Job Search, Job Findings and the Role of Unemployment Insurance History*

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Abstract

Standard search theory suggests that (1) job search intensity increases with the relative gain from searching, and that (2) job search intensity increases the job finding probability. Firstly, this paper presents new empirical findings that are at odds with these theoretical predictions when workers are categorised by their unemployment insurance (UI) history. Unemployed workers who either are currently receiving or used to receive UI search harder than those who never take up UI during their unemployment spells. What's more, despite their higher search intensity, those with a UI history have a lower job finding probability. Subsequently, I introduce unproductive and inefficient job search, consistent with these empirical findings, to an otherwise standard stochastic equilibrium search-and-matching model with endogenous search intensity. Three key results emerge from these job search imperfections: (1) aggregate search intensity becomes acyclical leading to an underestimated matching efficiency, (2) the general equilibrium effects of UI extensions and the labour market fluctuations are dampened, and (3) unemployment and its duration are more persistent.

JEL Classification. E24, E32, J24, J64, J65.

Keywords. Business cycles, job search intensity, matching efficiency, unemployment insurance, unemployment dynamics

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1 Introduction/motivation

Standard search theory suggests that job search intensity increases with the relative gain from searching, and that it increases the job finding probability (Pissarides, 1984, 2000). Three main implications follow from this. First, amongst otherwise identical unemployed workers, those with unemployment insurance (UI) should search less intensely than those without UI. Second, amongst unemployed workers without UI, their job finding probabilities should be similar and higher than those with UI. Lastly, job search should be procyclical. Existing empirical studies indeed document that unemployed workers who currently receive UI tend to exit unemployment more slowly than those who do not have UI (Moffitt, 1985; Meyer, 1990; Krueger and Mueller, 2010). Subsequently, with the use of administrative data, surveys, and large online job board datasets, there is a growing body of literature documenting job search intensities and studying their connections to job findings along various individual and aggregate dimensions such as Shimer (2004), Krueger and Mueller (2010), Aguiar, Hurst and Karabarbounis (2013), Marinescu (2017), Mukoyama, Patterson and Şahin (2018), Faberman and Kudlyak (2019), Marinescu and Skandalis (2020), and Faberman et al. (2022).[1] However, less is known about how a worker's UI status and history are related to the intensity of job search and the resulting job-finding success. Understanding these connections is imperative for assessing the impact of UI policy changes on the macroeconomy from both normative and positive perspectives. Furthermore, it can help uncover the true matching efficiency in the aggregate labour market.

This paper first presents new empirical findings that are at odds with these theoretical predictions when workers are categorised by their UI history. Unemployed workers who either are currently receiving UI benefits or have previously received and exhausted them (i.e., those with a UI history) search for jobs more intensely than those who have never taken up UI during their current unemployment spells (i.e., those without a UI history). Furthermore, despite their higher search intensities, those with a UI history have a lower probability of finding a job than those without. Consistent with these empirical findings, I subsequently construct a stochastic equilibrium search-and-matching model where I allow for job search to be unproductive and/or inefficient, applicable mainly to those with a UI history. I then use the model to analyse the implications of these job search

[1] In particular, to measure job search intensity, Shimer (2004) uses the number of job search methods in the Current Population Survey. Krueger and Mueller (2010), Aguiar, Hurst and Karabarbounis (2013) and Mukoyama, Patterson and Şahin (2018) use the minutes spent on daily job search activities from the American Time Use Survey. Marinescu (2017) and Faberman and Kudlyak (2019) use the number of job applications from large online job board datasets whilst Faberman et al. (2022) use both the number of job applications and minutes spent on job search activities from the Survey of Consumer Expectations. Marinescu and Skandalis (2020) combine administrative and large online job board datasets to study job search behaviour.

imperfections on the aggregate job search behaviour, matching efficiency, labour market dynamics, and the effects of UI extensions.

Based on the U.S.'s Current Population Survey (CPS) monthly data and CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplements as well as the American Time Use Survey (ATUS), I consider two measurements of job search intensity: (1) the number of job search methods, and (2) the time spent on job search activities. These measurements have been used extensively in the literature; however, I utilise the information regarding the UI statuses and histories of workers to study their relationship with job search intensities and job finding probabilities. I find that unemployed workers with a UI history search harder than those without a UI history even after controlling for observable worker characteristics and aggregate market conditions. What's more, the high job search intensities of those with a UI history translate into lower job finding probabilities than those who have never taken up UI. However, once the unemployment duration is controlled for, being a former UI recipient does not lower the job finding probability, but being a current UI recipient still does. Additionally, I exploit the variations across states in the U.S. in work search requirements imposed by the UI offices upon current UI recipients in order to maintain their UI eligibility. I find evidence that job search intensity is higher in states where work search requirements are stricter and vice versa. Henceforth, current UI recipients are defined as unemployed workers who are currently taking up UI. Former UI recipients are defined as unemployed workers who have collected and exhausted UI during the current unemployment spell. Non-UI recipients are defined as unemployed workers who have never received UI during the current unemployment spell.

Motivated by these empirical findings, I posit that there exists unproductive and/or inefficient job search amongst unemployed workers which is related to a worker's UI history and unemployment duration. For current UI recipients, unproductive job search may arise endogenously because their optimal job search intensity is lower than what is required by the UI office in order to maintain their UI eligibility. Therefore, they intentionally lower their job search productivity and, in effect, their job search cost.[2] I refer to this decision as job search censoring throughout the paper. This job censoring process is consistent with the classical moral hazard problem related to the UI programme design. See, for example, Wang and Williamson (1996, 2002) who study optimal UI policies when job search efforts are private information. Relatedly, Hall and Mueller

[2]For example, a UI office may require that UI recipients must submit at least 5 job applications each week to maintain their UI eligibility. However, for a given UI recipient, she may have ideally wanted to apply for only 2 jobs in a week, but she has to send 5 job applications to continue receiving the UI benefits. To minimise the search cost, she then decides to exert little or no effort in the 3 extra job applications.

(2018) and Faberman et al. (2022) also study job search models with job censoring where the emphasis is on the censoring of wage offers.

As for former UI recipients, on the other hand, they experience inefficient job search that is due to the so-called duration dependence in job findings where the job finding probability diminishes with the unemployment duration. It is useful to note that this duration dependence may affect all unemployed workers but former UI recipients are, by definition, more heavily affected since they have a longer unemployment duration on average. Several works have examined the factors contributing to the duration dependence in the job finding probability including employer screening, loss of networks, human capital, genuine duration dependence and unobserved heterogeneity. See, for example, van den Berg and van Ours (1996), Hornstein (2012), Kroft, Lange and Notowidigdo (2013), Kroft et al. (2016), Hall and Schulhofer-Wohl (2018), Jarosch and Pilossoph (2019), Ahn and Hamilton (2020), and Ahn (2023). This paper is agnostic about the sources of duration dependence and assumes that there is a genuine duration dependence in the job finding probability which is exogenous to workers. Nevertheless, the framework in this paper allows for other sources of duration dependence to be later incorporated into the study.

Subsequently, I extend a stochastic general equilibrium search-and-matching model with endogenous job search intensity, endogenous job separations and countercyclical UI extensions, by considering two types of job search imperfections: (1) endogenously unproductive job search which arises from job search censoring of current UI recipients, and (2) exogenously inefficient job search which arises from the duration dependence structure of job findings. I use the model to study the implications of job search imperfections on the macroeconomy. I focus on the cyclical behaviour of the aggregate search intensity, matching efficiency, labour market dynamics and, lastly, the general equilibrium effects of UI extensions (particularly during the Great Recession).

There are 3 key quantitative results that follow from the introduction of job search imperfections. Firstly, the observed aggregate job search intensity becomes acyclical which is due to the changing composition of job searchers during a recession when the UI is extended. In such a scenario, there is a larger share of unemployed workers with a UI history (who posses higher observed search intensities) which counteracts the standard procyclicality of individual job search intensity. Henceforth, I define the observed intensity as the intensity that can be observed by the econometrician (such as the number of job search methods or the minutes spent on job search activities), and the effective intensity as the intensity once corrected for job search imperfections if any. In the context of the aggregate matching efficiency, by simply using the observed aggregate search intensity (without correcting for job search imperfections), one could overestimate the decline in the matching efficiency between 18 and 21 percent during the Great Recession.

Secondly, I find that the general equilibrium effects of UI extensions are significantly smaller when exogenously inefficient job search is present. The model without this job search inefficiency overestimates the effects by at least 50 percent.[3] Primarily, this is because current UI recipients respond less strongly to UI extensions when there exists a negative duration dependence in job findings. This result in part reconciles the discrepancy between the small microeconomic and large macroeconomic effects of UI extensions documented in the literature.

The final key result from the quantitative model is that the exogenously inefficient job search in fact decreases the volatility of the main labour market variables (such as the unemployment rate, average unemployment duration, job finding rate, and job separation rate) by 10-35 percent. Furthermore, exogenously inefficient job search increases the persistence of these variables and brings it closer to the empirical counterparts which are known to be highly persistent.[4] These labour market variables become more persistent and less volatile because (1) unproductive and inefficient job search lowers the job finding probability per search unit and implies a longer unemployment duration and persistent unemployment, and (2) the negative-duration-dependence aspect of job search inefficiency encourages unemployed workers to exit unemployment more quickly and respond less strongly to the countercyclical UI extensions. Mukoyama, Patterson and Şahin (2018) also find that the labour market fluctuations are dampened once search intensity is incorporated into the model. However, their results are driven mainly by the countercyclicality of job search intensity.

The behaviour of job search of workers has been studied in various aspects in the literature. Faberman et al. (2022) study the job search behaviour for employed and non-employed workers with an emphasis on searching on the job. Krueger and Mueller (2010), Marinescu and Skandalis (2020) and DellaVigna et al. (2021) study how the unemployment duration structure matters for the job search behaviour. Particularly, prior to UI benefit exhaustion, job search intensity rises. Using a large online job search engine data, Faberman and Kudlyak (2019) document that those with ex post longer unemployment durations tend to search harder throughout their unemployment spells which is congruent with the empirical findings in this paper. The cyclicality of job search has been studied extensively by Shimer (2004), DeLoach and Kurt (2013), Gomme and

[3] Under the baseline model, the 73-week extension of the maximum UI duration during the Great Recession implies a 1.24 percentage-point increase in the unemployment rate and a 12-week increase in the average unemployment duration.

[4] For example, the baseline model produces around 40 percent of the autocorrelation coefficient for unemployment at two-year lag whilst a model without exogenously inefficient job search produces only 4 percent.

Lkhagvasuren (2015), Mukoyama, Patterson and Şahin (2018), and Leyva (2018). These studies conclude that the aggregate search intensity is either acyclical or countercyclical. Additionally, Ferraro et al. (2022) study the roles of non-pecuniary and pecuniary search costs on job search decisions and their interactions with unemployment insurance.

This paper contributes to this strand of literature by providing insights into the job search behaviour across both workers and time. For the job search behaviour across workers, I utilise the information on UI history provided in the CPS January supplements and merge them with the basic CPS monthly data to analyse the intensity of job search and the job finding probability of unemployed workers by their UI statuses. For the job search behaviour across time, this paper also offers an alternative explanation for which the observed aggregate job search intensity may not be procyclical. This is due to the worker composition effect. During a given recession with a UI extension, those with a UI history, who posses higher search intensities, are relatively more abundant than those without a UI history. The rising share of those with higher search intensities counteracts with the procyclical search intensity at the individual level, which is standard in canonical search models, rendering the observed aggregate search intensity acyclical or even mildly countercyclical.

This result on the acyclicality of the observed aggregate job search intensity (and its departure from the effective aggregate job search intensity), in turn, has an important implication on the behaviour of the matching efficiency, i.e., the productivity of the matching function. Particularly, many studies have documented a substantial decline in the matching efficiency during the Great Recession. See, for example, Barnichon and Figura (2015) and Hornstein and Kudlyak (2016). A notable exception is Hall and Schulhofer-Wohl (2018) who find that the matching efficiency may not decline as much during the Great Recession once the changing composition of workers with different unemployment exit rates is taken into account. As Hall and Schulhofer-Wohl (2018) do not consider separately the role of job search intensity in their analysis, this paper complements their findings by decomposing the matching efficiency into job search intensity, job search efficiency/imperfections and the aggregate job finding rate per unit search, and studying the roles of these components. Specifically, without correcting for job search imperfections, the matching efficiency can be largely underestimated during recessions.

This paper also contributes to the literature studying the effects of UI extensions on job findings and unemployment. Empirical studies on this topic tend to find rather small effects of UI extensions during the Great Recession. See, for example, Aaronson, Mazumder and Schechter (2010), Kuang and Valletta (2010), Fujita (2011), Mazumder (2011), Rothstein (2011), Barnichon and Figura (2014), and Farber and Valletta (2015).

