European Economic Review 178 (2025) 105106

Contents lists available at ScienceDirect

European Economic Review

journal homepage: www.elsevier.com/locate/eer

Unemployment dynamics and endogenous unemployment insurance extensions ☆

W. Similan Rujiwattanapong *

Faculty of Political Science and Economics, Waseda University, 1-6-1 Nishi-Waseda, Shinjuku-ku, Tokyo, 169-8050, Japan
Centre for Macroeconomics, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, United Kingdom

A R T I C L E I N F O

JEL classification:
E24
E32
J24
J64
J65

Keywords:
Business cycles
Long-term unemployment
Rational expectations
Search and matching
Unemployment insurance
Unemployment duration
Worker heterogeneity

A B S T R A C T

This paper investigates the general equilibrium effects of endogenous unemployment insurance (UI) extensions on the dynamics of unemployment and its duration in the US. Using a stochastic random-search-and-matching model with worker heterogeneity, I allow for the maximum UI duration to endogenously depend on unemployment, and for UI benefits to depend on worker characteristics replicating the US benefit system. The model is able to generate the observed incidence of (long-term) unemployment over the past six decades. Responses of job search to UI extensions (microeconomic effect of UI) are important for both long-term and total unemployment whilst responses of job separations (general equilibrium effect of UI) is important for total unemployment. Worker heterogeneity in terms of benefit levels is crucial for the unemployment duration dynamics via heterogeneous job finding rates. Disregarding the rational expectations of UI extensions may overestimate unemployment by almost 2 percentage points.

1. Introduction/motivation

From the onset of the Great Recession, the US labour market exhibits dynamics never seen before in previous recessions. Underlying persistently high unemployment is an unprecedented rise in long-term unemployment (represented by those whose unemployment duration is 6 months or longer).[1] as seen in Fig. 1. Long-term unemployment had always been below a quarter of total unemployment apart from two occasions: the Great Recession when it represented almost half of the total unemployment population and the early 1980s recession where it represented a quarter of total unemployment.[2]

☆ I am indebted to Morten Ravn for invaluable guidance and support, and to Fabien Postel-Vinay and Vincent Sterk for their insightful discussions and suggestions. I am grateful to the editor, Peter Rupert, as well as the associate editor and three anonymous referees. I also want to thank Wei Cui, Gregor Jarosch, Fatih Karahan, Jeremy Lise, Kurt Mitman, Suphanit Piyapromdee, Stan Rabinovich, Shouyong Shi, Ludo Visschers and Randall Wright as well as seminar participants at Aarhus University, Bank of Thailand, University of Bath, GRIPS, Hitotsubashi University, University of Konstanz, Queen Mary University of London, University of Tokyo, UCL, Waseda University, Bristol Search and Matching Workshop, and Nordic summer symposium in Macroeconomics for helpful comments and conversations. I gratefully acknowledge the financial support from the Japan Society for the Promotion of Science Grant-in-Aid for Early-Career Scientists Number 21K13297 and Aarhus University Research Foundation Grant Number 28165. This paper subsumes two working papers: "Long-term Unemployment and Unemployment Insurance Extensions" and "Unemployment Dynamics and Unemployment Insurance Extensions under Rational Expectations".

* Correspondence to: Faculty of Political Science and Economics, Waseda University, 1-6-1 Nishi-Waseda, Shinjuku-ku, Tokyo, 169-8050, Japan.
E-mail address: sruji@waseda.jp.

[1] As defined by the US Bureau of Labor Statistics.

[2] Abraham et al. (2016) find that long-term unemployed workers face worse labour market outcomes in terms of re-employment probabilities and subsequent earnings even when controlled for individual heterogeneity.

https://doi.org/10.1016/j.euroecorev.2025.105106
Received 30 August 2024; Received in revised form 21 May 2025; Accepted 9 July 2025
Available online 19 July 2025

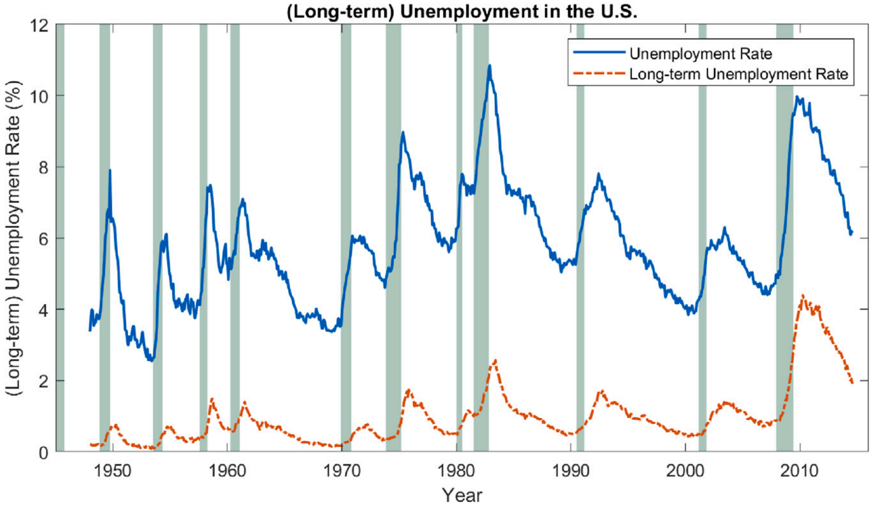

Fig. 1. Unemployment and long-term unemployment (those unemployed ≥6 months) in the US. Shaded areas denote the recessions. *Data sources:* CPS and NBER.

This paper investigates the general equilibrium effects of endogenous unemployment insurance (UI) extensions on the dynamics of unemployment and its duration structure under rational expectations using a stochastic search-and-matching model. Whilst the analysis applies to 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 a maximum of 99 weeks (whereas the standard maximum UI duration is 26 weeks) as depicted in Fig. 2. The same figure also shows that the maximum UI duration has been extended in every recession since late 1950s, and its generosity, measured by weeks of maximum UI duration, has been increasing over time (except for one extension in the early 1980s). There are primarily two types of UI extensions in the US: (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 recessions.[3] It is the first type that endogenises UI extensions and makes them countercyclical.[4]

Based on this countercyclical UI system, I extend the standard stochastic random-search-and-matching model to incorporate unemployment-dependent UI extensions, endogenous job search intensity, endogenous job separations, on-the-job search, and worker heterogeneity (in terms of worker–firm match quality, individual productivity, employment status, UI status, and benefit level). Job search and job acceptance decisions of a worker depend not only on her individual characteristics but also on the aggregate variables (including the unemployment rate) which determine when and for how long UI extensions will occur. UI extensions are triggered when the unemployment rate exceeds a certain threshold. With varying degrees, workers respond to the extensions by lowering job search intensity as well as being more selective with regards to the match quality (due to their higher outside options). Worker heterogeneity in this model implies that an insured unemployed worker with a higher benefit level responds more strongly whilst an uninsured unemployed worker does not respond at all to the extensions. Furthermore, UI extensions may induce low-quality matches to separate as well as prevent these matches to be formed, both of which can further exacerbate the unemployment inflows and outflows during recessions. Nonetheless, UI extensions may contribute positively to wages and labour productivity by increasing the match quality thresholds. Firms also respond to the higher wage pressure by lowering vacancies.

The main contributions of this paper are twofold. First, it quantifies the microeconomic and general equilibrium effects of unemployment-dependent UI extensions not only on unemployment but also on the entire unemployment duration distribution. Second, it demonstrates the importance of rational expectations on the timings of endogenous UI extensions. The framework is useful for policy experiments to study the mechanisms through which state-dependent UI extensions affect the aggregate labour market.

[3] 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 called Temporary Unemployment Extended Compensation Act (TEUC). From 1991 onwards, the discretionary extensions have been under the name Emergency Unemployment Compensation (EUC). Acosta et al. (2023) provide a detailed account of the UI extensions in the US over the past 50 years.

[4] We can also see from Fig. 2 that both the automatic and discretionary extensions have been increasing in their generosity and that they are a feature of every recession since late 1950s. It is also worth noting that UI extensions have often been accompanied by increases in UI benefit levels, including during the recessions of the 1970s, 1980s, and the Great Recession. However, according to the UI replacement rates report (1997–2024) by the Employment and Training Administration (ETA) of the U.S. Department of Labor, replacement ratios remained relatively stable during the Great Recession. In particular, the weighted average of claimants' weekly benefit amounts relative to their average weekly wages in fact declined by 0.2 percentage points, from 47 to 46.8 percent, between 2007 and 2008. It is possible that, during a recession, the composition of UI claimants may shift more towards those with lower replacement rates (i.e., those with higher previous wages) potentially offsetting the effect of the countercyclical benefit level.

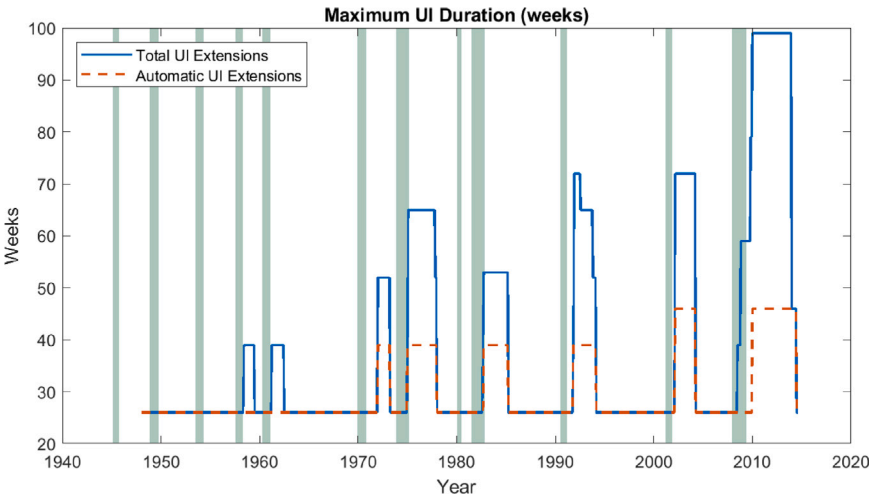

Fig. 2. Maximum unemployment insurance duration in the US. Shaded areas denote the recessions.
Data sources: Employment and Training Administration (ETA), U.S. Department of Labor, and NBER.

To preview the results, I find that UI extensions account for 8–18 percent of the rise on unemployment during the Great Recession, but the UI effect is non-linear and of a smaller magnitude in other recessions. The main mechanisms through which UI extensions impact total unemployment are job search and job separation margins whilst the job search behaviour is most important for long-term unemployment. UI extensions are important for explaining the incidence of (long-term) unemployment; however, the extensions alone cannot fully capture the persistence of long-term unemployment. Additionally, worker heterogeneity helps explain most of the dynamics of the unemployment duration structure via heterogeneous job finding rates. Lastly, I demonstrate that assuming adaptive expectations, in lieu of rational expectations, on the likelihood of UI extensions implies an overestimation of unemployment by almost 2 pp.

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. Fujita and Moscarini (2017) also show that the recall rate rises during recessions. I also contribute to this literature by providing further empirical evidence that insured unemployed workers have a lower unemployment exit rate than the uninsured, and that this gap widened during the Great Recession when UI extensions took place. Furthermore, I find that the job finding rate of insured unemployed workers decreases in their unemployment benefit level, and that this relationship was stronger during the Great Recession. Without targeting, the model is able to replicate these empirical findings with strikingly similar magnitudes.

There is a large empirical literature studying the effects of the UI extensions on the unemployment exit rate and total unemployment during the Great Recession. For example, Rothstein (2011) and Farber and Valletta (2015) utilise the variations in timing and generosity of UI extensions across states. Dieterle et al. (2020) and Boone et al. (2021) also exploit these variations focusing on bordering counties in neighbouring states. Fujita (2011), Aaronson et al. (2010), and Barnichon and Figura (2014) study the historical unemployment flows. Kuang and Valletta (2010) utilise the distribution of unemployment duration to construct a measure of expected unemployment duration whilst Mazumder (2011) uses the steady-state unemployment framework. Most of these studies focus on the microeconomic effect of the UI extensions, namely, the impact on the probability of exiting unemployment or on the job search intensity of the unemployed, in which they find a small but significant impact of UI extensions. At the macro level, empirical results are rather mixed. Chodorow-Reich et al. (2019) exploit the variation in measurement error of real-time unemployment data, and find a limited impact of UI extensions on unemployment. Hagedorn et al. (2013) take into account the response of job creation to benefit extensions using border county data, and find a very large UI effect on unemployment. In this paper, however, the additional effect is from the job separation margin. Henceforth, I define job separations as the employment-to-unemployment transitions. Acosta et al. (2023) construct a "UI Benefits Calculator" and exploit the variations in the potential UI durations across states and time. They find that UI extensions do not affect unemployment unless the initial potential UI duration is below 60 weeks. I also find non-linear effects of UI extensions in this paper with a similar magnitude to theirs.

A benefit of using a general equilibrium model is that I can distinguish between the microeconomic and general equilibrium effects of UI extensions on unemployment. I define the former as the effect of UI via the job search channel, and the latter as the effect of UI when the responses of match formation and job separation decisions are taken into account. I find that UI extensions contribute to a 0.8–1.4 percentage point (pp) increase in unemployment under the micro effect during the Great Recession which is consistent with existing empirical estimates.[5] I find that the general equilibrium effect of UI adds an additional 0.4 pp increase to the unemployment rate.

Studies on the effects of UI extensions in general equilibrium are conducted by Goensch et al. (2024) whose focus is on labour force participation and job-to-job transitions, Birinci and See (2023) who study the labour market responses of UI extensions under incomplete markets and wealth heterogeneity, Kekre (2022) and Gorn and Trigari (2024) on the role of UI extensions on macroeconomic stabilisations under incomplete markets, Rujiwattanapong (2022) on the cyclical behaviour of labour productivity, Mitman and Rabinovich (2019) on jobless recoveries, Faig et al. (2016) on the volatility of unemployment and vacancies, Nakajima (2012) whose focus is on the Great Recession, and, more recently, Landais et al. (2018) and Auray and Eyquem (2024) on the optimal UI policy over the business cycle.[6] Birinci and See (2023) consider a multitude of worker heterogeneity in terms of wealth, income and idiosyncratic productivity, and evaluate the insurance-incentive trade-off of UI along these dimensions. This paper complements Birinci and See (2023) by focusing on the role of worker heterogeneity in terms of match quality, UI status, benefit level and worker productivity in explaining the dynamics of the unemployment duration distribution under unemployment-dependent UI extensions. Given the focus on the labour force participation margin, Goensch et al. (2024) study UI reforms under a stationary equilibrium framework, whilst this paper's focus is on the business-cycle and state-dependence aspects of UI extensions. This paper also complements Rujiwattanapong (2022) and Mitman and Rabinovich (2019) by considering an additional set of worker heterogeneity which translates into further heterogeneity in the job finding rates, the job separation rates and the composition of newly unemployed workers.[7]

This paper demonstrates that such heterogeneity is vital in explaining the dynamics of unemployment and its duration structure in the US labour market. Wiczer (2015) shows that assuming a single type of unemployed workers (leading to a single job finding rate) implies an average unemployment duration and long-term unemployment that are just over half of what we observed in the data. Rujiwattanapong (2022) shows that considering two types of unemployed workers (being those with and without UI) can hardly explain the average unemployment duration, not to mention the entire distribution of unemployment durations. This paper allows the job finding rates to vary with the UI status, benefit level and individual productivity (in addition to the aggregate variables) and is able to substantially explain the dynamics of the unemployment duration distribution over the past six decades. Furthermore, the endogenous job separations and heterogeneous match quality in this paper imply that, during recessions with UI extensions, there will be a larger fraction of newly unemployed workers who collect UI and have, on average, lower job finding rates (due to higher benefit levels) than during booms.[8] A higher benefit level decreases the relative gain from searching and, in effect, job search intensity.

This result is consistent with the literature on the incidence of long-term unemployment and worker heterogeneity. Particularly, Ahn and Hamilton (2020) use a non-linear state space model to uncover the unobserved heterogeneity of workers' unemployment exit rate. They empirically show that accounting for changes in the composition of the newly unemployed who are UI recipients can explain most of the increase in unemployment during the Great Recession. Ahn (2023) extends Ahn and Hamilton (2020) to incorporate the observable characteristics of workers (but not the UI status), and finds that workers with a low unemployment exit rate are likely to have experienced permanent job losses. Since typically workers become eligible for UI if they are unemployed through no fault of their own, her finding is congruent with this paper's main hypothesis. Worker heterogeneity is the focus of Hornstein (2012) in accounting for unemployment dynamics with different durations. Ravn and Sterk (2017) consider the difference in unemployment exit rates together with incomplete markets and price rigidities to study the amplification mechanism on unemployment. Carrillo-Tudela and Visschers (2023) study the role of unemployed workers' occupational mobility on the fluctuations of unemployment and its duration over business cycles. Kroft et al. (2016) analyse the impact of a genuine duration dependence in unemployment exit rate on the rise of long-term unemployment. They find little account for the observable characteristics of workers although a worker's UI status is not included in their analysis.

This paper considers a degree of observed and unobserved worker heterogeneity where the former comes from the UI status and benefit level, and the latter is from the individual productivity and match quality, all of which affect the job finding rate. I also estimate the same model in Ahn and Hamilton (2020) using Maximum Likelihood and demonstrate that their interpretation of unobserved heterogeneity is related to the UI status in the baseline model since insured unemployed workers have a lower

[5] Existing estimates are in the range of 0.1–1.8 pp. Fujita (2011) finds the UI extensions contribute to a 0.8–1.8 pp increase in the unemployment rate during the Great Recession. Aaronson et al. (2010)'s estimates are between 0.5–1.25 pp. Kuang and Valletta (2010)'s estimate is 0.4 pp. Rothstein (2011)'s estimates are between 0.1–0.5 pp. Chodorow-Reich et al. (2019)'s estimate is 0.34 pp. Dieterle et al. (2020)'s estimate is 0.5 pp. On the other hand, Boone et al. (2021) focus on the employment-to-population ratio and find no significant impact of UI extensions on this ratio with a point estimate of 0.18–0.43 pp.

[6] In particular, Kekre (2022) and Gorn and Trigari (2024) examine the positive effect of UI extensions on aggregate demand and demonstrate that, in the presence of nominal rigidities, these extensions stabilise the economy, given that unemployed workers possess high marginal propensities to consume. Since this channel is absent in this paper, I discuss its potential implications in the results section. Nakajima (2012) studies an economy with transitional dynamics and perfect foresight, and finds that the UI extensions contribute to a 1.4 pp increase in the unemployment rate. Birinci and See (2023) use a directed-search model with wealth heterogeneity and aggregate risks, and obtain a moderate impact of UI extensions on the unemployment rate of 0.38–0.65 pp during the Great Recession. Due to the block recursivity, Birinci and See (2023) model UI extensions as a function of the aggregate productivity whilst, in this paper, they are a function of the unemployment rate which is highly persistent and tends to respond to shocks with lags. Landais et al. (2018) document that the macroeconomic elasticity of UI on unemployment is smaller than the microeconomic elasticity leading to a positive effect of UI on tightness during slumps. Auray and Eyquem (2024) demonstrate that UI should be countercyclical in response to demand shocks and quasi-constant in response to productivity shocks.

[7] In Rujiwattanapong (2022), workers differ by their match quality and UI status, and in Mitman and Rabinovich (2019), workers differ by their UI status during unemployment and employment.

[8] Birinci and See (2023) also document a considerable degree of heterogeneity in labour market flows, take-up rates and replacement rates along the wealth and income dimensions.

Table 1
Monthly transition rate (%).
Data source: CPS.

	Current UI recipients			Non-UI recipients								
				All non-UI			Exhausted UI			Never received UI		
	Jan-08	Jan-10	Δpp	Jan-08	Jan-10	Δpp	Jan-08	Jan-10	Δpp	Jan-08	Jan-10	Δpp
U2E	21.4	7.2	−14.2	27.5	17.8	−9.7	19.5	13.4	−6.1	30.7	19.4	−11.3
U2U	68.4	84.4	+16.0	48.0	60.2	+12.2	51.8	71.9	+20.1	46.9	56.4	+9.5
U2O	10.3	8.5	−1.8	24.5	22.0	−2.5	28.7	14.7	−14.0	22.4	24.2	+1.8
N	535	1779	–	1965	2968	–	405	675	–	1560	2293	–

• "Current UI Recipients" refers to unemployed workers who received UI benefits after the job ended and did not exhaust their UI eligibility. "Non-UI Recipients" refers to those who either did not receive UI benefits after the job ended or those who received but exhausted their UI eligibility. "Exhausted UI" refers to unemployed workers who received UI benefits after the job ended and exhausted their UI eligibility. "Never received UI" refers to those who did not receive UI benefits after the job ended. Δpp ≡ change in rate (in pp) from January 2008 to January 2010. U: Unemployment, E: Employment, O: Out of labour force, *N*: number of observations.

unemployment exit rate. I find that individual productivity does not matter much once the UI status and benefit level are taken into account.

The rest of the paper is organised as follows. Section 2 discusses motivating data on UI extensions and unemployment duration during the Great Recession. Section 3 describes the model. Section 4 discusses the calibration exercise. Section 5 analyses the results. Section 6 concludes.

2. Empirical evidence

I examine the empirical evidence that (1) unemployed workers with UI (the insured unemployed) have a lower job finding rate than unemployed workers without UI (the uninsured unemployed), and (2) the job finding rate of the insured unemployed decreases in their unemployment benefit level. Moreover, during the Great Recession, these empirical evidence become more pronounced. Namely, the insured unemployed experienced a larger fall in their job finding rate compared to the uninsured unemployed, and, amongst the insured unemployed, their job finding rate responded more negatively to their unemployment benefit levels. These findings have a direct consequence on the unemployment duration and the incidence of long-term unemployment, and motivate the model features in the next section.

