The Effect of Removing On-the-job Search (OJS) on Long-term Unemployment (%) (top panel), Unemployment (%) (middle panel) and Average Unemployment Durations (bottom panel): Data, Baseline Model and Model without OJS (Data source: CPS)

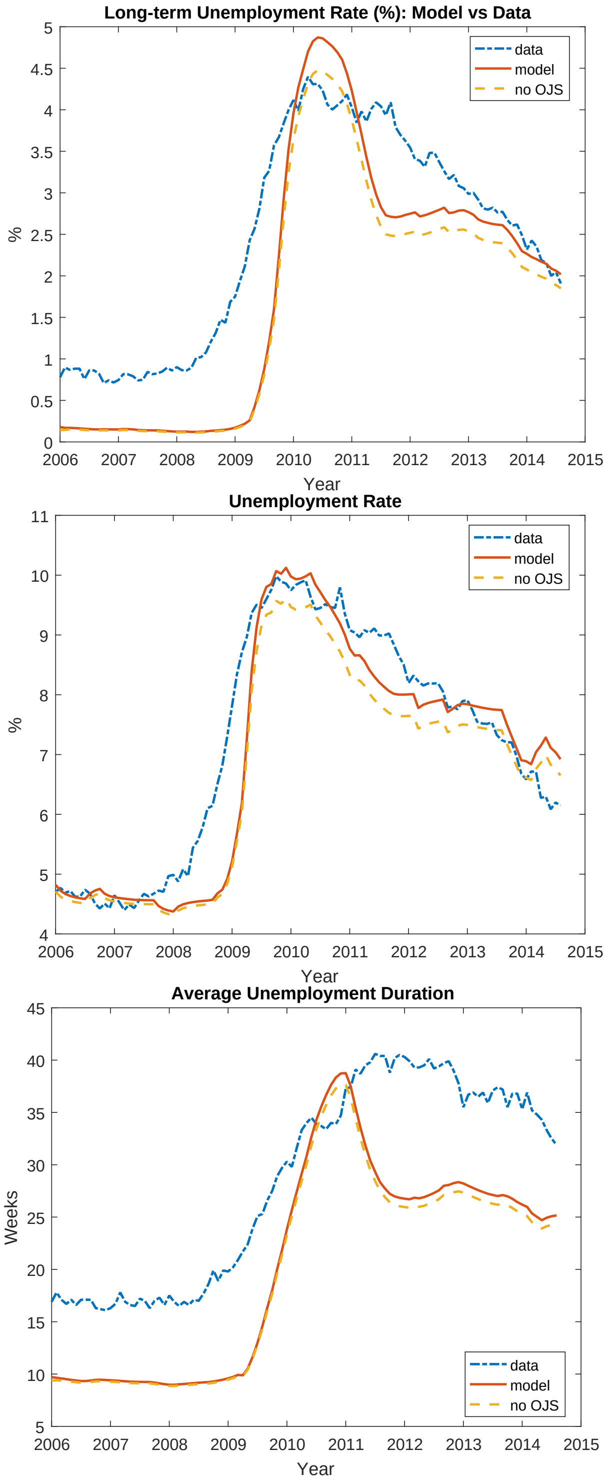


Figure 3.31: Hazard Rate (%) of Exiting Unemployment

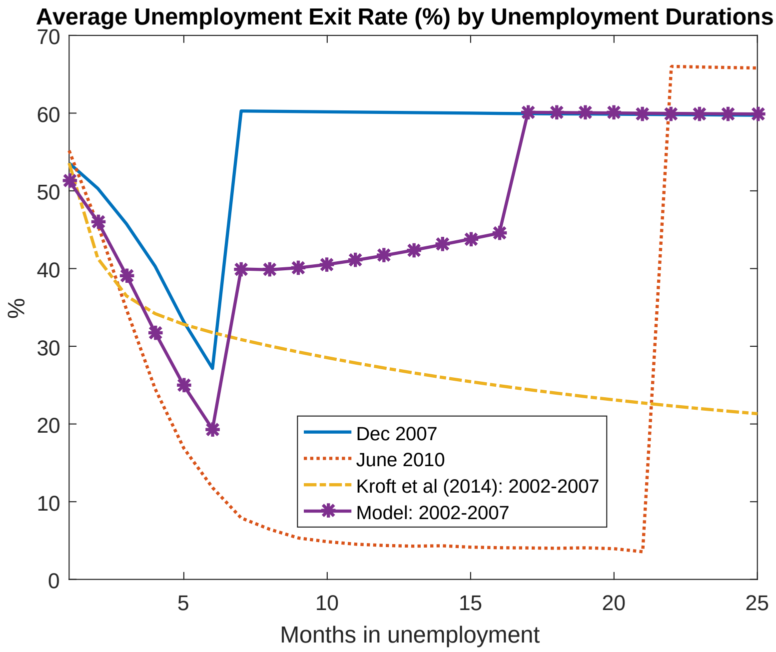


Figure 3.32: Probability that the newly unemployed workers of each type remain unemployed the following month: model's prediction (left panel) and empirical prediction from Ahn & Hamilton (2016) (right panel, source: Ahn & Hamilton, 2016)

Figure 3.33: Number of newly unemployed workers of each type: model's prediction (left panel) and empirical prediction from Ahn & Hamilton (2016) (right panel, source: Ahn & Hamilton, 2016)

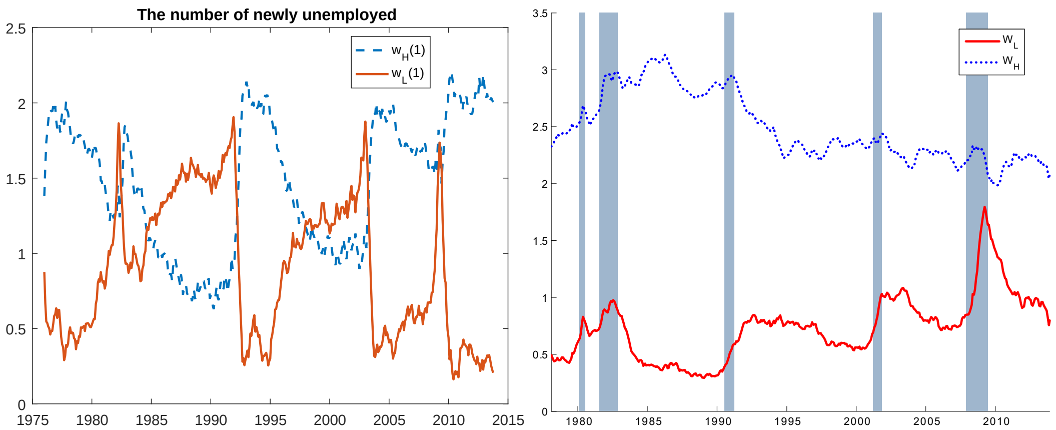


Figure 3.34: Share of unemployment by worker's type: model's prediction (left panel) and empirical prediction from Ahn & Hamilton (2016) (right panel, source: Ahn & Hamilton, 2016)

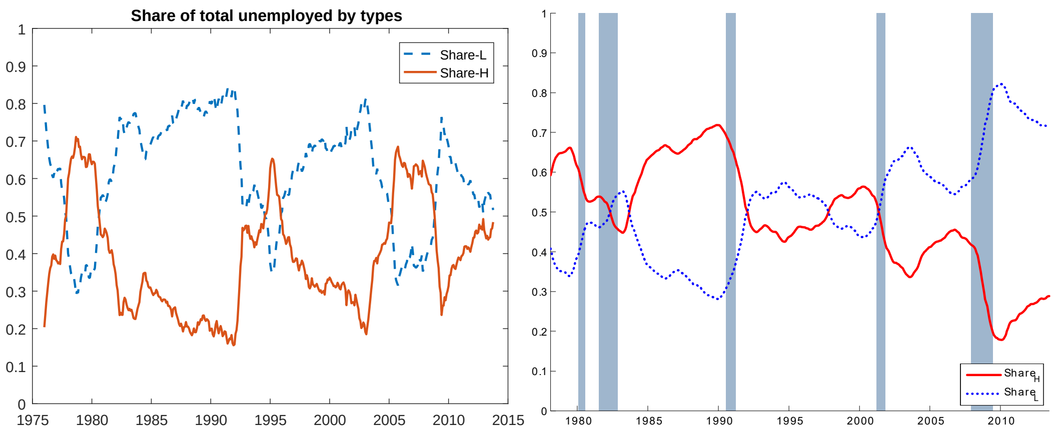


Figure 3.35: Shares (%) of unemployment by UI Status and Worker's Productivity

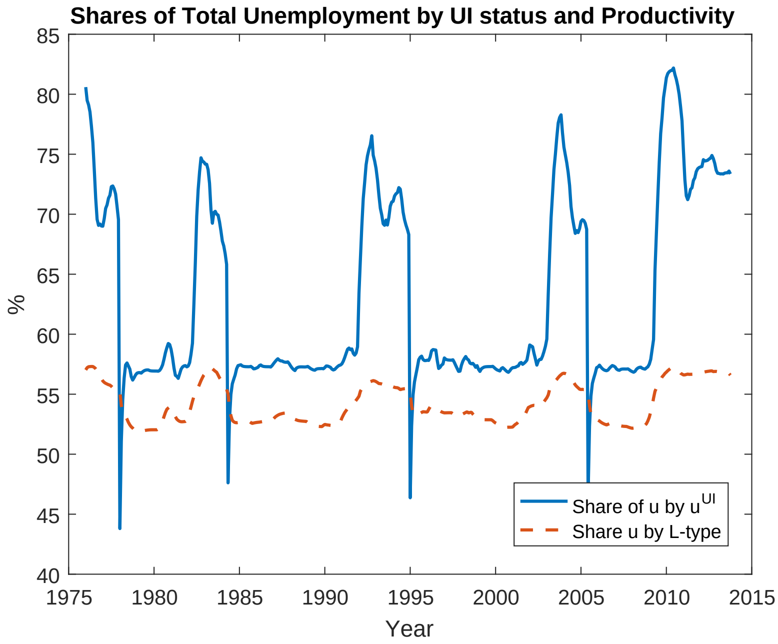
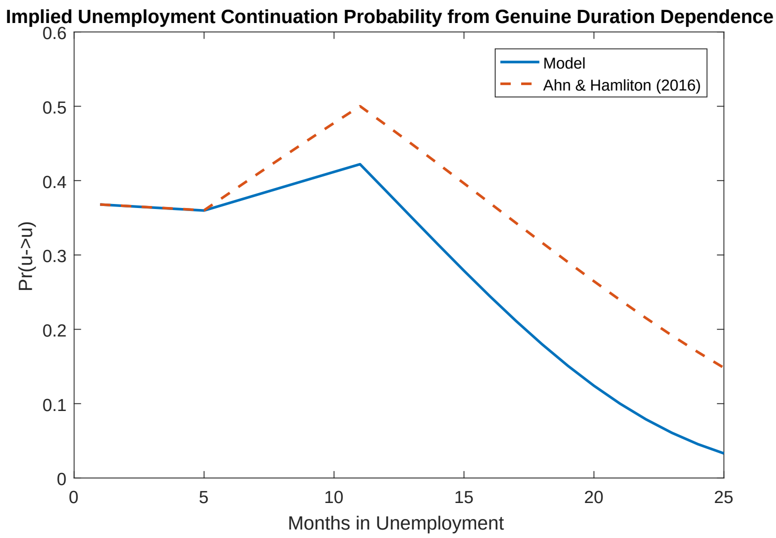


Figure 3.36: Implied Unemployment Continuation Probability from Genuine Duration Dependence: model's prediction (solid) and empirical prediction from Ahn & Hamilton (2016) (dashed)



- Note: The time varying factors governing the outflow rates for type-i workers (x_{it}) are normalised to zero when calculating these probabilities.

Table 3.2: Unemployment-to-Employment (UE) Monthly Transition Rate (%)

	Current UI Recipients			Non-UI Recipients		
	Jan-08	Jan-10	Δpp.	Jan-08	Jan-10	Δpp.
Age						
16 years or older	21.4	7.2	−14.2	27.5	17.8	−9.7
25−54 years	24.3	7.1	−17.1	30.7	19.7	−11.0
Gender						
Male	24.9	7.2	−17.6	28.4	18.3	−10.1
Female	16.3	7.2	−9.1	26.3	17.1	−9.2
Education						
Less than High School	25.0	4.7	−20.3	25.4	16.2	−9.2
High School	9.0	7.5	−1.5	28.9	16.0	−12.9
Some College	27.4	7.4	−20.0	28.0	20.5	−7.5
College or higher	26.8	7.4	−19.3	28.4	24.5	−3.9
Industry						
Manufacturing	22.5	6.5	−16.0	25.6	14.9	−10.7
Construction	18.3	9.6	−8.7	36.3	21.6	−14.7
Wholesale & Retail	n/a	6.4	n/a	26.0	16.3	−9.7
Prof./Business Services	45.9	4.3	−41.6	22.5	19.9	−2.6
Occupation						
High-skilled	27.4	7.8	−19.5	27.4	24.6	−2.9
Middle-skilled	18.6	6.6	−12.0	30.1	17.9	−12.2
Low-skilled	20.6	10.4	−10.2	26.6	17.6	−9.0
Reasons for Unemployment						
Temporary Layoff	50.7	12.2	−38.5	46.2	40.4	−5.8
Permanent Separation	13.6	6.7	−6.9	25.6	15.6	−10.0
Recall						
Date Given	56.4	9.9	−46.5	53.9	47.00	−6.9
No Date Given	22.4	7.7	−14.7	29.4	22.9	−6.5
Some indication	48.3	13.3	−35.0	36.6	33.8	−2.8
No indication	16.5	7.0	−9.5	22.2	17.5	−4.7

- Data source: CPS
  Δpp. ≡ change in UE rate (in percentage points) $= UE_{Jan10} - UE_{Jan08}$
  Occupation skills are defined as in the job polarisation literature (where high-, middle- and low-skilled occupations respectively are abstract, routine and manual jobs)

Table 3.3: Unemployment-to-Unemployment (UU) Monthly Transition Rate (%)

	Current UI Recipients			Non-UI Recipients		
	Jan-08	Jan-10	Δpp.	Jan-08	Jan-10	Δpp.
Age						
16 years or older	68.4	84.4	+16.0	48.0	60.2	+12.2
25−54 years	65.4	84.9	+19.6	50.8	62.6	+11.8
Gender						
Male	62.5	85.5	+23.0	50.9	63.0	+12.1
Female	77.0	81.9	+4.9	43.9	56.0	+12.1
Education						
Less than High School	60.7	82.4	+21.7	43.8	58.1	+14.3
High School	77.6	87.8	+10.2	49.8	63.2	+13.4
Some College	65.1	81.7	+16.6	49.3	58.8	+9.5
College or higher	61.1	81.2	+20.1	51.7	60.4	+8.8
Industry						
Manufacturing	68.2	82.0	+13.8	51.9	62.6	+10.7
Construction	65.6	84.4	+18.8	50.5	66.5	+16.0
Wholesale & Retail	80.9	86.1	+5.2	49.5	60.1	+10.6
Prof./Business Services	52.5	88.9	+36.3	55.5	60.2	+4.7
Occupation						
High-skilled	68.5	86.1	+17.6	49.8	60.7	+10.9
Middle-skilled	69.1	83.9	+14.8	48.3	62.3	+14.0
Low-skilled	62.9	81.0	+18.1	47.8	55.8	+8.0
Reasons for Unemployment						
Temporary Layoff	36.2	81.1	+44.9	42.2	49.5	+7.2
Permanent Separation	78.5	84.5	+6.0	57.2	69.1	+11.9
Recall						
Date Given	28.5	81.4	+52.9	35.9	47.0	+11.1
No Date Given	68.7	84.0	+15.3	52.6	63.5	+11.0
Some indication	39.5	80.9	+41.4	50.2	52.4	+2.2
No indication	77.6	84.3	+6.8	55.2	69.1	+13.9