However, the results on the general equilibrium or macroeconomic effects of UI extensions are rather mixed. See, for example, Nakajima (2012), Hagedorn et al. (2013), Chodorow-Reich, Coglianese and Karabarbounis (2019), Mitman and Rabinovich (2019), Rujiwattanapong (2019), Birinci and See (2023), and Acosta et al. (2023). This paper provides a bridge attempting to reconcile the smaller microeconomic effect with the larger macroeconomic effect of changes in UI generosity. Particularly, the duration-dependent job search inefficiency weakens the response of UI recipients' job search strategy to changes in UI generosity and moderates the aggregate effect of UI extensions.[5]

The paper is organised as follows. Section 2 presents the new empirical findings on job search behaviour and job finding probability amongst unemployed workers. Section 3 describes the model. Section 4 discusses the calibration exercise. Section 5 presents the results. Section 6 concludes.

2 Empirical evidence

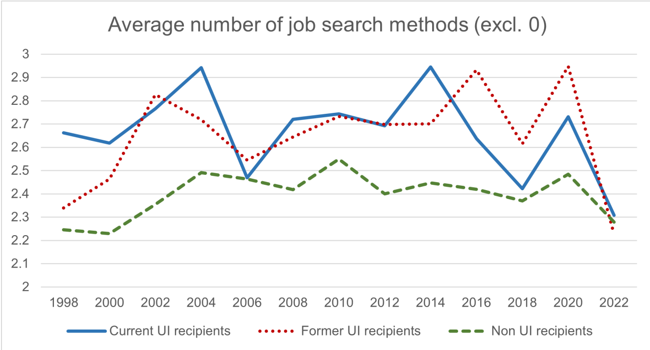
This section empirically analyses the job search behaviours of unemployed workers and the entailing job finding probabilities based on their UI history. Particularly, I find that current and former UI recipients have a higher search intensity than those who never received UI during their current unemployment spells after controlling for all available worker characteristics. Furthermore, despite the higher search intensity, current and former UI recipients have a smaller probability of finding a job contrary to the standard search theory prediction.

Job search intensity Following Shimer (2004) and Mukoyama, Patterson and Şahin (2018), I use the number of job search methods as a proxy for job search intensity.[6] To construct the job search intensity data, I merged the CPS Basic Monthly Data with the CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplement from

[5]Rujiwattanapong (2019) focuses on the role of worker heterogeneity (particularly in terms of benefit level and individual productivity) and heterogeneous job finding rates in explaining the dynamics of unemployment and its duration, Apart from the empirical contribution, this paper instead focuses on the role of UI history in understanding the effective job search intensity and the implications on the matching efficiency and labour market dynamics. The model in this paper also differs from Rujiwattanapong (2019) with the introduction of endogenous job search censoring decisions and exogenous duration-dependent job search inefficiency.

[6]Mukoyama, Patterson and Şahin (2018) also use another measure of search intensity based on information from the American Time Use Survey. However, this survey does not report the UI status of the respondents. Existing literature using this survey such as Krueger and Mueller (2010), Rothstein (2011) and Mukoyama, Patterson and Şahin (2018) use the UI eligibility criteria (unemployed workers who are job losers or temporary job enders) as a proxy for UI recipients. To be the best of my knowledge, this paper is the first to report the search intensity of unemployed workers categorised by their actual UI history which is the most accurate measurement for whether an unemployed worker receives and/or has exhausted the UI benefits.

Figure 1: Search intensity by UI history defined as the average number of job search methods (excluding those reporting zero method).



Source: CPS monthly data & CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplements.

1998 to 2022.[7] The former contains information regarding basic worker characteristics and the job search method(s) used whilst the latter contains the history of UI receipts during the workers' current unemployment spells. This UI history allows me to distinguish unemployed workers into 3 categories: (1) current UI recipients, (2) former UI recipients and (3) non-UI recipients. The supplement is released every two years in January. I focus on unemployed workers of age between 21 and 64 years who reported a strictly positive number of job search methods.[8] Summary statistics of unemployed workers by their UI history are reported in Table A.1 in Appendix A. Compared to non-UI recipients, current UI recipients are more likely to be college educated, job losers, not on lay-off, and have a longer unemployment duration as well as a longer previous job's tenure and higher previous job's weekly earnings.

Raw data on job search intensity by UI history is summarised in Figure 1. On average, unemployed workers without a UI history use 2.4 search methods whilst the current and former UI recipients use 2.7 and 2.6 methods respectively (12 percent and 11 percent higher than non-UI recipients respectively). To study the role of the UI history in determining job search intensity, I regress the number of job search methods on relevant worker characteristics, aggregate factors and UI status dummies (being either current, former or non-UI recipients) using a linear regression model. Worker characteristics in-

[7]Based on the CPS data, job search methods are categorised into active and passive methods. I present the results when all methods are considered but the main findings prevail when only the active methods are considered. Active methods are as follows: (1) contacted employer directly/interview, (2) contacted public employment agency, (3) contacted private employment agency, (4) contacted friends or relatives, (5) contacted school/university employment center, (6) sent out resumes/filled out application, (7) checked union/professional registers, (8) placed or answered ads, and (9) other active. The passive methods are as follows: (10) looked at ads, (11) attended job training programs/courses, (12) nothing, and (13) other passive. I exclude method (12), which is labelled "nothing", from the calculation of job search intensity; nonetheless, the main results are qualitatively unaffected by this exclusion.

[8]Unemployed workers who reported zero search method consist only of a subset of unemployed workers who expected to be recalled by their previous employers.

clude race, education, gender, age (quartic), marital status (including a dummy variable for being female and married), occupation, industry, unemployment duration (quartic), recall expectation, potential UI exhaustion month, reason for unemployment, previous job's tenure, and previous job's weekly earnings. Aggregate factors include a linear time trend, a recession dummy, state fixed effects, and state unemployment rates. Column 1 of Table 1 shows that even after controlling for all possible worker characteristics and aggregate factors, current and former UI recipients search harder than non-UI recipients.

Table 1: Linear regression model for two definitions of job search intensity: (1) the number of job search methods, and (2) the imputed minutes of job search à la Mukoyama, Patterson and Şahin (2018).

	Dependent variable: Job search intensity	
	(1)	(2)
	Number of methods	Imputed minutes
Current UI recipient	0.162***	2.605**
	(0.053)	(1.201)
Former UI recipient	0.127***	2.192**
	(0.042)	(0.955)
N	7,561	7,561
R^2	0.354	0.486

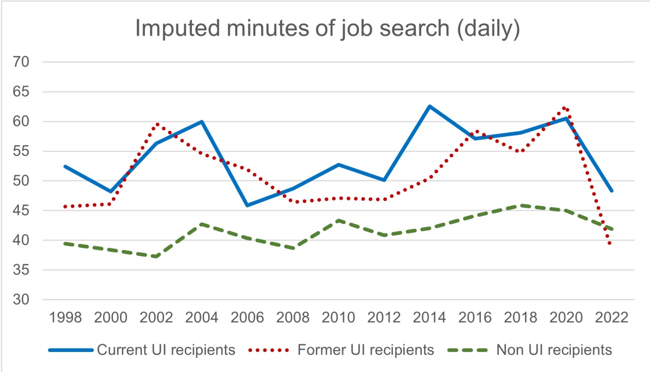
- Source: CPS. * p<0.05, ** p<0.01, *** p<0.001.
- Other control variables include race, education, gender, age (quartic), marital status, female and married, occupation, industry, unemployment duration (quartic), recall expectation, potential UI exhaustion month, reason for unemployment, previous job's tenure, previous job's weekly earnings, a linear time trend, a recession dummy, state fixed effects, and state unemployment rates.

Mukoyama, Patterson and Şahin (2018) also find that the search intensity for UI-eligible unemployed workers is generally higher than that of UI-ineligible workers. However, since not all UI-eligible workers actually take up UI benefits, the search behaviour of the UI recipients may differ from UI-eligible workers.[9] Specifically, the moral hazard problem may be more pronounced. This paper complements Mukoyama, Patterson and Şahin (2018) by using search intensity data based on the actual UI recipients.

Since each job search method may require a different amount of time used and could vary with individual characteristics, I also consider an alternative definition of job search intensity which is the amount of time a worker spends on job search. Following Mukoyama, Patterson and Şahin (2018), I construct the imputed minutes of job search for each worker by first using the American Time Use Survey (ATUS) during 2003-2014 to estimate a relationship between the minutes spent on job search, worker characteristics, and job search

[9] Auray, Fuller and Lkhagvasuren (2019) reported that, between 1989 and 2012, only 77% of UI-eligible unemployed workers collected their benefits on average.

Figure 2: Search intensity by UI history defined as the average minutes of daily job search.



Source: CPS monthly data, CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplements, and American Time Use Survey.

methods. Subsequently, I calculate the imputed minutes of job search of each worker in the merged CPS monthly and CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplement data based on the two-stage Heckman selection model using ATUS data. The raw imputed minutes by UI status are plotted in Figure 2. Current and former UI recipients spend on average 54 and 51 minutes, respectively, on job search activities whilst those who never received UI spend around 41 minutes on job search daily. I also regress the imputed minutes on worker characteristics (including UI status) and aggregate factors, and present the results in column 2 of Table 1. These results as well as Figure 2 also suggest that current and former UI recipients search harder than non-UI recipients for both definitions of job search intensity.

This paper hypothesises that current UI recipients have a high search intensity because they need to show their UI case workers they have been actively looking for jobs to maintain their UI eligibility, and that they would have not searched harder had the job-search requirement not been imposed. To further investigate this point, I utilise the fact that each state in the U.S. has a freedom to design its own UI job search requirements. For example, stricter states, such as Florida, Nebraska and Missouri, require that UI recipients contact 4-5 new potential employers weekly and they must submit a report every 1-2 weeks. At the same time, more lenient states, such as California, Delaware and Massachusetts, have broader definitions of work search activities, only require 1-2 search activities each week and only ask for a job search report from UI recipients upon request.[10]

Consistent with the proposed hypothesis, the results reported in Table 2, which is from the same linear regression model estimation as in Table 1, suggest that indeed workers

[10]This information is retrieved from the websites of respective states' departments overseeing the UI programme as of June 2024.

in the states with stricter job search requirements search more intensely than those in the states with more lenient requirements. Note that Alabama is the reference state (requiring 3 work search contacts weekly) in these regressions. This finding suggests that the observed job search intensities of current UI recipients, which are affected by the strictness of search requirements, may be less important in explaining their job finding probabilities. Additionally, Ashenfelter, Ashmore and Deschênes (2005) find no evidence that strict job search requirements lead to shorter durations of UI claims.

Table 2: Job search intensities by state and UI job search requirements.

Dependent variable: (1) Number of job search methods (2) Imputed minutes of job search à la Mukoyama, Patterson and Şahin (2018)					
Strict UI search requirements	(1)	(2)	Lenient UI search requirements	(1)	(2)
Florida	0.263*	3.070	California	-0.100	-2.062
	(0.142)	(3.198)		(0.130)	(2.919)
Missouri	0.200	2.984	Delaware	-0.249	-3.880
	(0.158)	(3.560)		(0.198)	(4.447)
Nebraska	0.237	8.188*	Massachusetts	-0.011	-4.011
	(0.200)	(4.492)		(0.167)	(3.760)
N	7,561	7,561	N	7,561	7,561
R^2	0.354	0.486	R^2	0.354	0.486

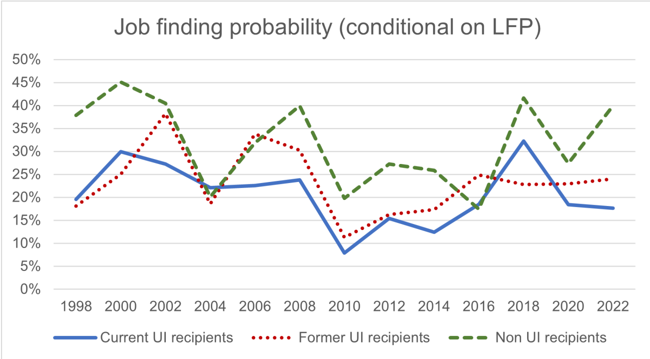
- Source: CPS. * p<0.05, ** p<0.01, *** p<0.001.
- Other control variables include race, education, gender, age (quartic), marital status, female and married, occupation, industry, unemployment duration (quartic), recall expectation, UI status dummies, potential UI exhaustion month, reason for unemployment, previous job's tenure, previous job's weekly earnings, a linear time trend, a recession dummy, and state unemployment rates.

As for former UI recipients, their higher search intensity may be deemed sensible since they no longer have UI and, therefore, have more incentives to search for a job. As mentioned earlier, however, the high search intensity of current and former UI recipients in fact does not translate into a high probability of finding a job (in comparison to non-UI recipients) which will be discussed next.

Job findings To construct the job finding probability, I compute the monthly transition probability of unemployed workers becoming employed in the next month conditional on remaining in the labour force.[11] The raw data on job finding probability by UI history is summarised in Figure 3. On average, both current and former UI recipients have lower job finding probabilities (of 21 and 23 percent respectively) compared to those who never received UI (of 32 percent). To control for possible individual and aggregate factors,

[11]The results remain largely the same when the sample includes those exiting the labour force. The job finding probabilities in this case are just lower for all types of workers.