I study the transition rates from unemployment to employment, unemployment and out-of-labour-force (OLF) (namely U2E, U2U, and U2O rates respectively), as well as the distributions of unemployment duration during the periods surrounding the Great Recession according to the UI status and several 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 the CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplement between 1998 and 2016. This CPS supplement contains questions on the status and history of UI receipts, and it is released every two years in January (except for 1998 and 2000 when it was released in February).[9] I consider workers whose age is 16 years or older.

Henceforth, I define "current UI recipients" as unemployed workers who received UI benefits after the job ended and did not exhaust their UI eligibility, and "non-UI recipients" as those who either did not receive UI benefits after the job ended or those who received but exhausted their UI eligibility. I obtain the monthly transition rates by merging the CPS supplement (for either January or February) with the CPS Basic Monthly Data of the following month. Transition rates are calculated as a fraction of unemployed workers conditioned on their UI status and UI history moving into either employment, unemployment, or OLF in the following month.

Job findings. Table 1 demonstrates that the job finding rate of current UI recipients is generally lower than that of non-UI recipients (the uninsured unemployed), and this gap became larger during the Great Recession. In January 2008, when there were 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 pp lower than that of the uninsured unemployed. The main findings prevail across different subgroups of workers based on their UI receipt history as well as other observable characteristics as shown in Tables A.1 in Appendix A.[10]

To study the relationship between the job finding rate and the unemployment benefit level, I estimate a linear probability model where I regress a worker's job finding rate on her (log) unemployment benefit level whilst controlling for age (quadratic),

9 Particularly, the CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplement contains the following two questions (1) "Did you receive unemployment insurance benefits after that job ended?" and (2) "Did you exhaust your eligibility for unemployment benefits?". The variable names are PESD20 and PESD21, respectively.

10 Specifically, after separating non-UI recipients into those who exhausted UI and those who never received UI, both of these subgroups experienced a decline in their job finding rates from 2008 to 2010. However, the decline was smaller in magnitude than that of current UI recipients. Furthermore, insured unemployed workers had a lower job finding rate than uninsured unemployed workers in most subgroups in 2008 and in all subgroups in 2010. The job finding rates from 2008 to 2010 for current UI recipients in most subgroups fell by a larger magnitude than for non-UI recipients.

Table 2
Linear probability model for the unemployment-to-employment transition rate.
Data source: CPS.

Dependent variable: Job finding rate				
	(1)	(2)	(3)	(4)
log unemployment benefit level	−0.086** (0.038)	−0.113** (0.045)	−0.134* (0.072)	−0.001 (0.034)
Only unemployed workers with UI	✓	✓	✓	
During the Great Recession		✓	✓	
UI benefits not at the maximum amount			✓	
Only unemployed workers without UI				✓
N	1854	912	642	2568
R^2	0.055	0.037	0.032	0.067

• NB: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
• Control variables include age (quadratic), gender, race, education, unemployment duration (quartic), occupation, marital status, recall expectations, previous job's weekly earnings, a linear time trend, a recession dummy, state fixed effects, and state unemployment rates.

gender, race, education, unemployment duration (quartic), occupation, marital status, recall expectations, and previous job's weekly earnings. Additionally, to control for the aggregate and local market conditions, I also include a linear time trend, a recession dummy, state fixed effects, and state unemployment rates. As the actual unemployment benefit levels are not reported in the CPS, I calculate the implied benefit levels based on the reported last job's weekly earnings which can be found in the CPS January Supplements. Furthermore, each state has a freedom to determine their own (1) replacement rate(s), (2) minimum benefit amount, and (3) maximum benefit amount. I also apply these state-level rules in order to compute the implied benefit levels.[11] To focus on the decision whether to remain unemployed or to exit to employment (i.e., job finding), I condition on workers who remain in the labour force in the next period in this exercise.

The regression results from the linear probability model are reported in Table 2. From this table, Column 1 suggests that the job finding rate of the insured unemployed indeed decreases in the unemployment benefit level, and that this negative relationship is more pronounced during the Great Recession by comparing to the result in Column 2. Since there are some insured unemployed workers whose unemployment benefits are truncated according to their respective state's UI rules, Column 3 demonstrates that the job finding rate responds even more strongly to the unemployment benefit level when only those whose benefits are not truncated are considered. Lastly, as a placebo test, I report the result when the observations consist of only unemployed workers who do not receive UI in Column 4. It is found that the "potential" unemployment benefit does not affect the job finding rate of uninsured unemployed workers.

To stay unemployed or to exit the labour force? Accompanying the drop in job findings during the Great Recession are an increase in the U2U rate and a relatively small change in the U2O rate. This is the case regardless of the UI status. Table 1 demonstrates that from 2008 to 2010 the U2U rate increased by 16 pp for workers with UI and by 12 pp for workers without UI. At the same time, Table 1 demonstrates that the fall in the U2O rate was only 2(3) pp for the (un)insured unemployed.[12] The same results apply when I condition on other observable worker characteristics as shown in Table A.2 and A.3 of Appendix A.

Distribution of unemployment duration and worker heterogeneity. The share of long-term unemployed workers who were current UI recipients rose substantially by 36 pp (from 15 percent to 51 percent) between 2008 and 2010 as shown in Table A.4 of Appendix A. In contrast, the share of current UI recipients amongst the newly unemployed increased by only 20 pp (from 21 percent to 41 percent) between 2008 and 2010 as shown in Table A.5 of Appendix A. This suggests that current UI recipients tend to stay longer in unemployment than those without UI. Table A.4 also suggests that, during the Great Recession, the substantial rise in the share of UI recipients is pervasive across all the subgroups considered (which are by age, gender, education, industry, occupation,

[11] The state-level UI data are provided by the Employment and Training Administration (ETA), U.S. Department of Labor. Particularly, the data is available online at https://oui.doleta.gov/. As the UI replacement rate is typically calculated based on the highest quarter(s) of wages during the base period, there is a possibility that using the reported previous job's weekly earning may underestimate the actual UI benefits a worker received if such worker experienced a wage decline prior to job separation.

[12] Given the relatively smaller responses in flows from unemployment to OLF, the model I present in the following section will not feature the labour force participation margin. It should be noted that incorporating the OLF status is crucial for a complete analysis of the effects of UI extensions; however, for the OLF margin to be active and realistic, it requires further heterogeneity amongst workers (which creates a non-trivial computational burden) such as idiosyncratic home production, as in Goensch et al. (2024), who consider the interaction between UI and the OLF margin in general equilibrium. Whilst a linear search cost function can potentially allow workers to choose between searching and not searching (thereby becoming OLF), several issues arise. First, job search intensity (and, therefore, job finding rates) of unemployed workers becomes homogeneous, which shuts down a key driver of unemployment dynamics. It is possible to allow unemployed workers to have different job finding rates, but this would have to be imposed exogenously. Second, realistic transitions to and from OLF (i.e., E2O, U2O, O2E, and O2U) still require additional worker heterogeneity. One could instead construct a more flexible cost function that produces both interior solutions (to allow for heterogeneous search intensity) and occasional corner solutions, but such extensions are beyond the scope of this paper. Empirically, Rothstein (2011) and Farber and Valletta (2015) find that UI extensions contribute to a reduction in labour force exits, whilst Barnichon and Figura (2014) find that the extensions did not affect the labour force participation rate.

reasons for unemployment and recall expectations) amongst the long-term unemployed. There is a multitude of worker heterogeneity that is shown to be important for the dynamics of unemployment and its duration as acknowledged in the introduction. This paper aims to explore the role of UI extensions on these dynamics.

In summary, these empirical findings motivate the model in the next section to feature a degree of worker heterogeneity (including benefit levels) and endogenous job search intensity which together imply heterogeneous job finding probabilities.

3. Model

I present a stochastic random-search-and-matching model à la Pissarides (2000) with endogenous job separations, endogenous job search intensity, and on-the-job search.[13] In addition, I allow for the maximum UI duration to depend on the unemployment rate. Workers differ in terms of UI status, benefit level, permanent individual productivity, and, if employed, time-varying match quality. These differences affect not only how hard workers search for jobs, but also how likely worker–firm matches are formed and separated. Workers with higher outside options, e.g., those with higher (potential) UI benefits, tend to exit unemployment more slowly and their matches are more likely to separate. 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 I present the equilibrium conditions.

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 individual productivity (type H or L). A match consists of one worker and one firm whose output depends on the aggregate productivity (z_t), its match quality (m_t), and type-i worker's individual productivity (η_i). Specifically, $y_{it}(m_t) = z_t \times m_t \times \eta_i \; ; \; i \in \{H, L\}$. The price of output $y_{it}(m_t)$ is normalised to one. The aggregate productivity z_t has an AR(1) representation: $\ln z_t = \rho_z \ln z_{t-1} + \epsilon_t$ where $\epsilon_t \sim N(0, \sigma_z^2)$ is the only exogenous shock in the model. The match quality m_t is drawn at the start of every new worker–firm match from an invariant distribution $F(m)$. A given match keeps its match quality m_t to the next period with probability $1 - \lambda$, otherwise it redraws a new m_{t+1} from $F(m)$ for its production next period. η_i is type-i worker's individual productivity where $\eta_L < \eta_H \equiv 1$, and it is permanent.

In terms of 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). Type-i workers choose job search intensity $s_{i,t}$ at the cost of $v_e(s_{i,t})$ when employed, and at the cost of $v_u(s_{i,t})$ when unemployed regardless of their UI status. The search cost functions $v_e(\cdot)$ and $v_u(\cdot)$ are strictly increasing and convex. In addition to the aggregate conditions, job search intensity of the unemployed varies with UI statuses, benefit levels, and individual productivities, whilst for the employed, it varies with match qualities and individual productivities.[14] For employment status $j \in \{e, u\}$, a worker's period utility flow is $c_{i,t} - v_j(s_{i,t})$, and $c_{i,t}$ is type-i worker's consumption:

$$c_{it} = \begin{cases} w_{it}(m_t, \tilde{m}) & \text{if employed with match quality } m_t\text{, not } UU \text{ last period} \\ w_{it}(m_t) & \text{if employed with match quality } m_t\text{, } UU \text{ last period} \\ h + b_i(\tilde{m}) & \text{if insured unemployed} \\ h & \text{if uninsured unemployed} \end{cases}$$

where $w_{i,t}(m_t, \tilde{m})$ is the wage of type-i worker that depends on m_t, the current match quality, and $\tilde{m}$, the match quality in her most recent employment. $\tilde{m}$ matters for the worker's wage if and only if she was employed or insured unemployed last period. 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 and the wage determination in the next subsections.

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

[13] As demonstrated in Fujita and Ramey (2012), on-the-job search helps a (random) search-and-matching model with endogenous job separations produce a more realistic correlation between unemployment and vacancies which is highly negative in the data. Such a model without on-the-job search tends to produce a highly positive correlation since, following a negative productivity shock, a high enough rise in unemployment (due to endogenous job separations) increases the job filling probability for firms and induces them to post more vacancies. On-the-job search widens the pool of job searchers and lowers the impact of a rise in unemployment on the job filling probability. I also explore the interactions between UI extensions and on-the-job search in the result section.

[14] Unemployment duration could be an important factor since the insured unemployed closer to benefit exhaustion (or with a higher rate of exhaustion) search harder for jobs. I allowed for unemployment duration to be an individual state variable and find that the results remain largely the same. This is due to the risk neutrality assumption. If workers are instead risk averse, their job search response to unemployment duration is expected to be stronger but such analysis is beyond the scope of the paper.

3.1.1. UI duration policy and UI eligibility

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

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

where $\mathbb{1}\{\cdot\}$ is an indicator function, and $\phi_L < \phi_H$, i.e., the UI exhaustion rate is a decreasing function of the unemployment rate u_t.[15] Since the inverse of $\phi(u_t)$ is the expected duration of receiving UI benefits, a fall in the rate implies a UI extension. This is set to mimic the rules for UI extensions in the US where they depend on the state unemployment rate (above which UI extensions are triggered). Specifically, during normal times ($u_t < \bar{u}$), 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 generosity of UI extensions in the US by lowering the value of ϕ_L. Economic agents can predict whether a UI extension will be triggered or terminated next period by keeping track of unemployment and relevant distributions.

UI eligibility. Upon losing a job, employed workers become uninsured at rate ψ. This reflects how some unemployed workers do not take up UI benefits. In reality, this can be due to workers not satisfying the UI eligibility requirements. It can also be due to UI-eligible workers choosing not to apply for and collect UI benefits. In addition, insured unemployed workers lose UI eligibility after an unproductive meeting with a firm at rate ξ to reflect how UI recipients' job search is monitored (albeit imperfectly).[16]

UI payment is financed each period by lump-sum tax (τ_t) levied on matched firms:

$$\tau_t(1-u_t) = \sum_{i\in\{H,L\}} \sum_{\tilde{m}} u^{UI}_{i,t}(\tilde{m}) b_i(\tilde{m}) \tag{1}$$

where $u^{UI}_{i,t}(\tilde{m})$ is the number of type-i insured unemployed workers whose UI benefit is $b_i(\tilde{m})$ in period t.

3.1.2. Search and matching

Workers and unmatched firms meet via a meeting function $M(s_t, v_t)$ where s_t is the aggregate search intensity, and v_t is the number of job vacancies in period t. The meeting function $M(\cdot,\cdot)$ has constant returns to scale. It is strictly increasing and concave in its arguments. Market tightness can be defined as $\theta_t \equiv v_t/s_t$. The conditional job finding probability per unit of search is $\frac{M_t}{s_t} = M(1,\theta_t)$; therefore, the conditional job finding probability of type-i worker with employment status j is $s^j_{i,t} M(1,\theta_t) \equiv p^j_i(\theta_t)$.[17] Analogously, the probability that a firm meets a worker is $\frac{M_t}{v_t} \equiv q(\theta_t)$.

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 intensity. 3. Current matches draw a new m at rate λ. 4. Some workers and unmatched firms meet. 5. Aggregate productivity z_{t+1} next period is realised. 6. Some matches and meetings are dissolved. 7. u^{UI}_t 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.

3.1.4. Workers' value functions

Without loss of generality, the time subscripts are henceforth dropped and a prime ($'$) denotes that the variable is of the next period. I define the set of state variables as $\omega \equiv \{z, u, u_H, u^{UI}_i(\tilde{m}), u^{UU}_i, e_i(m);\ \forall m,\ \forall \tilde{m}, i \in \{H, L\}\}$ where u_H is the number of type-H unemployed workers, $u^{UI}_i(\tilde{m})$ is the number of type-i insured unemployed workers whose match quality in their most recent employment was $\tilde{m}$, u^{UU}_i 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.[18]

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

$$W^j_i(m;\omega) = \max_{s^e_i(m;\omega)} \quad w^j_i(m;\omega) - \nu_e(s^e_i(m;\omega)) + \beta E_{\omega'|\omega}\Big[\ldots$$

[15] This stochastic UI exhaustion is first used in Fredriksson and Holmlund (2001). Rujiwattanapong (2022) allows the UI exhaustion rate to vary with the unemployment rate. Faig et al. (2016) and Mitman and Rabinovich (2019) also treat this rate to be state-dependent.

[16] Auray et al. (2019) document that 23 percent of UI-eligible workers did not collect UI benefits between 1989 and 2012. They study a directed-search model with endogenous UI take-up by allowing for heterogeneous utility costs of collecting UI benefits. They find that UI recipients remain unemployed longer than those not collecting UI benefits. Additionally, they also show the UI take-up rate is cyclical. For simplicity, I assume that ψ and ξ are constant in the model. However, if ψ becomes endogenous and countercyclical, it could amplify the agents' responses when UI is extended as well as delivering a lower insured unemployment rate during expansions. In such a case, parameters governing endogenous job separations, such as those related to the match quality distribution, would also be affected. Similarly, if ξ becomes more relaxed during recessions — whether due to more lenient policies or a limited number of officers monitoring UI claims — it could further amplify agents' responses to UI extensions, analogous to endogenous ψ. That being said, given the simple assumption on the fixed values of ψ and ξ, the model is able to capture the dynamics of the insured unemployment rate relatively well, as shown in the results section, due to the endogenous job separation margin.

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

[18] u_L is excluded from ω since its measure can be deducted from the normalised measure of the labour force.

$$
\begin{aligned}
&\underbrace{(1-\delta)(1-\lambda)}_{\text{Pr(stay matched, keep } m)}\Big[\underbrace{(1-p_i^e(m;\omega)(1-F(m)))}_{\text{Pr(stay with current firm)}} W_i^{e(m)+}(m;\omega') \\
&\quad + \underbrace{p_i^e(m;\omega)(1-F(m))}_{\text{Pr(move to new firm)}} E_{m'|m'>m}[W_i^{e(m)+}(m';\omega')]\Big] \\
&\quad + \underbrace{(1-\delta)\lambda}_{\text{Pr(stay matched, new } m)} E_{m'}\Big[\underbrace{(1-p_i^e(m;\omega)(1-F(m')))}_{\text{Pr(stay with current firm)}} W_i^{e(m)+}(m';\omega') \\
&\quad + \underbrace{p_i^e(m;\omega)(1-F(m'))}_{\text{Pr(move to new firm)}} E_{m''|m''>m'}[W_i^{e(m)+}(m'';\omega')]\Big] \\
&\quad + \underbrace{\delta}_{\text{Pr(match exogenously separated)}} \Big((1-\psi)U_i^{UI}(m,\omega') + \psi U_i^{UU}(\omega')\Big)\Big]
\end{aligned} \tag{2}
$$

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 receive unemployment insurance at rate $1-\psi$.[19] $U_i^{UI}(m)$ 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 the optimal search intensity of employed workers are in Appendix B.

Unemployed workers. The difference between insured and uninsured workers stems from the per-period utility flows during unemployment. Amongst insured unemployed workers, their per-period utility flows vary with $\tilde{m}$, the match quality in their most recent employment, because UI benefits are calculated based on this variable. Therefore, the values of type-i uninsured unemployed workers and insured unemployed workers with benefit $b_i(\tilde{m})$ are respectively

$$
\begin{aligned}
U_i^{UU}(\omega) = \max_{s_i^{UU}(\omega)} \quad & h - v_u(s_i^{UU}(\omega)) + \beta E_{m'\omega'|\omega}\Big[\ldots \\
& p_i^{UU}(\omega)\max\{W_i^{UU}(m';\omega'), U_i^{UU}(\omega')\} + (1-p_i^{UU}(\omega))U_i^{UU}(\omega')\Big]
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
U_i^{UI}(\tilde{m},\omega) = \max_{s_i^{UI}(\tilde{m},\omega)} \quad & b_i(\tilde{m}) + h - v_u(s_i^{UI}(\tilde{m},\omega)) + \beta E_{m'\omega'|\omega}\Big[p_i^{UI}(\tilde{m},\omega)\max\Big\{W_i^{UI(\tilde{m})}(m';\omega'), \ldots \\
& \underbrace{(1-\phi(u))(1-\xi)}_{\text{Pr(keep UI | meeting a firm)}} U_i^{UI}(\tilde{m},\omega') + \underbrace{\big(\phi(u)+(1-\phi(u))\xi\big)}_{\text{Pr(lose UI | meeting a firm)}} U_i^{UU}(\omega')\Big\} \\
& + (1-p_i^{UI}(\tilde{m},\omega))\Big((1-\phi(u))U_i^{UI}(\tilde{m},\omega') + \phi(u)U_i^{UU}(\omega')\Big)\Big]
\end{aligned} \tag{4}
$$

When insured and uninsured unemployed workers meet a firm (with probability $p^{UI}(\cdot)$ and $p^{UU}(\cdot)$ respectively), they can either (1) go into production and work, or (2) remain unemployed in the next period. The expressions for the optimal search intensity of insured and uninsured unemployed workers are in Appendix B.

3.1.5. Firms' value functions

Matched firms. The value of a matched firm with type-i worker whose work history is $j \in \{e(\tilde{m}), UI(\tilde{m}), UU\}$ is

$$
\begin{aligned}
J_i^j(m;\omega) \; = \; & y_i(m;\omega) - w_i^j(m;\omega) - \tau(\omega) + \beta E_{\omega'|\omega}\Big[\ldots \\
& (1-\delta)(1-\lambda)\Big[(1-p_i^e(m;\omega)(1-F(m)))J_i^{e(m)+}(m;\omega')\Big] \\
& + (1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))J_i^{e(m)+}(m';\omega')\Big]\Big]
\end{aligned} \tag{5}
$$

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 the search is random, the distribution of workers' search intensity over employment status, UI status, benefit level, individual productivity, and match quality of on-the-job searchers (as denoted by ζ's in the following equation) enters

[19] 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 intensity 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.

the unmatched firms' problem and, therefore, becomes a state variable. The value of an unmatched firm is

$$
\begin{aligned}
V(\omega) = -\kappa + \beta q(\omega) E_{\omega'|\omega}\Bigg[\sum_{i\in\{H,L\}}\Big(\sum_m \zeta_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[J_i^{e(m)+}(m';\omega')] \\
+ \sum_m \zeta_i^{UI}(m;\omega)E_{m'}[J_i^{UI(m)+}(m';\omega')] + \zeta_i^{UU}(\omega)E_{m'}[J_i^{UU+}(m';\omega')]\Big)\Bigg]
\end{aligned} \tag{6}
$$

where

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

3.2. Wages and surpluses

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

$$
w_i^j(m;\omega) = \text{argmax} \left(WS_i^j(m;\omega)\right)^{\mu}\left(J_i^j(m;\omega)\right)^{(1-\mu)} \tag{7}
$$

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 defined as 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 B.