- Data source: CPS
  Δpp. ≡ change in UU rate (in percentage points) $= UU_{Jan10} - UU_{Jan08}$
  Occupation skills are defined as in the job polarisation literature (where high-, middle- and low-skilled occupations respectively are abstract, routine and manual jobs)

Table 3.4: Unemployment-to-Out-of-Labour-Force (UOLF) Monthly Transition Rate (%)

	Current UI Recipients			Non-UI Recipients		
	Jan-08	Jan-10	Δpp.	Jan-08	Jan-10	Δpp.
Age						
16 years or older	10.3	8.5	−1.8	24.5	22.0	−2.5
25−54 years	10.4	8.0	−2.4	18.5	17.7	−0.8
Gender						
Male	12.6	7.3	−5.4	20.7	18.7	−2.0
Female	6.8	10.9	+4.1	29.8	26.8	−3.0
Education						
Less than High School	14.3	12.9	−1.4	30.8	25.7	−5.1
High School	13.4	4.6	−8.7	21.3	20.8	−0.5
Some College	7.5	11.0	+3.5	22.7	20.7	−2.0
College or higher	12.1	11.3	−0.8	19.9	15.1	−4.8
Industry						
Manufacturing	9.3	11.6	+2.3	22.5	22.5	0.0
Construction	16.1	5.9	−10.2	13.2	11.9	−1.3
Wholesale & Retail	19.1	7.5	−11.6	24.4	23.6	−0.8
Prof./Business Services	1.5	6.8	+5.3	22.0	19.9	−2.1
Occupation						
High-skilled	4.1	6.0	+1.9	22.8	14.8	−8.0
Middle-skilled	12.3	9.5	−2.8	21.7	19.9	−1.8
Low-skilled	16.5	8.6	−7.9	25.6	26.6	+1.0
Reasons for Unemployment						
Temporary Layoff	13.2	6.7	−6.4	11.6	10.2	−1.4
Permanent Separation	7.9	8.8	+0.9	17.2	15.3	−1.9
Recall						
Date Given	15.1	8.6	−6.5	10.2	6.1	−4.1
No Date Given	8.9	8.3	−0.6	18.0	13.6	−4.4
Some indication	12.3	5.8	−6.5	13.2	13.8	+0.56
No indication	6.0	8.7	+2.7	22.6	13.4	−9.2

- Data source: CPS
  Δpp. ≡ change in UOLF rate (in percentage points) = $UOLF_{Jan10} - UOLF_{Jan08}$
  Occupation skills are defined as in the job polarisation literature (where high-, middle- and low-skilled occupations respectively are abstract, routine and manual jobs)

Table 3.5: Fraction (%) of Long-term Unemployment Represented by Current UI Recipients in each Subgroup

	Jan-06	Jan-08	Jan-10	Jan-12	Jan-14	Δpp. from 2008 to 2010
Age						
16 years or older	18	15	51	39	16	+36
25-54 years	18	14	50	41	18	+36
Gender						
Male	15	13	50	38	14	+38
Female	22	18	54	40	19	+36
Education						
Less than High School	13	23	34	32	12	+11
High School	21	2	53	34	14	+51
Some College	17	21	56	44	17	+35
College or higher	22	22	56	40	22	+34
Industry						
Manufacturing	27	25	62	38	17	+37
Construction	8	16	47	40	21	+31
Wholesale & Retail	6	n/a	53	34	18	n/a
Prof./Business Services	13	11	43	35	6	+32
Occupation						
High-skilled	29	22	61	46	27	+39
Middle-skilled	14	15	53	39	12	+38
Low-skilled	11	6	29	30	14	+23
Reasons for Unemployment						
Temporary Layoff	n/a	30	61	49	12	+31
Permanent Separation	22	18	56	41	17	+38
Recall						
Date Given	n/a	n/a	42	63	10	n/a
No Date Given	15	26	60	46	26	+34
Some indication	n/a	5	68	43	12	+63
No indication	16	29	60	46	27	+31

- Data source: CPS
  Long-term unemployment is defined as unemployed workers whose duration is longer than six months.
  Occupation skills are defined as in the job polarisation literature (where high-, middle- and low-skilled occupations respectively are abstract, routine and manual jobs)

Table 3.6: Fraction (%) of Newly Unemployed Workers Represented by Current UI Recipients in each Subgroup

	Jan-06	Jan-08	Jan-10	Jan-12	Jan-14	Δpp. from 2008 to 2010
Age						
16 years or older	23	21	41	30	25	+20
25-54 years	24	21	42	33	31	+21
Gender						
Male	26	20	40	33	27	+20
Female	18	23	42	26	21	+19
Education						
Less than High School	23	18	25	28	8	+7
High School	29	17	48	27	33	+30
Some College	16	26	41	33	26	+14
College or higher	18	24	46	33	30	+22
Industry						
Manufacturing	45	30	44	36	31	+15
Construction	33	17	44	45	32	+27
Wholesale & Retail	25	21	51	20	24	+30
Prof./Business Services	13	19	26	33	22	+7
Occupation						
High-skilled	22	24	55	34	30	+31
Middle-skilled	26	18	41	36	25	+23
Low-skilled	6	30	22	12	18	−8
Reasons for Unemployment						
Temporary Layoff	34	25	44	27	31	+19
Permanent Separation	25	21	47	33	28	+26
Recall						
Date Given	25	25	49	23	24	+24
No Date Given	32	30	49	34	36	+20
Some indication	39	26	42	31	40	+16
No indication	28	31	51	34	35	+19

- Data source: CPS
  Newly unemployed workers are defined as unemployed workers whose duration is less five weeks.
  Occupation skills are defined as in the job polarisation literature (where high-, middle- and low-skilled occupations respectively are abstract, routine and manual jobs)

Table 3.7: Targeted Moments

Moment	Data	Model
E(u)	0.0583	0.0577
E(ρ_{UE})	0.4194	0.4286
E(ρ_{EU})	0.0248	0.0251
E(ρ_{EE})	0.0320	0.0320
E(u_{dur})	15.416	13.063
E(u^{UI})	0.0290	0.0327
std(u)	0.1454	0.1453
std(ρ_{UE})	0.0999	0.1402
std(ρ_{EU})	0.0890	0.0641
std(u_{dur})	6.9327	6.1954
std(LP)	0.0131	0.0104
corr(LP, LP_{-1})	0.7612	0.7593

- ρ_{UE}: job finding rate // ρ_{EU}: job separation rate // ρ_{EE}: job-to-job transition rate
  u_{dur}: mean unemployment duration (weeks) // $LP = y/(1-u)$: labour productivity
  Data source: CPS

Table 3.8: Fixed Parameters For Baseline Model

Parameter	Description	Value	Sources/Remarks
β	Discount factor	0.9967	Annual interest rate of 4%
κ	Vacancy posting cost	0.0392	Fujita & Ramey (2012)
μ	Worker's bargaining power	0.5	Den Haan, Ramey & Watson (2000)
ϕ_H	UI exhaustion rate	1/6	6 months max UI duration, ETA
ϕ_{L1}	UI exhaustion rate	1/9	9 months max UI duration, ETA
ϕ_{L2}	UI exhaustion rate	1/12	12 months max UI duration, ETA
ϕ_{L3}	UI exhaustion rate	1/16	16 months max UI duration, ETA
ϕ_{L4}	UI exhaustion rate	1/21	21 months max UI duration, ETA
$\bar{u}$	UI policy threshold	0.065	ETA
a_u	Search cost function	0.1116	Normalisation
d_u, d_e	Search cost function	1	Christensen et al (2004), Yashiv (2000)
h	Leisure flow	0.5835	Gruber (1997)

Table 3.9: Values of UI benefits by match quality in most recent employment and worker's productivity

	m_{10}	m_{20}	m_{30}	m_{40}	m_{50}	m_{60}	m_{70}	m_{80}	m_{90}	m_{100}
$b_H(m)$	0.001	0.002	0.012	0.028	0.043	0.064	0.077	0.104	0.130	0.296
$b_L(m)$	0.001	0.002	0.012	0.027	0.042	0.062	0.076	0.103	0.129	0.295
m	0.526	0.563	0.618	0.655	0.692	0.748	0.785	0.859	0.933	1.396

- m_x is the x-th percentile of the match quality distribution $F(m)$

Table 3.10: Calibrated Parameters For Baseline Model

Parameter	Description	Value
l	Meeting function	0.51
δ	Exogenous separation rate	0.023
λ	Pr(redrawing new m)	0.50
ψ	Pr(losing UI after becoming unemployed)	0.49
ξ	Pr(losing UI after meeting firm)	0.50
a_e	Search cost function	0.15
$\underline{m}$	Lowest match-specific productivity	0.396
β_1	Match-specific prod. distribution	2.55
β_2	Match-specific prod. distribution	5.26
ρ_z	Persistence of TFP	0.9562
σ_z	Standard deviation of TFP shocks	0.0075
η_L	Productivity of type-L	0.985

Table 3.11: Moments Not Targeted

Moment	Data	Model
E($U1$)	0.0233	0.0237
E($U2$)	0.0172	0.0180
E($U4$)	0.0080	0.0085
E(LTU)	0.0098	0.0076
std($U1$)	0.0048	0.0017
std($U2$)	0.0046	0.0030
std($U4$)	0.0035	0.0035
std(LTU)	0.0085	0.0107
std(u^{UI})	0.1780	0.2523
std(v)	0.1226	0.0327
corr(u,v)	-0.6682	-0.1906

- $U1$: Unemployed less than 1 month // $U2$: Unemployed with 2-3 month duration
  $U4$: Unemployed with 4-6 month duration // LTU: Unemployed longer 6 months
  u_{dur}: mean unemployment duration (weeks)
  Data source: CPS

Table 3.12: Performance of the Model during the Great Recession

x	Data max(x)	Model max(x)	Data mean(x)	Model mean(x)	mean % deviation (in modulus) from data
$u(\%)$	10.0%	10.1%	8.3%	8.3%	4.6%
u_{dur} (weeks)	40.6	38.8	36.3	28.5	23.0%
$LTU(\%)$	4.4%	4.9%	3.4%	3.1%	12.9%

- LTU: Unemployed longer 6 months // u_{dur}: mean unemployment duration (weeks)
  - These statistics are computed between October 2009 (the peak of the US unemployment rate) and June 2014
  - The last column shows the time-average percentage deviation in modulus of each variable from its empirical counterpart
  - Data source: CPS

Table 3.13: Counterfactual Experiments: Effects of Decreasing Maximum UI Duration from 90 Weeks to 26 Weeks during the Great Recession

	Data	Baseline	$\Delta\phi$	$\Delta(\phi,s)$	$\Delta(\phi,s,S)$
max(u) (%)	10.0%	10.1%	9.2%	8.4%	6.8%
max(u_{dur}) (weeks)	40.6	38.8	14.8	12.9	12.2
max(LTU) (%)	4.4%	4.9%	1.2%	0.6%	0.5%
Δ max(u)			−0.9pp	−1.7pp	−3.4pp
Δ max(u_{dur})			−24.0	−25.9	−26.6
Δ max(LTU)			−3.7pp	−4.3pp	−4.4pp

- $\Delta\phi$: only maximum UI duration changes
  $\Delta(\phi,s)$: maximum UI duration and job search effort change
  $\Delta(\phi,s,S)$: maximum UI duration, job search effort and match surplus change
  LTU: Unemployed longer 6 months // u_{dur}: mean unemployment duration (weeks)
  Δ max($\cdot$): difference between the model's and counterfactual experiments' maxima
  - These statistics are computed between October 2009 (the peak of the US unemployment rate) and June 2014
  - Data source: CPS

Table 3.14: Counterfactual Experiments: Effects of Removing the Reachback Provision Programme during the Great Recession

	Data	Baseline	No Reachback
max(u) (%)	10.0%	10.1%	9.8%
max(u_{dur}) (weeks)	40.6	38.7	38.4
max(LTU) (%)	4.4%	4.9%	4.7%
Δ max(u)			-0.3pp
Δ max(u_{dur})			-0.3
Δ max(LTU)			-0.2pp

- LTU: Unemployed longer 6 months // u_{dur}: mean unemployment duration (weeks)
  Δ max($\cdot$): difference between the model's and counterfactual experiment's maxima
  - These statistics are computed between October 2009 (the peak of the US unemployment rate) and June 2014
  - Data source: CPS

Table 3.15: Parameter Estimates from State Space Model in Ahn and Hamilton (2016)

Parameter	A&H (2016)	Model
σ_L^w	0.0434	0.0439
	(0.0041)	(0.0086)
σ_H^w	0.0456	0.0487
	(0.0059)	(0.0060)
σ_L^x	0.0446	0.0469
	(0.0049)	(0.0096)
σ_H^x	0.0209	0.0211
	(0.0028)	(0.0030)
δ_1	0.0053	0.0055
	(0.0138)	(0.0010)
δ_2	-0.0647	-0.0283
	(0.0242)	(0.0383)
δ_3	0.0724	0.0981
	(0.0250)	(0.0231)
$R1$	0.0981	0.0966
	(0.0058)	(0.0156)
$R2.3$	0.0759	0.0755
	(0.0043)	(0.0111)
$R4.6$	0.0775	0.0765
	(0.0068)	(0.0123)
$R7.12$	0.0597	0.0626
	(0.0051)	(0.0080)
$R13+$	0.0366	0.0390
	(0.0026)	(0.0057)

- Standard errors are reported in parentheses. Please refer to Appendix E for variables' definitions

Chapter 4

The Persistence of Unemployment and the Role of Unemployment Insurance History

4.1 Introduction/Motivation

The effects of unemployment insurance (UI) extensions on unemployment and its duration structure have long been studied from both theoretical and empirical perspectives.[1] The generous UI extensions and the unprecedented rise in unemployment duration during the Great Recession in the US have sparked a greater interest in quantifying the effect of UI extensions. This question becomes more complicated since the extensions themselves were triggered by the state unemployment rate. Some studies find a limited role of UI extensions on unemployment and its duration structure. For example, Rothstein (2011) finds that UI extensions contributes to 0.1-0.5 percentage point increase in the unemployment rate while Fujita (2011) estimates the UI effect to be around 0.5-1.25 percentage point increase.[2] At the same time, other studies find a more substantial effect of the UI extensions. For

[1] For example, see Shavell and Weiss (1979), Moffitt and Nicholson (1982), Moffitt (1985), and Katz and Meyer (1990), Wang and Williamson (1996), Hopenhayn and Nicolini (1997), Chetty (2008), Shimer and Werning (2008), and Krueger and Mueller (2010, 2011).

[2] Other studies that find a small but significant impact of UI extensions within the range of 0.1-1.8 percentage point increase in unemployment include Aaronson, Mazumder, and Schechter (2010), Valletta and Kuang (2010), Farber and Valletta (2011), Mazumder (2011), Nakajima (2012), and Barnichon and Figura (2014).

example, Hagedorn, Karahan, Manovskii, and Mitman (2015) find that without UI extensions the unemployment rate would have been 2.5 percentage points lower. Mitman and Rabinovich (2014) link the emergence of jobless recoveries in the past three recessions to UI extensions.

Chapter 3 develops a framework which helps reconcile these mixed results by studying a general equilibrium search and matching model that distinguishes between the microeconomic and macroeconomic effects of UI extensions. I find that the extensions can account for a large part of the increase in the average unemployment duration and long-term unemployment (those unemployed longer than six months) during the Great Recession. However, the model overstate the size of the changes of these labour market variables, and also understate their persistence.