Figure 3: Monthly transition probability from unemployment to employment by UI history (conditional on staying in the labour force next month).



Source: CPS monthly data & CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplements.

Table 3 reports the results of linear probabilistic regression models with the job finding rate being the dependent variable. Regressors include the UI status dummies, search intensity (the average number of job search methods), unemployment duration (quartic), race, education, gender, age (quartic), marital status, a dummy variable for being female and married, occupation, industry, recall expectation, potential UI exhaustion month, reason for unemployment, previous job's tenure, previous job's weekly earnings, a linear time trend, a recession dummy, state fixed effects, and state unemployment rates.

Table 3: Linear probability model for the unemployment-to-employment transition probability.

Dependent variable: Job finding probability		
	(1)	(2)
Current UI recipient	-0.096***	-0.084***
	(0.013)	(0.013)
Former UI recipient	-0.053***	-0.014
	(0.015)	(0.016)
Search intensity	0.098*	0.096*
	(0.058)	(0.058)
Unemployment duration (quartic)		✓
N	5,919	5,919
R^2	0.069	0.078

- Source: CPS. * p<0.05, ** p<0.01, *** p<0.001.
- Other control variables include race, education, gender, age (quartic), marital status, female and married, occupation, industry, recall expectation, potential UI exhaustion month, reason for unemployment, previous job's tenure, previous job's weekly earnings, a linear time trend, a recession dummy, state fixed effects, and state unemployment rates.

One important result from these regressions is that, once the unemployment duration is controlled for, being a current UI recipient is still associated with having a lower job finding probability but being a former UI recipient is not. Column 1 of Table 3 indicates that without controlling for the unemployment duration, the former UI recipient status becomes an important factor for the job finding rate. The results from these two regression specifications suggest that former UI recipients have a lower job finding probability than non-UI recipients mainly due to the longer average unemployment duration of the former group. This finding is intuitive since former UI recipients by definition have at least 6 months of unemployment duration (and even more whenever the UI is extended).

Columns 1 and 2 from Table 3 suggest that being a current UI recipient is still an important determinant for explaining a lower job finding probability on top of other worker characteristics including unemployment duration.[12] The combination of a higher search intensity and a smaller job finding success of current UI recipients suggests that these workers may search harder to remain eligible for UI but they may not intend to exit unemployment as fast as their search intensity suggests. This is consistent with the prediction from a standard search model with endogenous search intensity. That is, workers with UI would optimally exert lower search intensity than workers without UI since the former type has a lower gain from job search. Lastly, it is useful to note that search intensity still has a positive impact on the job finding probability as can be seen in Table 3.

Additionally, it is possible that the lower job finding probability of current UI recipients compared to that of non-UI recipients may be associated with a higher job selectivity of current UI recipients. That being said, this job selectivity is not evident from the dataset used. Particularly, I control for observations in the 4th and 8th months-in-sample in which current weekly earnings are reported in the CPS. I then regress the (log) re-employment weekly earnings on UI statuses, other worker characteristics, and aggregate factors similar to the previous linear probability model. The results, as reported in Table A.2 in Appendix A, suggest that being a current UI recipient does not explain significantly the re-employment wages.[13] However, being a former UI recipient is associated with lower

[12]Given that all available observable worker characteristics which may influence the UI take-up decision are controlled for, adverse selection can be ruled out. One exception could be that there exists unobserved worker heterogeneity that affects the observed job search intensity and/or the job finding probability. For example, some workers may inherently have a lower search ability and, therefore, are more likely to have a UI history. However, this would imply that being a former UI recipient should have still explained the lower job finding probability, even after controlling for the unemployment duration. That is, the coefficient for the former UI recipient in column 2 of Table 3 should have been statistically significant (and negative) which is not the case. It is worth noting that there could still be unobserved heterogeneity that affects job search intensity and job findings; nonetheless, it cannot be inferred from the datasets used in this paper.

[13]Despite this, the stochastic model in study will still allow for the possibility of job selectivity.

re-employment wages which can also be due to the duration dependence.

Based on these empirical findings regarding the relationship between job search intensity and job findings, the model in the next section will feature UI job search requirements and job search censoring for current UI recipients as well as a duration-dependent job search inefficiency, particularly for former UI recipients.

3 Model

To highlight the main mechanism of unproductive and inefficient job search, I present the deterministic version of the model in this section. I introduce into an otherwise standard Diamond-Mortensen-Pissarides random search and matching model with endogenous vacancy creation and endogenous job search intensity the following 3 features: (1) job search censoring amongst current UI recipients, (2) duration-dependent job search inefficiency, and (3) heterogeneous search costs. In the model, current UI recipients must comply with the UI job search requirements to maintain their UI eligibility, but they are able to censor their job search intensity which can lower their search cost at the expense of a lower job finding probability. The heterogeneous search cost feature, which will be discussed later in this section, is necessary to enable a high search intensity amongst exogenously inefficient job searchers.

At the end of this section, I briefly introduce the stochastic version of the model which is built onto Rujiwattanapong (2019). The model further contains (1) stochastic aggregate productivity, (2) stochastic match-specific productivity, (3) unemployment-dependent UI extensions, (4) heterogeneous benefit levels, and (5) on-the-job search. These dynamic features enable the model to generate endogenous match separations, endogenous match formations, and countercyclical UI extensions which are suitable to study the effects of job search imperfections on the behaviour of aggregate search intensity, matching efficiency, labour market dynamics and the extent of UI extensions.

3.1 Preferences

Time is discrete and goes on forever. The economy is populated by a continuum of workers of mass one and a large continuum of firms. Both workers and firms are infinitely-lived, risk neutral and ex ante identical. They both discount future payoffs by the factor $\beta \in (0, 1)$. A worker-firm match consists of one worker and one firm. It produces output of amount z. Its price is normalised to one. A given match is exogenously separated with probability $\delta \in (0, 1)$.

3.1.1 Workers

Workers can either be employed (E) or unemployed. There are 3 unemployment statuses: (1) current UI recipient (B), (2) former UI recipient (X) and (3) non-UI recipient (N). Only current UI recipients receive UI benefits. Workers can only become former UI recipients if they exhaust UI and still remain unemployed. The difference between former UI recipients and non-UI recipients is that the former have a lower job search efficiency due to the duration dependence. Only unemployed workers search for a job.[14]

Job search I assume that, in order to maintain UI eligibility, current UI recipients (B) must comply with UI job search requirements. Specifically, they must exert $\underline{s_B}$ each period as required by the UI office. Nonetheless, they may optimally censor their search intensity at rate $1 - \gamma_B$; $\gamma_B \in (0, 1)$ in order to lower their disutility from job search at the expense of a lower job finding probability. As a result, current UI recipients' observed job search intensity is $\underline{s_B}$ whilst their effective search intensity is $\gamma_B \underline{s_B} (< \underline{s_B})$ since γ_B is unobservable to the econometrician. In principle, current UI recipients may exert more than $\underline{s_B}$ in terms of the effective job search intensity. However, under plausible sets of parameters, $\underline{s_B}$ is always higher than the intensity that a current UI recipient would have optimally exerted had there been no UI job search requirements. For the brevity of the model, I only present the possible case where γ_B is always less than unity.[15]

Former UI recipients (X) can freely and optimally choose their job search intensity, s_X, which is their observed intensity. However, since their job search is inefficient due to the duration dependence, I assume that one unit of their job search intensity translates into a fraction $\gamma_X \in (0, 1)$ in terms of the effective search intensity. That is, their effective job search intensity is $\gamma_X s_X (< s_X)$. As for non-UI recipients (N), they can also freely and optimally choose their job search intensity, s_N. Unlike former UI recipients, their job search is not inefficient, and hence s_N is both the observed and effective search intensities.[16] γ_X is unobservable to the econometrician and can be regarded as the search efficiency of former UI recipients relative to non-UI recipients.

[14]On-the-job search will be allowed in the stochastic model.

[15]If $\underline{s_B}$ is set to be low enough, a current UI recipient may optimally choose γ_B that is greater than unity. In which case, the censoring rate is bounded from below at zero, and both the observed and effective search intensities coincide at $\gamma_B \underline{s_B} (> \underline{s_B})$. The job finding probability and the search disutility cost are also functions of $\gamma_B \underline{s_B}$. As previously mentioned, under plausible sets of parameters, γ_B is always less than unity; that being said, the model solution nests the case where γ_B may be greater than unity.

[16]In the stochastic version of the model, I allow for the duration-dependent search inefficiency to apply to all unemployed workers including the non-UI recipients. Under the standard calibration, however, the results are largely unaffected since the expected unemployment duration of non-UI recipients is significantly lower than 6 months implying that the majority of these workers do not remain unemployed long enough to experience a search efficiency drop. In fact, non-UI recipients search harder in their first months of unemployment (to avoid the search efficiency drop) which in turn amplify the difference in the job search intensities between unemployed workers with and without a UI history even further.

Workers incur a disutility from job search according to a quadratic search cost function $c(s) = a \cdot s^2; a > 0$ where s is the search intensity.[17] I further allow the parameter in the cost function for former UI recipients to be different from others, namely, their cost function is $c_X(\cdot) = a_X \cdot s^2; a > a_X > 0$. This is necessary for the model to produce a higher optimal search intensity amongst former UI recipients than non-UI recipients (which will be discussed in detail in the Bellman equation subsection). It is useful to note that if current UI recipients decide to censor some of their job search, their search cost will fall. On the other hand, former UI recipients do not face a smaller cost of job search due to their search inefficiency. Therefore, for workers of statuses $\{B, X, N\}$, their search costs are respectively $c(\gamma_B \underline{s_B}), c_X(s_X)$ and $c(s_N)$.

Utility flows Employed workers receive a wage w determined via Nash bargaining. All unemployed workers receive some leisure flow h. On top of that, current UI recipients also receive UI benefit b.

3.1.2 Firms

Firms are either matched with one worker or unmatched. Unmatched firms pay a vacancy posting cost κ each period to attract workers. Matched firms produce and sell output of value z. They pay wage w to their workers. They also pay a lump-sum tax τ which is used to finance UI payments.

3.2 Matching technology

Workers and firm meet via a matching function $M(s, v) = \frac{sv}{(s^\alpha + v^\alpha)^{\frac{1}{\alpha}}}; \alpha > 0$, where s is the aggregate search intensity and v is the number of vacancies.[18] The aggregate search intensity is defined as the number of searchers augmented by their respective effective search intensity. Let $u_j; j \in \{B, X, N\}$ denote the number of unemployed workers of status j. The aggregate search intensity is then $s = \gamma_B \underline{s_B} u_B + \gamma_X s_X u_X + s_N u_N$.

Let us denote $\theta = \frac{v}{s}$ as the market tightness and the job finding probability per unit of search intensity as $p(\theta) \equiv \frac{M(s,v)}{s} = M(1, \theta)$. The job finding probability of a worker of status $j \in \{B, X, N\}$ is simply $p(\theta)$ augmented by his/her effective search intensity. As a result, for current UI recipients, former UI recipients and non-UI recipients, their job finding probabilities are, respectively, $p_B(\gamma_B, \theta) = \gamma_B \underline{s_B} p(\theta)$, $p_X(s_X, \theta) = \gamma_X s_X p(\theta)$

[17] The quadratic search cost function is consistent with Christensen et al. (2005) and Yashiv (2000). Additionally, the model-generated elasticity of unemployment duration with respect to the maximum UI duration is well in line with the existing empirical estimates which is discussed in the results section.

[18] This matching function is similar to that in den Haan, Ramey and Watson (2000) apart from the search intensity that is augmented in this model.

and $p_N(s_N, \theta) = s_N p(\theta)$. The job-filling rate of a firm with a vacancy can be defined analogously as $q(\theta) \equiv \frac{M(s,v)}{v} = M(\frac{1}{\theta}, 1)$.

3.3 UI take-up, exhaustion and finance

UI take-up I assume that once employed workers are separated from their matches, an event which occurs with probability δ, a fraction $\psi \in (0, 1)$ of the newly separated workers does not receive UI. That is, upon job separation, a fraction $(1 - \psi)$ becomes current UI recipients whilst the rest (ψ) becomes non-UI recipients. There is no direct transition from employment to the former UI recipient status. The parameter ψ represents factors that determine whether a worker would receive UI including eligibility as well as unobserved heterogeneity in costs related to taking up UI (such as stigma and leisure time).[19] Even though this is a simple way to capture the UI take-up, I relegate to the Results section to demonstrate that the model can replicate the empirical shares of unemployed workers with and without a UI history and their dynamics quite well.

UI exhaustion I assume that, in each period, current UI recipients exhaust their benefits with probability $\phi \in (0, 1)$ and, conditional on remaining unemployed, become former UI recipients. With probability $(1 - \phi)$, current UI recipients still receive UI in the next period given that they remain unemployed. Given that agents are risk neutral, the inverse of ϕ also represents the expected duration of collecting UI. It is impossible for current UI recipients to directly transition to a non-UI recipient status.