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 individual productivity, employment status, UI status, benefit level and match quality, 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 as well as the free entry condition, namely, Eqs. (2), (3), (4), (5), and (6).
2. The search decisions satisfy the FOCs for the optimal search intensity, which are Eqs. (B.1), (B.2), and (B.3) in Appendix B.
3. The wage functions satisfy the FOCs for the generalised Nash bargaining rule (Eq. (7)).
4. The government's budget constraint is satisfied each period (Eq. (1)).
5. The distribution of workers evolves according to the transition Eqs. (C.1), (C.3), and (C.4), which are in Appendix C, consistent with the maximising behaviour of agents.

3.4. Solving the model

In order to compute the market tightness in the model, economic agents must keep track of the distribution of workers over the individual 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 (Eq. (6)). To predict the next period's unemployment rate they need to know the inflow into unemployment and the outflow from unemployment which are based on this distribution. I use Krusell and Smith (1998)'s algorithm to predict the laws of motion for both the insured and total unemployment rates as a function of current unemployment (u) and aggregate productivity (z). As the distribution of employed workers by match quality and the distribution of insured unemployed

Table 3
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 and Ramey (2012)
μ	Worker's bargaining power	0.5	den Haan et al. (2000)
ϕ_H	UI exhaustion rate	$52/(26 \times 12)$	26 weeks max UI duration, ETA
ϕ_{L1}	UI exhaustion rate	$52/(39 \times 12)$	39 weeks max UI duration, ETA
ϕ_{L2}	UI exhaustion rate	$52/(46 \times 12)$	46 weeks max UI duration, ETA
ϕ_{L3}	UI exhaustion rate	$52/(52 \times 12)$	52 weeks max UI duration, ETA
ϕ_{L4}	UI exhaustion rate	$52/(65 \times 12)$	65 weeks max UI duration, ETA
ϕ_{L5}	UI exhaustion rate	$52/(72 \times 12)$	72 weeks max UI duration, ETA
ϕ_{L6}	UI exhaustion rate	$52/(79 \times 12)$	79 weeks max UI duration, ETA
ϕ_{L7}	UI exhaustion rate	$52/(99 \times 12)$	99 weeks max UI duration, ETA
$\bar{u}$	UI policy threshold	0.065	ETA
a_u	Search cost function	0.1116	Normalisation
d_e, d_u	Search cost function	1	Christensen et al. (2005) and Yashiv (2000)
h	Leisure flow	0.5835	Gruber (1997)

Table 4
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 xth percentile of the match quality distribution $F(m)$.

Table 5
Calibrated parameters for baseline model.

Parameter	Description	Value
l	Meeting function	0.5087
δ	Exogenous separation rate	0.0230
λ	Pr(redrawing new m)	0.5001
ψ	Pr(losing UI after becoming unemployed)	0.4901
ξ	Pr(losing UI after meeting firm)	0.5002
a_e	Search cost function	0.2011
$\underline{m}$	Lowest match quality	0.3960
β_1	Match quality distribution	2.5495
β_2	Match quality distribution	5.2702
ρ_z	Persistence of TFP	0.9562
σ_z	Standard deviation of TFP shocks	0.0075
η_L	Productivity of type-L	0.9850

workers by benefit level do not vary much over time, I use the stochastic steady state distributions and adjust for the employment rate inferred from the state variables.[20] I report the performance of this approximation in Appendix D.

4. Calibration

Before I calibrate the model to match the US economy, I specify the functional forms for the search cost functions, the distribution of the match quality, and the meeting function between workers and firms. I obtain a subset of the parameters using the simulated method of moments. The remaining parameters are taken from the empirical data and the literature. Tables 3 and 4 summarise the pre-specified parameters, and Table 5 describes the calibrated ones.

Functional forms. The search cost function takes the following power function: $v_j(s) = a_j s^{1+d_j}; j \in \{e, u\}$ where $a_j > 0$ and $d_j > 0$. I distinguish the search cost only between employment (e) and unemployment (u) to control for the relationship between the job-to-job transition rate and the job finding rate.[21] Regarding the match quality distribution, 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 $\beta_1 > 0$ and $\beta_2 > 0$, and $\underline{m} > 0$ is the lowest match quality. The

[20] Stochastic steady state distributions are obtained by simulating the economy over long periods and controlling for the aggregate productivity (z) to be constant at its mean. For the distribution of the insured unemployed, I also separate between high and low unemployment states as UI extensions affect the shape of this distribution.

[21] Workers of type-H and type-L face the same cost of search and so do unemployed workers with and without UI.

Table 6
Possible maximum UI durations (in weeks) during recessions.
Data source: ETA.

Parameter	Duration (weeks)	Time periods (MM/YYYY)
ϕ_{L1}	39	01/1948–12/1971, 01/1975, 09/1982, 11/1991, 07/2008–10/2008.
ϕ_{L2}	46	01/2014–06/2014.
ϕ_{L3}	52	01/1971–12/1974, 11/1977–08/1982, 10/1982–10/1991, 11/1993–02/2002.
ϕ_{L4}	65	02/1975–10/1977, 08/1992–10/1993, 11/2008–10/2009.
ϕ_{L5}	72	12/1991–07/1992, 03/2002–06/2008.
ϕ_{L6}	79	11/2009–12/2009.
ϕ_{L7}	99	01/2010–12/2013.
ϕ_H	26	01/1948–06/2014. Remark: Standard maximum UI duration (ϕ_H) applies when $u_t < 6.5\%$.

meeting function between unmatched firms and workers is similar to that in den Haan et al. (2000) with the introduction of search intensity: $M(s,v) = \frac{sv}{(s^l+v^l)^{1/l}}; l > 0$.

Discretisation. I discretise the aggregate productivity (z) using Rouwenhorst (1995)'s method to approximate an AR(1) process with a finite-state Markov chain. For both z and $F(m)$, I use 51 nodes when solving the model and 5100 nodes by linear interpolation in the simulations.[22] 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 US economy by feeding in (1) productivity shocks that match the deviations of output (GDP per capita) from its HP trend and (2) the observed maximum UI durations during each recession. It is useful to note that both the timing of each UI extension and how long it lasts are not predetermined. They are a result of the model's simulated unemployment series which can be used to measure how well the model mimics the US labour market dynamics. Additionally, from May 2007, the Emergency Unemployment Compensation law has included the "Reachback Provision" providing UI eligibility to unemployed workers who have already exhausted their benefits prior to the extensions of UI. I simulate the model accordingly and study the impact of this programme in the results section as well.

4.1. Pre-specified parameters

The pre-specified parameters are summarised in Tables 3 and 4. The model is monthly, and I assign the discount factor β to be 0.9967, implying an annual interest rate of 4% which is the US average. Following Fujita and Ramey (2012), the vacancy creation cost κ is set to be 0.0392.[23] I assign μ, the worker's bargaining power, to be 0.5 following den Haan et al. (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. To capture the generosity of UI extensions and its changes during recessionary episodes, I sort them into 7 main UI duration groups as observed in the data which are 39, 46, 52, 65, 72, 79, and 99 weeks. The time periods during which each of the extended maximum UI duration group may apply are reported in Table 6. The value ϕ_L changes and implies the maximum UI durations according to these UI duration regimes.[24] It is useful to note that ϕ_L's represent the maximum UI durations applicable only when the unemployment rate is above the threshold $\bar{u}$. For example, in the model simulation, the UI extension in the Great Recession is not triggered until March 2009, i.e., between August 2008 and February 2009, the simulated unemployment rate is below $\bar{u}$ and, therefore, the UI exhaustion rate is ϕ_H despite the value of ϕ_L exogenously changes since July 2008 (based on the 7 main duration groups).[25] To prevent excessive UI extension triggers, I set $\bar{u}$ to be 6.5% which historically has been used as a criterion in most UI extensions, albeit towards the upper end.

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 newly unemployed workers is 10% when receiving UI and 24% when not receiving UI given the replacement rate of 50%.[26] To find the implied h and $b_i(m)$ given a set of parameters, I first guess the mean wages for the (type-i) employed 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 over match qualities to compute the weighted average). $b_i(m)$ is set such that

[22] I define $f(m)$ as $F'(m)/\sum_m F'(m)$ where $F'(m)$ is the probability density function of $F(m)$.

[23] Using survey evidence on vacancy durations and hours spent on vacancy posting, Fujita and Ramey (2012) find the vacancy cost to be 17% of a 40-h-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 quality.

[24] Effectively, the agents have an adaptive expectation regarding how generous the UI extensions are, i.e., they base the maximum extended UI duration on the previously observed UI extension. They, however, have a rational expectation regarding the timing of when UI extensions are triggered on and off.

[25] It is worth noting that during the Great Recession, the extended UI duration in the US was implemented in tiers starting from 13 weeks in June 2008 and reaching a total of 73 weeks towards the end of 2009 (see Nakajima (2012) for a detailed account). I model these changes as exogenous changes in the value of ϕ_L.

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

Table 7
Targeted and non-targeted moments.
Data sources: BLS and CPS.

Targeted moments				Non-targeted moments			
Moment	Data	Model	S.E.	Moment	Data	Model	S.E.
$E(u)$	0.0583	0.0555	(0.0095)	$E(U1)$	0.0233	0.0238	(0.0007)
$E(\rho_{U2E})$	0.4194	0.4450	(0.0198)	$E(U2)$	0.0172	0.0181	(0.0014)
$E(\rho_{E2U})$	0.0248	0.0252	(0.0002)	$E(U4)$	0.0080	0.0079	(0.0017)
$E(\rho_{E2E})$	0.0320	0.0304	(0.0096)	$E(LTU)$	0.0098	0.0066	(0.0058)
$E(u_{dur})$	14.116	11.938	(1.2420)	$std(U1)$	0.0048	0.0014	(0.0005)
$E(u^{UI})$	0.0290	0.0327	(0.0079)	$std(U2)$	0.0046	0.0029	(0.0009)
$std(u)$	0.1454	0.1502	(0.0194)	$std(U4)$	0.0035	0.0032	(0.0012)
$std(\rho_{U2E})$	0.0999	0.1207	(0.0138)	$std(LTU)$	0.0085	0.0081	(0.0057)
$std(\rho_{E2U})$	0.0890	0.0580	(0.0102)	$std(u^{UI})$	0.1780	0.2184	(0.0236)
$std(u_{dur})$	6.9327	5.2730	(0.5806)	$std(v)$	0.1226	0.0456	(0.0029)
$std(LP)$	0.0131	0.0104	(0.0003)	$corr(u, v)$	−0.8786	−0.2701	(0.0241)
$corr(LP, LP_{-1})$	0.7612	0.7568	(0.0181)				

• ρ_{U2E}: job finding rate. ρ_{E2U}: job separation rate. ρ_{E2E}: job-to-job transition rate. u_{dur}: mean unemployment duration (weeks). $LP = y/(1-u)$: labour productivity. $U1$: Unemployed less than 1 month. $U2$: Unemployed with 2–3 month duration. $U4$: Unemployed with 4–6 month duration. LTU: Unemployed more than 6 months.

the ratio of $h + b_i(m)$ to $w_i^0(m)$ is 0.9 for each match quality m. I then solve and simulate the model to check if the guess is close to its simulated counterpart. If it is not, I replace the guessed wages with the simulated ones and repeat until they are close enough.[27]

The slope of the unemployed's search cost function a_u is normalised such that the search intensity of the uninsured unemployed (s^{UU}) is unity when the economy is in the steady state, similar to Nagypál (2006). 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 et al. (2005) and Yashiv (2000) implying a quadratic search cost function. The chosen values of $\{d_e, d_u\}$ deliver the elasticity of unemployment duration with respect to the maximum UI duration of 0.12 which is consistent with the existing empirical findings of around 0.10–0.25.[28] See, for example, Johnston and Mas (2018), Katz and Meyer (1990), Moffitt (1985), and Moffitt and Nicholson (1982).

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 US labour market and the labour productivity process during 1948–2007. Generally, each parameter affects multiple moments in the model but specific associations can be made. The first moments of the unemployment rate and job finding rate can be attributed to the meeting function parameter (l) and the lowest match quality ($\underline{m}$). δ and a_e are responsible for, respectively, the average job separation rate and the average job-to-job transition rate. UI-related parameters (ψ and ξ) govern the average insured unemployment rate and the average unemployment duration. Match-quality-related parameters (β_1, β_2 and λ) control the second moments of the unemployment rate, the job separation rate and the job finding rate. η_L captures the second moment of the average unemployment duration. ρ_z and σ_z pin down, respectively, the autocorrelation and the second moment of labour productivity. The values of calibrated parameters are in Table 5. The targeted and non-targeted moments are reported in Table 7 along with their empirical counterparts.[29]

For 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. For non-targeted moments, the model matches 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.[30]

[27] It is useful to note that there is a benefit cap in the US which varies from state to state. The average maximum UI benefit is around USD 441 per week. Given a 50-percent replacement rate, this implies that anyone whose income is above the 58th percentile will face a cap on their UI benefits in the US. Since the benefit levels are calibrated to match the consumption drops for newly unemployed workers, these benefits levels are in fact always smaller than half of the labour income at the 58th percentile in the baseline model. Specifically, the maximum UI benefit payment in the model is 0.3 whereas the 58th percentile of the labour income is 0.73 implying a benefit cap at 0.36 with a 50-percent replacement rate.

[28] To compute this elasticity, I extend the maximum UI duration by one month and average the responses of unemployment duration keeping the aggregate productivity constant at its mean. It is useful to note that this statistic depends on the rational expectations of the agents with respect to the extended UI duration. The reported elasticity of 0.12 is based on the expectations that UI extensions may imply the maximum UI duration to be either 39, 46, 52, 65, 72, 79, or 99 weeks according to the simulated time period as earlier described in this section. Had the expectations be of a one-month UI extension, this elasticity would be revised downwards.

[29] 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 quarterly series for non-farm output per job from the Bureau of Labor Statistics (BLS) to represent the labour productivity. All the data series are detrended using the HP filter with a smoothing parameter of 1600 for quarterly data and 129 600 for monthly data.

[30] 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 job separations which makes vacancy posting less costly, and this counteracts with the effect of negative aggregate shocks. This is also documented in Fujita and Ramey (2012).

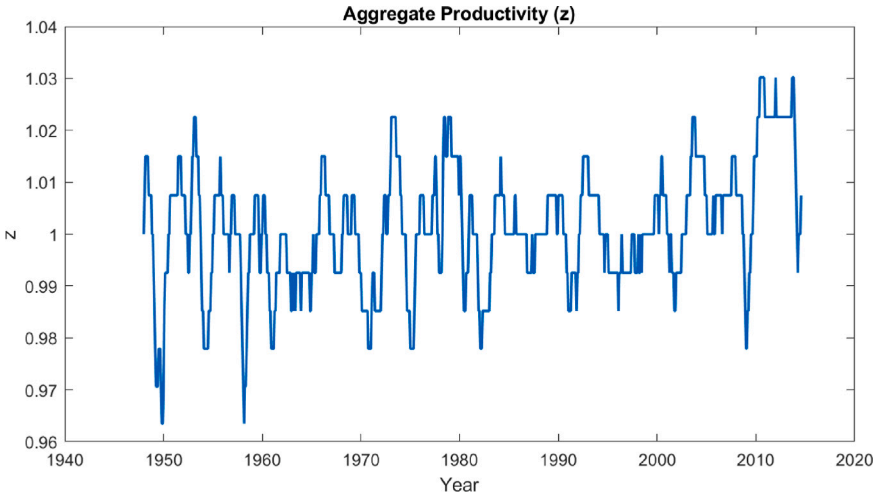

Fig. 3. Aggregate productivity series (z).

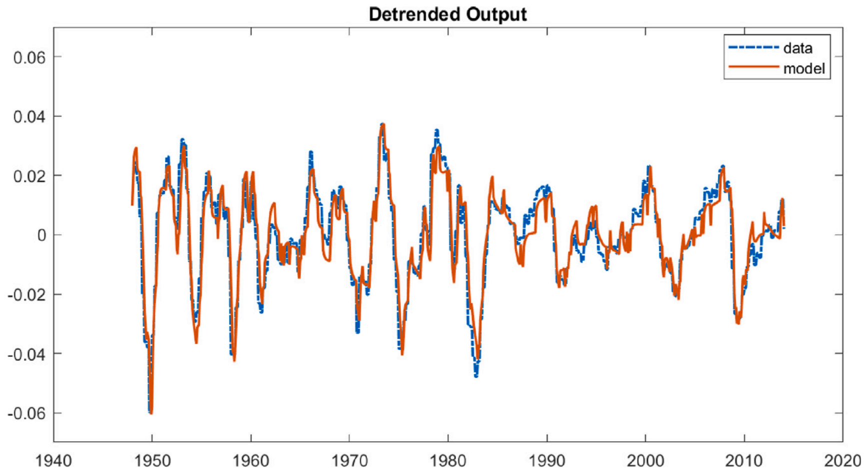

Fig. 4. Detrended output (using HP filter): Model and data.
Data source: BEA.

5. Results

The results in this section are based on the aggregate productivity series chosen to best match the deviations of output from its HP trend over the past six decades as described in the Calibration section regarding the simulation. Fig. 3 depicts the aggregate productivity series whilst Fig. 4 plots the baseline model's detrended output series (using HP filter) against the data. The drop in the aggregate productivity during the Great Recession is neither of larger magnitude nor does it exhibit more persistence than in previous recessions. As a robustness check, Fig. 5 shows that the non-targeted (detrended) labour productivity series, defined as output per worker, is also in line with the data.[31]

[31] Due to the match quality distribution, the labour productivity (or output per worker) in the model can be different from the aggregate productivity, z. For example, during recessions, low quality matches are more often separated which can put an upward pressure on the average match quality.

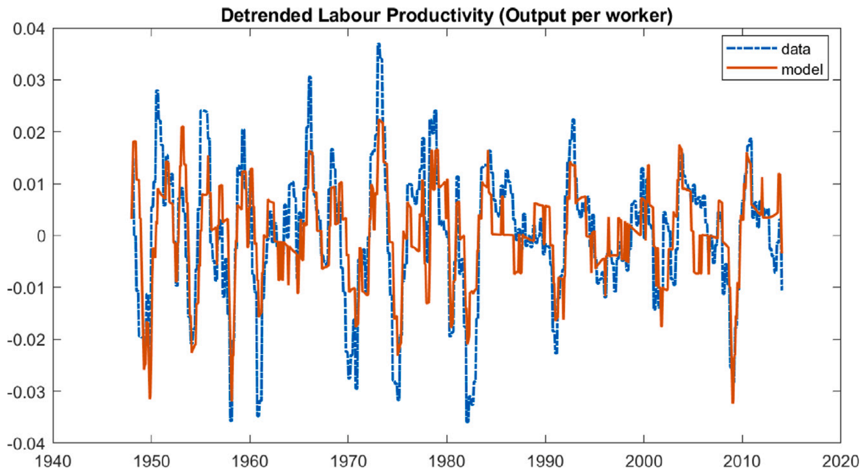

Fig. 5. Detrended labour productivity (output per worker) (using HP filter): Model and data.
Data source: BLS.

5.1. Performance

As UI extensions are triggered when the actual unemployment rate (in lieu of a detrended value) exceeds a given threshold, I focus on how the model fares in terms of its raw data series compared to the empirical counterparts, but the discussion also includes the detrended data series.

Endogenous UI extensions. Fig. 6 shows that the model is successful in generating realistic UI extensions in terms of both when they are triggered and how long each extension lasts. This is due to how well the model replicates the US unemployment series (of which UI extensions are a function) as shown in Figs. 7 (raw data) and 8 (detrended data). The model does exceptionally well in capturing the dynamics of unemployment during the Great Recession.[32] Regarding the overshoot in the early 2000s recession, I address this issue by correcting for the state-level implementations of UI extensions in the last part of this subsection. Despite having a fixed UI take-up rate (ψ), the model effectively captures the dynamics of the insured unemployment rate, especially after detrending, as shown in Figs. E.1 and E.2 in Appendix E.[33]

Long-term unemployment. Fig. 9 shows that the model can account for a large fraction of the observed rise in long-term unemployment in the Great Recession. However, the model produces little persistence once UI extensions are not in place. The main reason for this is due to the sudden change in the optimal job search behaviour of insured unemployed workers when a UI extension is terminated, a mechanism that I will discuss in the next subsection. This result suggests that the model is useful for explaining the incidence of (long-term) unemployment but further unobserved heterogeneity may be needed to explain the persistence.

Distribution of unemployment duration. Fig. 10 shows that the model produces a substantial rise in the average unemployment duration in the Great Recession, but, similar to long-term unemployment, it generates little persistence relative to the data. It does very well in producing a realistic shift in the distribution of unemployment duration towards longer duration bins. In Fig. 11, I

[32] As discussed in the second paragraph of Section 4.1, the relatively high unemployment threshold $\bar{u}$ results in the model's UI extensions being triggered slightly later than observed in the data. As a result, the model's unemployment rate also responds with a slight delay during the Great Recession. That being said, in both the model and the data, UI extensions reached their peak of 99 weeks simultaneously in January 2010. On a related note, under the assumption that both discretionary and automatic UI extensions are treated as endogenous (i.e., triggered by high unemployment), agents' responses to UI extensions could become too sensitive when unemployment approaches the UI threshold. However, in this model, rather the opposite occurs since the relatively high UI threshold ($\bar{u}$) leads a slightly delayed response in unemployment, as previously discussed. Additionally, the adaptive expectation assumption regarding the generosity of UI extensions, as discussed in footnote 24, means that agents update their expectations after observing the combined discretionary and automatic UI extensions in the first period (despite not yet triggered in the model). Therefore, in the model, only agents' responses in the periods leading up to the start of UI extensions may be too sensitive. Given the slight delay in the model's UI extensions, treating discretionary UI extensions as endogenous may have a rather limited impact on the main results whilst it greatly simplifies the computation.