The purpose of this paper is to address these issues by exploiting the fact that there are further heterogeneities the job finding rates of unemployed workers. By distinguishing unemployed workers into three categories: currently receiving UI benefits (henceforth insured unemployed), having exhausted UI benefits in the current unemployment spell (formerly insured unemployed), and having never collected benefits in the current spell (uninsured unemployed), I show that in the US data the job finding rate of the formerly insured is significantly lower than that of the uninsured. This finding is at odds with models that incorporate job search intensity including the one in Chapter 3 since they predict that both the formerly insured and the uninsured exert the same search effort (due to having the same outside option), and, therefore, have the same job finding rate. Following Shimer (2004), I measure the search effort based on the number of job search methods, and find that both types of unemployed workers (formerly insured and uninsured) do exert similar job search intensities.

Motivated by these empirical findings, I extend an equilibrium search and matching model with variable job search intensity by introducing a drop in job search efficiency during an unemployment spell of insured unemployed workers. I argue that this drop in search efficiency can be interpreted as a loss of career network or a loss of skills/tools to conduct job search efficiently after a period of less activity (whilst being insured). This feature allows the formerly insured, whose search efficiency has fallen, to exert similar search efforts to the uninsured, and at the same time find a job at a slower rate than do the uninsured. Because of the fall in the formerly insured workers' job finding rate, the model can potentially increase the persistence of unemployment duration and long-term unemployment. Furthermore, the drop in job search efficiency lowers the value of being insured unemployed which has two implications. First, it lowers the job separations of employed workers who are on the margin of returning to unemployment. Second, it increases the job search intensity of the insured (to avoid losing the search efficiency), and thereby shortens the unemployment spells. This means that the response of insured unemployment to UI extensions is expected to be more moderated.

This paper is also related to the literature studying the dynamics of unemployment and its duration structure by exploring worker heterogeneities. Ahn and Hamilton (2016), Ahn (2016), Hornstein (2012), and Ravn and Sterk (2013) study the role of unobserved heterogeneity of workers that affects the unemployment exit probabilities. Kroft, Lange, Notowidigdo and Katz (2016) study the roles of the genuine duration dependence in the job finding rate together with the non participation margin. Elsby, Hobijn, Şahin and Valetta (2011) also study the contribution of flows between non-participation and unemployment. Carrillo-Tudela and Visschers (2014) study the role of occupational choices of unemployed workers on aggregate unemployment and its duration distribution. This paper contributes to this literature by focussing on the roles of worker's UI history and how this affects the effects of UI extensions on the unemployment duration distribution over the business cycles.

The main contributions of this paper is two folds. Empirically, I show that the worker's UI history is an important determinant for the labour market outcomes. I then present an equilibrium model that is made consistent with the empirical findings by introducing a drop in job search efficiency for unemployed workers who have received UI benefits, and study the impact of UI extensions on unemployment and its duration structure from both positive and normative aspects.

I find that the introduction of a search efficiency drop for the formerly insured unemployed improves the persistence of unemployment, average unemployment duration and long-term unemployment by at least 14, 5 and 7 percent respectively (as measured by the autocorrelation coefficients up to 2-year lags) when compared to a model without a search efficiency drop. At the same time, the effect of UI extensions is also revised downwards where the elasticity of unemployment duration is 5 percentage points lower, and a 1-week increase in maximum UI duration implies a [0.33, 0.38] week increase in average unemployment duration. However, the effect on total unemployment is hardly affected by this drop in search efficiency. Additionally, I find that on average there is a welfare gain from eliminating all UI extensions during the Great Recession of 0.14 percent, which is a combination of 0.27 percent welfare increase for the employed and 1.27 percent welfare drop for the unemployed. Consistent with the results From Mitman and Rabinovich (2015) who study the optimal UI policy over the business cycles, I find that the welfare gain subsides as the economy recovers.

The paper is organised as follows. Section 2 presents empirical findings related to worker's UI history. Section 3 describes the model. Section 4 discusses the calibration exercise. Section 5 discusses the results including the welfare analysis. Section 6 concludes.

4.2 Empirical Evidence

To motivate the main assumption of this paper that there is a drop in search efficiency for unemployed workers who have received UI benefits, I present two empirical findings in this section. First, unemployed workers who have exhausted their UI benefits (the formerly insured) have a significantly lower job finding rate than that of unemployed workers who never received the benefits (the uninsured). Second, despite the smaller job finding rate, the formerly insured exert a similar job search effort to the uninsured. This second finding rules out the possibility that the lower job finding rate of the formerly insured is simply due to a lower job search effort.[3]

[3] Another possible explanation would be unobserved heterogeneity where workers with inherently lower job finding rates are more likely to take up and exhaust UI benefits. Those with lower

Job Findings I use the CPS Basic Monthly Data and CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplement from 2006 to 2014 to construct monthly transition rates from unemployment to employment, unemployment and out of labour force similar to Chapter 3. Additionally, I consider 3 UI statuses amongst unemployed workers: current UI recipients (insured), non-UI recipients (uninsured), and exhausted-UI recipients (formerly insured). Figure 4.1 plots the unemployment-to-employment transition (job finding) rates. It shows that the formerly insured find a job at a slower rate than the uninsured, especially during the Great Recession when the rate becomes lower and much closer to that of the insured. Table 4.1 shows that this finding still holds when I control for several observable characteristics that may influence the UI take-up decision, and that adverse selection could be ruled out.[4] Lastly, Figure 4.3 shows that the formerly insured represent a large fraction of the long-term unemployed (those unemployed longer than 6 months) and therefore acknowledging the difference in the job finding rates between the formerly insured and the uninsured can be important in explaining the unemployment duration structure and its persistence that this paper aims to address.

Job Search Intensity Following Shimer (2004) and Mukoyama, Patterson and Şahin (2017), I use the number of active job search methods as a proxy for job search intensity.[5] Figure 4.2 plots the average number of active job search methods for unemployed workers with different UI histories over the 2006-2014 period.[6] On

finding rates should also exert less search efforts; however, the data does not suggest the search efforts are significantly different between the formerly insured (with lower finding rates) and the uninsured (with higher finding rates).

[4]The only exception is for unemployed workers who are expecting to be recalled and/or are on temporary layoff whose job finding rates remain quite high which is consistent with findings in Fujita and Moscarini (2015). However, the share of these workers did not go up during the Great Recession.

[5]Mukoyama et al (2017) also use another measure of search intensity based on information from the American Time Use Survey. However, this survey does not report the UI status of the respondents. Existing literature using this survey such as Krueger and Mueller (2010), Rothstein (2011) and Mukoyama et al (2017) use the UI eligibility criteria (unemployed workers who are job losers or temporary job enders) as a proxy for UI recipients but this paper is the first to report the search intensity based on the reported receipt of UI which is a more accurate measurement.

[6]Active methods are the following: (1) contacted employer directly/interview, (2) contacted public employment agency, (3) contacted private employment agency, (4) contacted friends or relatives, (5) contacted school/university employment center, (6) sent out resumes/filled out application, (7) checked union/professional registers, (8) placed or answered ads, and (9) other active. The survey also lets the respondents answer the following passive methods: (1) looked at ads, (2) attended job

average, the formerly insured use 2.48 methods in job searching which is very close to the uninsured who use 2.44 methods whilst the insured use less at 2.25 methods.

This finding is not surprising given that both the formerly insured and the uninsured are supposed to have similar outside options (without UI benefits) they should exert similar job search intensities. What is interesting, however, is when we consider this with the fact that the job finding rate for the formerly insured is significantly lower than that of the uninsured. To reconcile these two findings, I impose an assumption that insured unemployed workers experience a drop in job search efficiency during their unemployment spells. As an intuition, this can be the case when they lose the career/professional network, and/or skills and tools to conduct job search efficiently after having not been searching as actively for some time whilst on the benefits. Therefore, even if the formerly insured exert the same search effort as the uninsured, they will have a lower probability of meeting a potential employer due to having a lower search efficiency.

4.3 Model

In this section, I describe a Diamond-Mortensen-Pissarides search and matching model with endogenous job separation, variable job search intensity with on-the-job search, endogenous UI extensions and a degree of worker heterogeneity. The model is built upon Chapter 3 with an additional unemployment state, namely, formerly insured unemployment. Based on empirical findings in the previous section, I introduce a drop in job search efficiency for unemployed workers who have collected UI benefits. I purposefully retain all features in Chapter 3 so that the results can be compared straightforwardly.

4.3.1 Technology and Preferences

Time is discrete and goes on forever. The economy is populated by workers and firms. Workers are ex-ante heterogeneous with respect to their productivity which is either high (H) or low (L) whilst firms are ex-ante identical. A match consists of one worker and one firm. It produces output whose price is normalised to one. The

training programs/courses, (3) nothing, and (4) other passive.

output of a match is a function of the aggregate productivity (z), the match-specific productivity (m), and the worker-specific productivity (η_i; $i \in \{H, L\}$). Namely,

$$y_{it}(m) \quad = \quad z_t \times m \times \eta_i$$

The aggregate productivity (z) evolves according to an AR(1) process: $\ln z_t = \rho_z \ln z_{t-1} + \varepsilon_t$ where $\varepsilon_t \sim N(0, \sigma_z)$. The match-specific productivity (m) is drawn at the start of a worker-firm match from a distribution $F(m)$, and may be redrawn in each subsequent period at the rate λ from the same distribution $F(m)$. Worker's productivity (η_i) is permanent and therefore remains the same throughout the duration of a match. I normalise the productivity of type-H workers such that $(\eta_L <)\eta_H \equiv 1$. A given match is exogenously separated at rate δ and may be endogenously separated whenever the value of workers and/or firms becoming unmatched is higher than the value of being in production.

4.3.1.1 Workers

Workers are risk neutral and infinitely-lived. They discount future payoffs by the factor β. As previously mentioned, there are two types of workers distinguished by their productivity which can either be high or low. A worker can either be employed (e), insured unemployed with higher search efficiency (u^{UI1}), insured unemployed with lower search efficiency (u^{UI0}), formerly insured unemployed with higher search efficiency (u^{UIx1}), formerly insured unemployed with lower search efficiency (u^{UIx0}), or uninsured unemployed (u^{UU}). I assume that unemployed workers who have collected UI benefits experience a drop in job search efficiency at rate γ in each period during their unemployment spells. Workers are formerly insured unemployed if and only if they were insured unemployed and have exhausted their UI benefits. The worker's UI history is important because the formerly insured and the uninsured are made different due to different search efficiencies.

Both employed and unemployed workers decide each period how much effort they exert in searching for a job (particularly, a new one in case of employed workers). The search effort increases a worker's probability of meeting a firm, and gives a disutility to the worker. The search cost function is strictly concave so a unique search effort is determined for all states. Specifically, the disutility from exerting search effort s of workers with status $k \in \{e, u1, u0\}$

$$\nu_k(s) \quad = \quad a_k s^{d_k};\ a_k, d_k > 0,$$

I distinguish between the search cost of employed workers $-\nu_e(\cdot)$, insured and formerly insured with higher search efficiency as well as uninsured unemployed workers $-\nu_{u1}(\cdot)$, and, lastly, insured and formerly insured workers with low search efficiency, $\nu_{u0}(\cdot)$ where $a_{u0} > a_{u1}$ and/or $d_{u0} > d_{u1}$. Therefore, one unit of search effort yields the insured and formerly insured with higher search efficiency as well as uninsured unemployed workers the same probability of meeting a firm, whilst the insured and formerly insured with lower search efficiency have a lower probability. The search cost for the employed is separated from the unemployed only to discipline the job-to-job transition rate. It is useful to note that workers of different productivity types (H or L) face the same search cost function.

All unemployed workers receive a utility flow h in each period which can be interpreted as home production or leisure flow from not working. Insured unemployed workers further receive unemployment benefits $b_i(\tilde{m});\ i \in \{H, L\}$ that depend on the worker's type (i) and the match-specific productivity in the most recent employment ($\tilde{m}$).[7] Employed workers receive a wage $w_i^j(m)$ where $i \in \{H, L\}$ and $j \in \{e(\tilde{m}), UI1(\tilde{m}), UI0(\tilde{m}), UIx1, UIx0, UU\}$. The wage depends on the worker's type (i), previous employment status and associated unemployment benefits (j), and the current match-specific productivity (m).

UI Duration Policy and UI Eligibility I assume that any employed worker returning to unemployment becomes insured unemployed at rate $1 - \psi$, and become uninsured unemployed at rate ψ, so that I can target the UI take-up rate and the size of insured unemployment.

I follow Chapter 3 in modelling the UI duration policy to be a function of the

[7] As unemployment benefits are calculated as a fraction of a worker's past wage, I use the worker's type along with the match-specific productivity as a proxy for their wages.

unemployment rate as observed in the US economy. In particular, the maximum UI duration is extended when the unemployment rate in the economy reaches a threshold $\bar{u}$. Similar to Fredíksson and Holmlund (2001), I do not explicitly model the length of an unemployment spell of a worker and instead use a UI exhaustion rate to govern the number of insured unemployed workers losing UI eligibility each period. Additionally, I allow this UI exhaustion rate to vary with total unemployment (u). Namely, the rate an insured unemployed worker loses their UI benefit given the unemployment rate is u_t is

$$\phi(u_t) \equiv \phi_L \mathbb{1}\{u_t \geq \bar{u}\} + \phi_H \mathbb{1}\{u_t < \bar{u}\}$$

where $\phi_L < \phi_H$. Whenever the unemployment rate goes above the threshold $\bar{u}$ the exhaustion rate becomes smaller and therefore the expected maximum UI duration, which equals the inverse of the exhaustion rate, becomes longer/extended.

I assume that, on top of the UI exhaustion rate, insured unemployed workers face an additional probability of losing UI eligibility at rate ξ when they meet a firm but do not proceed to employment.

Workers' Value Functions I define the set of state variables as $\omega \equiv \{z, u, u_i, u_i^{UI1}(\tilde{m}), u_i^{UI0}(\tilde{m}), u_i^{UIx1}, u_i^{UIx0}, u_i^{UU}, e_i(m); \forall m, \tilde{m} \text{ and } i \in \{H, L\}\}$ where u_i is the measure of type-i unemployed workers, $u_i^{UI1}(\tilde{m})$ is the measure of type-i insured unemployed workers with higher search efficiency whose match quality in the most recent employment was $\tilde{m}$, u_i^{UIx1} is the measure of type-i formerly insured unemployed workers with higher search efficiency, u_i^{UU} is the measure of type-i uninsured unemployed workers, and $e_i(m)$ is the measure of type-i employed workers with current match quality m. $u_i^{UI0}(\tilde{m})$ and u_i^{UIx0} are defined analogously but for workers with lower search efficiency.