UI finance The budget for UI is balanced every period by imposing lump-sum tax on producing firms. Let u and u_B denote respectively the numbers of unemployed workers and current UI recipients. We have that $bu_B = \tau(1 - u)$.

[19]It should be noted that, due to the current UI recipients' ability to censor job search applications in this model, the value of being a current UI recipient always exceeds that of a non-UI recipient for ex ante identical workers. Therefore, if presented with a choice whether to take up UI, workers in the model will always prefer to take up unless further heterogeneity is present. For example, costs related to taking up UI and maintaining UI eligibility may be heterogeneous in reality. The probability ψ is assumed to be fixed mainly due to model tractability. As documented in Auray, Fuller and Lkhagvasuren (2019), endogenising the UI take-up rate will primarily reinforce the effects of UI as those more unlikely to exit unemployment will be the majority of UI recipients. Therefore, the results in this paper can be regarded as the lower bound of these effects.

3.4 Value functions

Unemployed workers The values of being current UI recipients (B), former UI recipients (X) and non-UI recipients (N) can be expressed, respectively, as

$$
\begin{aligned}
U_B &= \max_{\gamma_B} \; b + h \underbrace{-c(\gamma_B \underline{s_B})}_{\text{disutility from not censoring}} \\
&\quad + \beta\Big[\underbrace{p_B(\gamma_B,\theta)}_{Pr(B\to E)} W_B + \big(1 - p_B(\gamma_B,\theta)\big)\Big((1-\phi)U_B + \underbrace{\phi}_{\text{Pr(UI exhausted)}} U_X\Big)\Big] \qquad (1) \\
U_X &= \max_{s_X} \quad h \underbrace{-c_X(s_X)}_{\text{disutility from search}} + \beta\Big[\underbrace{p_X(s_X,\theta)}_{Pr(X\to E)} W_X + \big(1-p_X(s_X,\theta)\big)U_X\Big] \qquad (2) \\
U_N &= \max_{s_N} \quad h \underbrace{-c(s_N)}_{\text{disutility from search}} + \beta\Big[\underbrace{p_N(s_N,\theta)}_{Pr(N\to E)} W_N + \big(1-p_N(s_N,\theta)\big)U_N\Big] \qquad (3)
\end{aligned}
$$

where $U_j \; ; j \in \{B, X, N\}$ denotes the value of being unemployed with status j, and $W_j \; ; j \in \{E, B, X, N\}$ denotes the value of being employed with the last-period status being j. The worker's (un)employment status last period matters because of the Nash-bargained wages. Workers with a higher outside option may be able to bargain for a higher wage than workers with a lower outside option. The wage bargaining process is discussed in detail later in this section.

Employed workers The value of being an employed worker whose status last period is $j \in \{E, B, X, N\}$ is

$$
W_j = w_j + \beta\Big[\underbrace{(1-\delta)}_{\text{Pr(match survives)}} W_E + \underbrace{\delta}_{\text{Pr(match destroyed)}} \Big((1-\psi)U_B + \underbrace{\psi}_{\text{Pr(not taking up UI)}} U_N\Big)\Big]
$$

where W_E represents the value of an employed worker who was also employed last period, and $w_j \; ; j \in \{E, B, X, N\}$ is the Nash-bargained wage of an employed worker whose status last period is j.

Matched firms The value of a firm being matched to a worker whose status last period is $j \in \{E, B, X, N\}$ is

$$
J_j = z - w_j - \tau + \beta(1-\delta)J_E
$$

Note that, in the above equation, I already assume the free entry condition which implies that the value of an unmatched firm (with a vacancy) is always zero.

Unmatched firms The value of an unmatched firm with a vacancy under the free entry condition is

$$0 \;=\; -\kappa + \beta q(\theta)\left[\frac{\sum_{j\in\{B,X,N\}} \tilde{s}_j u_j J_j}{s}\right]$$

where $\tilde{s}_j$; $j \in \{B, X, N\}$ denotes the effective search intensity of type-j workers, u_j ; $j \in \{B, X, N\}$ denotes the number of unemployed workers of type j, and s is the aggregate search intensity. Specifically, we have $\tilde{s}_B = \gamma_B \underline{s_B}$, $\tilde{s}_X = \gamma_X s_X$, $\tilde{s}_N = s_N$, and $s = \sum_{j\in\{B,X,N\}} \tilde{s}_j u_j$.

3.5 Optimal search intensity and heterogeneous search costs

Due to the convex disutility cost of job search and the fact that the job finding probability increases linearly in the search intensity, the presence of search inefficiency ($0 < \gamma_X < 1$) only discourages workers from searching. To demonstrate this, let us consider the first order conditions for the optimal job search intensities for former UI and non-UI recipients using equations (2) and (3), respectively:

$$\begin{aligned}
\frac{\partial c_X(s_X^*)}{\partial s_X} = 2 \cdot a_X \cdot s_X^* \;&=\; \beta \cdot \gamma_X \cdot p(\theta) \cdot (W_X - U_X) \\
\frac{\partial c(s_N^*)}{\partial s_N} = \;\; 2 \cdot a \cdot s_N^* \;&=\; \beta \cdot p(\theta) \cdot (W_N - U_N)
\end{aligned}$$

where s_j^* denotes the optimal search intensity of worker of status $j \in \{X, N\}$. For simplicity, let us further assume that employment is an absorbing state, i.e., there is no job separation. Then we have the limiting case where the gains from being employed for unemployed workers of status $j \in \{X, N\}$ are the same. This implies $\lim_{\delta\to 0} \frac{W_X - U_X}{W_N - U_N} = 1$. It is now obvious that in order for former UI recipients to optimally search harder than non-UI recipients, i.e., $s_X^* > s_N^*$, it must be the case that $\frac{a_X}{a} < \gamma_X < 1$.[20] Namely, the search cost parameter for former UI recipients (a_X) must be strictly smaller than that of other unemployed workers without search inefficiency (a). Intuitively, one may interpret the smaller search cost for former UI recipients as the job search experience accumulated for at least 6 months prior to exhausting UI.

Moving away from the limiting case, it is useful to note that generally $\frac{W_X - U_X}{W_N - U_N} < 1$ when $\delta > 0$ because former UI recipients have a lower potential wage than non-UI recipients and, therefore, have a lower gain from being employed. This implies the search cost parameter for former UI recipients must be strictly smaller than the one considered in

[20]Had workers of these two statuses shared the same search cost parameters ($a_X = a$), it would have been impossible to observe $s_X^* > s_N^*$ unless γ_X is less than unity.

the limiting case of $\delta \to 0$ above.

Optimal censoring For current UI recipients who face job search requirement $\underline{s_B}$ and can choose the rate at which they censor their job search intensity optimally, solving for the optimal censoring rate is comparable to solving for the optimal job search intensity had they not faced UI job search requirement. Let s_B^* denote the optimal search intensity if there was no search requirement. The optimal censoring rate $(1-\gamma_B^*)$ satisfies $\gamma_B^* \underline{s_B} = s_B^*$.

3.6 Wages and surpluses

Wages are negotiated every period between a worker and a firm using a generalised Nash bargaining rule. Workers whose last-period employment status is $j \in \{E, B, X, N\}$ receive a wage

$$w_j \quad = \quad \text{argmax} \Big(WS_j\Big)^{\mu} \Big(J_j\Big)^{(1-\mu)}$$

where $\mu \in (0,1)$ is the worker's bargaining power, $(1-\mu)$ is the firm's bargaining power, and WS_j denotes the surplus from being employed for workers with the last-period status j. This surplus can vary by their (un)employment status last period due to the associated outside options. Specifically, for $j \in \{E, B, X, N\}$, we have

$$\begin{aligned}
WS_E &= W_E - \big((1-\psi)U_B + \psi U_N\big) \\
WS_B &= W_B - \big((1-\phi)U_B + \phi U_X\big) \\
WS_X &= W_X - U_X \\
WS_N &= W_N - U_N
\end{aligned}$$

Furthermore, we can define the total surplus of match between a worker whose status last period is j and a firm as $S_j \equiv WS_j + J_j$ for $j \in \{E, B, X, N\}$. Given the Nash-bargained wage w_j, the worker's surplus and the firm's surplus are simply a fraction of the total match surplus where the weights are their respective bargaining powers. Namely, we have $WS_j = \mu S_j$ and $J_j = (1-\mu)S_j$.

3.7 Transitions

The evolutions of the stocks of current UI recipients (u_B), former UI recipients (u_X) and non-UI recipients (u_N) can be summarised, respectively, as

$$\begin{aligned} u_{B,t+1} &= \big(1 - p_B(\gamma_{B,t}, \theta_t)\big)(1-\phi)u_{B,t} + \delta\psi(1-u_t) && (4) \\ u_{X,t+1} &= \big(1 - p_X(s_{X,t}, \theta_t)\big)u_{X,t} + \big(1 - p_B(\gamma_{B,t}, \theta_t)\big)\phi u_{B,t} && (5) \\ u_{N,t+1} &= \big(1 - p_N(s_{N,t}, \theta_t)\big)u_{N,t} + \delta(1-\psi)(1-u_t) && (6) \end{aligned}$$

In equations (4), (5) and (6), the first term on the right hand side represents the number of workers who remain in the same unemployment status in the next period, and the second term on the right hand side represents the number of workers who transition into the respective unemployment status in the next period. Total unemployment (u) is the sum of unemployed workers of the 3 statuses $\{B, X, N\}$:

$$u_t = \sum_{j \in \{B,X,N\}} u_{j,t}$$

Lastly, the evolution of employment can be written as

$$e_{t+1} = 1 - u_{t+1} = (1-\delta)(1-u_t) + p_B(\gamma_{B,t}, \theta_t)u_{B,t} + p_X(s_{X,t}, \theta_t)u_{X,t} + p_N(s_{N,t}, \theta_t)u_{N,t}$$

3.8 Stochastic model

One of the main implications in the deterministic version of the model, where there is no aggregate shock in the economy, is that there are only few workers in the former UI recipient status (X). This is because, given the maximum UI duration of 6 months (as is in the U.S.) and the duration-dependent search inefficiency, most current UI recipients try to exit unemployment relatively quickly.

To study the role of job search imperfections, a stochastic model is therefore suitable as negative shocks to the economy may increase unemployment and trigger UI extensions (as is the case in the U.S. following every recession since the 1950s). I focus on the Great Recession in the U.S. when the maximum UI duration was extended from 26 weeks to 99 weeks. An increase in the UI generosity, such as UI extensions, increases the outside option of current UI recipients who, as a result, may exit unemployment more slowly. At the individual level, I consider two decisions that may lead to a slower unemployment exit rate of current UI recipients: (1) they lower their effective search intensity - via higher search censoring, and (2) they look for a relatively higher wage - via raising the match quality threshold. By allowing worker-firm matches to vary in terms of the match quality, I can also study the endogenous responses of match separation, match retention, match formation and match rejection during a recessionary period with UI extensions.

For the rest of this section, I discuss the additional features and assumptions introduced in the stochastic model (which are built onto Rujiwattanapong (2019)), the resulting state variables and the policy functions. I relegate the following to Appendix B: (1) the timing of the stochastic model, (2) the Bellman equations, (3) the expressions for wages and surpluses, (4) the optimal search intensity/censoring, (5) the transition equations, (6) the government's UI budget, and (7) the equilibrium definition. The model's computational solution is discussed in section 3.4 of Rujiwattanapong (2019).

3.8.1 Additional features and assumptions in the stochastic model

Stochastic aggregate productivity The aggregate productivity, z, evolves stochastically over time according an AR(1) process: $\ln z_t = \rho_z \ln z_{t-1} + \varepsilon_t$; $\varepsilon_t \sim N(0, \sigma_z^2)$. ε_t represents the independent and normally distributed shocks to the aggregate productivity whose variance is σ_z^2.

Match quality and output Once a worker and a firm meet via the matching function, they together draw a match quality m from an exogenous distribution $F(m)$. The output of a match is defined as $y = mz$. For existing worker-firm matches, they face a probability λ of having their match qualities being redrawn from $F(m)$ in each period. Since the match quality affects output and wages, I also assume that the UI benefits are a function of m in the last employment period for current UI recipients.

Endogenous UI extensions To replicate the UI extension system in the U.S. where a high unemployment rate triggers UI extensions, I assume the UI exhaustion rate is a function of unemployment, $\phi(u)$. Namely,

$$\phi(u) \quad = \quad \begin{cases} \phi & \text{when} \quad u < \bar{u} \\ \phi_L & \text{when} \quad u \geq \bar{u} \end{cases}$$

where $\phi_L < \phi$ and $\bar{u}$ denotes the unemployment threshold above which the maximum UI duration is extended. As the inverse of the UI exhaustion rate represents the expected duration of receiving UI conditional on remaining unemployed, a drop in the exhaustion rate when unemployment is high implies an increase in the expected maximum UI duration.