[33] This is primarily driven by the endogenous job separation margin, which responds to aggregate shocks (productivity z and UI extensions). The model could better capture the rise in uninsured unemployment, particularly during the mid-1980s recession. However, after removing the low-frequency trend (which the model does not account for), it replicates the dynamics of the uninsured unemployment rate relatively well as shown in Figs. E.3 and E.4 in Appendix E. There are a few factors that could improve the model's uninsured unemployment response. First, endogenising the UI take-up rate (see Auray and Eyquem (2024)) could amplify its response, especially during expansions. Second, introducing further heterogeneity amongst uninsured unemployed workers could lead to more heterogeneous job finding rates and a stronger response of uninsured unemployment. Lastly, worker flows to and from the out-of-labour-force (OLF) may also be crucial in explaining the dynamics of uninsured unemployment, since OLF-to-unemployment transitions are potentially associated with a higher likelihood of ineligibility for UI. That is, workers who (re-)enter the labour force may not meet the recent employment conditions required for UI eligibility. It is also useful to note that the peaks of uninsured unemployment tend to lag those of unemployment.

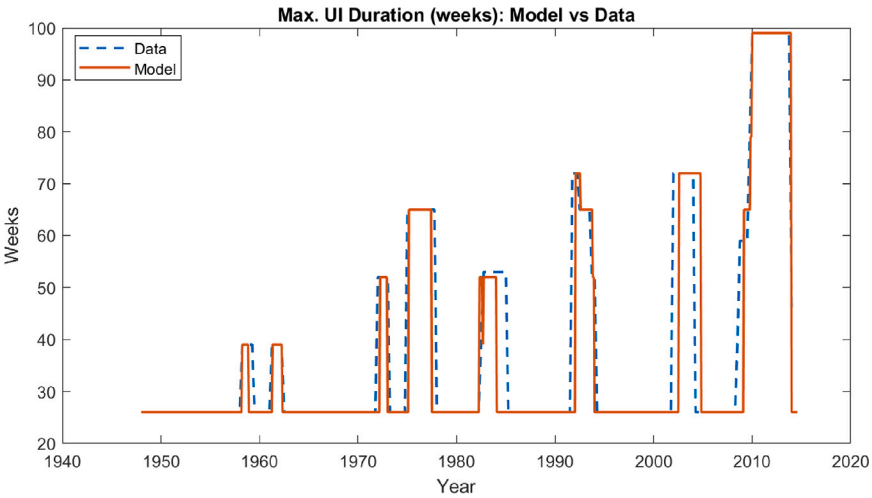

Fig. 6. UI extensions: Model and data.
Data source: ETA.

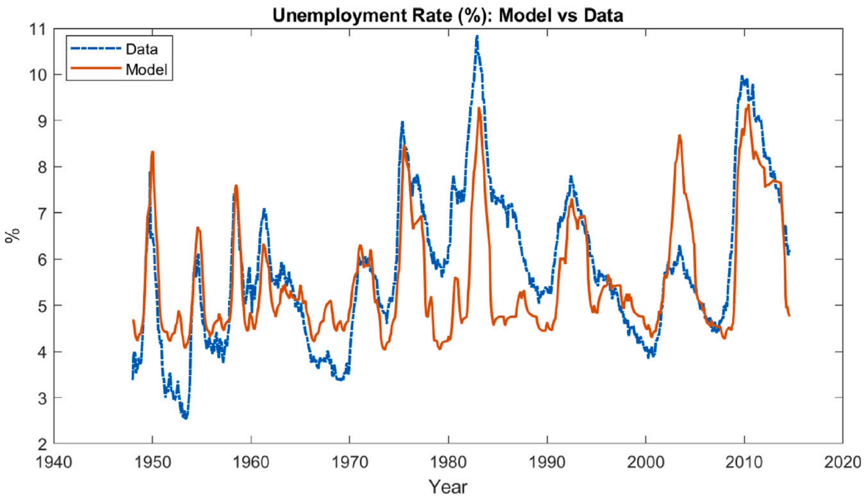

Fig. 7. Unemployment rate (%): Model and data.
Data source: CPS.

plot the distributions in December 2007 and June 2010, where UI was only extended in the latter case.[34] With respect to the entire 1948–2014 period, I show in Fig. 12 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 suggest that the model is suitable for studying the dynamics of the entire distribution of unemployment duration and not just the long-term unemployment dynamics.

Worker heterogeneity in terms of the UI status and, particularly, benefit level tremendously helps the model explain the dynamics of the unemployment duration distribution via the heterogeneous job finding rates. I show in the next subsection that by shutting down the heterogeneity in benefit level, the model can generate less than 20 percent of the observed rise in the average unemployment duration.

Job finding rates. In the left panel of Fig. 13, I compare the model's job finding rate with the empirical series. Despite a clear negative trend that the model does not feature, it produces a fall in the job finding rate during the Great Recession similar in magnitude to that in the data. When I condition on the UI status of workers as displayed in the right panel of same figure, we can see that the job finding rate of the insured unemployed is always lower and falls more dramatically than that of the uninsured during the Great Recession. Both features are consistent with findings from the empirical evidence section.

[34] 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.

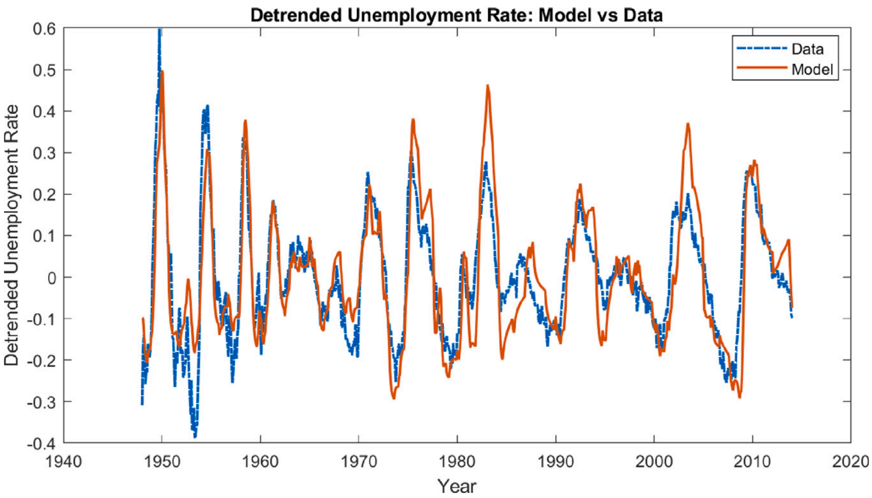

Fig. 8. Detrended unemployment rate (using HP filter): Model and data.
Data source: CPS.

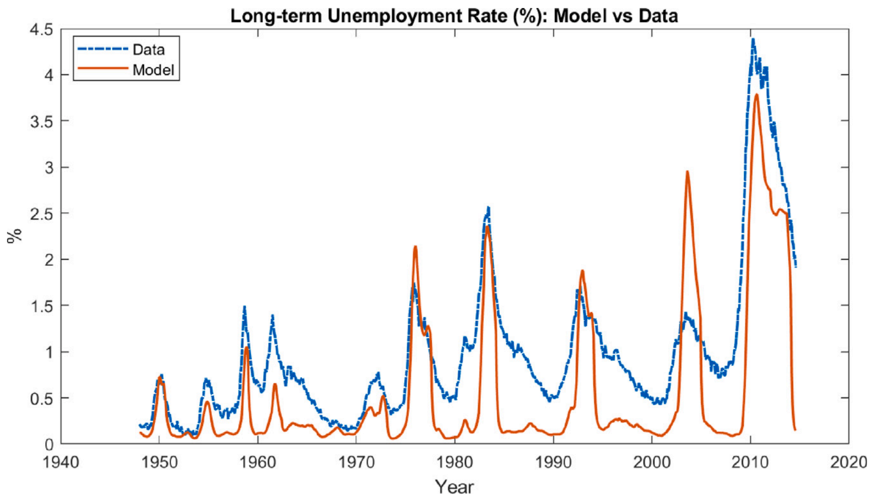

Fig. 9. Long-term unemployment rate (%): Model and data.
Data source: CPS.

State-level implementation of UI extensions. In the US, implementations of UI extensions are at the state level. Therefore, it is possible that the maximum potential UI duration announced at the federal level does not coincide with the average maximum potential UI duration implemented across states, especially when only few states implement UI extensions. This is exactly the case in the early 2000 recession where only 5 states implemented UI extensions making the average maximum potential UI duration to be 30 weeks shorter than the federally announced maximum duration. This stark difference affects the model's results significantly. Fig. 14 shows that, for the 2000 recession, total unemployment no longer overshoots (if anything, slightly undershoots) when the average UI duration is used in the simulation. As a result, UI extension is not triggered, and thus long-term unemployment is only mildly affected.

That said, the results for the Great Recession are robust to using the cross-state average of maximum UI duration since 49 states actually implemented the extensions, and therefore the federally announced maximum UI duration is just 5 weeks longer than the average across states. However, as the focus of the paper is on the Great Recession, all the results during this episode are computed based on the actual implementation of UI extensions across states.

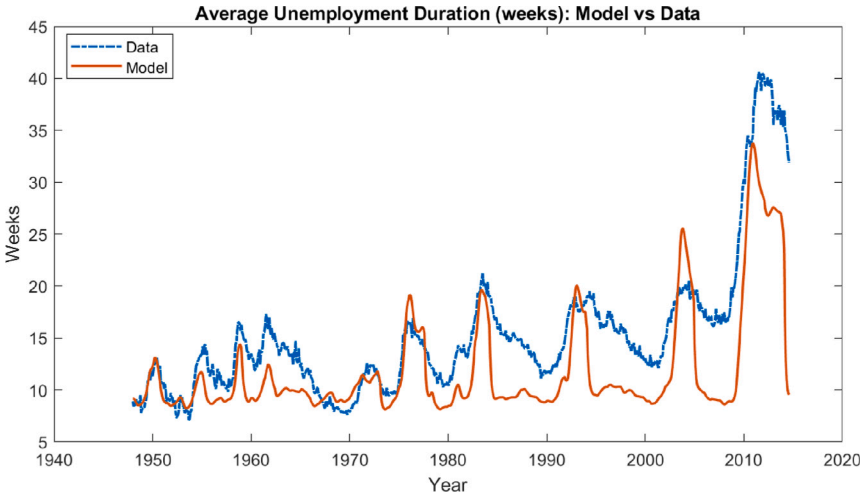

Fig. 10. Average unemployment duration: Model and data.
Data source: CPS.

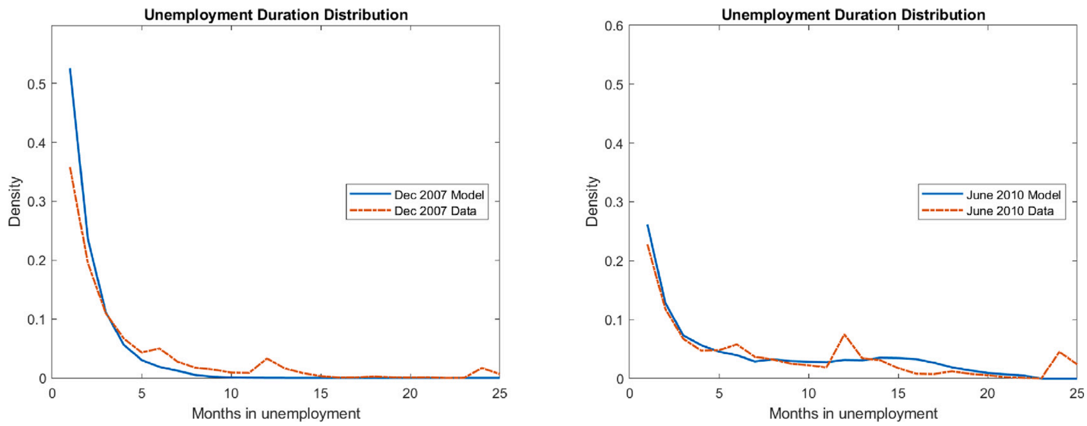

Fig. 11. Distribution of unemployment durations during the Great Recession.
Data source: CPS.

To improve the fit, and further address the overshooting and the low persistence of long-term unemployment, it is important to note that, apart from the increasing UI extension generosity, the model does not account for other low-frequency changes in the US economy. Ahn (2023) shows that the share of long-term unemployment prone workers (which is unobserved in the data) and their unemployment continuation probability are (1) rising over time, and (2) crucial for understanding the dynamics of long-term unemployment. This is consistent with Figs. 12 and 13, respectively, that the share of long-term unemployment increases over time whilst the job finding rate decreases over time. Although I can relate the unobserved worker heterogeneity in Ahn (2023) to UI statuses in this model (as demonstrated in the later subsection), further heterogeneity is still required to explain these empirical low-frequency changes.[35]

[35] One potential improvement is to introduce (1) endogenous UI take-up (see Auray et al. (2019)), and (2) duration dependence in job finding rates. The former ensures that the insured unemployed are more likely to remain unemployed than the uninsured unemployed, and that the share of insured unemployment responds to the increasing UI extension generosity. The latter can reduce the overshooting of (long-term) unemployment by discouraging an average worker from collecting UI, and increase its persistence by lowering the job finding rates of those who collect UI even after they have exhausted the benefits. Various mechanisms for duration dependence have been explored, including unobserved heterogeneity in Doppelt (2016), human capital depreciation and skill loss in Ortego-Marti (2016, 2017) and Flemming (2020), and statistical discrimination in Jarosch and Pilossoph (2019), whilst Kospentaris (2021) examines both unobserved worker heterogeneity and skill loss.

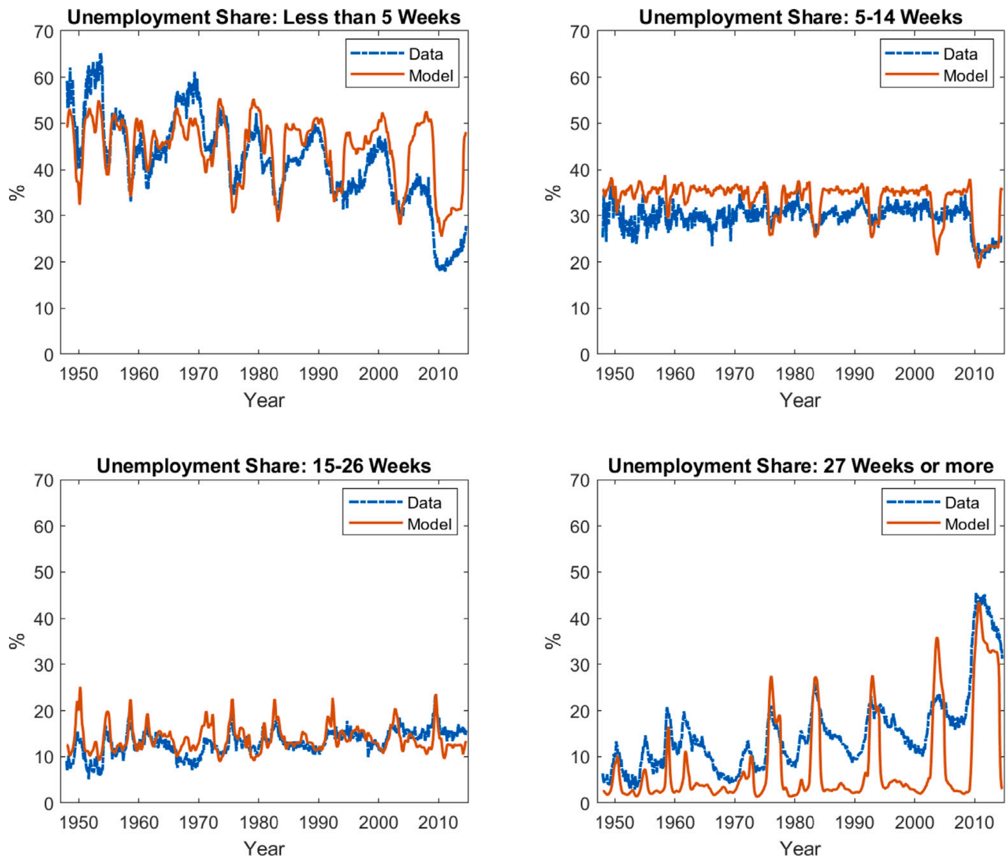

Fig. 12. Unemployment shares (%) by durations.
Data source: CPS.

Fig. 13. Job finding rate (%): Model and data (left panel) and the model's job finding rate by UI status (right panel).
Data source: CPS.

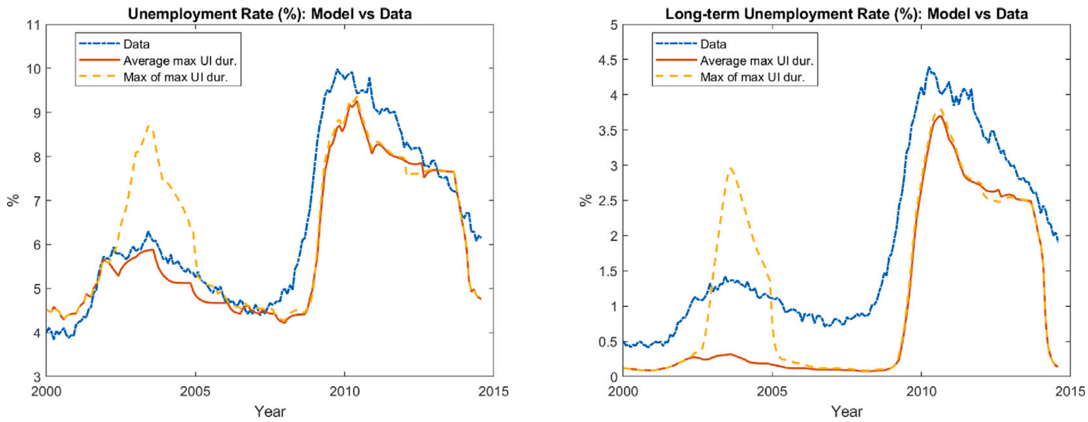

Fig. 14. Unemployment (left) and long-term unemployment (right) when using the average maximum potential UI duration across states ("Average max UI dur".) and the maximum UI duration ("Max of max UI dur".).
Data source: CPS.

5.2. Mechanisms

Job search behaviour. The optimal job search behaviour of workers responds to UI extensions in the following ways: (1) only the search intensity of insured unemployed workers varies with the maximum UI duration, and (2) the higher the benefit level the lower the search intensity, and such behaviour is more pronounced when the extended UI duration is longer.[36]

Fig. 15's top left panel shows that the conditional job finding rate of the insured unemployed workers drops when UI is extended (implied by $u \geq \bar{u} = 6.5\%$) whilst the rates for the employed and uninsured unemployed are largely constant. Fig. 15's top right panel shows that, amongst the insured unemployed, job search intensity decreases rather exponentially in the amount of benefit. This reverberates the importance of allowing unemployed workers to differ not only by the UI status but also by the benefit level since the resulting heterogeneous job finding rates substantially help the model explain the dynamics of the unemployment duration distribution.

With regards to the sensitivity of the job finding rate to unemployment benefit levels, I revisit the exercise conducted in the empirical evidence section. Using a linear probability model, I regress a worker's job finding rate on her log unemployment benefit level whilst controlling for individual and aggregate productivities, a linear time trend, and unemployment rates during the same period. The model's results are in line with the empirical findings, as shown in Table 8, even though the match quality distribution parameters are not targeted to match these findings in the calibration exercise. Particularly, Columns 1 and 3 in Table 8 demonstrate that the model-generated negative response of the job finding rate to benefit levels matches the CPS data very well. Furthermore, this negative relationship is more prominent during the Great Recession in both the model and the data with a similar magnitude (Columns 2 and 4 in Table 8).

As for the individual productivity, the high type have slightly higher search intensity as their value during employment is higher than the low type. Nonetheless, the job finding rates of these two types during 1948–2014 are quite similar. On the contrary, the differences between the job finding rates of the insured and uninsured unemployed are noticeably more pronounced (with that of the insured being lower and more volatile). This suggests that once we condition on the UI status, the workers' individual productivities contribute little to the rise of long-term unemployment and unemployment duration.

Job findings 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 along with job separation decisions are also affected by the endogenous UI extensions as I discuss next.

Match formation and job separation. We know that the worker's surplus from being employed and the value of a producing firm ($WS_i^j(m;\omega)$ 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). Therefore, both workers and firms always agree when a match should be formed (when $S_i^j(m;\omega) > 0$) and when it should be separated (when $S_i^j(m;\omega) \leq 0$). A match surplus when a worker is currently employed, $S_i^{e(\tilde{m})}(m;\omega)$, determines endogenous job separations. A match surplus when a worker is currently unemployed, either $S_i^{UI(\tilde{m})}(m;\omega)$ or $S_i^{UU}(m;\omega)$, determines how many matches will be formed, given that unemployed workers and firms have met.

[36] It is useful to note that, by construction, job search intensity in this model is procyclical (as they increase in the aggregate productivity z). However, Rujiwattanapong (2022) shows that the response of search intensity to changes in z is of a much smaller magnitude than their response to changes in the UI status and the maximum UI duration, and that imposing that search intensity does not respond to z does not substantially change the results.