Given this setup, I can write the Bellman equation for type-i insured unemployed workers with unemployment benefits $b_i(\tilde{m})$ and higher search efficiency as

$$\begin{aligned} U_i^{UI1}(\tilde{m};\omega) &= \max_{s_i^{UI1}(\tilde{m};\omega)} \quad b_i(\tilde{m}) + h - \nu_{u1}(s_i^{UI1}(\tilde{m};\omega)) \\ &\quad + \beta E_{m'\omega'|\omega}\Bigg[p_i^{UI1}(\tilde{m};\omega) \max\Big\{ W_i^{UI1(\tilde{m})}(m';\omega'), \ldots \\ &\quad \underbrace{(1-\phi(u))(1-\xi)}_{\text{Pr(keep UI | meeting a firm)}} \bar{U}_i^{UI}(\tilde{m};\omega') + \underbrace{(\phi(u) + (1-\phi(u))\xi)}_{\text{Pr(lose UI | meeting a firm)}} \bar{U}_i^{UIx}(\omega') \Big\} \\ &\quad + (1 - p_i^{UI1}(\tilde{m};\omega)) \Big((1-\phi(u))\bar{U}_i^{UI}(\tilde{m};\omega') + \phi(u)\bar{U}_i^{UIx}(\omega') \Big) \Bigg] \end{aligned} \tag{4.1}$$

where $\bar{U}_i^{UI}(\cdot;\cdot) \equiv (1-\gamma)U_i^{UI1}(\cdot;\cdot) + \gamma U_i^{UI0}(\cdot;\cdot)$ and $\bar{U}_i^{UIx}(\cdot) \equiv (1-\gamma)U_i^{UIx1}(\cdot) + \gamma U_i^{UIx0}(\cdot)$. $p_i^{UI1}(\tilde{m};\cdot)$ is the probability that type-i insured unemployed workers with benefit $b_i(\tilde{m})$ and higher search efficiency meets a firm which is increasing in their job search intensity $s_i^{UI1}(\tilde{m};\cdot)$. This job finding probability is explained in detail in the next subsection. Once these workers meet a firm, they draw a match-specific productivity m, and decide whether to stay unemployed (with some probability of losing UI eligibility) or start working for that firm. If they lose UI eligibility, they become formerly insured unemployed whose value is $U_i^{UIx1}(\cdot)$ ($U_i^{UIx0}(\cdot)$) for higher (lower) efficiency searchers. The Bellman equation for type-i insured unemployed workers with unemployment benefits $b_i(\tilde{m})$ and lower search efficiency can be written as

$$\begin{aligned} U_i^{UI0}(\tilde{m};\omega) &= \max_{s_i^{UI0}(\tilde{m};\omega)} \quad b_i(\tilde{m}) + h - \nu_{u0}(s_i^{UI0}(\tilde{m};\omega)) \\ &\quad + \beta E_{m'\omega'|\omega}\Bigg[p_i^{UI0}(\tilde{m};\omega) \max\Big\{ W_i^{UI0(\tilde{m})}(m';\omega'), \ldots \\ &\quad \underbrace{(1-\phi(u))(1-\xi)}_{\text{Pr(keep UI | meeting a firm)}} U_i^{UI0}(\tilde{m};\omega') + \underbrace{(\phi(u) + (1-\phi(u))\xi)}_{\text{Pr(lose UI | meeting a firm)}} U_i^{UIx0}(\omega') \Big\} \\ &\quad + (1 - p_i^{UI0}(\tilde{m};\omega)) \Big((1-\phi(u))U_i^{UI0}(\tilde{m};\omega') + \phi(u)U_i^{UIx0}(\omega') \Big) \Bigg] \end{aligned} \tag{4.2}$$

It is useful to note that the search cost function of these workers, $\nu_{u0}(\cdot)$, is the only reason why $U_i^{UI1}(\cdot;\cdot)$ is different from $U_i^{UI0}(\cdot;\cdot)$.

As for type-i formerly insured unemployed workers with higher and lower search efficiency, I can write their Bellman equations respectively as

$$U_i^{UIx1}(\omega) = \max_{s_i^{UIx1}(\omega)} h - \nu_{u1}(s_i^{UIx1}(\omega)) + \beta E_{m'\omega'|\omega}\Big[\ldots \tag{4.3}$$
$$p_i^{UIx1}(\omega)\max\{W_i^{UIx1}(m';\omega'), \bar{U}_i^{UIx}(\omega')\} + (1 - p_i^{UIx1}(\omega))\bar{U}_i^{UIx}(\omega')\Big]$$
$$U_i^{UIx0}(\omega) = \max_{s_i^{UIx0}(\omega)} h - \nu_{u0}(s_i^{UIx0}(\omega)) + \beta E_{m'\omega'|\omega}\Big[\ldots \tag{4.4}$$
$$p_i^{UIx0}(\omega)\max\{W_i^{UIx0}(m';\omega'), U_i^{UIx0}(\omega')\} + (1 - p_i^{UIx0}(\omega))U_i^{UIx0}(\omega')\Big]$$

Analogous to the insured unemployed, $p_i^{UIx1}(\cdot)$ is the probability that type-i formerly insured unemployed workers with higher search efficiency meets a firm, and it is increasing in $s_i^{UIx1}(\cdot)$. After the meeting takes place, a match-specific productivity m is drawn and these workers decide whether to stay formerly insured unemployed or start working for that firm. The notations for the formerly insured with lower search efficiency can be similarly defined.

I can write the Bellman equation for type-i uninsured unemployed workers as

$$U_i^{UU}(\omega) = \max_{s_i^{UU}(\omega)} h - \nu_{u1}(s_i^{UU}(\omega)) + \beta E_{m'\omega'|\omega}\Big[\ldots \tag{4.5}$$
$$p_i^{UU}(\omega)\max\{W_i^{UU}(m';\omega'), U_i^{UU}(\omega')\} + (1 - p_i^{UU}(\omega))U_i^{UU}(\omega')\Big]$$

It is useful to note that the values of uninsured unemployed workers are different from formerly insured unemployed workers only because of the possibility that the latter type face a drop in search efficiency.

Lastly, I can write the Bellman equation for type-i employed workers with current match quality m, and previous employment status and associated unemployment benefits $j \in \{e(\tilde{m}), UI1(\tilde{m}), UI0(\tilde{m}), UIx1, UIx0, UU\}$ as

$$\begin{aligned}
W_i^j(m;\omega) \;=\; & \max_{s_i^e(m;\omega)} \; w_i^j(m;\omega) - \nu_e(s_i^e(m;\omega)) + \beta E_{\omega'|\omega}\Bigg[\\
& \underbrace{(1-\delta)(1-\lambda)}_{\text{Pr(stay matched, keep } m)} \Big[\underbrace{(1-p_i^e(m;\omega)(1-F(m)))}_{\text{Pr(stay with current firm)}} W_i^{e(m)+}(m;\omega') \\
& + \underbrace{p_i^e(m;\omega)(1-F(m))}_{\text{Pr(move to new firm)}} E_{m'|m'>m}[W_i^{e(m)+}(m';\omega')] \Big] \\
& + \underbrace{(1-\delta)\lambda}_{\text{Pr(stay matched, new } m)} E_{m'} \Big[\underbrace{(1-p_i^e(m;\omega)(1-F(m')))}_{\text{Pr(stay with current firm)}} W_i^{e(m)+}(m';\omega') \\
& + \underbrace{p_i^e(m;\omega)(1-F(m'))}_{\text{Pr(move to new firm)}} E_{m''|m''>m'}[W_i^{e(m)+}(m'';\omega')] \Big] \\
& + \underbrace{\delta}_{\text{Pr(match exogenously separated)}} \Big((1-\psi)U_i^{UI1}(m,\omega') + \psi U_i^{UU}(\omega') \Big) \Bigg] \qquad (4.6)
\end{aligned}$$

where $W_i^{e(m)+}(m';\omega') \equiv \max\{W_i^{e(m)}(m';\omega'), (1-\psi)U_i^{UI1}(m,\omega') + \psi U_i^{UU}(\omega')\}$ showing that employed workers are free to return to unemployment in which case they become insured at rate $1-\psi$ and uninsured at rate ψ. The expressions for optimal job search intensities for all types of workers can be found in Appendix 4.7.1.

4.3.1.2 Firms

Similar to workers, firms are risk neutral and infinitely-lived. They also discount future payoffs by the factor β. Firms are ex-ante identical, and either matched with one worker or unmatched. Matched firms are only made different by the type of workers they are matched with and the match-specific productivity they have drawn together. Matched firms produce and sell output, pay wage to their workers, and lump-sum tax to finance UI payments. Unmatched firms pay a fixed cost κ to post a job vacancy, and have no ability to direct their search to a certain type of workers.

The Bellman equation for unmatched firms is

$$
\begin{aligned}
V(\omega) \;=\; & -\kappa+\beta q(\omega)E_{\omega'|\omega}\bigg[\sum_{i\in\{H,L\}}\Big(\sum_m \zeta_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[J_i^{e(m)+}(m';\omega')] \\
& +\sum_m \zeta_i^{UI1}(m,\omega)E_{m'}[J_i^{UI1(m)+}(m';\omega')]+\sum_m \zeta_i^{UI0}(m,\omega)E_{m'}[J_i^{UI0(m)+}(m';\omega')] \\
& +\zeta_i^{UIx1}(\omega)E_{m'}[J_i^{UIx1+}(m';\omega')]+\zeta_i^{UIx0}(\omega)E_{m'}[J_i^{UIx0+}(m';\omega')] \\
& +\zeta_i^{UU}(\omega)E_{m'}[J_i^{UU+}(m';\omega')]\Big)\bigg] \qquad (4.7)
\end{aligned}
$$

$$
\begin{aligned}
\text{where}\quad \zeta_i^e(m) &= \frac{(1-\lambda)s_i^e(m)e_i(m)+\lambda f(m)\sum_m s_i^e(m)e_i(m)}{s} \\
\zeta_i^{UI1}(m) &= \frac{s_i^{UI1}(m)u_i^{UI1}(m)}{s};\quad \zeta_i^{UI0}(m)=\frac{s_i^{UI0}(m)u_i^{UI0}(m)}{s}; \\
\zeta_i^{UIx1} &= \frac{s_i^{UIx1}u_i^{UIx1}}{s};\quad \zeta_i^{UIx0}=\frac{s_i^{UIx0}u_i^{UIx0}}{s};\quad \zeta_i^{UU}=\frac{s_i^{UU}u_i^{UU}}{s}; \\
s &= \sum_{i\in\{H,L\}}\Big(\sum_m\big(s_i^e(m)e_i(m)+s_i^{UI1}(m)u_i^{UI1}(m)+s_i^{UI0}(m)u_i^{UI0}(m)\big) \\
& \quad +s_i^{UIx1}u_i^{UIx1}+s_i^{UIx0}u_i^{UIx0}+s_i^{UU}u_i^{UU}\Big)
\end{aligned}
$$

$J_i^j(\cdot)$ denotes the value of a firm being matched to a worker of type-i and previous employment status $j\in\{e(\tilde{m}),UI1(\tilde{m}),UI0(\tilde{m}),UIx1,UIx0,UU\}$ and $J_i^{j+}(m;\omega)\equiv \max\{J_i^j(m;\omega),V(\omega)\}$. Since the meeting process between workers and firms is random, unmatched firms must take into account the entire distribution of workers over productivity types, employment statuses and associated (potential) UI benefits to compute the probability they meet a certain type of workers. I also assume that firms can enter and leave the market freely; therefore, the value of being an unmatched firm is always zero, i.e. $V(\omega)=0,\forall\omega$.

Given the free entry condition, I can write the Bellman equation for matched firms as

$$\begin{aligned} J_i^j(m;\omega) &= y_i(m;\omega) - w_i^j(m;\omega) - \tau(\omega) + \beta E_{\omega'|\omega}\Big[\ldots \\ &\quad (1-\delta)(1-\lambda)\Big[(1-p_i^e(m;\omega)(1-F(m)))J_i^{e(m)+}(m;\omega')\Big] \\ &\quad +(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))J_i^{e(m)+}(m';\omega')\Big]\Big] \end{aligned} \quad (4.8)$$

where $J_i^{e(m)+}(m;\omega) \equiv \max\{J_i^{e(m)}(m;\omega),0\}$ implying that matched firms are free to endogenously separate from their current matched workers.

4.3.1.3 Search and Matching

A meeting function $M(s,v)$ determines the number of meetings between workers and firms. It is concave in its arguments which are the total job search intensity (s) and the total number of job vacancies (v), and has constant returns to scale. Conventionally, I define the rate a worker meets a firm per unit of job search to be $\frac{M(s,v)}{s} = M(1,\theta) \equiv p(\theta)$; therefore, the rate a worker of type i with history j meets a firm is $s_i^j p(\theta) \equiv p_i^j(\theta)$. The rate a firm meets a worker is $\frac{M(s,v)}{v} = M(1/\theta,1) \equiv q(\theta)$, where $\theta \equiv \frac{v}{s}$ is the market tightness.

4.3.2 Wage and Surplus

A wage in the model is determined by the generalised Nash bargaining rule. That is, the Nash bargained wage solves

$$w_i^j(m;\omega) = \text{argmax} \left(WS_i^j(m;\omega)\right)^{\mu} \left(J_i^j(m;\omega)\right)^{(1-\mu)} \quad (4.9)$$

where μ is the worker's bargaining power. The worker's previous employment status $j \in \{e(\tilde{m}), UI1(\tilde{m}), UI0(\tilde{m}), UIx1, UIx0, UU\}$ is important for the determination of wage because workers use their outside options in the bargaining process. Specifically, WS_i^j denotes the surplus of type-i employed workers with history j. It is defined as the difference between the value of being employed and the corresponding outside option. Define the total match surplus as $S_i^j \equiv WS_i^j + J_i^j$. Nash bargaining results in $WS_i^j = \mu S_i^j$ and $J_i^j = (1-\mu)S_i^j$. I can write the surpluses of employed workers as follows

$$\begin{aligned}
WS_i^{e(\tilde{m})}(m;\omega) &\equiv W_i^{e(\tilde{m})}(m;\omega) - (1-\psi)U_i^{UI1}(\tilde{m},\omega) - \psi U_i^{UU}(\omega) \\
WS_i^{UI1(\tilde{m})}(m;\omega) &\equiv W_i^{UI1(\tilde{m})}(m;\omega) - (1-\phi(u))(1-\xi)\bar{U}_i^{UI}(\tilde{m},\omega) \\
&\quad -(\phi(u)+(1-\phi(u))\xi)\bar{U}_i^{UIx}(\omega) \\
WS_i^{UI0(\tilde{m})}(m;\omega) &\equiv W_i^{UI0(\tilde{m})}(m;\omega) - (1-\phi(u))(1-\xi)U_i^{UI0}(\tilde{m},\omega) \\
&\quad -(\phi(u)+(1-\phi(u))\xi)U_i^{UIx0}(\omega) \\
WS_i^{UIx1}(m;\omega) &\equiv W_i^{UIx1}(m;\omega) - \bar{U}_i^{UIx}(\omega) \\
WS_i^{UIx0}(m;\omega) &\equiv W_i^{UIx0}(m;\omega) - U_i^{UIx0}(\omega) \\
WS_i^{UU}(m;\omega) &\equiv W_i^{UU}(m;\omega) - U_i^{UU}(\omega)
\end{aligned}$$

where $\bar{U}_i^{UI}(\tilde{m},\omega) = (1-\gamma)U_i^{UI1}(\tilde{m},\omega) + \gamma U_i^{UI0}(\tilde{m},\omega)$. $\bar{U}_i^{UIx}(\omega)$ is analogously defined. The expressions for total match surpluses can be found in Appendix 4.7.1.