Duration dependence By assuming that the duration-dependent search inefficiency occurs to all unemployed workers whose unemployment duration is at least 6 months, i.e., long-term unemployed workers, some current UI recipients may already experience a drop in search efficiency before exhausting UI if the UI is extended by more than 6 months. Due to this, UI recipients are separated into (1) short-term-unemployed UI recipients, denoted by Bs, and (2) long-term-unemployed UI recipients, denoted by $B\ell$. Additionally, non-UI recipients may also experience this search efficiency drop if they become long-term unemployed. Therefore, they can either be (1) short-term-unemployed non-UI recipients, denoted by Ns, and (2) long-term-unemployed non-UI recipients, denoted by $N\ell$. All long-term unemployed workers face the same search cost $c_X(\cdot)$.

UI Monitoring Additionally, I assume that in each period there is a probability $\xi \in (0,1)$ that a current UI recipient who has a meeting with a firm but decides to remain unemployed (which is more likely amongst those with a higher UI benefit) becomes ineligible for UI next period. This assumption captures the (imperfect) monitoring of the UI system where UI recipients are required to be "able, ready and willing to accept a suitable job" to maintain their UI eligibility according to the Employment and Training Administration (ETA), the U.S. Department of Labor.

On-the-job search On-the-job search allows employed workers with low match qualities to find better matches and improve their wage outcomes and potential UI benefits (since the benefits are a function of the previous wage). On the mechanical side, on-the-job search enables a random search and matching model with endogenous match separations to generate a qualitatively realistic correlation between vacancies and unemployment, namely, the Beveridge curve.[21] I allow for the scaling parameter of the employed workers' search cost function to be different from those of the unemployed workers so that the model can replicate the empirical job-to-job transition rate which is noticeably lower than the job finding rate of the unemployed. Namely, the search cost function of the employed is $c_E(s) = a_E \cdot s^2; a_E > 0$.

3.8.2 State variables

Given the additional features introduced in the stochastic model, the set of state variables is $\{z, e(m), u_{Bs}(m), u_{B\ell}(m), u_X, u_{Ns}, u_{N\ell}; \forall m\}$. Namely, they are the aggregate productivity, the distribution of employed workers by match quality, the distribution of current UI recipients by unemployment duration (short- and long-term) and benefit level (as proxied by the match quality in their last employment period), the number of former UI recipients, and the numbers of short-term and long-term non-UI recipients respectively.[22] Note that the distribution of workers by employment, match quality, UI status and unemployment duration is important for the agents in the model for two reasons.

[21]See, for example, Fujita and Ramey (2012) and Rujiwattanapong (2019).

[22]One of the worker measures may be dropped out of this set since the population size is always unity.

First, this distribution is necessary for the unmatched firms to computed the expected discounted value of posting a vacancy since the search is random and firms cannot direct their search towards a specific type of workers. Second, workers need to know this distribution to accurately predict the unemployment rate next period and, in effect, how likely the maximum UI duration will change.

3.8.3 Policy functions

In this section, I discuss how the relevant policy functions (namely, match separation, match formation and optimal search intensity) can be affected by the state variables in the stochastic model.

Match separation and formation For both workers and firms, the decision to form a match or to separate from a match boils down to whether the total match surplus has a positive value. This is because a worker and a firm always take a fixed fraction from the match surplus (with the fraction determined by the respective bargaining power) as discussed earlier in the Wages section.[23] Hence, analysing the responses of match formation and separation to shocks is analogous to analysing how the total match surplus responds to those shocks.

Since both the aggregate productivity z and match quality m positively affect the size of the total match surplus, match formation (separation) is more (less) likely when the values of z and/or m are high. On the other hand, higher unemployment, u, implies that UI is more likely to be extended or that the UI extension is more likely to be sustained. Since a more generous UI policy increases the current UI recipients' outside option, the gain or the surplus of being employed for these workers fall. A current UI recipient with a higher UI benefit level, $b(m)$, also has a smaller gain from being employed. As a result, the total match surplus with a current UI recipient tend to decrease when u or $b(m)$ becomes higher.

Optimal search intensity Since a higher aggregate productivity z increases the value of being employed, the optimal search intensities for both former and non-UI recipients increases in z. That is, their individual search intensity is procyclical.[24] For current UI recipients, they censor their job search more when the gain from searching is smaller. Therefore, job search censoring is more severe when u is high (and a UI extension is

[23]It is useful to note that in the general search-and-matching framework, including this paper, the decision to form a match or to separate from a match is always mutual between a worker and a firm.

[24]In the result section, I will also explore a scenario where individual job search does not respond to the aggregate productivity.

more likely) as well as when their UI benefit level, $b(m)$, is high.[25] For employed workers who search on the job in this stochastic model, their optimal search intensity tend to fall when they have a higher match quality since the gain from searching on the job becomes smaller.

4 Calibration

For the main calibration strategy, there are in total 12 parameters to be calibrated to match 12 targeted moments for the U.S. economy during 1948-2007 using the Simulated Method of Moments. Table 4 summarises the targeted moments used in the calibration exercise. To study the implications of the duration-dependent search inefficiency, the same table also reports the results from a model where this feature is shut down, i.e., when γ_X is set to unity.[26]

Table 4: Targeted and non-targeted moments.

Targeted moments				Non-targeted moments			
Moment	Data	Baseline	$\gamma_X = 1$	Moment	Data	Baseline	$\gamma_X = 1$
E(u)	0.0583	0.0569	0.0577	E($U1$)	0.0233	0.0243	0.0237
E(ρ_{UE})	0.4194	0.4414	0.4286	E($U2$)	0.0172	0.0183	0.0180
E(ρ_{EU})	0.0248	0.0259	0.0251	E($U4$)	0.0080	0.0075	0.0085
E(ρ_{EE})	0.0320	0.0316	0.0320	E(LTU)	0.0098	0.0066	0.0076
E($udur$)	15.416	12.251	13.063	std($U1$)	0.0048	0.0015	0.0017
E(u_B)	0.0290	0.0314	0.0327	std($U2$)	0.0046	0.0027	0.0030
std(u)	0.1454	0.1123	0.1453	std($U4$)	0.0035	0.0033	0.0035
std(ρ_{UE})	0.0999	0.1035	0.1402	std(LTU)	0.0085	0.0090	0.0107
std(ρ_{EU})	0.0890	0.0517	0.0641	std(u_B)	0.1780	0.2059	0.2523
std(LP)	0.0131	0.0106	0.0104	std(v)	0.1226	0.0557	0.0123
corr(LP, LP_{-1})	0.7612	0.7609	0.7593	corr(u, v)	-0.6682	-0.2077	-0.0706
E(ρ^X_{UE}/ρ^N_{UE})	0.7983	0.8012	1.0000				

- $\gamma_X = 1$: no duration-dependent job search inefficiency. ρ_{UE}: job finding probability. ρ_{EU}: job separation probability. ρ_{EE}: job-to-job transition probability. u_{dur}: average unemployment duration (weeks). $LP = y/(1-u)$: output per worker (quarterly). ρ^j_{UE}: job finding probability of type-j workers. $U1$: unemployed less than 1 month. $U2$: unemployed with 2-3 months of duration. $U4$: unemployed with 4-6 months of duration. LTU: unemployed longer than 6 months (long-term unemployment). Data source: BEA and CPS. Job finding and job separation probabilities are calculated following Shimer (2005).

[25] Using the CPS monthly data and CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplements, Rujiwattanapong (2024) documents that the job finding probability of current UI recipients is decreasing in the unemployment benefit level (implied by the weekly earnings in the worker's previous job and the respective state's unemployment benefit calculation) and to a greater extent during the Great Recession.

[26] Note that in this scenario, there are 11 parameters to be calibrated and the one moment not included in the calibration is the relative job finding probability of former UI recipients to non-UI recipients.

Table 5 reports the parameters to be calibrated which can be categorised into 6 groups: (1) search cost functions, (2) matching function, (3) match quality, (4) job separation, (5) UI, and (6) aggregate productivity. Although each parameter may affect more than one moment but certain relationships can be distinguished. The scaling parameters in the search cost functions for the former UI recipients and the employed workers (a_X and a_E) are calibrated to match, respectively, the relative job finding probability of former UI recipients to non-UI recipients and the job-to-job transition probability. The matching function parameter (α) is set to match the average unemployment rate. I assume that the match quality m follows a Beta distribution with three parameters $\{\underline{m}, \beta_1, \beta_2\}$. Specifically, $F(m) = \underline{m} + \text{betacdf}(m - \underline{m}, \beta_1, \beta_2)$. These 3 parameters along with the probability of redrawing a new match quality (λ) are calibrated to match the average job finding probability, the average unemployment duration, and the standard deviations of job finding and job separation probabilities. The exogenous job separation probability (δ) is responsible for the average job separation probability. Parameters related to UI (ψ and ξ) are calibrated to match the average share of current UI recipients in the labour force and the standard deviation of unemployment. Lastly, the aggregate productivity parameters (ρ_z and σ_z) are set to match the autocorrelation and the standard deviation of the labour productivity.

Table 5: Calibrated parameters.

Parameter	Description	Baseline	$\gamma_X = 1$
a_X	Search cost parameter	0.0717	n/a
a_E	Search cost parameter	0.2002	0.2011
α	Matching function parameter	0.4986	0.5087
$\underline{m}$	Lowest match-specific productivity	0.3836	0.3960
β_1	Match-specific productivity distribution	2.5734	2.5495
β_2	Match-specific productivity distribution	5.3948	5.2649
λ	Pr(redrawing new m)	0.5001	0.5001
δ	Exogenous separation rate	0.0249	0.0230
ψ	Pr(losing UI after becoming unemployed)	0.4901	0.4901
ξ	Pr(losing UI after meeting firm)	0.4999	0.5002
ρ_z	Persistence of TFP	0.9581	0.9562
σ_z	Standard deviation of TFP shocks	0.0086	0.0075

- $\gamma_X = 1$: no duration-dependent job search inefficiency.

Overall, the baseline model performs well in matching the targets as shown in Table 4. Particularly, the baseline model generates a realistically lower job finding probability of former UI recipients compared to non-UI recipients. In the model without search inefficiency ($\gamma_X = 1$), however, former UI recipients and non-UI recipients have an identical job finding probability. The baseline model also generates a more realistic share of current UI recipients as well as a more realistic volatility of job findings. With respect to the non-targeted moments as summarised in Table 4, since the baseline model delivers a more moderated share of current UI recipients, it produces a much more realistic volatility of the series. In effect, this makes total unemployment more moderated and generates a more realistic Beveridge curve as measured by the correlation between unemployment and vacancies compared to the model without search inefficiency. The volatility of the vacancies in the baseline model also improves upon the alternative model without search inefficiency despite being lower than the empirical counterpart.

Pre-specified parameters Tables 6, 7 and 8 summarise the pre-specified parameters. I set the discount factor β to imply a 4% annual interest rate. The vacancy posting cost κ is set according to the findings in Fujita and Ramey (2012) regarding the time an average firm spent on recruiting a worker. Following den Haan, Ramey and Watson (2000), the worker bargaining power μ is set to be 0.5. The UI exhaustion rates are set according to the observed maximum UI durations in the U.S. during normal and recessionary periods. That is, ϕ is set to imply an average duration of collecting UI for 6 months whilst ϕ_L's are set to imply the extended durations of collecting UI during different recessions in the U.S. with the Great Recession being the longest of 99 weeks. To capture the UI extension policy that was gradually implemented in different tiers throughout the Great Recession, I assume that ϕ_L changes exogenously to match the policy announcements following Rujiwattanapong (2024).[27] Table 7 summarises the full timeline for the values that ϕ_L takes. It is useful to note that the model's UI exhaustion rate is still a function of unemployment, and any UI extension only occurs when the unemployment rate exceeds the threshold $\bar{u}$ which is set to be 6.5% based on information from the Employment and Training Administration (ETA), the U.S. Department of Labor. The search cost function parameter for (short-term) current and non-UI recipients, a, is normalised such that the search intensity for the non-UI recipients is unity when the aggregate productivity is at its mean (also unity). Using the results on consumption drop after losing employment in Gruber (1997), I set $b(m)$'s and h to imply an average 10% consumption drop for those receiving UI (given 50% replacement rate) and a 24% consumption drop for those not receiving UI. The resulting unemployment benefit levels are summarised in Table 8. The search inefficiency parameter γ_X is set such that the former UI recipients' optimal search intensity is 11 percent higher than that of the non-UI recipients on average. Lastly, the UI job search requirement $\underline{s_B}$ is set based on the average search intensity of the current UI recipients relative to non-UI recipients.

[27] Acosta et al. (2023) provides a detailed account of UI extensions at the state level and relevant trigger variables. They also developed a "UI Benefits Calculator" that accurately predicts whether a given state experienced UI extension(s) dating back to 1976.

Table 6: Pre-specified parameters.