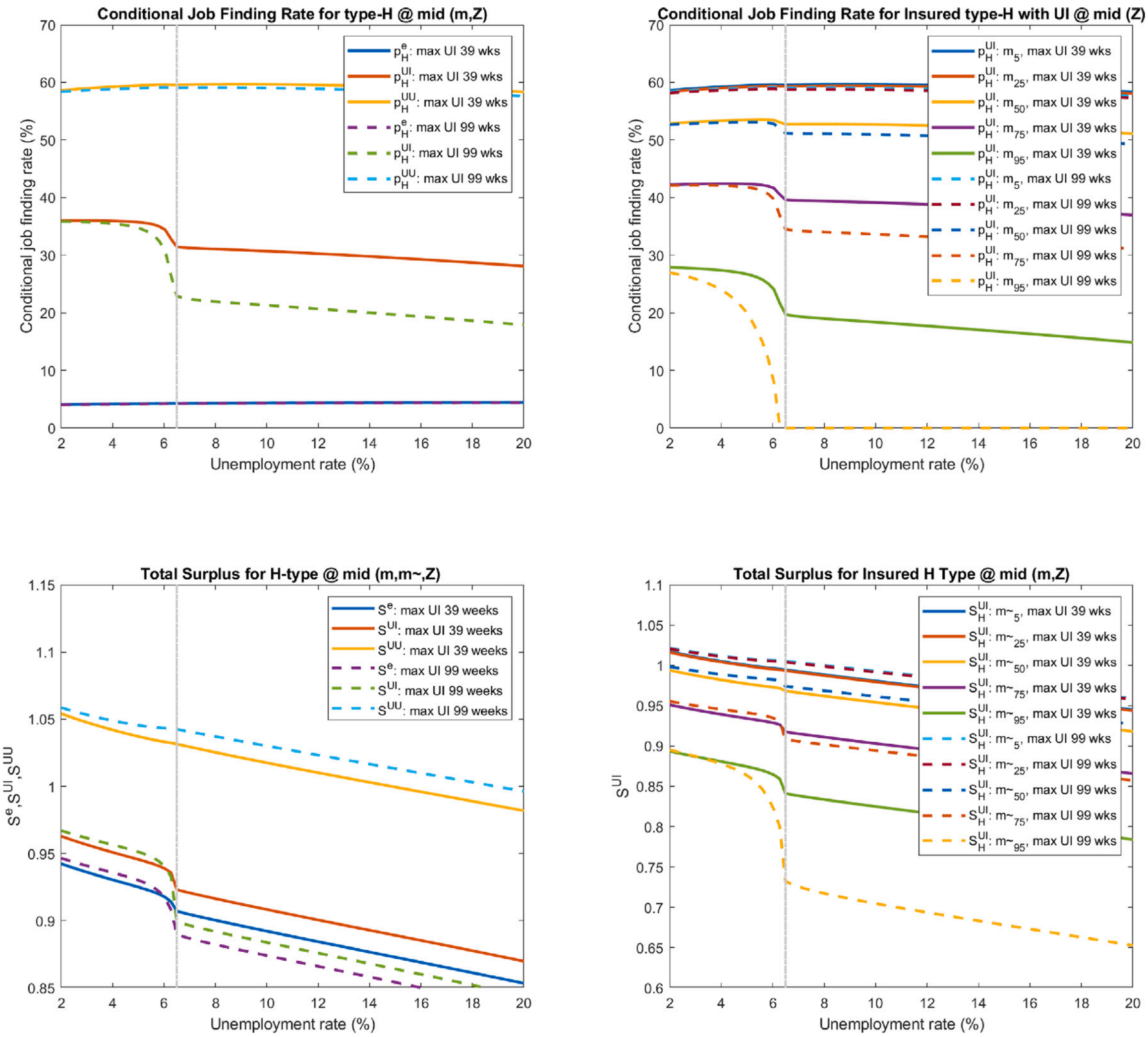

Fig. 15. Conditional job finding rate (top panels) and total match surplus (bottom panels) by UI status $\{e, UI, UU\}$ (left panels) and benefit levels ($\tilde{m}$) (right panels): For solid (dashed) lines, maximum UI duration is 39 (90) weeks. UI is extended when $u \geq 6.5\%$. m_x denotes the xth percentile of the match quality distribution $F(m)$.

Table 8
Linear probability model for the unemployment-to-employment transition rate: Model vs. Data.
Data source: CPS.

Dependent variable: Job finding rate				
	CPS Data		Model	
	(1)	(2)	(3)	(4)
log unemployment benefit level	−0.086** (0.038)	−0.134* (0.072)	−0.085*** (0.009)	−0.1477*** (0.020)
Only unemployed workers with UI	✓	✓	✓	✓
During the Great Recession		✓		✓
UI benefits not at the maximum amount		✓		✓
N	1854	642	1,000,000	346,278
R^2	0.055	0.032	0.856	0.523

• NB: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables for the CPS data include age (quadratic), gender, race, education, unemployment duration (quartic), occupation, marital status, recall expectations, previous job's weekly earnings, a linear time trend, a recession dummy, state fixed effects, and state unemployment rates. Control variables for the model's data include individual and aggregate productivities, a linear time trend, and the unemployment rate.

Fig. 15's bottom left panel 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 they decrease at a faster rate when UI is extended ($u \geq \bar{u}$).[37] The longer is the extended UI duration, the more drastic is the drop in the match surplus. Furthermore, $S_i^{UI(\tilde{m})}(m;\omega)$ decreases in $\tilde{m}$ (Fig. 15's bottom right panel). A higher $\tilde{m}$ implies a higher outside option of the insured unemployed, $h + b_i(\tilde{m})$, meaning that a match is less likely to be formed.[38] 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 an employed worker if she quits and is eligible for UI.

Fundamental surplus. Related to match surplus, Ljungqvist and Sargent (2017) introduce the concept of fundamental surplus, a single measure that captures fluctuations in unemployment over the business cycle in a standard Diamond–Mortensen–Pissarides (DMP) model. Given the additional features incorporated into the baseline model, a direct comparison with a standard DMP model might not be feasible. In particular, allowing unemployed workers to have different UI statuses introduces heterogeneity in the fundamental surplus, implying that the worker distribution needs to be considered.

However, to focus solely on the impact of a countercyclical UI generosity on unemployment volatility within the fundamental surplus framework, one can consider a standard DMP model in which unemployed workers are homogeneous and always insured. In particular, they receive higher UI benefits when unemployment is high. That is, the per-period utility flow for unemployed workers is given by $\big(1-\phi(u)\big)(b+h)+\phi(u)h$, where $\phi(u) \in (0,1)$ is smaller when $u \geq \bar{u}$ (similarly to UI extensions being triggered) and larger otherwise.[39] The fundamental surplus fraction then takes the form: $\frac{z}{z-\big(1-\phi(u)\big)(b+h)-\phi(u)h}$. It is worth noting that this fraction is not constant and increases when unemployment is high. That is, unemployment volatility is amplified when unemployment itself reaches a certain threshold leading to asymmetric responses of unemployment to positive and negative productivity shocks. This is consistent with Wang (2023) who further demonstrates that it is rather a high elasticity of the fundamental surplus to productivity shocks that generates large unemployment responses.

What drives (long-term) unemployment? On the sources of (long-term) unemployment, I focus on (1) how different UI channels (job search behaviour, match formations and job separations) contribute to the dynamics of unemployment and its duration during the Great Recession, and (2) how heterogeneities in UI benefits and individual productivities contribute to these dynamics.

To study the contribution of each UI channel, I shut one channel down at a time by assuming a given channel does not respond to UI extensions.[40] I plot the responses of total unemployment, long-term unemployment, and the average unemployment duration in the left panels of Fig. 16. I find that unemployment and its duration structure are largely unaffected by the responses of match formations. The job search channel is most important for the dynamics of long-term unemployment and the average unemployment duration. Despite a smaller impact on the duration structure, the job separation channel is as important as the job search channel in explaining total unemployment.[41] The importance of job separations in explaining unemployment dynamics has also been emphasised in Fujita and Ramey (2009), and Ahn and Hamilton (2020).

In a separate exercise, I study the role of worker heterogeneity in understanding the dynamics of unemployment and its duration structure. In the baseline model, worker heterogeneity is present in terms of UI status, UI benefit level and permanent individual productivity. These different aspects of worker heterogeneity lead to heterogeneous job finding rates which can be particularly important for the unemployment duration structure. The right panels of Fig. 16 show how total unemployment, long-term unemployment, and the average unemployment duration would be during the Great Recession when (1) all insured unemployed workers receive the same amount of UI benefit (set to the mean benefit level), and (2) all workers possess the same individual productivity (set to the mean productivity value).

In an alternative model with a homogeneous benefit level, total unemployment still responds strongly during the Great Recession (despite little persistence), but this model can generate only less than 20 percent of the responses of both long-term unemployment and the average unemployment duration during the same period. This finding re-emphasises the role of the heterogeneity in the job finding rates (via heterogeneous benefit levels) in understanding the dynamics of the unemployment duration structure. From the right panels of Fig. 16, we can also see that the heterogeneity in the individual productivity has a small but significant role in understanding the dynamics of unemployment and its duration.

---

[37] 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.

[38] m instead increases $S_i^{UI(\tilde{m})}(m;\omega)$ because a higher match quality in the production raises the firm's profit and the worker's wage and potential UI benefit after being employed with m. In the simulation, the success rate of worker–firm meetings is, despite procyclical, always very close to one. The reasons are (1) for insured workers, those likely to have an unproductive meeting have 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.

[39] This is similar to the current-period flow in the expression for the total match surplus between an insured unemployed worker and a firm, $S_i^{UI(\tilde{m})}(m;\omega)$, in Appendix B.

[40] For the following counterfactual exercises, I first maintain the path of the aggregate shocks (z) as in the baseline model (i.e., Fig. 3). I then shut down each channel by assuming that such channel does not respond to the UI extensions during the Great Recession. This is done by fixing the unemployment rate used in the respective policy function to be at the pre-Great Recession value, which is less than $\bar{u}$, corresponding to the maximum UI duration of 26 week throughout the recessionary episode. Job search channel corresponds to the policy function for job search intensity of unemployed workers ($s_i^{UI}(m,\omega)$, and $s_i^{UU}(\omega)$). Match formation channel corresponds to the total match surplus for unemployed workers ($W_i^{UI(\tilde{m})}(m;\omega)$, and $W_i^{UU}(m;\omega)$). Job destruction channel corresponds to the total match surplus for employed workers ($W_i^{e(\tilde{m})}(m;\omega)$).

[41] I also study the contribution of vacancy creation on long-term unemployment. However, its effect is small because the volatility of vacancies in the model is rather low relative to the data. Footnote 30 discusses why this is the case. Nonetheless, Marinescu (2017) uses data from a large online job board in the US and finds that UI extensions during the Great Recession did not affect the number of job openings.

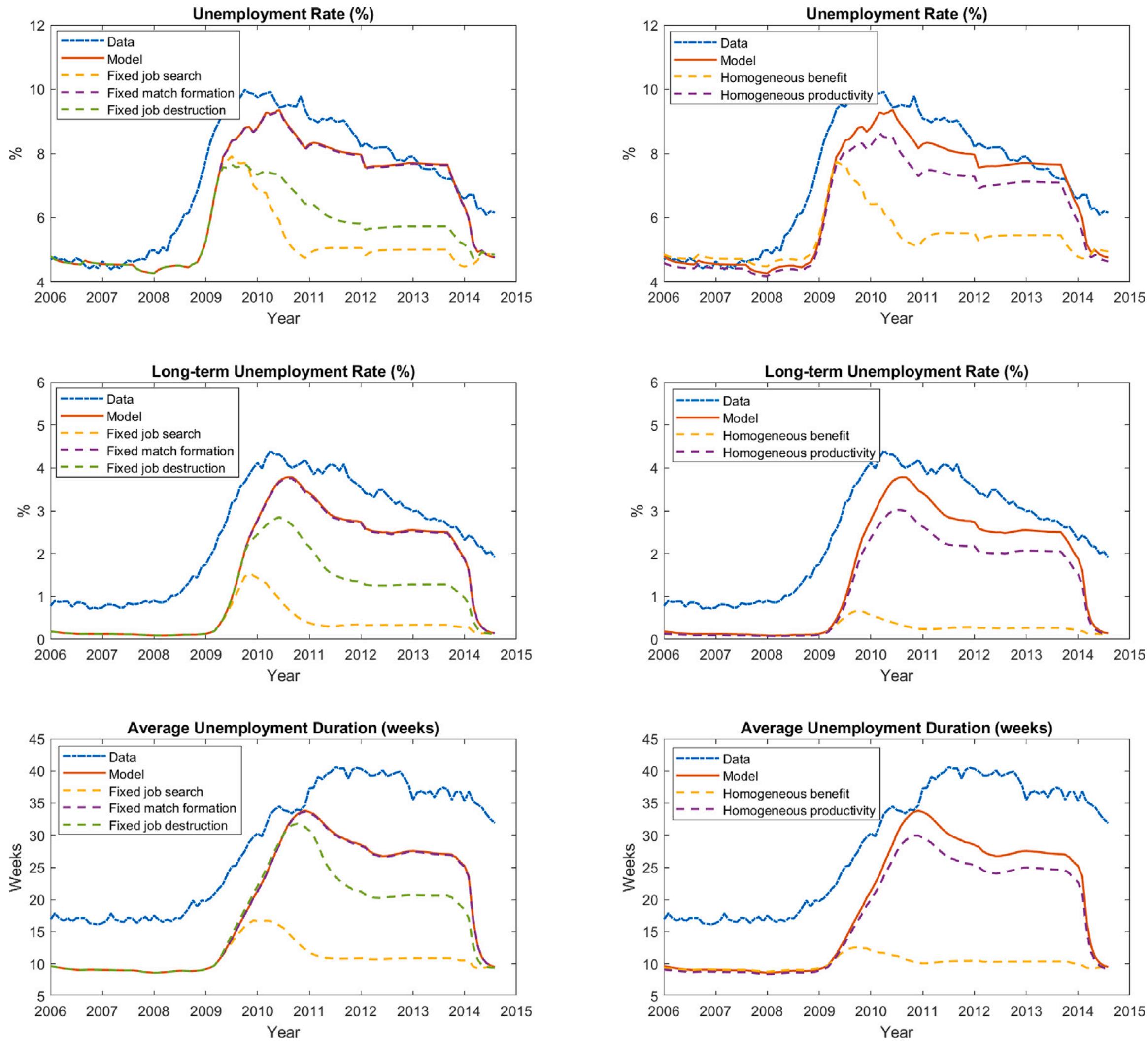

Fig. 16. Responses of total unemployment, long-term unemployment, and average unemployment duration. Left panels: Decomposition of the effects of UI extensions (where each channel does not respond to UI extensions). Right panels: Counterfactual scenarios where either UI benefit or individual productivity is homogeneous across workers.
Data source: CPS.

5.3. Policy experiment

In this counterfactual exercise, I first eliminate the UI extensions during the Great Recession by increasing the UI exhaustion rate, $\phi(u)$, to be ϕ_L — implying a shortening of the maximum UI duration from 99 weeks to 26 weeks. Subsequently, I quantify the effects on unemployment and its duration structure given the same path of aggregate productivity shocks (z) as in the baseline model (Fig. 3). I compute both the microeconomic and general equilibrium effects of UI. For the microeconomic effect of UI, I further separate into (1) the effect that comes purely from a higher UI exhaustion rate (effectively, a shorter UI duration), and (2) the effect of a higher exhaustion rate together with the response of job search behaviour to the shorter UI duration (of 26 weeks). I find that the microeconomic effect of UI is comparable to findings from the existing literature. The general equilibrium effect of UI considers also the responses of job separations and match formations to the shorter UI duration.[42] Table 9 summarises the results from this experiment.

Long-term unemployment. The removal of UI extension has a significant impact on long-term unemployment even when workers and firms do not react to this change. This is not surprising because, given the standard UI duration (of 26 weeks), all long-term

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

Table 9
Effects of eliminating UI extensions during recessions.
Data source: CPS.

	Data	Baseline	Change from baseline		
			Micro effect		Total effect
			$\Delta\phi$	$\Delta(\phi, s)$	$\Delta(\phi, s, S)$
The Great Recession (from 99 weeks to 26 weeks of UI)					
$\max(u)$ (%)	10.0%	9.3%	−0.8 pp	−1.4 pp	−1.8 pp
$\max(u_{dur})$ (weeks)	40.6	33.6	−18.3	−19.0	−19.3
$\max(LTU)$ (%)	4.4%	3.8%	−2.1 pp	−2.5 pp	−2.5 pp
The Early 1990s Recession (from 72 weeks to 26 weeks of UI)					
$\max(u)$ (%)	7.8%	7.3%	−0.3 pp	−0.8 pp	−1.1 pp
$\max(u_{dur})$ (weeks)	20	20	−7.6	−8.6	−8.7
$\max(LTU)$ (%)	1.7%	1.8%	−1.2 pp	−1.4 pp	−1.4 pp

• $\Delta\phi$: UI exhaustion rate changes. $\Delta(\phi, s)$: UI exhaustion rate and job search behaviour change. $\Delta(\phi, s, S)$: UI exhaustion rate, job search behaviour, job separations, and match formations change. LTU: Unemployed more than 6 months. u_{dur}: mean unemployment duration. These statistics are computed between October 2009 (the peak of the US unemployment rate) and June 2014 for the Great Recession and between July 1990 and June 1996 for the Early 1990s Recession.

unemployed workers are uninsured by definition, and uninsured unemployed workers have a much higher job finding rate than do insured unemployed workers. As a result, by removing all UI extensions during the Great Recession, the peak of long-term unemployment falls noticeably from 3.8 percent in the baseline model to 1.7 percent when workers and firms do not react to the shorter maximum UI duration (as shown in Table 9).[43]

Unemployment. Total unemployment is less affected by the removal of UI extensions than long-term unemployment. The impact of increasing the UI exhaustion rate is a fall of 0.8 pp in the unemployment rate (measured at its peak) as shown in Table 9. When the job search behaviour responds to the extension removal, the peak falls by 1.4 pp. In the general equilibrium context, where the job separation decisions also respond to the extension removal, that the peak of the unemployment rate falls by 1.8 pp in total.

The microeconomic effect of UI extensions concerns only a subgroup of unemployed workers (namely, those with UI). Whereas for the general equilibrium effect, the job separation margin applies to all employed workers and determines the inflow of (insured) unemployed workers. Therefore, total unemployment is more affected by the general equilibrium effect compared to long-term unemployment since the latter consists more of unemployed workers with UI during the Great Recession.

This result is consistent with the existing literature on the effects of UI extensions on unemployment in the Great Recession. Most studies focus on the micro effect where the worker–firm relationship dynamics are not taken into account and find that the unemployment rate would have been 0.1–1.8 pp lower had there been no UI extensions (see footnote 5 for a list of relevant papers). This is in line with the micro effect of UI extensions previously discussed.[44] The larger general equilibrium effect of UI extensions in this model is derived from the responses of job separations.[45] Fig. 17 shows that indeed the empirical job separation rate was particularly high during the Great Recession compared to other recessions.[46] Lastly, the unemployment rate is much less persistent when there is no UI extension which is consistent with the findings in Mitman and Rabinovich (2019).

Non-linearity of UI effects. In Table 9, I also report the effects of removing UI extensions during the early 1990s recession (equivalent to cutting 46 weeks of UI duration). There is a non-linearity of the UI effects on all variables considered. For example, a one-week reduction of UI duration reduces an average unemployment duration by 0.19 weeks during the 1990s recession and by 0.27 weeks during the Great Recession. However, the elasticity of unemployment duration to an increase in the maximum UI duration of one month is 0.12. This reported elasticity is smaller because it is computed by averaging the responses of unemployment duration conditional on the aggregate productivity being fixed at its mean whilst, for the 1990s recession and the Great Recession, the aggregate productivity path is chosen to match the deviations of output from its trend in the US (Fig. 3). Furthermore, the

[43] It is useful to note that the large microeconomic effect of UI on long-term unemployment relies on the higher job finding rate of uninsured unemployed workers when compared to the insured. By incorporating genuine duration dependence in the job finding rate, the UI effect could become smaller since unemployed workers who recently exhausted UI cannot increase their job finding rate as much as in the baseline model. Therefore, the insured unemployment state is less desirable and there will be fewer insured unemployed workers during UI extensions.

[44] It is undeniable that the risk preference assumption is important for this estimate. If, instead of risk-neutral, workers are risk-averse and can accumulate wealth to buffer against uninsurable shocks, they may place a smaller weight on unemployment insurance which can lead a smaller response to changes in the UI extension generosity (see, for example, Birinci and See (2023)). Therefore, the reported estimates can be regarded as the upper bound of the range. On top of adding another individual state variable, introducing risk aversion into the model also breaks down the transferable utility assumption which makes the model more difficult to solve. Birinci and See (2023) assume block recursivity to solve such a model where there is only one aggregate state variable; however, an unemployment-dependent UI extension policy (as in this paper) breaks down such block recursivity since the distribution of workers becomes another aggregate state variable.

[45] Fredriksson and Söderström (2020) use the Swedish data between 1992–2014 and find that the macro elasticity of UI on unemployment is twice as large as the micro elasticity.

[46] Ahn and Hamilton (2020) find that the inflow into unemployment (and the composition thereof) can explain a substantial part of the rise in unemployment during the Great Recession.

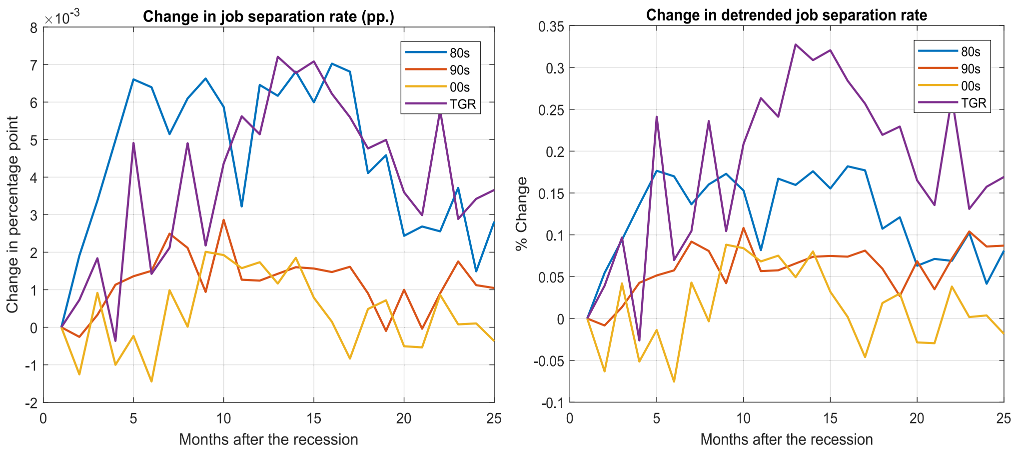

Fig. 17. Job separation rates from the start of each recession. TGR denotes the Great Recession. The starting date of each recession is based on NBER. The series in the right panel is detrended using HP filter.
Data sources: CPS and NBER.