4.3.3 Recursive Competitive Equilibrium

A recursive competitive equilibrium is characterised by

- Value functions: $W_i^{e(\tilde{m})}(m;\omega)$, $W_i^{UI1(\tilde{m})}(m;\omega)$, $W_i^{UI0(\tilde{m})}(m;\omega)$, $W_i^{UIx1}(m;\omega)$, $W_i^{UIx0}(m;\omega)$, $W_i^{UU}(m;\omega)$, $U_i^{UI1}(\tilde{m};\omega)$, $U_i^{UI0}(\tilde{m};\omega)$, $U_i^{UIx1}(\omega)$, $U_i^{UIx0}(\omega)$, $U_i^{UU}(\omega)$, $J_i^{e(\tilde{m})}(m;\omega)$, $J_i^{UI1(\tilde{m})}(m;\omega)$, $J_i^{UI0(\tilde{m})}(m;\omega)$, $J_i^{UIx1}(m;\omega)$, $J_i^{UIx0}(m;\omega)$, $J_i^{UU}(m;\omega)$, and $V(\omega)$;
- Market tightness $\theta(\omega)$;
- Search policy: $s_i^e(m;\omega)$, $s_i^{UI1}(m,\omega)$, $s_i^{UI0}(m,\omega)$, $s_i^{UIx1}(\omega)$, $s_i^{UIx0}(\omega)$ and $s_i^{UU}(\omega)$; and
- Wage functions: $w_i^{e(\tilde{m})}(m;\omega)$, $w_i^{UI1(\tilde{m})}(m;\omega)$, $w_i^{UI0(\tilde{m})}(m;\omega)$, $w_i^{UIx1}(m;\omega)$, $w_i^{UIx0}(m;\omega)$ and $w_i^{UU}(m;\omega)$,

such that, given the initial distribution of workers over productivity level, employment status, UI status, benefit level and match productivity, the government's policy $\tau(\omega)$ and $\phi(\omega)$, and the law of motion for z:

1. The value functions and the market tightness satisfy the Bellman equations for workers and firms, and the free entry condition, namely, equations (4.1), (4.2), (4.3), (4.4), (4.5), (4.6), (4.7) and (4.8)

2. The search decisions satisfy the FOCs for optimal search intensity, which are equations (4.10), (4.11), (4.12), (4.13), (4.14) and (4.15)

3. The wage functions satisfy the FOCs for the generalised Nash bargaining rule (equation (4.9))

4. The government's budget constraint is satisfied each period

5. The distribution of workers evolves according to the transition equations (4.16), (4.18), (4.19), (4.20), (4.21) and (4.22), which can be found in Appendix 4.7.2, consistent with the maximising behaviour of agents

4.4 Calibration

For simplicity, I assume that the rate the insured unemployed workers experience a drop in their search efficiency is the same as the rate they exhaust their UI benefits, i.e. γ coincides with $\phi(u)$; $\forall u$. This implies that the employment statuses reduce to a set of $\{e(\tilde{m}), UI(\tilde{m}), UIx, UU\}$. Therefore, only the formerly insured unemployed (those with status UIx) have a lower search efficiency.

The calibration strategy follows Chapter 3 with the exception of an additional parameter to be calibrated and an additional target. Namely, the relative search efficiency of the formerly insured unemployed, $\frac{a_{u0}}{a_{u1}}$, is calibrated to match the average ratio of the job finding rates between the insured unemployed and the formerly insured unemployed.[8] Therefore, there are in total 13 targeted moments and 13 parameters to be calibrated using the Simulated Method of Moments (SMM). Table 4.2 summarises the targeted moments used in the calibration exercise, and also compares the baseline model's performance to that of the model without a drop in search efficiency of the formerly insured unemployed. Non-targeted moments are

[8] Despite this additional parameter directly affects the relative job finding rates between unemployed workers with and without UI benefits, it inevitably affects other moments in the calibration exercise.

reported in Table 4.3. Table 4.4 reports the calibrated parameters whilst Table 4.5 summarises the pre-specified parameters.

I continue to assume that the match-specific productivity m follows a Beta distribution with three parameters $\{\underline{m}, \beta_1, \beta_2\}$. Specifically, $F(m) = \underline{m} + \text{betacdf}(m - \underline{m}, \beta_1, \beta_2)$. The meeting function between workers and firms is similar to den Haan, Ramey and Watson (2000) but the number of job searchers is augmented by their search intensities, namely, $M(s,v) = (sv)/(s^l + v^l)^{\frac{1}{l}}$. I choose the same pre-specified parameters as in Chapter 3 including UI exhaustion rates during recessionary periods (ϕ_L) that vary to match the observed extended UI durations over the 1948-2007 period. It is useful to note that the UI extensions in the simulations are still endogenous and triggered when the unemployment rate is above the threshold.

Overall, the model performs well in matching the targets. It matches the average ratio of the job finding rates between insured and formerly insured unemployed workers unlike the model without a drop in search efficiency in Chapter 3 where this statistic is not targeted. It also improves on the average share of insured unemployment, and performs much better in producing the volatility of the job finding rates. With respect to the non-targeted moments, since the model delivers a more moderated insured unemployment series, it produces a much more realistic volatility of the series. In effect, this makes total unemployment more moderated and improves on the Beveridge curve as measured by the correlation between unemployment and vacancies. The volatilty of the vacancies also improves despite being somewhat far from the data.

4.5 Results

I obtain the results in this section by feeding in (1) the observed extended maximum UI durations between 1948 and 2014, and (2) the path of aggregate productivity z such that the model delivers the same series of deviations of output (GDP per capita) from its HP trend exactly as in the data. I then evaluate the performance of the baseline model with respect to the model without formerly insured unemployment in terms of how well it can account for the labour market activities over the business cycles as well as the increase in the persistence of unemployment. I show how the increased persistence affects the previously reported results regarding the effects of UI extensions during the Great Recession. Lastly, I report the welfare gains and losses from eliminating UI extensions during the recent recession.

4.5.1 Performance

Unemployment Firstly, Figure 4.4 shows how well the model can account for the total unemployment series in the data. Since UI extensions are a function of unemployment, it is expected that the model generated UI extensions are similar to the ones observed in the data. However, the model's unemployment series does not reach the threshold to trigger UI extension during the 90s recession. Overall, the model's series is more moderated than in the model without formerly insured unemployment. The right panel of Figure 4.4 shows that the series exhibits a slightly more persistent and subdued response during the Great Recession than does the series from the previous model without u^{UIx}. From Table 4.6, we can see that the baseline model does a better job in accounting for total unemployment during the Great Recession (96 percent of the observed series - as measured by percentage deviation) than the previous model (95.4 percent) as the series from the baseline model overshoots by less when UI is extended during a recession.

Unemployment Duration Structure The same observation can be made with regards to the average unemployment duration and long-term unemployment series shown in Figures 4.5 and 4.6. The persistence of these series are slightly higher than those in the previous model. Both series do improve in terms of their responses to negative aggregate shocks and UI extensions as observed by the significantly smaller spikes during recessionary episodes (i.e., less overshooting). However, both average unemployment duration and long-term unemployment in the baseline model are on average lower than those in the previous model. As a result, the model performs slightly worse in accounting for these two series (despite delivering the observed peak of long-term unemployment that the other model overshoots) as shown in Table 4.6.

Persistence To quantify the increase in the persistence of unemployment and its duration structure from the introduction of worker's UI history, I show in Figure 4.7 the autocorrelation coefficients of total unemployment, average unemployment duration and long-term unemployment from the models with and without a search efficiency drop and the empirical counterparts. The baseline model is successful in generating greater persistence for all three variables especially at longer lags (6 to 24 months). It yields higher autocorrelation coefficients on average by 0.03 (14 percent increase) for unemployment, 0.02 (5 percent increase) for average unemployment duration, and 0.03 (7 percent increase) for long-term unemployment in comparison to the previous model. I find similar improvement in the autocorrelation coefficients when I remove the quadratic time trend from the series as shown in Figure 4.8, but since the coefficients are smaller, the baseline model improves from the previous model by 41 percent for total unemployment, 10 percent for average unemployment duration, and 33 percent for long-term unemployment. Nonetheless, the observed persistence for all series in the data is significantly higher which may suggest that further worker heterogeneities can improve the persistence and match the structure of unemployment duration further.

4.5.2 Effects of UI Extensions on the Aggregate Labour Market

Now that I have established that the introduction of a drop in search efficiency for insured unemployed workers helps increase the persistence of unemployment that was lacking in the model in Chapter 3, I discuss in this section its implication on the revised effects of UI extensions on the aggregate labour market.

Table 4.7 shows the responses of main labour market variables to a reduction of maximum UI duration from 90 weeks to 26 weeks during the Great Recession, i.e., eliminating all UI extensions. To compare the effectiveness of UI duration policy, I report the responses from the previous model without a drop in search efficiency in the same table.

It can be seen from this table that introducing a drop in job search efficiency for formerly insured workers reduces the effects of UI extensions on the unemployment duration structure (as represented by the average unemployment duration and long-term unemployment) but it hardly affects the effects of UI extensions on total unemployment. This is expected since the formerly insured unemployed represent a small fraction of total unemployment but its (negative) effect on the job finding rates becomes more important for the unemployment duration due to Jensen's inequality, and they represent a larger fraction of long-term unemployment. The reason that the UI effects are smaller in the baseline model is because a drop in job search efficiency lowers the value of being insured unemployed in the first place. Insured unemployed workers then search for jobs more intensively than in the previous model regardless of the level of the benefit. As a result, these workers respond less strongly to UI extensions. The elasticity of unemployment duration on changes in the maximum UI duration is also revised downwards from [0.38, 0.41] weeks to [0.33, 0.38] weeks for a one-week increase in maximum UI duration.

4.5.3 Welfare Implication

Following the revised effects of UI extensions after the introduction of a search efficiency drop amongst insured unemployed workers, I show in this section how it is translated into welfare gains and/or losses for agents in the economy had UI extensions not been implemented during the Great Recession. I also compare this to the case where there is no drop in search efficiency. I summarise the welfare results in Table 4.8 and plot them in Figure 4.9 and 4.10. As in Lucas (1987), I define the welfare gain/loss to be the percentage change in consumption necessary in each period to make agents in the economy to be as satisfied as they would be in a counterfactual economy, which is the economy without UI extensions in this case.

I find that eliminating all UI extensions increases the total welfare of the economy by around 0.14 percent. This is expected since given the agents are risk neutral there is no role of UI provision as precautionary savings which may alter the results to be more in favour of UI extensions. However, Mitman and Rabinovich (2015) study the optimal UI policy over the business cycles using a search and matching model similar to this paper except that workers are risk averse. They find that the optimal

UI policy should be procyclical in terms of both level and duration.[9] Figure 4.9 shows that the welfare gain from eliminating UI extensions subsides as the economy recovers (the welfare loss is present from the second half of 2013), which also suggests that UI extensions should be procyclical.

Welfare gains and losses do vary with the types of workers. Only employed workers benefit from the removal of UI extensions (a welfare improvement of 0.27 percent). This is due to the fact that they have to indirectly pay taxes to finance the UI payments for the unemployed each period. The low-productivity employed benefit slightly more than the high-productivity type since they inherently earn lower wages and have to pay the same amount of lump-sum taxes.

Unemployed workers suffer a large welfare loss of 1.27 percent when UI extensions are removed, especially the insured unemployed whose welfare goes down by 1.64 percent. As expected, the insured unemployed with shorter unemployment durations (0-2 months) benefit more from UI extensions than those with longer durations since they are more likely to be insured (with a higher search efficiency) in subsequent periods and enjoy the extended benefits. The uninsured unemployed also suffer slightly from the UI extension removal mainly because the insured unemployed would search harder for jobs making the market less tight. As a result, the uninsured would have lower chances to meet a vacant firm unless they also search harder. However, the formerly insured unemployed are barely affected. The larger search cost they face implies that their search intensity varies only slightly in either case. Unemployed workers with a higher productivity suffer a larger welfare loss than those with a lower productivity as higher wages imply higher UI payments.

The welfare gain from eliminating UI extensions is revised downwards when the baseline model is compared to an economy without a drop in job search efficiency (which has a welfare gain of 0.23 percent). In this alternative scenario, insured unemployment respond more strongly to UI extensions than in the baseline model as discussed in previous subsections. Therefore, the tax burden for employed workers

[9] Landais, Michaillat, and Saez (2013) also study the optimal UI policy over the business cycles and find that the policy should be countercyclical; however, they assume a complete wage rigidity whilst wages in this model and in Mitman and Rabinovich (2015) are determined using Nash bargaining.

is higher and they benefit more from the UI extension removal than in the baseline case. The insured unemployed, on the contrary, suffer less than in the baseline model since their search efficiency now remain the same throughout the unemployment spell making being unemployed less unpleasant.

4.6 Conclusion

Building on Chapter 3 which studies the general equilibrium impact of UI extensions on unemployment and its duration structure in the US, this paper distinguishes between unemployed workers who never collected UI benefits and those who have exhausted the benefits as they face different labour market outcomes. To make the model consistent with the data, I assume that the job search efficiency falls during an unemployment spell of workers who have collected UI benefits. Given further heterogeneities in the job finding rates, the model improves from Chapter 3 in accounting for unemployment and its duration structure. In particular, it generates higher persistence (closer to the data) as well as a smaller degree of overshooting in recessionary periods. As a result, the effects of UI extensions on the unemployment duration structure have been revised slightly downwards. I also find that removing all UI extensions during the Great Recession improves the welfare of the economy given that agents are risk neutral.

Despite the model's success in creating more persistence in unemployment and its duration, a considerable improvement can be made in this aspect. Nonetheless, the findings from this paper suggest that further heterogeneities from either workers or firms that affect the unemployment exit probabilities could create more realistic dynamics of the aggregate labour market, and provide more accurate results from policy experiments.

4.7 Appendix for Chapter 4

4.7.1 Expressions for Optimal Search Intensity and Match Surplus

Given the worker's value functions when employed, insured unemployed and uninsured unemployed, we can take the first derivative to find the optimal search effort. The first order conditions for type-i workers are as follows

$$\begin{aligned} v_e'(s_i^e(m;\omega)) &= -\beta(1-\delta)M(\theta(\omega))E_{\omega'|\omega}\Big[\ldots \\ &\quad (1-\lambda)(1-F(m))\Big(WS_i^{e(m)+}(m;\omega') - E_{m'|m'>m}[WS_i^{e(m)+}(m';\omega')]\Big) \\ &+ \lambda E_{m'}\Big[(1-F(m'))(WS_i^{e(m)+}(m';\omega') - E_{m''|m''>m'}[WS_i^{e(m)+}(m'';\omega')])\Big]\Big] \end{aligned} \tag{4.10}$$

$$v_u'(s_i^{UI1}(m,\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UI1(m)}(m';\omega'),0\} - \xi(1-\phi(u))\bar{US}_i^x(m,\omega')\Big] \tag{4.11}$$

$$v_u'(s_i^{UI0}(m,\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UI0(m)}(m';\omega'),0\} - \xi(1-\phi(u))US_i^{x0}(m,\omega')\Big] \tag{4.12}$$

$$v_u'(s_i^{UIx1}(\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UIx1}(m';\omega'),0\}\Big] \tag{4.13}$$

$$v_u'(s_i^{UIx0}(\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UIx0}(m';\omega'),0\}\Big] \tag{4.14}$$

$$v_u'(s_i^{UU}(\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UU}(m';\omega'),0\}\Big] \tag{4.15}$$

where

$$\begin{aligned} \bar{US}_i^x(m,\omega') &\equiv (1-\gamma)US_i^{x1}(m,\omega') + \gamma US_i^{x0}(m,\omega') \\ US_i^{x1}(m,\omega') &\equiv U_i^{UI1}(m,\omega') - U_i^{UIx1}(\omega') \\ US_i^{x0}(m,\omega') &\equiv U_i^{UI0}(m,\omega') - U_i^{UIx0}(\omega') \end{aligned}$$