Parameter	Description	Value	Sources/remarks
β	Discount factor	0.9967	Annual interest rate of 4%
γ_X	Search inefficiency of X-type	0.7131	Relative search intensity of X- to N-type, CPS
κ	Vacancy posting cost	0.0392	Fujita and Ramey (2012)
μ	Worker's bargaining power	0.5000	den Haan, Ramey and Watson (2000)
a	Search cost function	0.1116	Normalisation
h	Leisure flow	0.5835	Gruber (1997)
$\underline{s_B}$	UI job search requirement	1.1230	CPS
$\bar{u}$	UI policy threshold	0.0650	ETA

Table 7: Possible UI exhaustion rates and implied potential maximum UI durations (weeks). Source: ETA and Rujiwattanapong (2024).

Parameter	Value	Duration (weeks)	Time periods (MM/YYYY)
ϕ_{L1}	52/(39×12)	39	01/1948-12/1971, 01/1975, 09/1982, 11/1991, 07/2008-10/2008.
ϕ_{L2}	52/(46×12)	46	01/2014-06/2014.
ϕ_{L3}	52/(52×12)	52	01/1971-12/1974, 11/1977-08/1982, 10/1982-10/1991, 11/1993-02/2002.
ϕ_{L4}	52/(65×12)	65	02/1975-10/1977, 08/1992-10/1993, 11/2008-10/2009.
ϕ_{L5}	52/(72×12)	72	12/1991-07/1992, 03/2002-06/2008.
ϕ_{L6}	52/(79×12)	79	11/2009-12/2009.
ϕ_{L7}	52/(99×12)	99	01/2010-12/2013.
ϕ	52/(26×12)	26	01/1948-06/2014. (whenever UI is not extended ($u_t < 6.5\%$))

Table 8: Unemployment benefit levels as a function of a worker's match quality in the most recent employment period. m_x denotes the x-th decile of the match quality distribution $F(m)$.

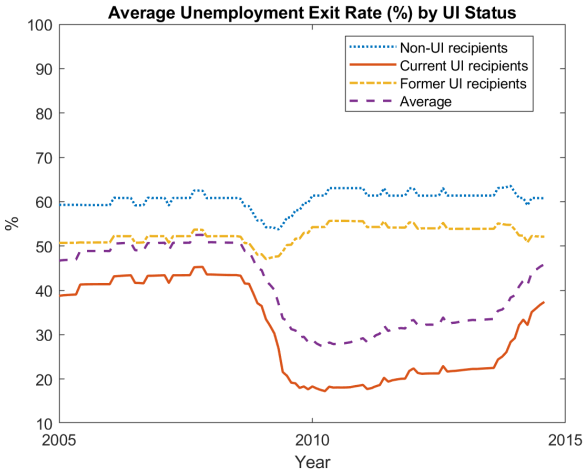
	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}
$b(m)$	0.001	0.008	0.020	0.035	0.049	0.063	0.084	0.103	0.135	0.284
m	0.495	0.550	0.606	0.643	0.680	0.717	0.772	0.828	0.921	1.365

5 Results

The results in this section are obtained by feeding in (1) the path of aggregate productivity, z, such that the model generates a series of deviations of output (GDP per capita) from its HP trend that is identical to the empirical counterpart, and (2) the potential extended UI durations, ϕ_L's, observed between 1948 and 2015, which can only be triggered when the model's unemployment rate is greater than 6.5 percent.

I first analyse the job search behaviour and job findings during the Great Recession, an episode during which the maximum UI duration was extended from 26 to 99 weeks in the model. Particularly, I study the implications on the aggregate search intensity and matching efficiency. To validate the model, I also discuss how the model fares in terms of generating dynamic shares of unemployed workers by UI history during the Great Recession. Subsequently, I proceed to discuss how the effects of UI extensions on labour market variables during the Great Recession interact with the duration-dependent search

Figure 4: Job finding probabilities during the Great Recession by UI status.



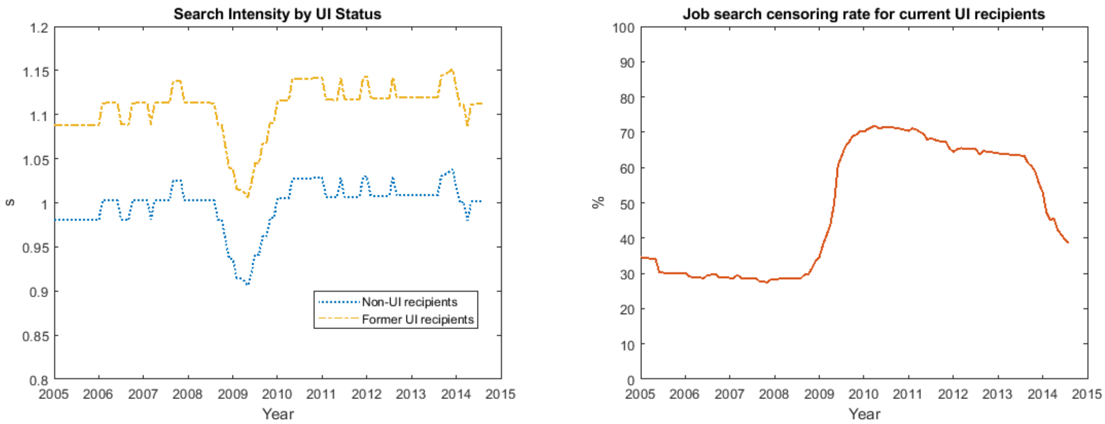
inefficiency. Lastly, I discuss the implications of introducing search inefficiency on the labour market persistence and fluctuations.

5.1 Job search and job findings during the Great Recession

Job findings Figure 4 summarises the responses of job finding probabilities by UI status during the Great Recession. As expected, the job finding probability of former UI recipients is lower than that of non-UI recipients but both are mildly procyclical. The average job finding probability, however, is strongly procyclical which is mainly due to a large fall in the job finding probability of current UI recipients.

Job search and job censoring Even though the former UI recipients find jobs more slowly than non-UI recipients, the baseline model generates a higher search intensity amongst former UI recipients comparing to non-UI recipients as depicted in the left panel of Figure 5. Note that the observed search intensity of current UI recipients is always $\underline{s_B} \equiv 1.12$ and does not reflect the true or effective search intensity. The right panel of Figure 5 summarises the job search behaviour of current UI recipients during the Great Recession. They censor their job search intensity more strongly when there are UI extensions because these extensions increase their outside option and, thereby, lower the gain from searching for a job. Additionally, the higher outside option increases the acceptable match quality threshold for current UI recipients and makes it less likely for them to transition back into employment. As a result, the job finding probability of current UI recipients responds more negatively during the Great Recession and contributes to a large fall in the average job finding probability. Considering that Faberman et al. (2022) find that, on average, unemployed workers reject 47% of their best job offers and 52% of all offers, the baseline model's average job search censoring rate of current UI recipients of 37% is reasonable and within the empirical range.

Figure 5: Job search intensities by UI status (left) and job search censoring of current UI recipients (right) during the Great Recession.



5.2 Aggregate search intensity and matching efficiency during the Great Recession

Aggregate search intensity Despite the fact that the effective search intensity at the individual level is always procyclical regardless of the UI status, the observed aggregate search intensity may behave differently due to the composition of unemployed workers and the fact that job search censoring and job search inefficiency are not observable to the econometrician. The UI extensions during the Great Recession increase the share of unemployed workers who are current UI recipients with a high observed search intensity (due to the UI job search requirement). As a result, the observed aggregate search intensity generated by the baseline model is actually acyclical and mimics the dynamics of the empirical counterpart relatively well as shown in the left panel of Figure 6, although the data exhibits a slightly stronger countercyclicality.[28] In the data, the higher share of former UI recipients with a high search intensity also contributes to this countercyclicality whilst the model does not generate enough former UI recipients (which will be discussed next in the unemployment decomposition exercise). Nonetheless, the observed search intensity is a stark contrast to the effective search intensity which takes into account search inefficiency and search censoring. The effective search intensity exhibits a strong procyclical pattern and its mean is lower than that of the observed search intensity.

Matching efficiency The contrasting cyclical behaviours of effective and observed job search intensities have a direct and important implication on the matching efficiency. Particularly, if one uses the observed aggregate search intensity as a measure for the aggregate search intensity in the matching function (instead of the effective aggregate search intensity), then the rise in unemployment during the Great Recession may be

[28] Given the model's normalisation of search intensity, the empirically observed aggregate search intensity is also normalised such that the average search intensity of non-UI recipients is the same as in the baseline model.

interpreted as a decline in the matching efficiency. To this extent, I compute the matching efficiency as the residual in the matching function when the observed aggregate search intensity is used. I then compare it to the baseline model where the matching efficiency is assumed to be constant and normalised to unity, and the effective aggregate search intensity is used. For both cases, the vacancy rates are the same and generated by the baseline model. Specifically, let us denote A_t as the matching efficiency (or the residual in the matching function) in period t. We can obtain A_t as follows:

$$A_t = \frac{s_t}{s_{obs,t}} \left(\frac{s_{obs,t}^{\alpha} + v_t^{\alpha}}{s_t^{\alpha} + v_t^{\alpha}} \right)^{\frac{1}{\alpha}}$$

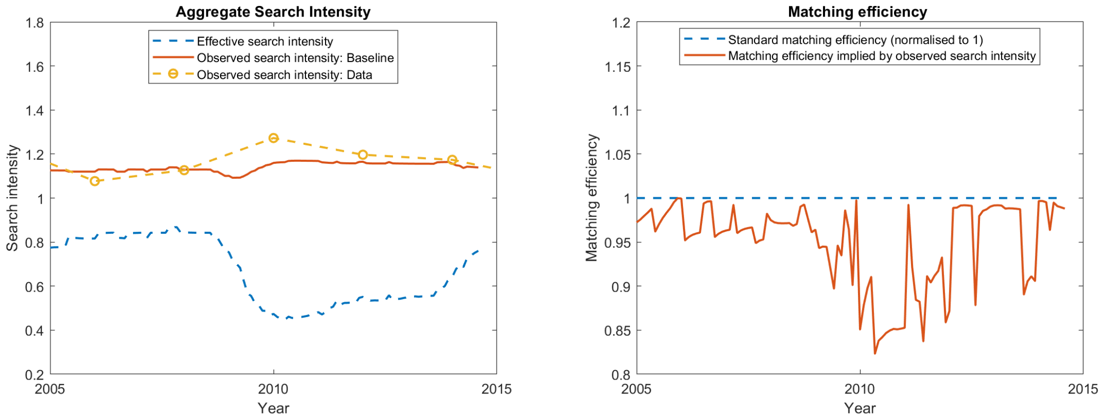
where $s_{obs,t}$ is the observed search intensity in period t, and s_t is the effective search intensity in period t.[29]

As shown in the right panel of Figure 6, we would have interpreted that the matching efficiency declined by up to 18 percent during the Great Recession had we used the observed aggregate search intensity to compute the labour market tightness (and, in effect, the number of potential matches) instead of the effective aggregate search intensity which falls significantly during the Great Recession (the left panel of Figure 6). The main implication of this finding is that using the number of workers (job searchers) to infer the matching efficiency may not be innocuous, especially during recessionary episodes when the unemployment population consists more of those with a UI history (whose job search may be unproductive and/or inefficient). In such scenarios, accounting for the effective search intensities, particularly based on the UI history of workers, can be crucial for accurately estimating the true matching efficiency and its dynamics. This is similar in spirit to the role of (unobserved) variable factor utilisation in estimating the total factor productivity as proposed in the seminal work of Basu, Fernald and Kimball (2006).

With regards to the cyclicality of individual job search intensity, this paper has so far maintained the standard assumption in canonical search models where the individual search intensity increases when the returns to search is higher. That is, the individual job search intensity is procyclical and positively correlated with the aggregate productivity (z). In addition, current UI recipients lower their effective search intensity (via censoring) whenever UI is extended. However, as discussed in the introduction, there is little empirical evidence supporting the procyclicality of search intensity. To explore whether the standard assumption of procyclical individual search intensity drives the main result on matching efficiency, I assume instead that the individual job search intensity and censoring do not respond to changes in the aggregate productivity (z), and that their values

[29] The expression for A_t is from the following equality: $1 \times \frac{s_t v_t}{(s_t^{\alpha} + v_t^{\alpha})^{1/\alpha}} = A_t \frac{s_{obs,t} v_t}{(s_{obs,t}^{\alpha} + v_t^{\alpha})^{1/\alpha}}$.

Figure 6: Aggregate job search intensities (left) and the matching efficiency implied by observed search intensity (right) during the Great Recession. Data source: CPS.