Great Recession features larger but less persistent negative shocks comparing to the early 1990s recession. This suggests that the unemployment cost of UI extensions is less pronounced when a recession is more persistent (e.g., the early 1990s) since it is more difficult for workers to find a job regardless of the maximum UI duration.

The non-linear effects of UI extensions are also emphasised in Acosta et al. (2023). They find that when the potential UI duration is below 60 weeks, a 13-week extension leads to a 0.28 pp increase in unemployment whereas when the potential UI duration is above 60 weeks, a 13-week extension does not affect unemployment. This is consistent with the findings from the baseline model where a 13-week extension leads to 0.31 pp increase in unemployment during the Early 1990s Recession (when the median extended UI duration is 65 weeks). To study the effects of extending UI above 60 weeks, I use the Great Recession as an experiment where I limit the maximum UI duration to be 79 weeks instead of 99 weeks and study the subsequent response of unemployment. I find that a 13-week extension during the Great Recession leads to a mere increase of 0.04–0.05 pp in unemployment.

Aggregate demand channel. As discussed in the introduction, Kekre (2022) and Gorn and Trigari (2024) find that UI extensions stabilise the economy through the aggregate demand channel. Since this channel is absent in this paper, studying the response of aggregate demand to UI extensions can help gauge the magnitude of this missing effect. I define aggregate demand as the total amount of consumption in the baseline model. Given the risk neutrality assumption, consumption consists of wage income for employed workers, a combination of home production and UI benefits for insured unemployed workers, and simply home production for uninsured unemployed workers.

Focusing on the Great Recession, I plot the responses for the aggregate demand and each of its component in the baseline model as a percentage of the aggregate demand in an economy without UI extensions in Fig. E.5 in Appendix E. There is a slight boost in aggregate consumption in the first few periods after UI extensions are triggered, but, on average, the baseline aggregate consumption is around 0.12 percent lower than in an economy without UI extensions.[47] This reflects the relatively small share of insured unemployed workers in the economy, as well as the relative sizes of UI benefits compared to wages and home production. This suggests that the potential magnitude of the aggregate demand channel in this model would be relatively small and negative during the Great Recession.[48]

The extent of the aggregate demand channel may depend on the source(s) of aggregate shocks. In particular, using a heterogeneous agent model with unemployment risk and sticky prices, Auray and Eyquem (2024) demonstrate that under negative productivity shocks (as in this paper), the stabilising role of countercyclical UI policy is limited as output and unemployment fluctuations are nearly efficient. On the other hand, when the negative shocks stem from either a rise in the discount factor (as in Kekre (2022)) or a markup shock, the optimal UI policy response is large and countercyclical, but its stabilising role is prominent only for discount factor shocks. As Gorn and Trigari (2024) consider three other sources of exogenous shocks (job separation probability, borrowing limit, and the probability of becoming long-term unemployed), it is therefore possible that the stabilisation role of UI extensions may differ in magnitude from the findings in this paper.

[47] If (some of the) home production is not counted towards aggregate demand, the response of aggregate demand during the Great Recession would have been significantly larger and negative. Particularly, the aggregate demand excluding home production in the baseline model is 2.78 percent smaller than in an economy without UI extensions.

[48] For comparison, the drop in the aggregate productivity in the baseline model is 2.2 percent below its mean during the Great Recession.

Table 10
Counterfactual experiments during the Great Recession.
Data source: CPS.

	Data	Baseline	No Reachback	No Rational Exp.	No OJS
$\max(u)$ (%)	10.0%	9.3%	−0.1 pp	+1.9 pp	−0.4 pp
$\max(u_{dur})$ (weeks)	40.6	33.6	−0.5	+3.6	−1.0
$\max(LTU)$ (%)	4.4%	3.8%	−0.1 pp	+1.6 pp	−0.3 pp

• No Reachback: the "Reachback Provision" programme is disabled. No Rational Exp.: agents are assumed to follow adaptive expectations on UI extensions. No OJS: on-the-job search is not allowed. LTU: Unemployed more than 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.

5.4. Reachback provision programme

From May 2007, the Emergency Unemployment Compensation law has included the "Reachback Provision" providing UI eligibility to unemployed workers who have already exhausted their benefits prior to the UI extensions. This programme can potentially affect long-term unemployment since it is targeted directly at this group of workers. As the programme is already incorporated in the baseline case, I can measure its effect by removing the programme and keeping everything else the same. The results are summarised in Table 10. I find that Reachback Provision does not have a significant impact on the aggregate labour market. The (long-term) unemployment rate is only 0.1pp smaller than in the baseline model. The small effect is explained by the fact that the subgroup of workers who are affected by the programme represents just 3.5% 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% of the long-term unemployed in January 2008. The model produces a 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 significantly higher unemployment exit rate than the insured.

5.5. Rational expectations

As a high unemployment rate triggers UI extensions, agents can form expectations about future unemployment to gauge the probability that a UI extension occurs or terminates. To quantify the importance of rational expectations about the likelihood of UI extensions, I compare the baseline results to an alternative scenario where UI extensions (and how long they last) are completely unexpected to the agents. This can be considered as the case of adaptive expectations where agents assume the maximum UI duration to remain the same until they observe otherwise.[49] In this scenario, the UI exhaustion rate is just a constant instead of a function of unemployment, i.e., ϕ instead of $\phi(u)$. It is a simpler way to model UI extensions. Furthermore, changes in ϕ can be regarded as the comparative statics analysis. Under this alternative scenario, where UI extensions are assumed to last forever, the UI effects are expected to be more drastic because (1) the insured unemployed will lower search intensity, (2) matches are less likely to be formed, and (3) matches are more likely to separate.

I find that disregarding rational expectations about the likelihood of UI extensions leads to a substantial overestimation of both total and long-term unemployment by, respectively, 1.9 pp and 1.6 pp at the peak of the Great Recession, as well as an overestimation of the average unemployment duration by almost 4 weeks (see Table 10). These results demonstrate that it is vital that rational expectations are taken into account when evaluating the effects of UI extensions in general equilibrium.

It is useful to note that this result also depends on how the UI extension policy is modelled. Existing general equilibrium models with stochastic UI durations, with the exception of Rujiwattanapong (2022), tend to assume that the UI extension is a function of the aggregate productivity which is an exogenous process. This may save the state space greatly compared to when the UI extension is a function of unemployment. However, UI extensions in the US are triggered by a high unemployment rate. Given that unemployment exhibits much higher persistence and responds more slowly to shocks than does the total factor productivity or labour productivity (which are the main candidates for the aggregate productivity), expectations of rational agents regarding UI extensions and their responses may also differ. Particularly, UI extensions as a function of the aggregate productivity (as opposed to the unemployment rate) would be shorter lived and, therefore, associated with weaker responses from the agents in that model.

5.6. On-the-job search

In this exercise, I show how on-the-job search contributes to unemployment and its duration during the Great Recession. On the one hand, on-the-job search allows employed workers to improve their match qualities and the associated UI benefits if they become insured unemployed. Since the job search intensity and job finding rates are decreasing in the benefit level, this would increase unemployment and its duration. On the other hand, on-the-job search 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 search on the job and leave their current matches with not-so-great match qualities) and spend less time in unemployment.

[49] Nakajima (2012) studies the effects of UI extensions under a perfect-foresight equilibrium in terms of productivity and job separations.

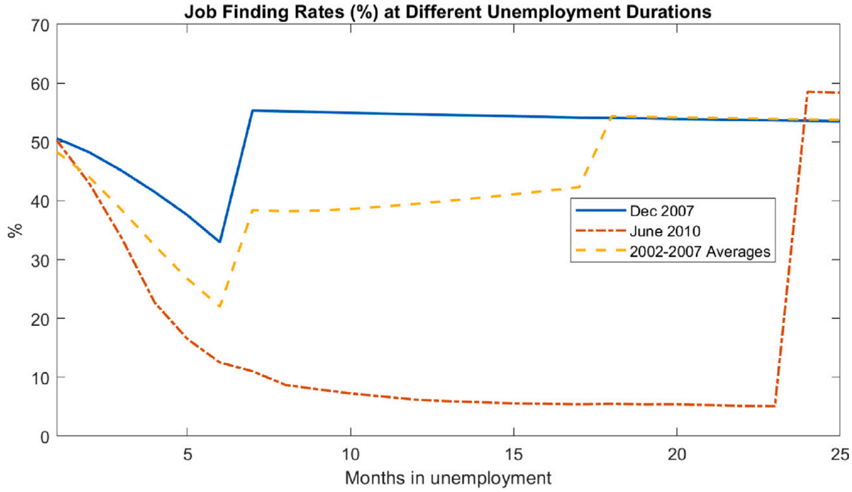

Fig. 18. The model's job finding rates (%) at different unemployment durations. Dec 2007 denotes the period in which the maximum UI duration is 26 weeks (standard), whilst June 2010 denotes the period in which the maximum UI duration is extended to 99 weeks.

To this extent, I remove the on-the-job search feature by assuming that the search cost for employed workers are substantially high enough such that no employed workers would have a positive search intensity in any state space. The last column of Table 10 shows the main results when on-the-job search is removed. I find that, during the Great Recession when UI is extended, on-the-job search contributes to a small but significant increase in (long-term) unemployment of up to (0.3) 0.4 pp from the baseline model as well as a 1-week increase in the average unemployment duration. On-the-job search, however, has a negligible impact outside recessionary periods.[50]

5.7. Duration dependence

Due to the heterogeneity in the job finding rates amongst unemployed workers, the model generates a negative duration dependence in the job finding rates that come purely from the changing composition of the stocks of unemployment.[51] Fig. 18 shows the model's job finding rates for unemployed workers at different unemployment durations in December 2007 (when the maximum UI duration is 26 weeks) and June 2010 (when the maximum UI duration is extended to 99 weeks) as well as the averages during 2002–2007.

As pointed out in Wiczer (2015), the negative duration dependence worsens during economic downturns. Furthermore, this duration dependence becomes more severe and persists as long as the UI extensions remain in place. As unemployment duration progresses within the maximum UI duration, the stocks of unemployment are more represented by those with lower exit rates (the insured unemployed with higher UI benefits in this case). However, upon reaching the maximum UI duration, the job finding rate rises before gradually declining. This rise occurs because uninsured unemployed workers exit unemployment at a faster rate than do the insured (also shown in Fig. 15's top left panel). The gradual decline in the job finding rates after UI exhaustion reflects the relatively small but persistent differences in the job finding rates between high- and low-productivity workers.[52] The higher job finding rates at long unemployment durations, particularly after UI exhaustion, help explain why the model does not generate enough persistence in long-term unemployment and the average unemployment duration (as shown in Figs. 9, 10 and 14's right panel) as well as the job finding rate (Fig. 13's left panel). Nonetheless, the model is able to produce realistic unemployment duration distributions both before and during the Great Recession as shown in Fig. 11.

[50] Additionally, using the imputed E2E transition series provided by Fujita et al. (2024), which corrects for missing answers in the CPS data, the E2E rate declined by 0.35 pp, from 2.45 percent in January 2008 to 2.1 percent in January 2010. UI extensions may negatively impact the E2E rate, as a higher outside option for workers can reduce total match surpluses and discourage more intensive job search. In this model, UI extensions during the Great Recession account for a 0.02 pp drop in the E2E rate. Similarly, Goensch et al. (2024) find that increasing the maximum UI duration from 26 to 99 weeks reduces the E2E rate by 0.1 pp.

[51] This finding is consistent with Ahn and Hamilton (2020). The duration-dependent unemployment exit rate is a featured result in several studies including Clark and Summers (1979), Machin and Manning (1999), and Elsby et al. (2011). See also footnote 35 for studies on the factors contributing to this duration dependence.

[52] The heterogeneity in individual productivity could potentially 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) conditional on being uninsured unemployed are rather similar and much higher than when insured. This results in a gradual decline in the job finding rates after UI exhaustion. 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 the individual productivity.

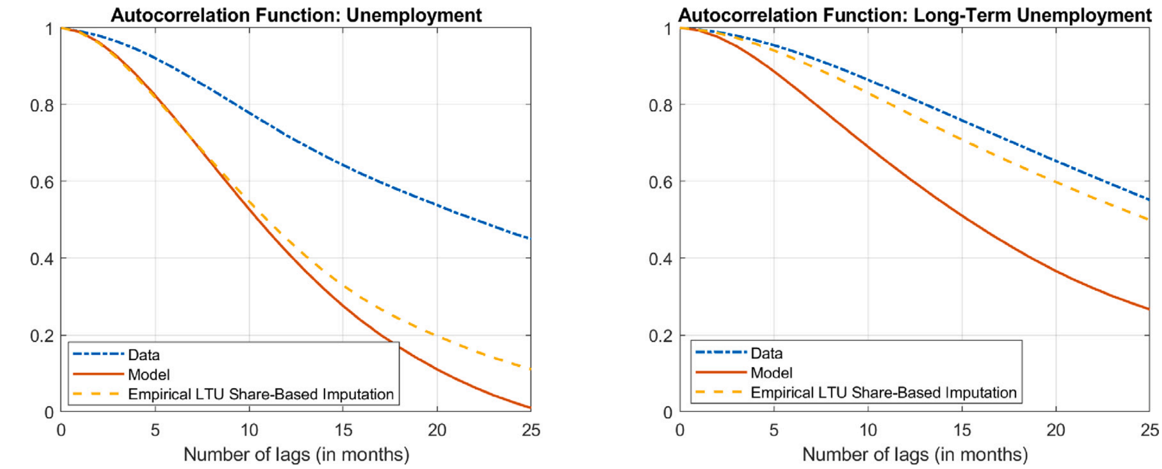

Fig. 19. Autocorrelation functions of unemployment and long-term unemployment (LTU) from the data, the model and an empirical LTU share-based imputation (during 1948–2014). The empirical LTU share-based imputation is constructed by multiplying the empirical shares of long-term unemployment with the model's aggregate unemployment series.
Data source: CPS.

5.8. The role of long-term unemployment

Given the model's limited persistence in long-term unemployment (LTU), I examine its role in the recovery and persistence of unemployment by constructing an alternative LTU series using the empirical LTU shares (bottom right panel of Fig. 12) and the model's unemployment series over the 1948–2014 period. I then construct an alternative unemployment series by replacing the model's LTU series with this alternative LTU series.[53] To assess how unemployment persistence is affected by this imputation, I compare the autocorrelation functions of unemployment and long-term unemployment across the data, the model and the imputed series as shown in Fig. 19. Unemployment recoveries following each recession between the 1980s and the Great Recession are summarised in Fig. E.6 in Appendix E.

As expected, the persistence of the imputed LTU series improves substantially (right panel of Fig. 19), given that the empirical LTU share is more persistent than in the model. However, the imputed LTU series does not noticeably improve the overall persistence of unemployment (left panel of Fig. 19). Only at lags of 9 months or more does the imputed unemployment series exhibit slightly higher persistence than the model. Even then, the empirical unemployment series remains significantly more persistent. This implies that even with realistic LTU dynamics, unemployment persistence is still not fully accounted for, particularly since the LTU share is relatively small during expansions.

Additionally, the role of LTU in contributing to unemployment recoveries varies in both the direction and magnitude, as shown in Fig. E.7 in Appendix E. For example, when excluding LTU, unemployment was much less persistent (i.e., recovered faster) after the Great Recession, whilst it was more persistent (i.e., recovered more slowly) following the 1980s recession. Given that the maximum UI duration was extended to 52 weeks during the 1980s recession (which lasted less than 3 years) and to 99 weeks during the Great Recession (which lasted over 6 years), this suggests that the impact of UI generosity on unemployment recovery may also operate through the dynamics of LTU.

5.9. Unobserved heterogeneity

To study the role of unobserved heterogeneity, I estimated the same non-linear state space model in Ahn and Hamilton (2020). They find that the unobserved heterogeneity of workers (in terms of unemployment exit rates) contributes to the rise in unemployment duration during the Great Recession. I can relate their interpretation of unobserved heterogeneity to the UI status in the baseline model as the insured unemployed have a lower unemployment exit rate than the uninsured, and their share increases during recessions.[54] I describe in full the state space model, the estimation and the results in Appendix F and G.

6. Conclusion

This paper quantifies the general equilibrium effects of endogenous UI extensions on the dynamics of unemployment and its duration which have an important implication on the recovery of the aggregate labour market. I develop a stochastic search-

---

53 Specifically, let $LTUShare_{data}$ denote the empirical LTU share, LTU_{model} denote the model's LTU series, and U_{model} denote the model's unemployment series. The imputed long-term unemployment and aggregate unemployment are calculated, respectively, as $LTU_{imputed} = LTUShare_{data} \times U_{model}$ and $U_{imputed} = U_{model} - LTU_{model} + LTU_{imputed}$.

54 The baseline model's heterogeneous individual productivities, on the other hand, produce little differences in the unemployment exit rates. Furthermore, Ahn and Hamilton (2020) find that changes in the composition of the newly unemployed who are UI recipients can account for most of the rise in unemployment during the Great Recession.

and-matching model where the maximum UI duration depends on the unemployment rate, and the UI benefits depend on the match quality during employment. Workers are heterogeneous in terms of individual productivity, match quality, UI status and the associated unemployment benefit level. Their job finding probabilities depend on these characteristics as well as the maximum UI duration and the aggregate productivity.

I find that the generous UI extensions during the Great Recession contribute to 8%–18% of the rise of unemployment. Both the microeconomic and general equilibrium effects of UI are important and consistent with existing empirical estimates. The UI effect on long-term unemployment is, however, much larger as it contributes to over half of the observed increase for which the microeconomic effect of UI is most responsible. That said, the UI effect is non-linear as its elasticity is smaller in the early 1990s recession. I also find that UI extensions are able to capture the incidence of (long-term) unemployment over the past six decades, but further unobserved heterogeneity may be required to explain the persistence of long-term unemployment. Lastly, I demonstrate that disregarding the rational expectations on the timings of UI extensions implies a substantial overestimation of the UI effects on unemployment and its duration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: W. Similan Rujiwattanapong reports financial support was provided by Aarhus University Research Foundation. W. Similan Rujiwattanapong reports was provided by Japan Society for the Promotion of Science. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Further tables

Table A.1
Unemployment-to-employment (U2E) monthly transition rate (%).
Data source: CPS.

	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

• Δpp ≡ change in U2E rate (in percentage points) = $U2E_{Jan10} - U2E_{Jan08}$. 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 A.2
Unemployment-to-unemployment (U2U) monthly transition rate (%).
Data source: CPS.

	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

• Δpp ≡ change in U2U rate (in percentage points) = $U2U_{Jan10} - U2U_{Jan08}$. 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 A.3
Unemployment-to-out-of-labour-force (U2O) monthly transition rate (%).
Data source: CPS.

	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

• Δpp ≡ change in U2O rate (in percentage points) = $U2O_{Jan10} - U2O_{Jan08}$. 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 A.4
Fraction (%) of long-term unemployment represented by current UI recipients in different subgroups.
Data source: CPS.

	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

• 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 A.5
Fraction (%) of newly unemployed workers represented by current UI recipients in different subgroups.
Data source: CPS.

	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

• Newly unemployed workers are defined as unemployed workers whose duration is less than 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).