Total match surpluses and unemployed worker's surplus are as follows (note that the expressions below are under the assumption that the rate an insured unemployed worker loses UI eligibility is the same as the rate she experiences a drop in her job search efficiency):

$$
\begin{aligned}
S_i^{e(\tilde{m})}(m;\omega) \quad = \quad & y_i(m,\omega) - \nu_e(s_i^e(m;\omega)) - \tau(\omega) - (1-\psi)(b_i(\tilde{m}) + h - \nu_u(s_i^{UI(\tilde{m})}(\omega))) \\
& -\psi(h - \nu_u(s_i^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
& (1-\delta)(1-\lambda)\Big((1-p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big) \\
& +(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big] \\
& -(1-\psi)p_i^{UI(\tilde{m})}(\omega)E_{m'}[\mu S_i^{UI(\tilde{m})+}(m';\omega')] \\
& -\psi p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')] \\
& +(1-\psi)\Big(US_i^x(m,\omega') - (1-\phi(u))\big(1-\xi p_i^{UI(\tilde{m})}(\omega)\big)US_i^x(\tilde{m};\omega')\Big)\Big]
\end{aligned}
$$

$$
\begin{aligned}
S_i^{UI(\tilde{m})}(m;\omega) \quad = \quad & y_i(m,\omega) - \nu_e(s_i^e(m;\omega)) - \tau \\
& -(1-\phi)(1-\xi)(b(\tilde{m}) + h - \nu_u(s_i^{UI(\tilde{m})}(\omega))) \\
& -(\phi + (1-\phi)\xi)(h - \nu_{ux}(s^{UIx}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
& (1-\delta)(1-\lambda)\Big((1-p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big) \\
& +(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')\ldots \\
& +p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big] \\
& -(1-\phi)(1-\xi)p_i^{UI(\tilde{m})}(\omega)E_{m'}[\mu S_i^{UI(\tilde{m})+}(m';\omega')] \\
& -(\phi + (1-\phi)\xi)p_i^{UIx}(\omega)E_{m'}[\mu S_i^{UIx+}(m';\omega')] \\
& +US_i^x(m,\omega') - \psi US_i(m,\omega') \\
& -(1-\phi)^2(1-\xi)\Big(1-\xi p_i^{UI(\tilde{m})}(\omega)\Big)US_i^x(\tilde{m};\omega')\Big]
\end{aligned}
$$

$$
\begin{aligned}
S_i^{UU}(m;\omega) \quad = \quad & y_i(m,\omega) - \nu_e(s_i^e(m;\omega)) - \tau - (h - \nu_u(s_i^{UU}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
& (1-\delta)(1-\lambda)\Big((1 - p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \\
& + p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big) \\
& + (1-\delta)\lambda E_{m'}\Big[(1 - p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')\ldots \\
& + p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big] \\
& - p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')] + (1-\psi)US_i(m,\omega')\Big]
\end{aligned}
$$

$$
\begin{aligned}
S_i^{UIx}(m;\omega) \quad = \quad & y_i(m,\omega) - \nu_e(s_i^e(m;\omega)) - \tau - (h - \nu_{ux}(s_i^{UIx}(\omega))) + \beta E_{\omega'|\omega}\Big[\ldots \\
& (1-\delta)(1-\lambda)\Big((1 - p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \\
& + p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big) \\
& + (1-\delta)\lambda E_{m'}\Big[(1 - p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')\ldots \\
& + p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big] \\
& - p_i^{UIx}(\omega)E_{m'}[\mu S_i^{UIx+}(m';\omega')] + US_i^x(m,\omega') - \psi US_i(m,\omega')\Big]
\end{aligned}
$$

$$
\begin{aligned}
US_i(m,\omega) \quad = \quad & b(m) - \nu_u(s_i^{UI(m)}(\omega)) + \nu_u(s_i^{UU}(\omega)) \\
& + \beta E_{\omega'|\omega}\Big[p_i^{UI(m)}(\omega)E_{m'}[\mu S_i^{UI(m)+}(m';\omega')]\ldots \\
& - p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')] \\
& + US_i(m,\omega') - \Big(\phi + (1-\phi)\xi p_i^{UI(m)}(\omega)\Big)US_i^x(m,\omega')\Big]
\end{aligned}
$$

$$
\begin{aligned}
US_i^x(m,\omega) \quad = \quad & b(m) - \nu_u(s_i^{UI(m)}(\omega)) + \nu_{ux}(s_i^{UIx}(\omega)) \\
& + \beta E_{\omega'|\omega}\Big[p_i^{UI(m)}(\omega)E_{m'}[\mu S_i^{UI(m)+}(m';\omega')]\ldots \\
& - p_i^{UIx}(\omega)E_{m'}[\mu S_i^{UIx+}(m';\omega')] \\
& + (1-\phi)\Big(1 - \xi p_i^{UI(m)}(\omega)\Big)US_i^x(m,\omega')\Big]
\end{aligned}
$$

4.7.2 Transitions

Employment The mass of type-i employed agents in t with match quality m, $e_{i,t}(m)$, evolves as follows

$$\begin{aligned} e_{i,t+1}(m) = & (1-\delta)(1-\lambda)(1-p^e_{i,t}(m)+p^e_{i,t}(m)F(m))e_{i,t}(m)\mathbb{1}\{S^{e(m)}_{i,t+1}(m)>0\} \\ & +(1-\delta)(1-\lambda)f(m)\int_{m'<m} p^e_{i,t}(m')e_{i,t}(m')\mathbb{1}\{S^{e(m')}_{i,t+1}(m)>0\}dm' \\ & +(1-\delta)\lambda f(m)\int_{m'}(1-p^e_{i,t}(m')+p^e_{i,t}(m')F(m))e_{i,t}(m')\mathbb{1}\{S^{e(m')}_{i,t+1}(m)>0\}dm' \\ & +(1-\delta)\lambda F(m)f(m)\int_{m'} p^e_{i,t}(m')e_{i,t}(m')\mathbb{1}\{S^{e(m')}_{i,t+1}(m)>0\}dm' \\ & +f(m)\int_{\tilde{m}} u^{UI1}_{i,t}(\tilde{m})p^{UI1}_{i,t}(\tilde{m})\mathbb{1}\{S^{UI1(\tilde{m})}_{i,t+1}(m)>0\}d\tilde{m} \\ & +f(m)\int_{\tilde{m}} u^{UI0}_{i,t}(\tilde{m})p^{UI0}_{i,t}(\tilde{m})\mathbb{1}\{S^{UI0(\tilde{m})}_{i,t+1}(m)>0\}d\tilde{m} \\ & +f(m)u^{UIx1}_{i,t}p^{Uix1}_{i,t}\mathbb{1}\{S^{UIx1}_{i,t+1}(m)>0\} \\ & +f(m)u^{UIx0}_{i,t}p^{Uix0}_{i,t}\mathbb{1}\{S^{UIx0}_{i,t+1}(m)>0\} \\ & +f(m)u^{UU}_{i,t}p^{UU}_{i,t}\mathbb{1}\{S^{UU}_{i,t+1}(m)>0\} \end{aligned} \tag{4.16}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function. The total employment is the sum of all employed workers over productviity types and match qualities $e_t = \sum_{i=H,L}\int e_{i,t}(m)\,dm$ and the aggregate output can be computed as $y_t = z_t\sum_{i=H,L}\int m\cdot e_{i,t}(m)\,dm$.

Job Destructions The job destruction rate of type-i employed workers with match quality m at the beginning of period t and m' at the end of period t, and the average job destruction rate are respectively

$$\begin{aligned} \rho_{x,it}(m,m') &= \begin{cases} \delta & \text{if } S^{e(m)}_{i,t+1}(m')>0, \\ 1 & \text{otherwise} \end{cases} \\ \rho_{x,it} &= \left(\delta\int\int_{\{(m,m'):S^{e(m)}_{i,t+1}(m')>0\}} e^{post}_{i,t}(m,m')dm\,dm' \right. \\ & \quad \left. +\int\int_{\{(m,m'):S^{e(m)}_{i,t+1}(m')\leq 0\}} e^{post}_{i,t}(m,m')dm\,dm'\right)/e_t \end{aligned} \tag{4.17}$$

$$\begin{aligned}\text{where } e_{i,t}^{post}(m,m') &= (1-\lambda)(1-p_{i,t}^{e}(m')+p_{i,t}^{e}(m')F(m'))e_{i,t}(m') \\ &+(1-\lambda)f(m')p_{i,t}^{e}(m)e_{i,t}(m)\mathbb{1}\{m<m'\} \\ &+\lambda f(m')(1-p_{i,t}^{e}(m)+p_{i,t}^{e}(m)F(m'))e_{i,t}(m) \\ &+\lambda F(m')f(m')p_{i,t}^{e}(m)e_{i,t}(m)\end{aligned}$$

denotes employed workers with match productivity m at the beginning of period t and m' at the end of the period t.

Job Findings The job finding rate for a type-i unemployed worker of status $j = \{UI1(\tilde{m}),\ UI0(\tilde{m}),\ UIx1, UIx0, UU\}$ and the average job finding rate are respectively

$$\begin{aligned}\rho_{f,it}^{j} &= \int \rho_{f,it}^{j}(m)f(m)dm \\ \rho_{f,t} &= \frac{\int_{\tilde{m}} u_{i,t}^{UI1}(\tilde{m})\rho_{f,it}^{UI1(\tilde{m})}d\tilde{m}+\int_{\tilde{m}} u_{i,t}^{UI0}(\tilde{m})\rho_{f,it}^{UI0(\tilde{m})}d\tilde{m}+u_{i,t}^{UIx1}\rho_{f,it}^{UIx1}+u_{i,t}^{UIx0}\rho_{f,it}^{UIx0}+u_{i,t}^{UU}\rho_{f,it}^{UU}}{\int_{\tilde{m}} u_{t}^{UI1}(\tilde{m})d\tilde{m}+\int_{\tilde{m}} u_{t}^{UI0}(\tilde{m})d\tilde{m}+u_{t}^{UIx1}+u_{t}^{UIx0}+u_{t}^{UU}} \\ \text{where } \rho_{f,it}^{j}(m) &= \begin{cases} p_{i,t}^{j} & \text{if } S_{i,t+1}^{j}(m)>0, \\ 0 & \text{otherwise}\end{cases}\end{aligned}$$

Job-to-job Transitions The match-specific and the average job-to-job transition rates are respectively

$$\begin{aligned}\rho_{i,t}^{ee}(m) &= (1-\delta)\Big((1-\lambda)p_{i,t}^{e}(m)(1-F(m))E_{m'>m}[\mathbf{1}\{S_{i,t+1}^{e}(m,m')>0\}] \\ &+\lambda\int_{m'} p_{i,t}^{e}(m)f(m')(1-F(m'))E_{m''>m'}[\mathbf{1}\{S_{i,t+1}^{e}(m,m'')>0\}]dm'\Big) \\ \rho_{i,t}^{ee} &= \frac{\int_m \rho_{i,t}^{ee}(m)e_{i,t}(m)dm}{e_t}\end{aligned}$$

Unemployment The mass of type-i unemployed workers with and without UI benefits as well as the total unemployment evolve respectively as follows

$$
\begin{aligned}
u_{i,t+1}^{UI1}(\tilde{m}) &= (1-\gamma)\Big(\underbrace{(1-\phi_t)(1-p_{i,t}^{UI1}(\tilde{m}))u_{i,t}^{UI1}(\tilde{m})}_{\text{unmatched, not losing UI}} + \underbrace{\chi_{i,t}^{UI1}(\tilde{m})(1-\phi_t)(1-\xi)p_{i,t}^{UI1}(\tilde{m})u_{i,t}^{UI1}(\tilde{m})}_{\text{bad match, not losing UI}}\Big) \\
&\quad \underbrace{+(1-\psi)\int_{m'}\rho_{x,it}(\tilde{m},m')e_{i,t}(\tilde{m},m')dm'}_{\text{destroyed match, not losing UI}} \qquad (4.18)\\
u_{i,t+1}^{UI0}(\tilde{m}) &= \underbrace{(1-\phi_t)(1-p_{i,t}^{UI0}(\tilde{m}))u_{i,t}^{UI0}(\tilde{m})}_{\text{unmatched, not losing UI}} + \underbrace{\chi_{i,t}^{UI0}(\tilde{m})(1-\phi_t)(1-\xi)p_{i,t}^{UI0}(\tilde{m})u_{i,t}^{UI0}(\tilde{m})}_{\text{bad match, not losing UI}} \\
&\quad +\gamma\Big(\underbrace{(1-\phi_t)(1-p_{i,t}^{UI1}(\tilde{m}))u_{i,t}^{UI1}(\tilde{m}) + \chi_{i,t}^{UI1}(\tilde{m})(1-\phi_t)(1-\xi)p_{i,t}^{UI1}(\tilde{m})u_{i,t}^{UI1}(\tilde{m})}_{\text{losing search efficiency}}\Big) \qquad (4.19)\\
u_{i,t+1}^{UIx1} &= (1-\gamma)\int_{\tilde{m}}\Big(\underbrace{\phi_t(1-p_{i,t}^{UI1}(\tilde{m}))u_{i,t}^{UI1}(\tilde{m})}_{\text{unmatched, losing UI}} + \underbrace{\chi_{i,t}^{UI1}(\tilde{m})\Big(\phi_t+(1-\phi_t)\xi\Big)p_{i,t}^{UI1}(\tilde{m})u_{i,t}^{UI1}(\tilde{m})}_{\text{bad match, losing UI}}\Big)d\tilde{m} \\
&\quad +(1-\gamma)(1-\rho_{f,it}^{UIx1})u_{i,t}^{UIx1} \qquad (4.20)\\
u_{i,t+1}^{UIx0} &= \gamma\int_{\tilde{m}}\Big(\underbrace{\phi_t(1-p_{i,t}^{UI1}(\tilde{m}))u_{i,t}^{UI1}(\tilde{m})}_{\text{unmatched, losing UI}} + \underbrace{\chi_{i,t}^{UI1}(\tilde{m})\Big(\phi_t+(1-\phi_t)\xi\Big)p_{i,t}^{UI1}(\tilde{m})u_{i,t}^{UI1}(\tilde{m})}_{\text{bad match, losing UI}}\Big)d\tilde{m} \\
&\quad +\int_{\tilde{m}}\Big(\underbrace{\phi_t(1-p_{i,t}^{UI0}(\tilde{m}))u_{i,t}^{UI0}(\tilde{m})}_{\text{unmatched, losing UI}} + \underbrace{\chi_{i,t}^{UI0}(\tilde{m})\Big(\phi_t+(1-\phi_t)\xi\Big)p_{i,t}^{UI0}(\tilde{m})u_{i,t}^{UI0}(\tilde{m})}_{\text{bad match, losing UI}}\Big)d\tilde{m} \\
&\quad +(1-\rho_{f,it}^{UIx0})u_{i,t}^{UIx0} + \gamma(1-\rho_{f,it}^{UIx1})u_{i,t}^{UIx1} \qquad (4.21)\\
u_{i,t+1}^{UU} &= (1-\rho_{f,it}^{UU})u_{i,t}^{UU} + \underbrace{\psi\rho_{x,it}e_{i,t}}_{\text{destroyed match, losing UI}} \qquad (4.22)\\
u_{t+1} &= \sum_{i=H,L}\Big(\int_{\tilde{m}}u_{i,t+1}^{UI1}(\tilde{m})d\tilde{m} + \int_{\tilde{m}}u_{i,t+1}^{UI0}(\tilde{m})d\tilde{m} + u_{i,t+1}^{UIx1} + u_{i,t+1}^{UIx0} + u_{i,t+1}^{UU}\Big) \qquad (4.23)
\end{aligned}
$$

where $\chi_{i,t}^{UI1}(\tilde{m}) \equiv \int \mathbf{1}\{S_{i,t+1}^{UI1}(\tilde{m},m) \leq 0\}f(m)dm$ denotes the rate the newly formed matches consisting of $u_i^{UI1}(\tilde{m})$ are not viable. $\chi_{i,t}^{UI0}(\tilde{m})$ is analogously defined.