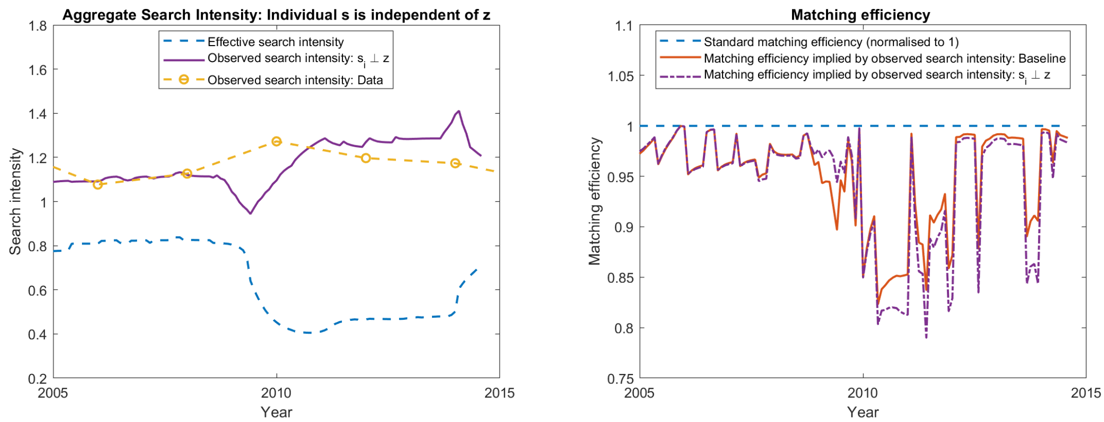
- For the left panel, the effective search intensity refers to the search intensity once job search censoring and job search inefficiency are accounted for. These job search imperfections are not accounted for in the observed search intensity.

are fixed at the mean when z is unity. With this alternative assumption, the observed aggregate search intensity becomes as countercyclical as in the data (since the individual search intensity does not drop after the negative aggregate productivity shocks) whilst the effective aggregate search intensity remains largely the same (as shown in the left panel of Figure 7). In this scenario, the observed aggregate search intensity is more volatile than and deviates from the data by at most 17 percent (whilst it is 9 percent in the baseline case). As a result, the discrepancy between the matching efficiency implied by the observed aggregate search intensity and the true matching efficiency is more pronounced (as shown in the right panel of Figure 7). Specifically, one would interpret that there is a drop in the matching efficiency of up to 21 percent during the Great Recession if the job search imperfections are not accounted for.[30]

Unemployment decomposition To accurately compute the effective aggregate search intensity and, in effect, its implication on the decline of the matching efficiency, it is vital that a model generates realistic shares and evolutions of unemployed workers by UI status (with potentially different effective search intensities) during the Great Recession. Figure 8 demonstrates that the baseline model is able to replicate both the shares and evolutions very well (despite having a simple assumption on the UI take-up). That said, the baseline

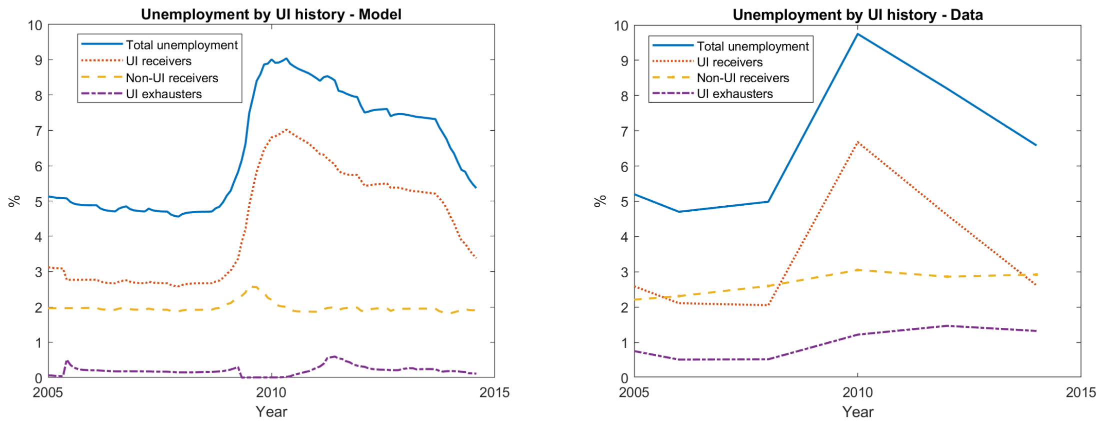
[30]Given that the CPS Displaced Worker, Employee Tenure, and Occupational Mobility Supplement is conducted every two years, it is not straightforward to estimate the cyclicality of job search intensity at both the aggregate and individual levels by UI status. Using the CPS monthly and ATUS data, Mukoyama, Patterson and Şahin (2018) estimate a generalised matching function allowing job search intensity to be either complementary to or substitute for the labour market tightness. They find evidence that the search intensity is countercyclical. Had I assumed a countercyclical individual search intensity, the main result on the matching efficiency would have likely been more pronounced given that the result with acyclical search is larger in magnitude than that with procyclical search.

Figure 7: Aggregate job search intensities (left) and the matching efficiency implied by observed search intensity (right) during the Great Recession when the individual search intensity is assumed to be independent of the aggregate productivity. Data source: CPS.



- For the left panel, the effective search intensity refers to the search intensity once job search censoring and job search inefficiency are accounted for. These job search imperfections are not accounted for in the observed search intensity. For both panels, "$s_i \perp z$" refers to the case where the individual search intensity is assumed to be independent of the aggregate productivity.

Figure 8: Decomposition of unemployment during the Great Recession by UI status. Data source: CPS.



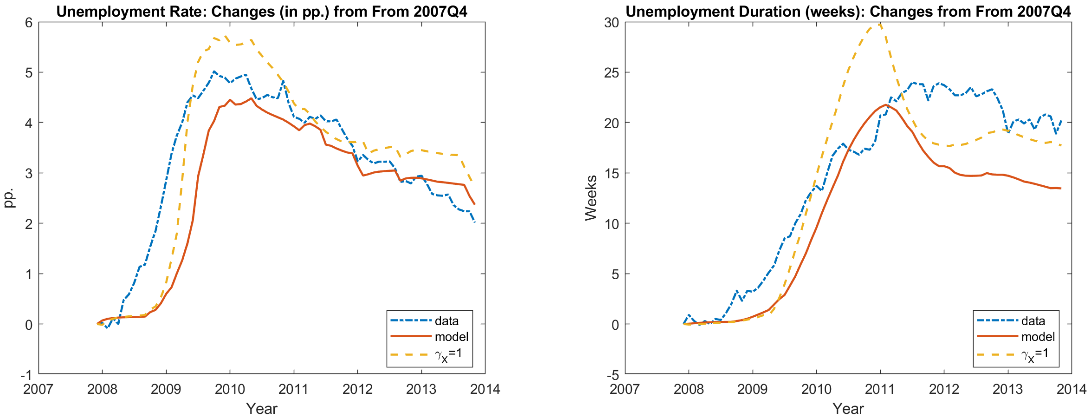
model generates on average slightly too many current UI recipients and not enough former UI recipients.[31] Given that the empirical share of former UI recipients is larger than the baseline model, the reported effects of the duration-dependent search inefficiency can be seen as the lower bound of the true effects.

5.3 Labour market during the Great Recession

In this subsection, I discuss the responses of the main labour market variables including unemployment, average unemployment duration, job findings, job separations, and vacancy rates during the Great Recession. I compare the baseline model's generated

[31] One model extension that could generate a higher share of former UI recipients is to allow for worker heterogeneity in terms of job search ability or a finer duration-dependent search inefficiency which can prolong the persistence of unemployment for these workers.

Figure 9: Changes in the unemployment rate (pp.) and the average unemployment duration (weeks) during the Great Recession. Data source: CPS.



$\gamma_X = 1$: No duration-dependent job search inefficiency.

responses to the empirical counterparts as well as those generated by the model without duration-dependent search inefficiency. What they all have in common is that the baseline model generates more moderated and realistic responses of these labour market variables compared to the model without search inefficiency. I also study the effects of shutting down UI extensions during the Great Recession on unemployment and its duration as well as how these effects interact with the search inefficiency.

Unemployment The left panel of Figure 9 shows that the evolution of unemployment during the Great Recession in the baseline model is more realistic than the model without search inefficiency, particularly, in terms of persistence. The series from a model without duration-dependent search inefficiency exhibits a noticeably stronger response (over 1.5 percentage points higher at the respective peaks) since the workers in this model do not face any drop in their job search inefficiency and respond more strongly to changes in the maximum UI duration.

I also study to what extent the UI extensions (from 26 to 99 weeks) are responsible for the rise in unemployment during the Great Recession. After shutting down the UI extensions and keeping the same series of aggregate productivity shocks, I find that in the baseline model, the peak of the unemployment rate is 1.2 percentage points smaller. On the other hand, in the model without search inefficiency, the peak of the unemployment rate falls by 1.8 percentage points. Therefore, not taking into account the duration-dependent search inefficiency could lead to an overestimation of the effect of UI extensions on unemployment by approximately 50 percent compared to the baseline model.

Unemployment duration Similar to the response of unemployment during the Great Recession, the response of the average unemployment duration from the baseline model is more moderated and closer to the empirical counterpart than the model without search inefficiency as shown in the right panel of Figure 9. Once again, this is because the current UI recipients in the baseline model face a drop in search efficiency if they exhaust their UI and still remain in unemployment. As a result, the duration-dependent search inefficiency weakens their responses to changes in the UI generosity. On the other hand, the current UI recipients in the alternative model do not face this drop in search efficiency and respond more strongly to aggregate changes (including UI extensions).

In terms of the effects of shutting down UI extensions during the Great Recession, the average unemployment duration in the baseline model would be 12 weeks shorter whilst it would be 19 weeks shorter in the alternative model without inefficient job search. Namely, the alternative model overestimates the effects of UI extensions on the average unemployment duration by over 50% compared to the baseline model.[32]

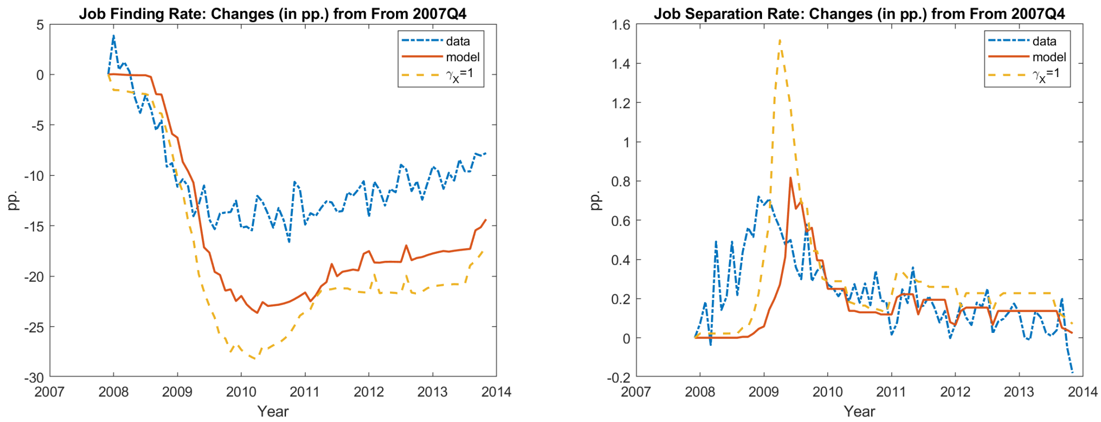
Job findings Once again, the response of the job finding probability during the Great Recession in the baseline model is more moderated than that in the alternative model without search inefficiency as shown in the left panel of Figure 10. Despite the fact that the baseline model exhibits a stronger magnitude than the empirical counterpart, it is worth noting that there is a clear negative trend in the empirical job finding probability whilst the baseline model features no low frequency changes. What can be regarded as more important is the resulting unemployment duration. In this aspect, the stronger negative response of the baseline model's job findings still delivers a realistic (and even smaller) response of the average unemployment duration compared to the data as previously discussed and shown in the right panel of Figure 9.[33]

Job separations The response of job separations during the Great Recession is shown in the right panel of Figure 10. The baseline model performs very well at replicating the empirical response in terms of both magnitude and persistence. The more lagged response from the baseline model is due to the fact that the UI extensions in the model are endogenous and are only triggered once unemployment exceeds the threshold $\bar{u}$. Since

[32]During the Great Recession, the elasticity of the average unemployment duration to an increase in the potential maximum UI duration is 0.16 in the baseline model whilst it is 0.26 in the alternative model without inefficient job search. Therefore, the baseline result is more in line with the existing empirical estimates of around 0.10-0.25. See Moffitt and Nicholson (1982), Moffitt (1985), Katz and Meyer (1990), and Johnston and Mas (2018) for example. It is useful to note that the average elasticity of the unemployment duration to UI extensions (from 1948 up to the Great Recession) is 0.10 in the baseline model whilst it is 0.12 in the alternative model. Acosta et al. (2023) and Rujiwattanapong (2024) also document this non-linearity in the effects of UI extensions in which the elasticity is significant only when the potential UI duration is below 60 weeks.

[33]This can be explained using the Jensen's inequality. For a low initial job finding probability, a small percentage-point drop can imply a larger increase in the expected unemployment duration than a large percentage-point drop for a higher initial job finding probability.

Figure 10: Changes in the job finding probability (pp.) and job separation probability (pp.) during the Great Recession. Data source: CPS.