Appendix B. Expressions for optimal search intensities and match surpluses

Given the worker's value functions when employed, insured unemployed and uninsured unemployed, we can take the first derivative to find the optimal search intensities. The first order conditions for type-i workers who are currently employed (e), insured unemployed (UI) and uninsured unemployed (UU) are, respectively,

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

$$v_u'(s_i^{UI}(m,\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UI(m)}(m';\omega'),0\} - \xi(1-\phi(u))US_i(m,\omega')\Big] \tag{B.2}$$

$$v_u'(s_i^{UU}(\omega)) = \beta M(\theta(\omega))E_{m'\omega'|\omega}\Big[\max\{WS_i^{UU}(m';\omega'),0\}\Big] \tag{B.3}$$

The total match surpluses of type-i workers who are currently employed (e), insured unemployed (UI) and uninsured unemployed (UU), and the unemployed worker's surplus from being insured are, respectively,

$$\begin{aligned} S_i^{e(\tilde m)}(m;\omega) &= y_i(m,\omega) - v_e(s_i^e(m;\omega)) - \tau(\omega) - (1-\psi)(b_i(\tilde m) + h - v_u(s_i^{UI(\tilde m)}(\omega))) \\ &-\psi(h - v_u(s_i^{UU}(\omega))) + \beta E_{\omega'|\omega}\bigg[\ldots \\ &(1-\delta)(1-\lambda)\Big((1-p_i^e(m;\omega)(1-F(m)))S_i^{e(m)+}(m;\omega')\ldots \end{aligned}$$

$$
\begin{aligned}
&+p_i^e(m;\omega)(1-F(m))E_{m'|m'>m}[\mu S_i^{e(m)+}(m';\omega')]\Big)\\
&+(1-\delta)\lambda E_{m'}\Big[(1-p_i^e(m;\omega)(1-F(m')))S_i^{e(m)+}(m';\omega')...\\
&+p_i^e(m;\omega)(1-F(m'))E_{m''|m''>m'}[\mu S_i^{e(m)+}(m'';\omega')]\Big]\\
&-(1-\psi)p_i^{UI(\tilde m)}(\omega)E_{m'}[\mu S_i^{UI(\tilde m)+}(m';\omega')]\\
&-\psi p_i^{UU}(\omega)E_{m'}[\mu S_i^{UU+}(m';\omega')]\\
&+(1-\psi)\Big(US_i(m,\omega')-US_i(\tilde m,\omega')...\\
&+(\phi(u)+p_i^{UI(\tilde m)}(\omega)\xi(1-\phi(u)))US_i(\tilde m,\omega')\Big)\Big]
\end{aligned}
$$

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

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

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

Appendix C. Transitions

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

$$
\begin{aligned}
e_{i,t+1}(m) = {} & (1-\delta)(1-\lambda)(1-p_{i,t}^e(m)+p_{i,t}^e(m)F(m))e_{i,t}(m)\mathbb{1}\{S_{i,t+1}^{e(m)}(m)>0\}\\
&+(1-\delta)(1-\lambda)f(m)\int_{m'<m}p_{i,t}^e(m')e_{i,t}(m')\mathbb{1}\{S_{i,t+1}^{e(m')}(m)>0\}dm'\\
&+(1-\delta)\lambda f(m)\int_{m'}(1-p_{i,t}^e(m')+p_{i,t}^e(m')F(m))e_{i,t}(m')\mathbb{1}\{S_{i,t+1}^{e(m')}(m)>0\}dm'\\
&+(1-\delta)\lambda F(m)f(m)\int_{m'}p_{i,t}^e(m')e_{i,t}(m')\mathbb{1}\{S_{i,t+1}^{e(m')}(m)>0\}dm'
\end{aligned}
$$

$$+f(m)\int_{\tilde{m}} u^{UI}_{i,t}(\tilde{m})p^{UI}_{i,t}(\tilde{m})\mathbb{1}\{S^{UI(\tilde{m})}_{i,t+1}(m)>0\}d\tilde{m}$$
$$+f(m)u^{UU}_{i,t}p^{UU}_{i,t}\mathbb{1}\{S^{UU}_{i,t+1}(m)>0\} \tag{C.1}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function. The total employment is the sum of all employed workers over productivity 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

$$\rho_{x,it}(m,m') = \begin{cases}\delta & \text{if } S^{e(m)}_{i,t+1}(m')>0,\\ 1 & \text{otherwise}\end{cases}$$
$$\rho_{x,it} = \left(\delta\int\int_{\{(m,m'):S^{e(m)}_{i,t+1}(m')>0\}} e^{post}_{i,t}(m,m')dm\ dm' + \int\int_{\{(m,m'):S^{e(m)}_{i,t+1}(m')\le 0\}} e^{post}_{i,t}(m,m')dm\ dm'\right)/e_t \tag{C.2}$$

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

denotes employed workers with match quality 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

$$\rho^j_{f,it} = \int \rho^j_{f,it}(m)f(m)dm$$
$$\rho_{f,t} = \frac{\int_{\tilde{m}} u^{UI}_{i,t}(\tilde{m})\rho^{UI(\tilde{m})}_{f,it}d\tilde{m} + u^{UU}_{i,t}\rho^{UU}_{f,it}}{\int_{\tilde{m}} u^{UI}_t(\tilde{m})d\tilde{m}+u^{UU}_t}$$

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

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

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

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

$$u^{UI}_{i,t+1}(\tilde{m}) = \underbrace{(1-\phi(u_t))(1-p^{UI}_{i,t}(\tilde{m}))u^{UI}_{i,t}(\tilde{m})}_{\text{unmatched, not losing UI}} + \underbrace{\chi^{UI}_{i,t}(\tilde{m})(1-\phi(u_t))(1-\xi)p^{UI}_{i,t}(\tilde{m})u^{UI}_{i,t}(\tilde{m})}_{\text{bad match, not losing UI}} \underbrace{+(1-\psi)\int_{m'}\rho_{x,it}(\tilde{m},m')e_{i,t}(\tilde{m},m')dm'}_{\text{destroyed match, not losing UI}} \tag{C.3}$$

$$u^{UU}_{i,t+1} = \int_{\tilde{m}}\Big(\underbrace{\phi(u_t)(1-p^{UI}_{i,t}(\tilde{m}))u^{UI}_{i,t}(\tilde{m})}_{\text{unmatched, losing UI}} + \underbrace{\chi^{UI}_{i,t}(\tilde{m})\Big(\phi(u_t)+(1-\phi(u_t))\xi\Big)p^{UI}_{i,t}(\tilde{m})u^{UI}_{i,t}(\tilde{m})}_{\text{bad match, losing UI}}\Big)d\tilde{m} +(1-\rho^{UU}_{f,it})u^{UU}_{i,t} + \underbrace{\psi\rho_{x,it}e_{i,t}}_{\text{destroyed match, losing UI}} \tag{C.4}$$

$$u_{t+1} = \sum_{i=H,L}\left(\int_{\tilde{m}} u^{UI}_{i,t+1}(\tilde{m})d\tilde{m} + u^{UU}_{i,t+1}\right) \tag{C.5}$$

where $\chi^{UI}_{i,t}(\tilde{m}) \equiv \int \mathbb{1}\{S^{UI}_{i,t+1}(\tilde{m},m)\le 0\}f(m)dm$ denotes the rate the newly formed matches with $u^{UI}_i(\tilde{m})$ are not viable.

Table D.1
Performance of the approximation method.

	Percentage deviations (%)	
	Mean	SE
1st moment	0.4762	0.3512
2nd moment	0.3164	0.4641
3rd moment	3.5648	3.324
4th moment	0.1982	0.2564

Appendix D. Performance of the approximation method

Table D.1 reports the average percentage deviations (in modulus) of the first four moments of the approximated distribution of employed workers over match quality, employment history, and individual productivity. This approximated distribution is on average less than 1% different in terms of the 1st, 2nd, and 4th moments from the simulated distributions. The 3rd moment is, however, more than 3% different from the simulation which is mainly due to the different cut-off points in the distributions coming from the endogenous job separations.

Appendix E. Further figures

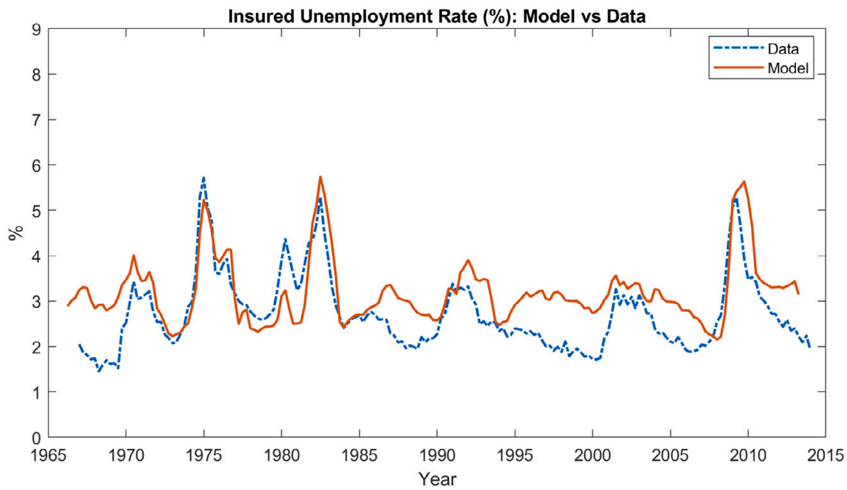

Fig. E.1. Insured unemployment rate (%): Model and data.
Data source: CPS.

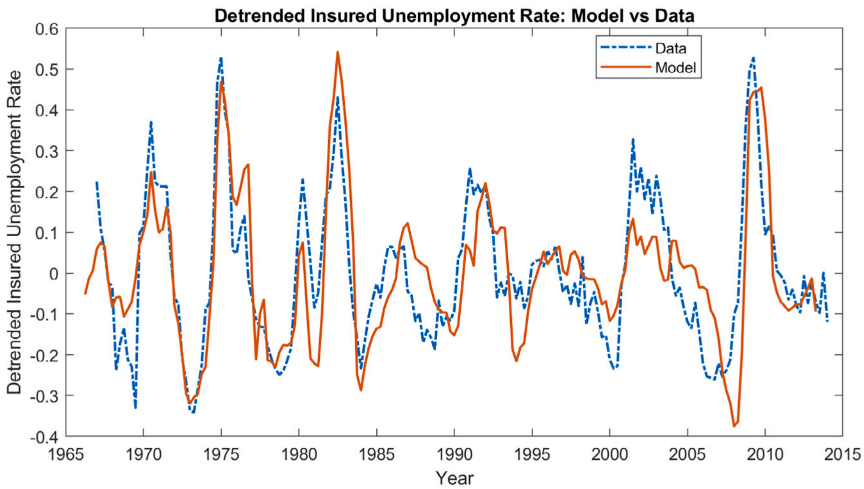

Fig. E.2. Detrended insured unemployment rate (using HP filter): Model and data.
Data source: CPS.

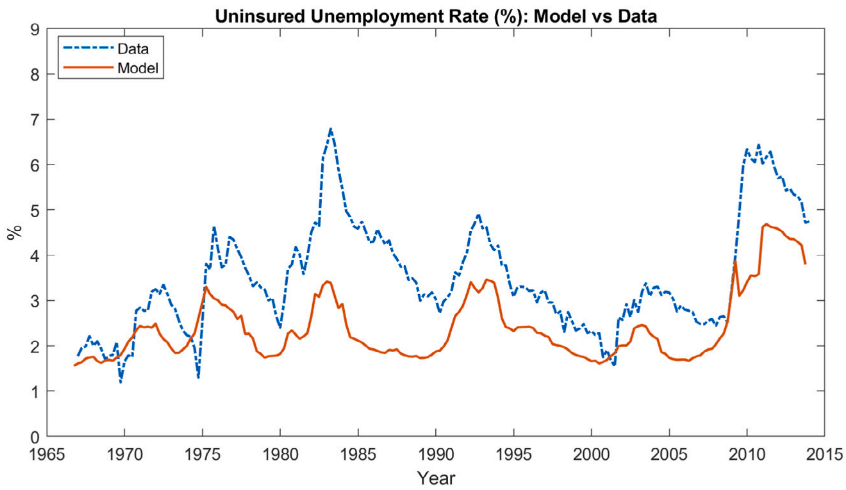

Fig. E.3. Uninsured unemployment rate (%): Model and data.
Data source: CPS.

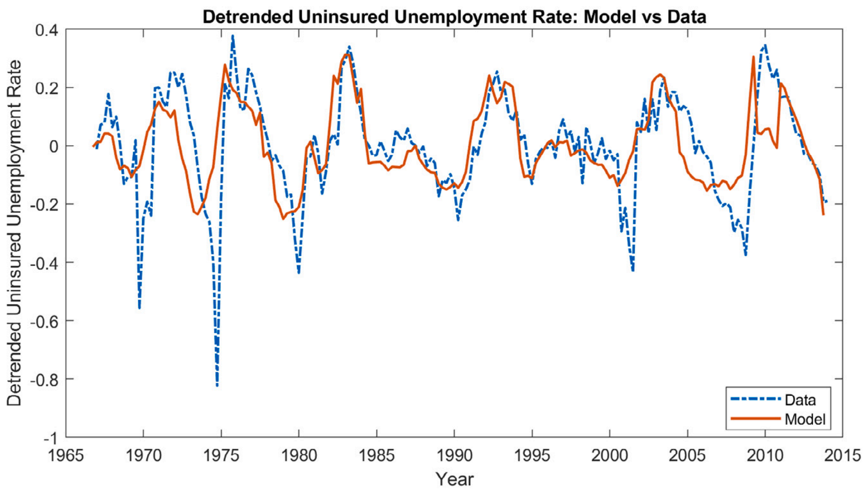

Fig. E.4. Detrended uninsured unemployment rate (using HP filter): Model and data.
Data source: CPS.

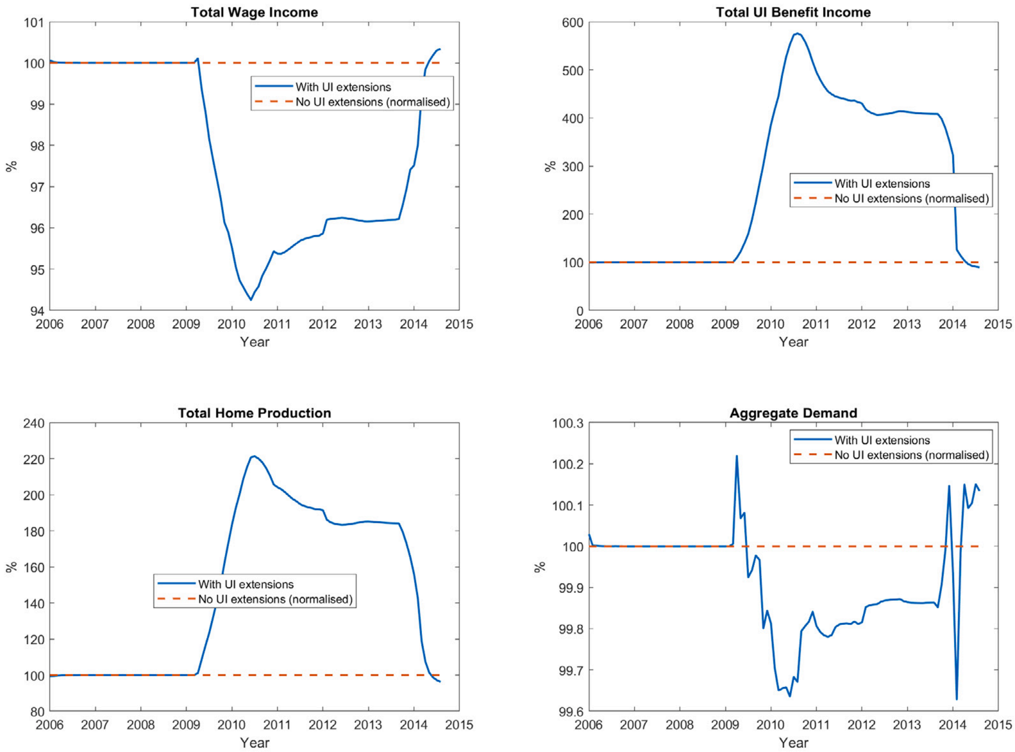

Fig. E.5. Aggregate demand and its components during the Great Recession. Solid lines represent variables in an economy with UI extensions as percentages of their respective counterparts in an economy without UI extensions.

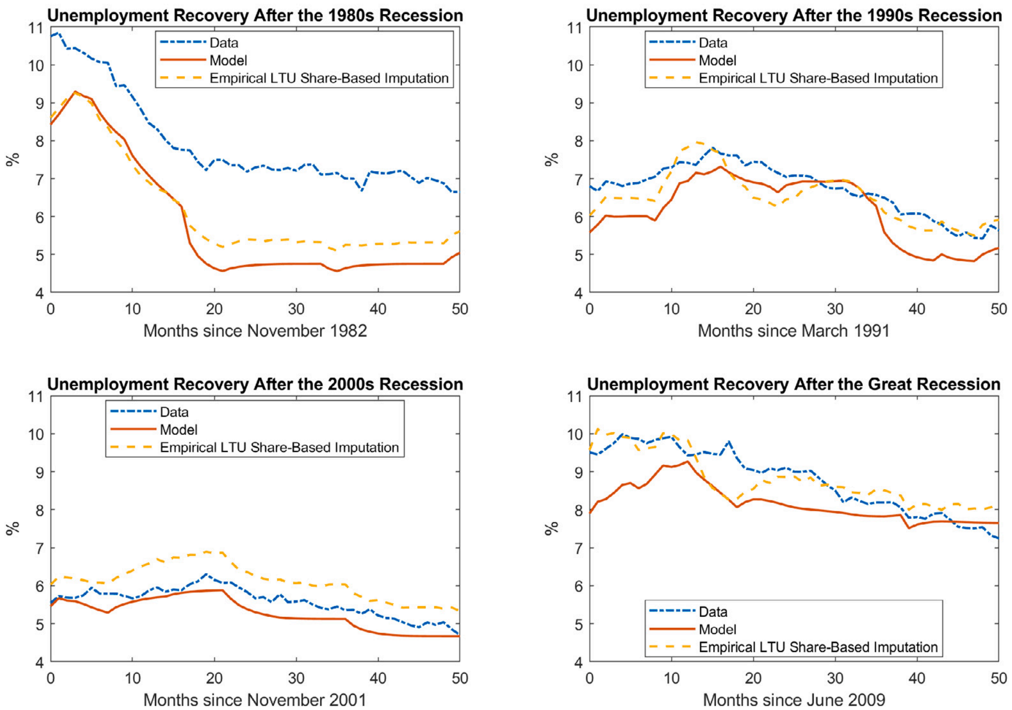

Fig. E.6. Unemployment recoveries following the end of recessions.
Data source: CPS and NBER.

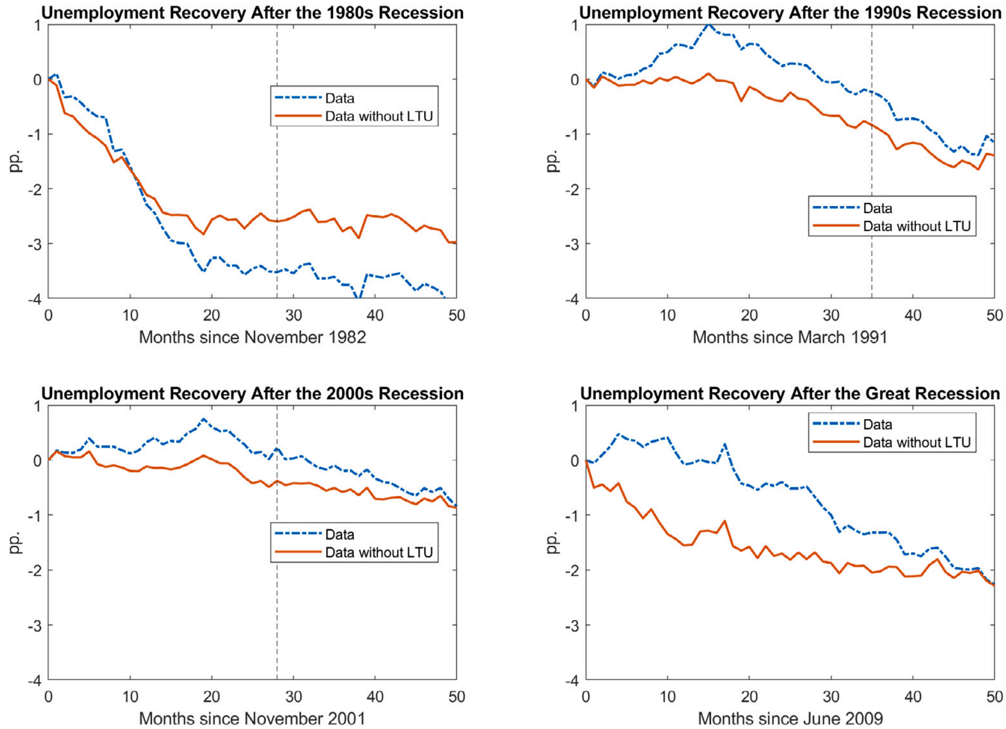

Fig. E.7. Responses of unemployment (in percentage points) from the end of each recession. Vertical dashed lines indicate the expiration of UI extensions, except during the Great Recession, where extensions lasted beyond the 50-month horizon since June 2009.
Data source: CPS and NBER.

Appendix F. 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 and Hamilton (2020) 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 G.

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 G. The extended Kalman filter is used to construct the likelihood function since some latent variables enter the equations for unemployment series non-linearly. Table G.1 reports these estimates and their standard errors.

Overall, the model's estimates are consistent with the empirical ones in Ahn and Hamilton (2020). 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 (2020) are shown in Fig. F.1, F.2, and F.3 respectively.

The probabilities that the newly unemployed workers stay unemployed in the following month from the model's estimates (Fig. F.1) 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 right panel of Fig. 13 in the manuscript that they complement well with the results from this estimation where the insured unemployed workers (the type with "lower" exit rate) have a much more volatile unemployment exit rate than the uninsured (the type with "higher" exit rate).

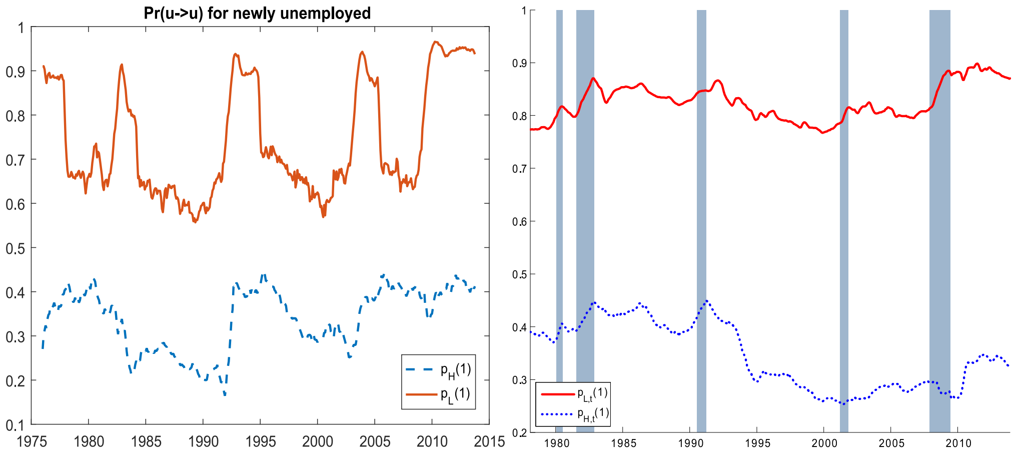

Fig. F.1. Probability that the newly unemployed workers of each type remain unemployed the following month ($p_i; i \in \{H, L\}$ – the notations follow Ahn and Hamilton (2020)): Model's prediction (left panel) and empirical prediction from Ahn and Hamilton (2020). Right panel's source: Ahn and Hamilton (2020).