Figure 4.1: Unemployment-to-Employment Monthly Transition Rate (%) by UI History (Data source: CPS)

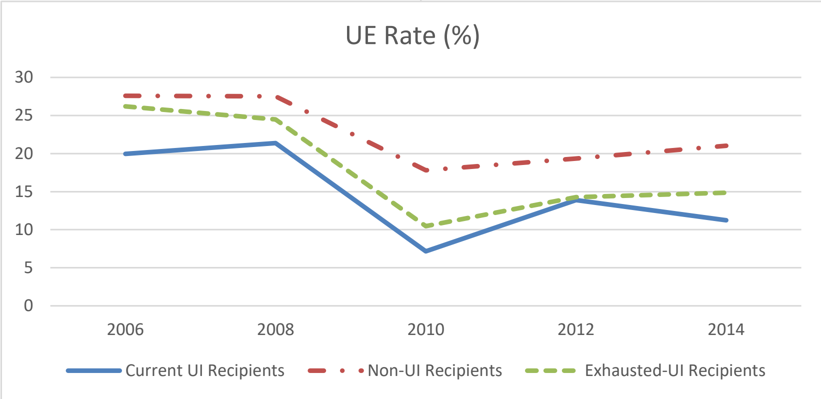


Figure 4.2: Average Number of Active Job Search Methods (Data source: CPS)

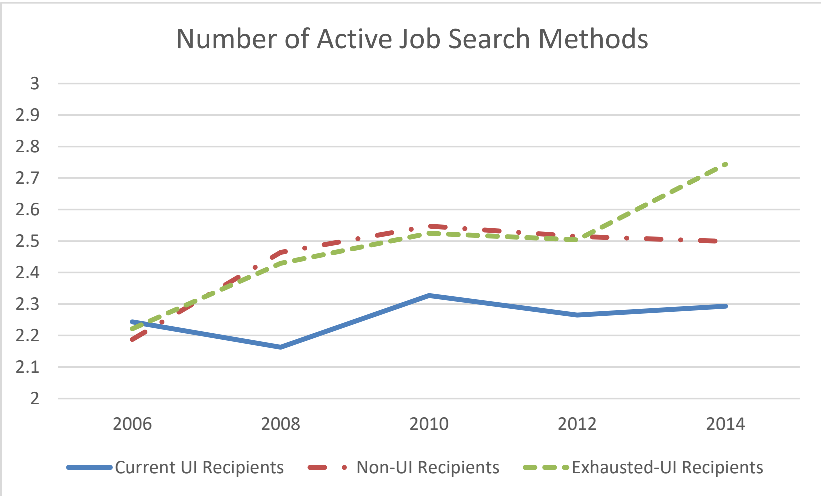


Figure 4.3: Shares of Formerly Insured Unemployed Workers amongst Total Unemployed Workers and Long-term Unemployed Workers (> 6 months duration) (Data source: CPS)

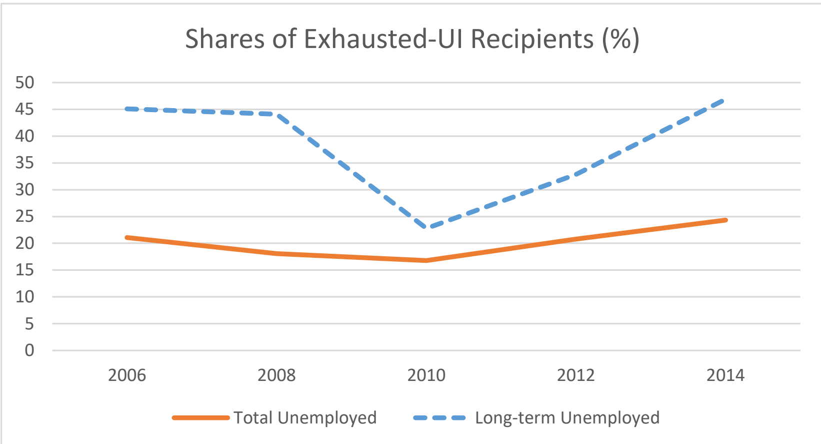


Figure 4.4: Unemployment Rate (%): Data and Models (Data source: CPS)

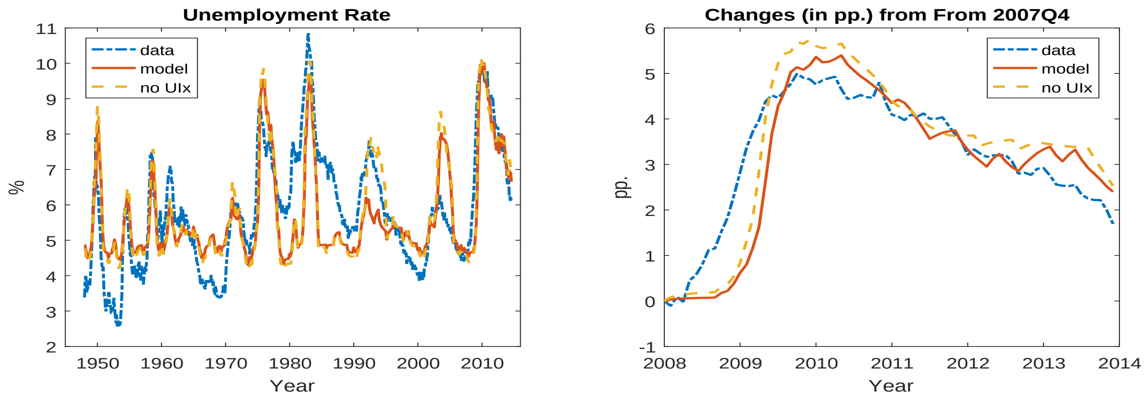


Figure 4.5: Average Unemployment Duration (%): Data and Models (Data source: CPS)

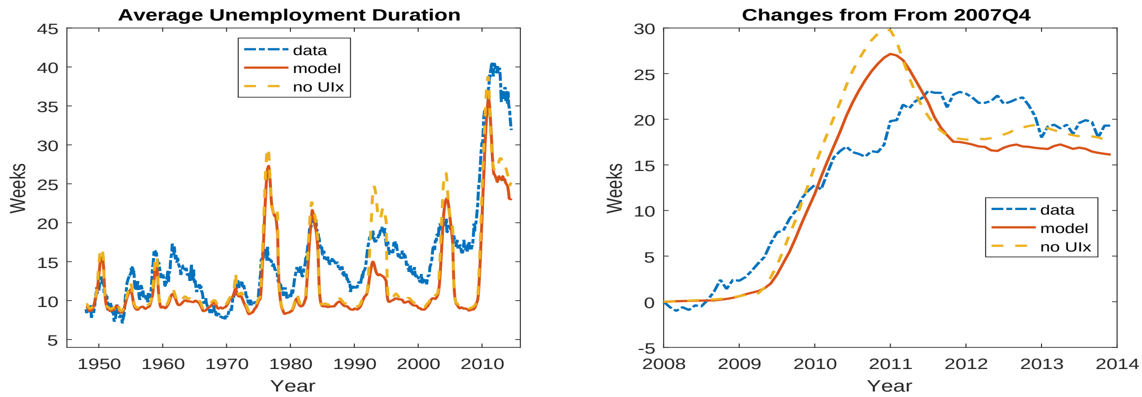


Figure 4.6: Long-term Unemployment Rate (%): Data and Models (Data source: CPS)

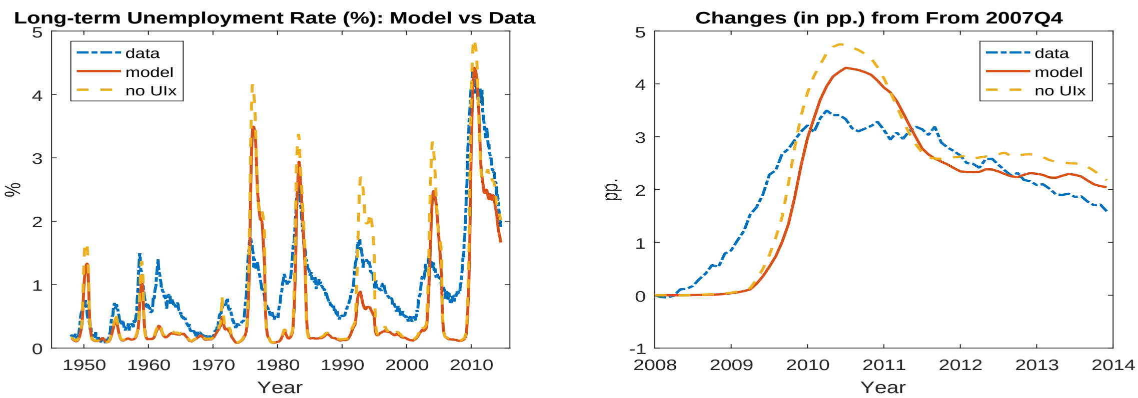


Figure 4.7: Autocorrelation Functions: Data and Models (Data source: CPS)

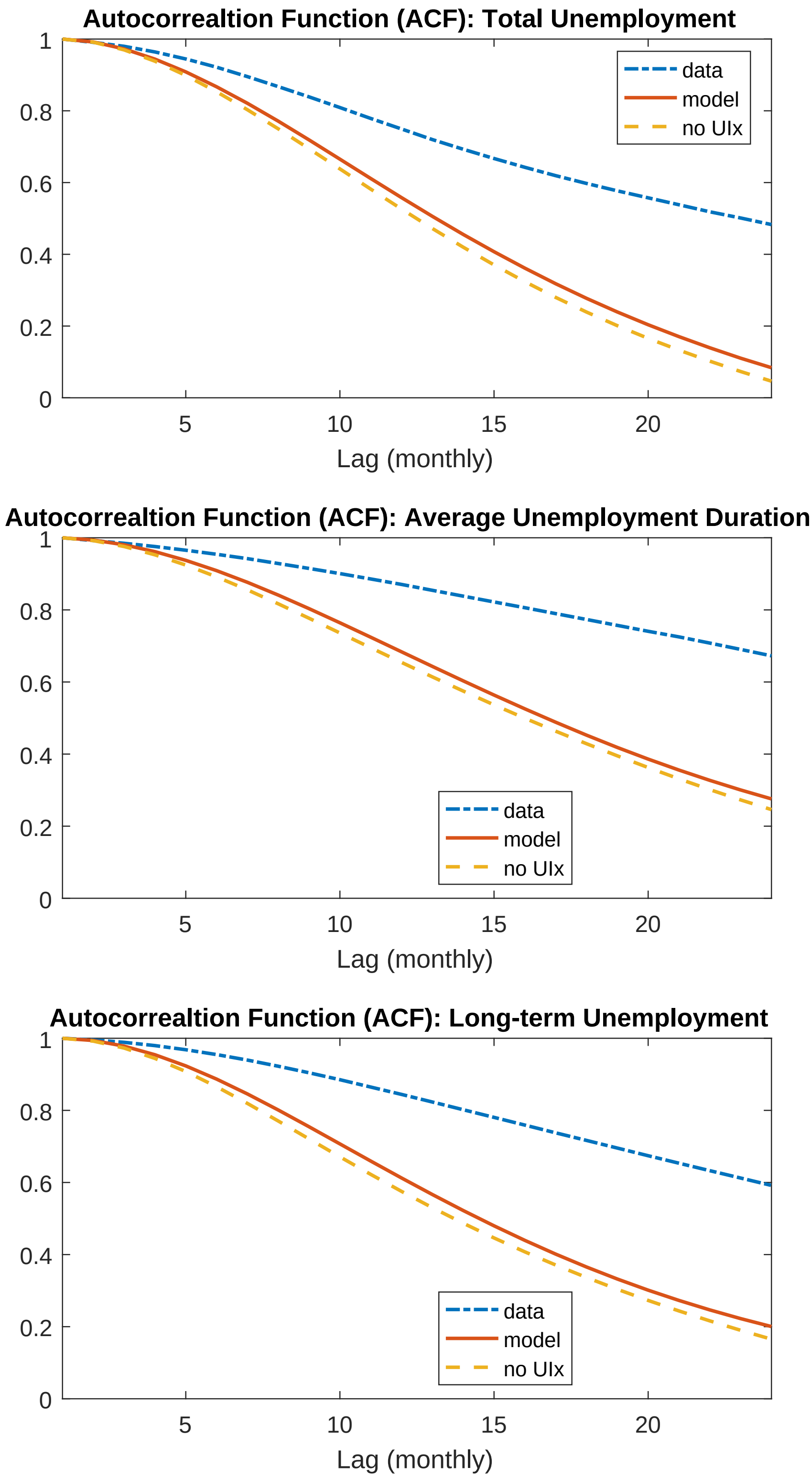


Figure 4.8: Autocorrelation Functions: Data and Models After Removing the Quadratic Time Trend (Data source: CPS)

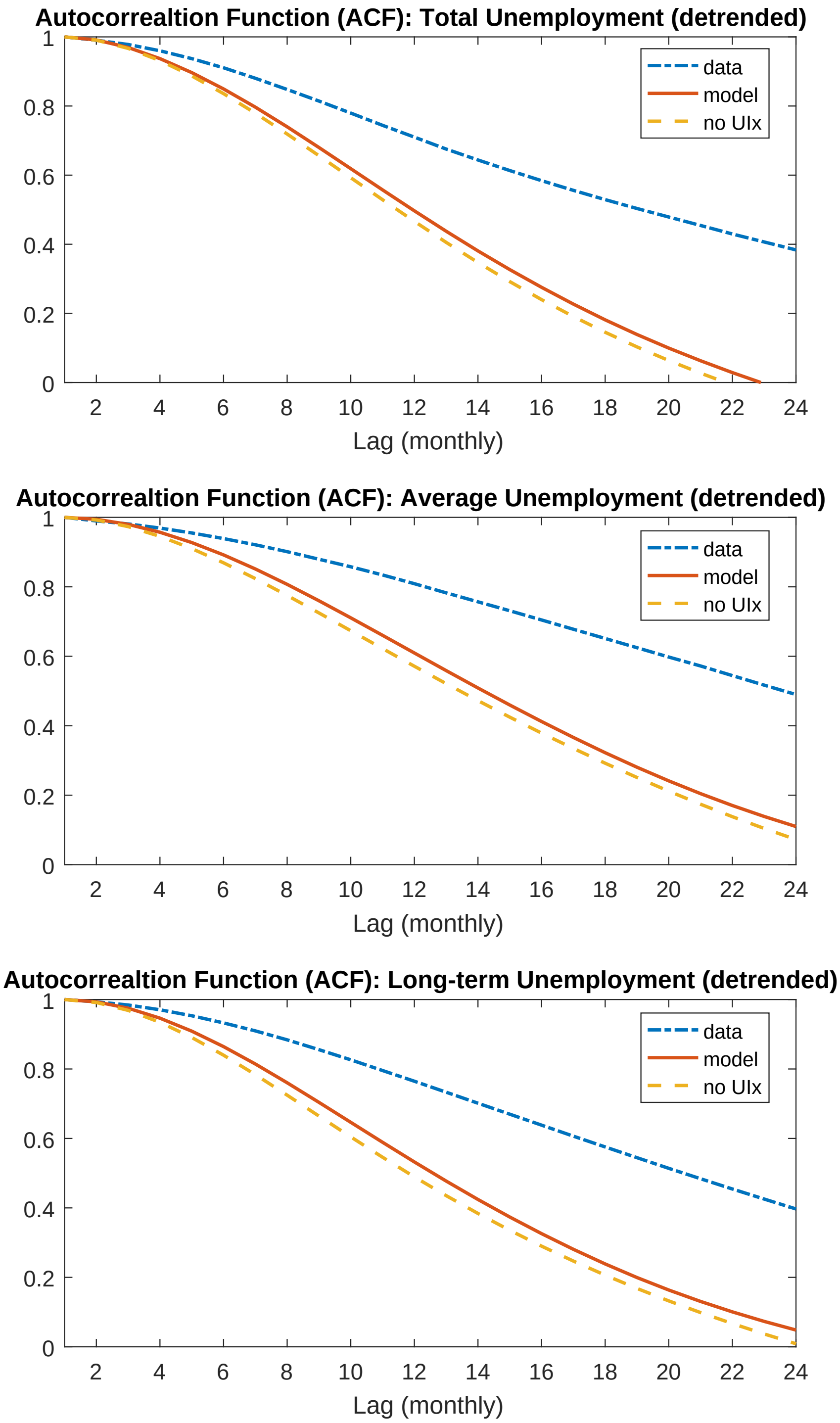


Figure 4.9: Welfare Gains and Losses from Eliminating All UI Extensions during the Great Recession