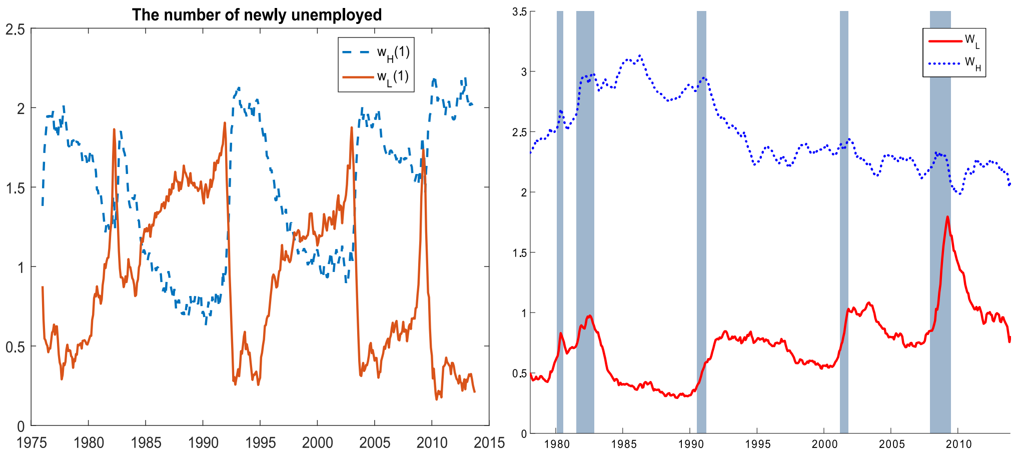

Fig. F.2. Number of newly unemployed workers of each type ($W_i; i \in \{H, L\}$ – the notations follow Ahn and Hamilton (2020)): Model's prediction (left panel) and empirical prediction from Ahn and Hamilton (2020). Right panel's source: Ahn and Hamilton (2020).

With respect to the number of newly unemployed during the Great Recession (Fig. F.2), 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 Fig. F.2. The series only differ as the workers remain unemployed which is related to Fig. F.3, 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 (2020), but this is expected since the model does not account for any low frequency changes or a trend in, e.g., the unemployment rate or the job finding rate. Fig. F.4 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 (Fig. F.3) 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).

Fig. F.5 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 it 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 consistent with the baseline model's implied hazard rate of exiting unemployment. 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

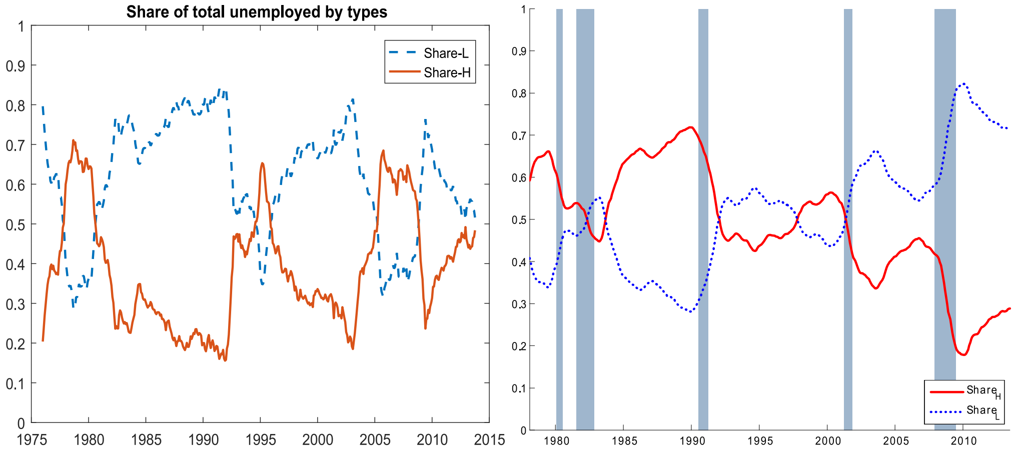

Fig. F.3. Share of unemployment by worker's type: Model's prediction (left panel) and empirical prediction from Ahn and Hamilton (2020). Right panel's source: Ahn and Hamilton (2020).

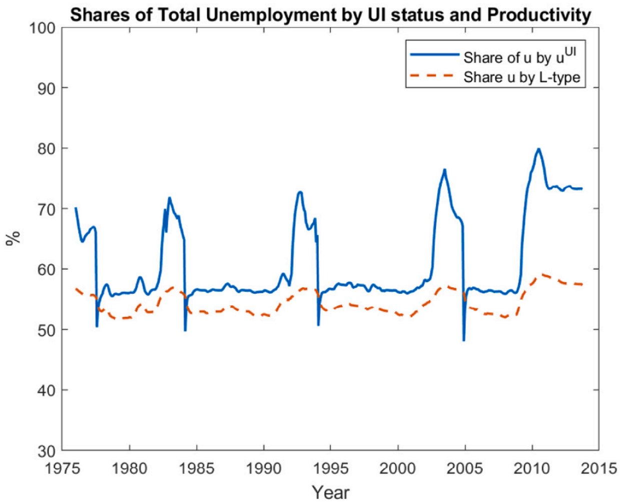

Fig. F.4. Shares (%) of unemployment by UI status and worker's productivity.

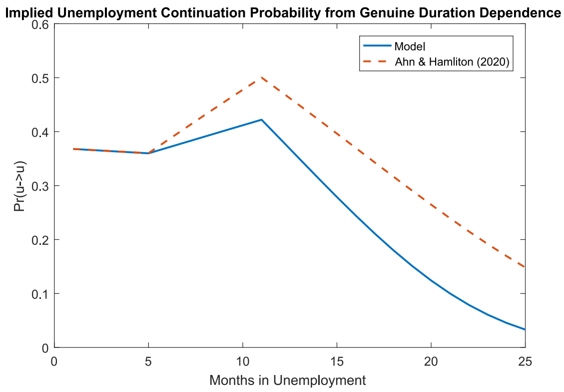

Fig. F.5. Implied unemployment continuation probability from genuine duration dependence: Model's prediction (solid) and empirical prediction from Ahn and Hamilton (2020) (dashed). The time varying factors governing the outflow rates for type-i workers (x_{it}) are normalised to zero when calculating these probabilities.

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 is consistent with the empirical data estimated by a state space model. I can relate Ahn and Hamilton (2020)'s interpretation of worker unobserved heterogeneity to the UI statuses of unemployed workers in the baseline model since the insured unemployed have a 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.

Appendix G. Ahn and Hamilton (2020)'s state space model

To summarise briefly, Ahn and Hamilton (2020)'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, $w_{H,t} = w_{H,t-1} + \epsilon^w_{H,t}$. The errors are independently and normally distributed with mean zero and standard deviation $\{\sigma^w_H, \sigma^w_L, \sigma^x_H, \sigma^x_L\}$ respectively. They assume the true duration dependence of unemployment exit rate is time invariant and summarised by $\{\tilde{\delta}_1, \tilde{\delta}_2, \tilde{\delta}_3\}$. The measurements or observables in their model are unemployment series by 5 duration bins $\{u^1_t, u^{2.3}_t, u^{4.6}_t, u^{7.12}_t, u^{13+}_t\}$. 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 $\{r^1_t, r^{2.3}_t, r^{4.6}_t, r^{7.12}_t, r^{13+}_t\}$ 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

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

where

$$
\begin{aligned}
P_{it}(j) &= p_{i,t-j+1}(1) \times p_{i,t-j+2}(2) \times \ldots \times p_{i,t}(j) \\
p_{it}(\tau) &= \exp[-\exp(x_{it} + d_\tau)] \\
d_\tau &= \tilde{\delta}_1((\tau-1)/48) + \tilde{\delta}_2[2((\tau-1)/48)^2 - 1] + \tilde{\delta}_3[4((\tau-1)/48)^3 - 3((\tau-1)/48)]
\end{aligned}
$$

Table G.1
Parameter estimates from Ahn and Hamilton (2020)'s state space model.

Parameter	Ahn and Hamilton (2020)	Baseline Model
σ^w_L	0.0422	0.0406
	(0.0039)	(0.0082)
σ^w_H	0.0437	0.0430
	(0.0057)	(0.0050)
σ^x_L	0.0476	0.0511
	(0.0054)	(0.0076)
σ^x_H	0.0204	0.0232
	(0.0027)	(0.0027)
$\tilde{\delta}_1$	5.0512	5.6691
	(1.9164)	(1.5841)
$\tilde{\delta}_2$	-0.0485	-0.0435
	(0.0532)	(0.0213)
$\tilde{\delta}_3$	2.1674	1.2406
	(0.8104)	(0.5758)
$R1$	0.1011	0.1017
	(0.0054)	(0.0103)
$R2.3$	0.0753	0.0822
	(0.0044)	(0.0043)
$R4.6$	0.0817	0.0815
	(0.0073)	(0.0108)
$R7.12$	0.0586	0.0633
	(0.0047)	(0.0070)
$R13+$	0.0393	0.0461
	(0.0025)	(0.0047)

• Standard errors are reported in parentheses. Please refer to Appendix F for variables' definitions.

The parameters to be estimated are the standard deviations of the errors $\{\sigma^w_H, \sigma^w_L, \sigma^x_H, \sigma^x_L,\ R1, R2.3, R4.6, R7.12, R13+\}$ and the parameters for true duration dependence $\{\tilde{\delta}_1, \tilde{\delta}_2, \tilde{\delta}_3\}$. I obtain 50 different series of $\{u^1_t, u^{2.3}_t, u^{4.6}_t, u^{7.12}_t, u^{13+}_t\}$ 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 filter is used to construct the likelihood function since $\{x_{H,t}, x_{L,t}\}$ enter the equations for unemployment series non-linearly. Table G.1 reports these estimates and their standard errors.

References

Aaronson, Daniel, Mazumder, Bhashkar, Schechter, Shani, 2010. What is behind the rise in long-term unemployment? Econ. Perspect. 34, 29–51.

Abraham, Katharine, Haltiwanger, John, Sandusky, L. Kristin, Spletzer, James, 2016. The Consequences of Long Term Unemployment: Evidence from Matched Employer-Employee Data. IZA Discussion Papers 10223., Institute of Labor Economics (IZA).

Acosta, Miguel, Mueller, Andreas I, Nakamura, Emi, Steinsson, Jón, 2023. Macroeconomic Effects of UI Extensions at Short and Long Durations. Working Paper 31784, In: Working Paper Series, National Bureau of Economic Research.

Aguiar, Mark, Hurst, Erik, 2005. Consumption versus expenditure. J. Political Econ. 113 (5), 919–948.

Ahn, Hie Joo, 2023. The role of observed and unobserved heterogeneity in the duration of unemployment. J. Appl. Econometrics 38 (1), 3–23.

Ahn, Hie Joo, Hamilton, James D., 2020. Heterogeneity and Unemployment Dynamics. J. Bus. Econom. Statist. 38 (3), 554–569.

Auray, Stéphane, Eyquem, Aurélien, 2024. Optimal unemployment insurance in a THANK model. Rev. Econ. Dyn. 53, 173–193.

Auray, Stéphane, Fuller, David L., Lkhagvasuren, Damba, 2019. Unemployment insurance take-up rates in an equilibrium search model. Eur. Econ. Rev. 112, 1–31.

Barnichon, Régis, Figura, Andrew, 2014. The Effects of Unemployment Benefits on Unemployment and Labor Force Participation: Evidence from 35 Years of Benefits Extensions. Discussion Series 2014-65, Board of Governors of the Federal Reserve System (U.S.).

Birinci, Serdar, See, Kurt, 2023. Labor market responses to unemployment insurance: The role of heterogeneity. Am. Econ. J.: Macroecon. 15 (3), 388–430.

Boone, Christopher, Dube, Arindrajit, Goodman, Lucas, Kaplan, Ethan, 2021. Unemployment insurance generosity and aggregate employment. Am. Econ. J.: Econ. Policy 13 (2), 58–99.

Card, David, Levine, Phillip B., 2000. Extended benefits and the duration of UI spells: evidence from the new jersey extended benefit program. J. Public Econ. 78 (1), 107–138.

Carrillo-Tudela, Carlos, Visschers, Ludo, 2023. Unemployment and endogenous reallocation over the business cycle. Econometrica 91 (3), 1119–1153.

Chodorow-Reich, Gabriel, Coglianese, John, Karabarbounis, Loukas, 2019. The macro effects of unemployment benefit extensions: a measurement error approach. Q. J. Econ. 134 (1), 227–279.

Christensen, Bent Jesper, Lentz, Rasmus, Mortensen, Dale T., Neumann, George R., Werwatz, Axel, 2005. On-the-job search and the wage distribution. J. Labor Econ. 23 (1), 31–58.

Clark, Kim B., Summers, Lawrence, 1979. Labor market dynamics and unemployemnt: A reconsideration. Brookings Pap. Econ. Act. 10 (1), 13–72.

Dieterle, Steven, Bartalotti, Otávio, Brummet, Quentin, 2020. Revisiting the effects of unemployment insurance extensions on unemployment: A measurement-error-corrected regression discontinuity approach. Am. Econ. J.: Econ. Policy 12 (2), 84–114.

Doppelt, Ross, 2016. The Hazards of Unemployment: A Macroeconomic Model of Job Search and Résumé Dynamics. Working Paper.

Elsby, Michael, Hobijn, Bart, Şahin, Ayşegül, Valletta, Robert, 2011. The labor market in the great recession — An update to september 2011. Brookings Pap. Econ. Act. 42 (2 (Fall)), 353–384.

Faig, Miquel, Zhang, Min, Zhang, Shiny, 2016. Effects of extended unemployment insurance benefits on labor dynamics. Macroecon. Dyn. 20 (5), 1174–1195.

Farber, Henry S., Valletta, Robert G., 2015. Do extended unemployment benefits lengthen unemployment spells? evidence from recent cycles in the U.S. labor market. J. Hum. Resour. 50 (4), 873–909.

Flemming, Jean, 2020. Skill accumulation in the market and at home. J. Econom. Theory 189, 105099.

Fredriksson, Peter, Holmlund, Bertil, 2001. Optimal Unemployment Insurance in Search Equilibrium. J. Labor Econ. 19 (2), 370–399.

Fredriksson, Peter, Söderström, Martin, 2020. The equilibrium impact of unemployment insurance on unemployment: Evidence from a non-linear policy rule. J. Public Econ. 187, 104199.

Fujita, Shigeru, 2011. Effects Of Extended Unemployment Insurance Benefits: Evidence from the Monthly CPS. Working Papers 10-35, Federal Reserve Bank of Philadelphia.

Fujita, Shigeru, Moscarini, Giuseppe, 2017. Recall and unemployment. Am. Econ. Rev. 107 (12), 3875–3916.

Fujita, Shigeru, Moscarini, Giuseppe, Postel-Vinay, Fabien, 2024. Measuring employer-to-employer reallocation. Am. Econ. J.: Macroecon. 16 (3), 1–51.

Fujita, Shigeru, Ramey, Garey, 2009. The cyclicality of separation and job finding rates. Internat. Econom. Rev. 50 (2), 415–430.

Fujita, Shigeru, Ramey, Garey, 2012. Exogenous versus endogenous separation. Am. Econ. J.: Macroecon. 4 (4), 68–93.

Goensch, Johannes, Gulyas, Andreas, Kospentaris, Ioannis, 2024. Worker mobility and UI extensions. Eur. Econ. Rev. 162, 104672.

Gorn, Alexey, Trigari, Antonella, 2024. Assessing the stabilizing effects of unemployment benefit extensions. Am. Econ. J.: Macroecon. 16 (1), 387–440.

Gruber, Jonathan, 1997. The consumption smoothing benefits of unemployment insurance. Am. Econ. Rev. 87 (1), 192–205.

den Haan, Wouter J., Ramey, Garey, Watson, Joel, 2000. Job destruction and propagation of shocks. Am. Econ. Rev. 90 (3), 482–498.

Hagedorn, Marcus, Karahan, Fatih, Manovskii, Iourii, Mitman, Kurt, 2013. Unemployment Benefits and Unemployment in the Great Recession: The Role of Macro Effects. Inc NBER Working Papers 19499, National Bureau of Economic Research, Inc.

Hornstein, Andreas, 2012. Accounting for Unemployment: the Long and Short of It. Working Paper 12-07, Federal Reserve Bank of Richmond.

Jarosch, Gregor, Pilossoph, Laura, 2019. Statistical discrimination and duration dependence in the job finding rate. Rev. Econ. Stud. 86 (4 (309)), pp. 1631–1665.

Johnston, Andrew C., Mas, Alexandre, 2018. Potential unemployment insurance duration and labor supply: The individual and market-level response to a benefit cut. J. Political Econ. 126 (6), 2480–2522.

Katz, Lawrence F., Meyer, Bruce D., 1990. The impact of the potential duration of unemployment benefits on the duration of unemployment. J. Public Econ. 41 (1), 45–72.

Kekre, Rohan, 2022. Unemployment Insurance in Macroeconomic Stabilization. Rev. Econ. Stud. 90 (5), 2439–2480.

Kospentaris, Ioannis, 2021. Unobserved heterogeneity and skill loss in a structural model of duration dependence. Rev. Econ. Dyn. 39, 280–303.

Krause, Michael U., Lubik, Thomas A., 2010. On-The-Job Search and the Cyclical Dynamics of the Labor Market. Working Paper 10-12, Federal Reserve Bank of Richmond.

Kroft, Kory, Lange, Fabian, Notowidigdo, Matthew J., Katz, Lawrence F., 2016. Long-term unemployment and the great recession: The role of composition, duration dependence, and nonparticipation. J. Labor Econ. 34 (S1), S7–S54.

Krueger, Alan B., Mueller, Andreas, 2010. Job search and unemployment insurance: New evidence from time use data. J. Public Econ. 94 (3), 298–307.

Krueger, Alan B., Mueller, Andreas, 2011. Job Search, Emotional Well-Being and Job Finding in a Period of Mass Unemployment: Evidence from High-Frequency Longitudinal Data. Brookings Pap. Econ. Act. 42 (1 (Spring), 1–81.

Krusell, Per, Smith, Jr., Anthony A., 1998. Income and wealth heterogeneity in the macroeconomy. J. Political Econ. 106 (5), 867–896.

Kuang, Katherine, Valletta, Robert, 2010. Extended unemployment and UI benefits. FRBSF Econ. Lett. April 2010 (12).

Landais, Camille, Michaillat, Pascal, Saez, Emmanuel, 2018. A macroeconomic approach to optimal unemployment insurance: Theory. Am. Econ. J.: Econ. Policy 10 (2), 152–181.
Ljungqvist, Lars, Sargent, Thomas J., 2017. The fundamental surplus. Am. Econ. Rev. 107 (9), 2630–2665.
Machin, Stephen, Manning, Alan, 1999. The causes and consequences of longterm unemployment in europe. In: Ashenfelter, O., Card, D. (Eds.), Handbook of Labor Economics, first ed. vol. 3, Part C, Elsevier, pp. 3085–3139.
Marinescu, Ioana, 2017. The general equilibrium impacts of unemployment insurance: Evidence from a large online job board. J. Public Econ. 150, 14–29.
Mazumder, Bhashkar, 2011. How did unemployment insurance extensions affect the unemployment rate in 2008–10? Chic. Fed Lett. April 2011 (285).
Meyer, Bruce, 1990. Unemployment insurance and unemployment spells. Econometrica 58 (4), 757–782.
Mitman, Kurt, Rabinovich, Stanislav, 2019. Do Unemployment Benefit Extensions Explain the Emergence of Jobless Recoveries?. IZA Discussion Papers 12365, Institute of Labor Economics (IZA).
Moffitt, Robert, 1985. Unemployment insurance and the distribution of unemployment spells. J. Econometrics 28 (1), 85–101.
Moffitt, Robert, Nicholson, Walter, 1982. The effect of unemployment insurance on unemployment: The case of federal supplemental benefits. Rev. Econ. Stat. 64 (1), 1–11.
Nagypál, Eva, 2006. On The Extent of Job-To-Job Transitions. Meeting Papers 10, Society for Economic Dynamics.
Nakajima, Makoto, 2012. A quantitative analysis of unemployment benefit extensions. J. Monet. Econ. 59, 686–702.
Ortego-Marti, Victor, 2016. Unemployment history and frictional wage dispersion. J. Monet. Econ. 78, 5–22.
Ortego-Marti, Victor, 2017. Loss of skill during unemployment and TFP differences across countries. Eur. Econ. Rev. 100, 215–235.
Pissarides, Christopher A., 2000. Equilibrium Unemployment Theory, 2nd Edition. MIT Press Books, vol. 1, (0262161877), The MIT Press.
Ravn, Morten O., Sterk, Vincent, 2017. Job uncertainty and deep recessions. J. Monet. Econ. 90, 125–141.
Rothstein, Jesse, 2011. Unemployment Insurance and Job Search in the Great Recession. Brookings Pap. Econ. Act. 42 (2 (Fall)), 143–213.
Rouwenhorst, K. Geert, 1995. Asset pricing implications of equilibrium business cycle models. In: Cooley, Thomas F. (Ed.), Frontiers of Business Cycle Research. Princeton University Press, Princeton, pp. 294–330.
Rujiwattanapong, W. Similan, 2022. Unemployment insurance and labour productivity over the business cycle. Rev. Econ. Dyn. 46, 196–223.
Shimer, Robert, 2006. On-the-job search and strategic bargaining. Eur. Econ. Rev. 50 (4), 811–830.
Wang, Bingsong, 2023. The fundamental surplus revisited. Rev. Econ. Dyn. 51, 1–15.
Wiczer, David, 2015. Long-Term Unemployment: Attached and Mismatched? Working Papers 2015-42, Federal Reserve Bank of St. Louis.
Yashiv, Eran, 2000. The determinants of equilibrium unemployment. Am. Econ. Rev. 90 (5), 1297–1322.