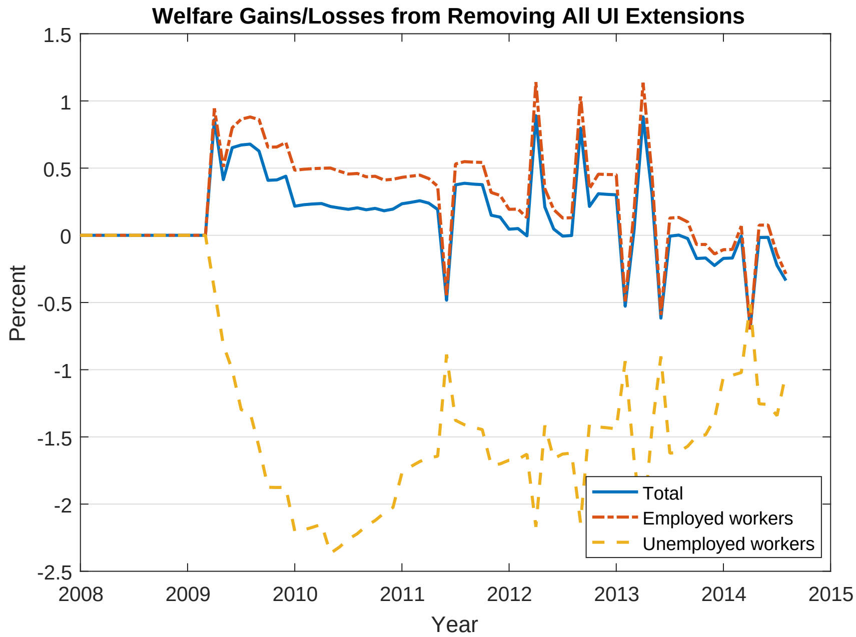


Figure 4.10: Welfare Gains and Losses from Eliminating All UI Extensions during the Great Recession: Unemployed Workers by UI History

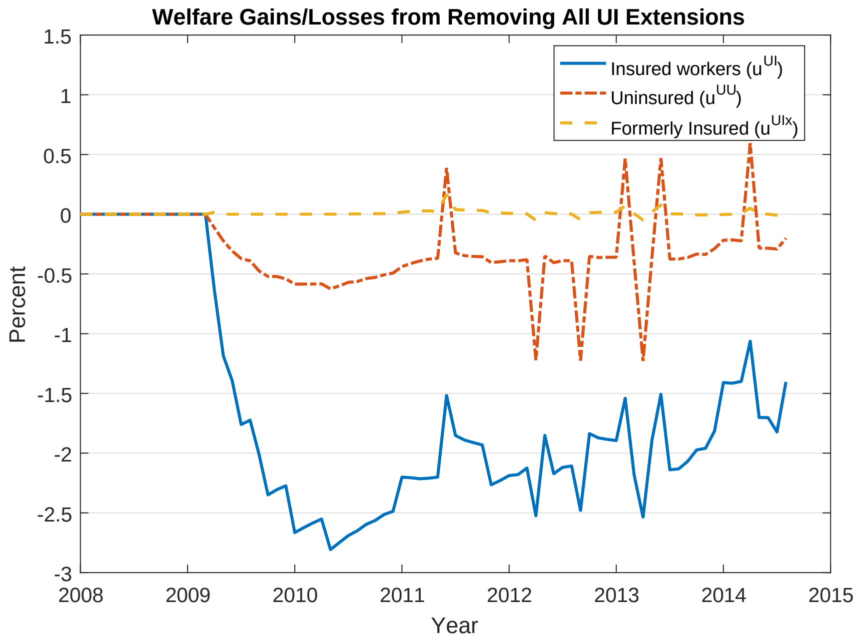


Table 4.1: Unemployment-to-Employment (UE) Monthly Transition Rate (%)

	Current UI Recipients			Non-UI Recipients			Former UI Recipients		
	Jan-08	Jan-10	Δpp.	Jan-08	Jan-10	Δpp.	Jan-08	Jan-10	Δpp.
Age									
16 years or older	21.4	7.2	−14.2	27.5	17.8	−9.7	24.5	10.5	−14.0
25−54 years	24.3	7.1	−17.1	30.7	19.7	−11.0	27.8	11.8	−16.0
Gender									
Male	24.9	7.2	−17.6	28.4	18.3	−10.1	22.2	12.6	−9.6
Female	16.3	7.2	−9.1	26.3	17.1	−9.2	26.9	6.3	−20.6
Education									
< High School	25.0	4.7	−20.3	25.4	16.2	−9.2	43.4	10.3	−33.1
High School	9.0	7.5	−1.5	28.9	16.0	−12.9	16.1	8.8	−7.3
Some College	27.4	7.4	−20.0	28.0	20.5	−7.5	26.2	12.0	−14.2
College or higher	26.8	7.4	−19.3	28.4	24.5	−3.9	30.3	8.3	−22.0
Industry									
Manufacturing	22.5	6.5	−16.0	25.6	14.9	−10.7	22.5	6.5	−16.0
Construction	18.3	9.6	−8.7	36.3	21.6	−14.7	n/a	12.1	−n/a
Wholesale & Retail	n/a	6.4	n/a	26.0	16.3	−9.7	34.6	10.2	−24.4
Prof./Business Services	45.9	4.3	−41.6	22.5	19.9	−2.6	39.3	23.6	−15.3
Occupation									
High-skilled	27.4	7.8	−19.5	27.4	24.6	−2.9	13.7	10.6	−3.1
Middle-skilled	18.6	6.6	−12.0	30.1	17.9	−12.2	22.0	10.7	−11.3
Low-skilled	20.6	10.4	−10.2	26.6	17.6	−9.0	43.9	9.1	−36.8
Reasons for Unemployment									
Temporary Layoff	50.7	12.2	−38.5	46.2	40.4	−5.8	27.1	34.5	7.4
Permanent Separation	13.6	6.7	−6.9	25.6	15.6	−10.0	28.0	8.0	−20.0
Recall									
Date Given	56.4	9.9	−46.5	53.9	47.00	−6.9	100.0	64.3	−35.7
No Date Given	22.4	7.7	−14.7	29.4	22.9	−6.5	32.2	10.0	−22.2
Some indication	48.3	13.3	−35.0	36.6	33.8	−2.8	18.0	18.8	0.8
No indication	16.5	7.0	−9.5	22.2	17.5	−4.7	38.4	8.9	−29.5

- Data source: CPS
  Δpp. ≡ change in UE rate (in percentage points) $= UE_{Jan10} - UE_{Jan08}$
  Occupation skills are defined as in the job polarisation literature (where high-, middle- and low-skilled occupations respectively are abstract, routine and manual jobs)

Table 4.2: Targeted Moments

Moment	Data	Baseline	Without UIx
E(u)	0.0583	0.0569	0.0577
E(ρ_{UE})	0.4194	0.4414	0.4286
E(ρ_{EU})	0.0248	0.0259	0.0251
E(ρ_{EE})	0.0320	0.0316	0.0320
E(u_{dur})	15.416	12.251	13.063
E(u^{UI})	0.0290	0.0314	0.0327
std(u)	0.1454	0.1449	0.1453
std(ρ_{UE})	0.0999	0.1221	0.1402
std(ρ_{EU})	0.0890	0.0617	0.0641
std(u_{dur})	6.9327	5.6412	6.1954
std(LP)	0.0131	0.0106	0.0104
corr(LP, LP_{-1})	0.7612	0.7609	0.7593
E($\rho_{UE}^{UI}/\rho_{UE}^{UIx}$)	0.8009	0.8018	0.5508

- ρ_{UE}: job finding rate // ρ_{EU}: job separation rate // ρ_{EE}: job-to-job transition rate
  u_{dur}: mean unemployment duration (weeks) // $LP = y/(1-u)$: labour productivity
  Data source: CPS

Table 4.3: Moments Not Targeted

Moment	Data	Model	Wihtout UIx
E($U1$)	0.0233	0.0243	0.0237
E($U2$)	0.0172	0.0183	0.0180
E($U4$)	0.0080	0.0075	0.0085
E(LTU)	0.0098	0.0066	0.0076
std($U1$)	0.0048	0.0015	0.0017
std($U2$)	0.0046	0.0027	0.0030
std($U4$)	0.0035	0.0033	0.0035
std(LTU)	0.0085	0.0090	0.0107
std(u^{UI})	0.1780	0.2059	0.2523
std(v)	0.1226	0.0436	0.0327
corr(u,v)	-0.6682	-0.2077	-0.1906

- $U1$: Unemployed less than 1 month // $U2$: Unemployed with 2-3 month duration
  $U4$: Unemployed with 4-6 month duration // LTU: Unemployed longer 6 months
  u_{dur}: mean unemployment duration (weeks)
  Data source: CPS

Table 4.4: Calibrated Parameters For Baseline Model

Parameter	Description	Baseline	No UIx
l	Meeting function	0.50	0.51
δ	Exogenous separation rate	0.025	0.023
λ	Pr(redrawing new m)	0.50	0.50
ψ	Pr(losing UI after becoming unemployed)	0.49	0.49
ξ	Pr(losing UI after meeting firm)	0.50	0.50
a_e	Search cost function	0.20	0.15
$\underline{m}$	Lowest match-specific productivity	0.384	0.396
β_1	Match-specific prod. distribution	2.57	2.55
β_2	Match-specific prod. distribution	5.39	5.26
ρ_z	Persistence of TFP	0.9581	0.9562
σ_z	Standard deviation of TFP shocks	0.0086	0.0075
η_L	Productivity of type-L	0.985	0.985
a_{ux}/a_u	Search cost for u^{UIx} compared to u^{UI}	1.351	1

Table 4.5: Fixed Parameters For Baseline Model (From Rujiwattanapong (2016))

Parameter	Description	Value	Sources/Remarks
β	Discount factor	0.9967	Annual interest rate of 4%
κ	Vacancy posting cost	0.0392	Fujita & Ramey (2012)
μ	Worker's bargaining power	0.5	Den Haan, Ramey & Watson (2000)
ϕ_H	UI exhaustion rate	1/6	6 months max UI duration, ETA
ϕ_{L1}	UI exhaustion rate	1/9	9 months max UI duration, ETA
ϕ_{L2}	UI exhaustion rate	1/12	12 months max UI duration, ETA
ϕ_{L3}	UI exhaustion rate	1/16	16 months max UI duration, ETA
ϕ_{L4}	UI exhaustion rate	1/21	21 months max UI duration, ETA
$\bar{u}$	UI policy threshold	0.065	ETA
a_u	Search cost function	0.1180	Normalisation
d_u, d_e, d_{ux}	Search cost function	1	Christensen et al (2004), Yashiv (2000)
h	Leisure flow	0.5695	Gruber (1997)

Table 4.6: Performance of the Model During the Great Recession

	Data	Model	No UIx	Data	Model	No UIx	mean % dev. from data	
x	max(x)	max(x)	max(x)	mean(x)	mean(x)	mean(x)	Model	No UIx
$u(\%)$	10.0%	10.0%	10.1%	8.3%	8.2%	8.3%	4.0%	4.6%
u_{dur} (weeks)	40.6	35.9	38.8	36.3	26.7	28.5	26.5%	23.0%
$LTU(\%)$	4.4%	4.4%	4.9%	3.4%	2.8%	3.1%	17.4%	12.9%

- LTU: Unemployed longer 6 months // u_{dur}: mean unemployment duration (weeks)
  - These statistics are computed between October 2009 (the peak of the US unemployment rate) and June 2014
  - The last 2 columns show the time-average percentage deviation in modulus of each variable from its empirical counterpart
  - Data source: CPS

Table 4.7: Counterfactual Experiments: Effects of Decreasing Maximum UI Duration from 90 Weeks to 26 Weeks During the Great Recession: Baseline Model (with Worker's UI History) and Model without Worker's UI History

With UIx	Data	Model	$\Delta\phi$	$\Delta(\phi,s)$	$\Delta(\phi,s,S)$
max(u) (%)	10.0%	10.0%	9.0%	8.1%	6.6%
max(u_{dur}) (weeks)	40.6	35.9	14.57	12.25	11.59
max(LTU) (%)	4.4%	4.4%	1.2%	0.6%	0.5%
Δ max(u)			−1.0pp	−1.9pp	−3.4pp
Δ max(u_{dur})			−21.3	−23.6	−24.3
Δ max(LTU)			−3.2pp	−3.8pp	−4.0pp
Without UIx	**Data**	**Model**	$\Delta\phi$	$\Delta(\phi,s)$	$\Delta(\phi,s,S)$
max(u) (%)	10.0%	10.1%	9.2%	8.4%	6.8%
max(u_{dur}) (weeks)	40.6	38.8	14.8	12.9	12.2
max(LTU) (%)	4.4%	4.9%	1.2%	0.6%	0.5%
Δ max(u)			−0.9pp	−1.7pp	−3.4pp
Δ max(u_{dur})			−24.0	−25.9	−26.6
Δ max(LTU)			−3.7pp	−4.3pp	−4.4pp

- $\Delta\phi$: only maximum UI duration changes
  $\Delta(\phi,s)$: maximum UI duration and job search effort change
  $\Delta(\phi,s,S)$: maximum UI duration, job search effort and match surplus change
  LTU: Unemployed longer 6 months // u_{dur}: mean unemployment duration (weeks)
  Δ max($\cdot$): difference between the model's and counterfactual experiments' maxima
  - These statistics are computed between October 2009 (the peak of the US unemployment rate) and June 2014
  - Data source: CPS

Table 4.8: Welfare Gains/Losses From Eliminating All UI Extensions During the Great Recession

Average Welfare Gains/Losses (%)	Baseline	No UIx
Total	0.14	0.23
Employed	0.27	0.33
Employed: High Productivity	0.25	0.32
Employed: Low Productivity	0.28	0.34
Unemployed	−1.27	−0.93
Unemployed: Insured	−1.64	−1.20
Unemployed: Insured (0−2 months)	−1.67	−1.30
Unemployed: Insured (3 months or longer)	−1.61	−1.16
Unemployed: Formerly Insured	0.00	n/a
Unemployed: Uninsured	−0.31	−0.15
Unemployed: High Productivity	−1.35	−1.00
Unemployed: Low Productivity	−1.21	−0.90

- These statistics are computed between June 2009 (the peak of the Great Recession and when UI extension is triggered in the model) and June 2014
- Welfare gains/losses are defined as in Lucas (1987). It is the percentage change in consumption necessary in each period to make agents in the economy with endogenous UI extensions be as satisfied as they would be in an economy where UI extensions are eliminated during the Great Recession.

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