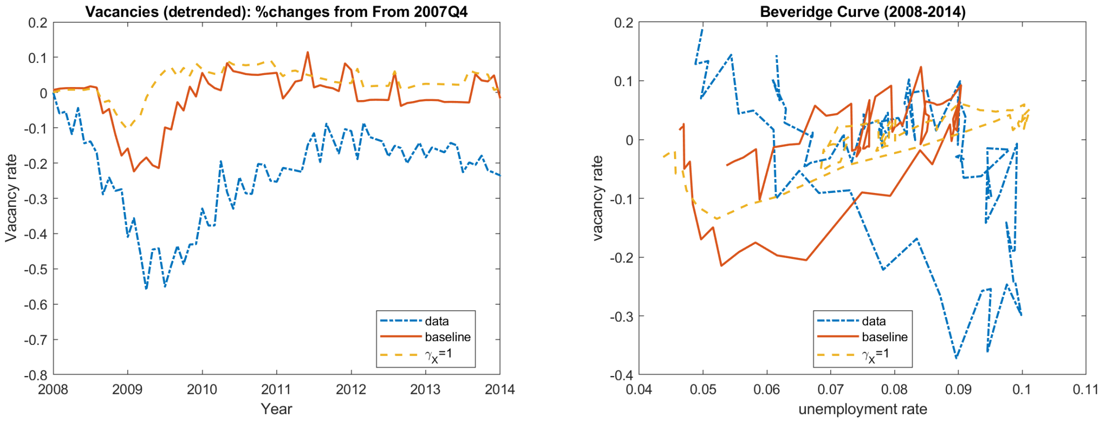
$\gamma_X = 1$: No duration-dependent job search inefficiency.

unemployment in the model also lags the empirical counterpart, so do the model's UI extensions. On the other hand, the model without search inefficiency heavily overestimates the response of job separations when compared to the baseline and the empirical counterparts (by over a 100 percent when measured the respective peaks). In this scenario, the outside option of current UI recipients is not affected by the duration-dependent search inefficiency. Therefore, the total match surplus and, in effect, the match separation decision respond more strongly to changes in aggregate conditions and UI extensions.

Unemployment and vacancies The response of the vacancy rate, defined as the ratio of vacancies to total employment, during the Great Recession is noticeably stronger in the data than in the baseline model as shown in the left panel of Figure 11. The reason for the weaker vacancy response in the baseline model is that, despite the negative aggregate productivity shock during the Great Recession, the large spike in the endogenous job separations ceteris paribus increases the chance of an unmatched firm with a vacancy to be matched with a worker. This offsets some of the negative impact coming from the aggregate productivity shocks.[34] Another potential reason for the weaker vacancy response can be related to the matching efficiency which is assumed to be constant in this paper. That said, the baseline model still fares noticeably better than the alternative model without search inefficiency where the vacancy response is more subdued. The standard deviation of the vacancy rates in the baseline model is around half of that in the data whilst the alternative model generates around 10 percent of that in the data. As a result, the Beveridge curve generated by the baseline model during the Great Recession is significantly more realistic than that generated by the alternative model without search

[34]This point is also discussed in Fujita and Ramey (2012) and Rujiwattanapong (2019) regarding the implications of search models with endogenous job separations. It is useful to note that the empirical job separation probability increases more gradually during the Great Recession than the series generated by the baseline model as shown in the right panel of Figure 10.

Figure 11: Changes in the vacancy rate (pp.) and the Beveridge Curve during the Great Recession. Data source: CPS.



$\gamma_X = 1$: No duration-dependent job search inefficiency.

inefficiency where unemployment and vacancies are mostly positively correlated as shown in the right panel of Figure 11.

5.4 Labour market persistence and fluctuations

There are two important implications at the macroeconomic level related to the persistence and fluctuations in the labour market that arise from job search inefficiency. First, despite having higher search intensities, both current and former UI recipients have persistently lower job finding probabilities throughout their unemployment spells. This directly leads to higher persistence in unemployment, average unemployment duration, job findings, and, to a smaller extent, job separations. Table 9 summarises the autocorrelation coefficients for these 4 labour market variables with 1-, 12- and 24-month lags, and compares them to the model without search inefficiency. Both the baseline and alternative models generate similar autocorrelations of labour market variables with a one-month lag. However, the baseline model performs much better when the autocorrelations with 12- and 24-month lags are computed. In particular, the baseline model generates respectively 82 percent and 38 percent of the empirical autocorrelation coefficients of unemployment with 12- and 24-month lags whilst the alternative model can generate only 65 percent and 4 percent respectively. The autocorrelation functions for unemployment and its duration are also plotted in Figure 12.

The second macroeconomic implication of job search inefficiency amongst workers with a UI history is that the main labour market variables (unemployment, average unemployment duration, job findings, and job separations) become less volatile compared to the alternative model without search inefficiency. The reason is that being a current UI recipient in the baseline model is not as desirable as in the model without search ineffi-

Table 9: Autocorrelation coefficients of labour market variables with 1-, 12- and 24-month lags. Numbers in parentheses represent a fraction of the respective empirical counterparts. Data source: CPS.

Moment	Data	Baseline	$\gamma_X = 1$
$\text{corr}(u, u_{-1})$	0.9921	(100%)	(99%)
$\text{corr}(\rho_{UE}, \rho_{UE_{-1}})$	0.9510	(103%)	(103%)
$\text{corr}(\rho_{EU}, \rho_{EU_{-1}})$	0.9616	(98%)	(98%)
$\text{corr}(udur, udur_{-1})$	0.9965	(100%)	(99%)
$\text{corr}(u, u_{-12})$	0.7302	(82%)	(65%)
$\text{corr}(\rho_{UE}, \rho_{UE_{-12}})$	0.8119	(69%)	(60%)
$\text{corr}(\rho_{EU}, \rho_{EU_{-12}})$	0.7850	(30%)	(6%)
$\text{corr}(udur, udur_{-12})$	0.9220	(80%)	(69%)
$\text{corr}(u, u_{-24})$	0.4783	(38%)	(4%)
$\text{corr}(\rho_{UE}, \rho_{UE_{-24}})$	0.6468	(20%)	(6%)
$\text{corr}(\rho_{EU}, \rho_{EU_{-24}})$	0.7138	(8%)	(0.1%)
$\text{corr}(udur, udur_{-24})$	0.7909	(47%)	(30%)

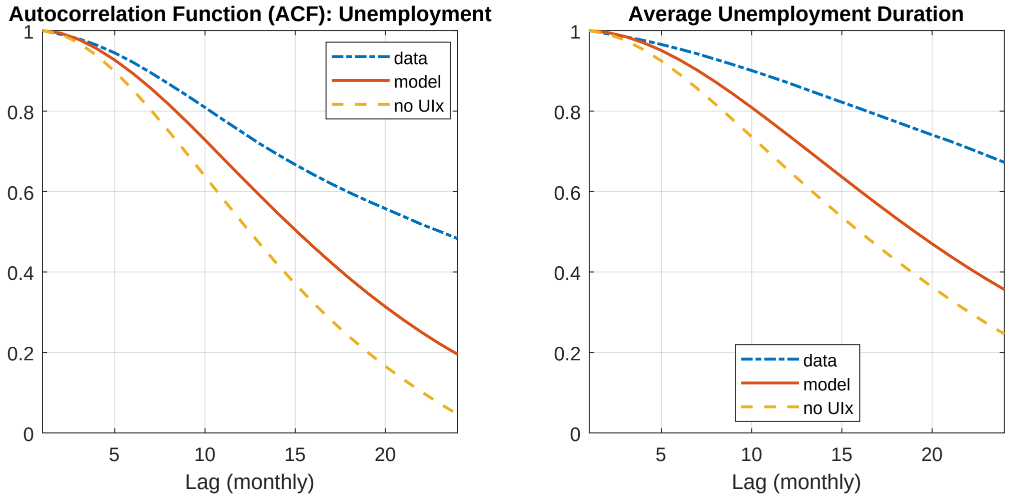
- $\gamma_X = 1$: no duration-dependent job search inefficiency. ρ_{UE}: job finding probability. ρ_{EU}: job separation probability. $udur$: average unemployment duration (weeks).

ciency. The duration-dependent search inefficiency lowers the value of being unemployed for former UI recipients since the re-employment probability is lower given the same unit of search intensity. Current UI recipients also take this into account and their value of being unemployed is consequently also lower. As a result, in the baseline model, current UI recipients do not censor their job search as much as in the model without search inefficiency. This leads to more moderated responses of the agents' policy functions with respect to job search, job censoring, job formation and job separation −and, in effect, unemployment and its duration− to UI extensions. Table 10 shows that the standard deviations of the main labour market variables are smaller in the baseline model than in the alternative model without search inefficiency. For the job finding probability, the baseline model delivers a more realistic volatility whilst the alternative model generates 40 percent higher than the empirical counterpart. Since there is only one source of exogenous shock in the model, it is reasonable to expect that the model produces fluctuations that are comparable to or less than that observed in the data.

6 Conclusion

This paper first documents new empirical findings that the observed job search intensities amongst unemployed workers with a UI history (either current or former UI recipients) are higher than that amongst unemployed workers without a UI history (non-UI recipients). Moreover, the empirical job finding probabilities of unemployed workers with a UI history are significantly lower than that of unemployed workers without a UI history despite the former having higher observed search intensities. To reconcile with these

Figure 12: Autocorrelation functions of unemployment and average unemployment duration. Data source: CPS.



$\gamma_X = 1$: No duration-dependent job search inefficiency.

Table 10: Standard deviations of labour market variables. Numbers in parentheses represent a fraction of the respective empirical counterparts. Data source: CPS.

Moment	Data	Baseline	$\gamma_X = 1$
std(u)	0.1454	0.1123	0.1453
		(77%)	(99%)
std(ρ_{UE})	0.0999	0.1035	0.1402
		(103%)	(140%)
std(ρ_{EU})	0.0890	0.0517	0.0641
		(58%)	(72%)
std($udur$)	6.9327	5.6412	6.1954
		(81%)	(90%)

- $\gamma_X = 1$: no duration-dependent job search inefficiency. ρ_{UE}: job finding probability. ρ_{EU}: job separation probability. $udur$: average unemployment duration (weeks).

empirical findings and explore their macroeconomic implications, I propose a model of job search censoring and duration-dependent job search inefficiency based on a stochastic general equilibrium search-and-matching framework where job search intensity, job separations, job formations, vacancies and UI extensions are endogenously determined. The model delivers optimally higher observed job search intensities for workers with a UI history but job search censoring and job search inefficiency lower their effective search intensities which eventually lead to lower job finding probabilities.

After calibrating the model to the U.S. economy, I find that the observed aggregate search intensity becomes acyclical and significantly overestimates the true or effective aggregate search intensity. This is particularly the case in recessions with UI extensions since there is a higher share of unemployed workers with a UI history who possess higher observed job search intensities. Without correcting for the share of workers with a UI history and their lower effective search intensities, one may substantially overestimate the decline in the matching efficiency during recessionary episodes with UI extensions based on the acyclical observed search intensity. Additionally, I find that the effects of UI extensions on unemployment and its duration are overestimated when job search inefficiency is not taken into account. Lastly, I find that the presence of job search inefficiency leads to dampened labour market fluctuations as well as more persistent unemployment and its duration.

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Online Appendix

A Further tables

Table A.1: Summary statistics of unemployed workers by UI history.

	Current UI recipients	Former UI recipients	Non-UI recipients
Basic information			
Share of total unemployment	39.21%	20.51%	40.27%
Average age (year)	42.68	44.49	38.27
Female	39.56%	41.65%	40.95%
Married female	20.54%	20.63%	17.80%
Black	10.02%	15.99%	16.88%
Education			
Less than high school	10.59%	11.61%	19.67%
High school	34.20%	36.30%	36.12%
Some College	22.26%	21.15%	19.28%
College and more	32.95%	30.95%	24.93%
Reason for unemployment			
Job loser/on lay off	14.10%	8.96%	13.46%
Other job loser	69.51%	60.93%	43.25%
Temp job ended	9.34%	11.86%	16.42%
Job leaver	1.75%	2.71%	8.05%
Re-entrant	5.26%	15.41%	18.65%
New entrant	0.03%	0.13%	0.16%
Unemployment duration			
Average unemployment duration (weeks)	23.3	42.26	19.4
Fraction of long-term unemployed	31.97%	63.83%	24.96%
Recall expectations			
Given and/or expecting a recall	14.10%	8.96%	13.46%
Previous job's information			
Average tenure (year)	5.72	5.53	3.15
Average weekly earning (USD)	854.08	789.31	589.18

- Source: CPS monthly data and January supplements (1998-2022). Number of observations: 7,561.
- "Current UI recipients" is defined as unemployed workers who are currently receiving unemployment benefits during the current unemployment spell. "Former UI recipients" is defined as unemployed workers who have received and exhausted unemployment benefits during the current unemployment spell. "Non-UI recipients" is defined as unemployed workers who have not received unemployment benefits during the current unemployment spell.
- Items in percent (%) represent the shares within the respective UI history group unless stated otherwise.

Table A.2: Linear regression model for the (log) re-employment wages.

Dependent variable: (log) re-employment weekly earnings	
Current UI recipient	-0.137
	(0.129)
Former UI recipient	-0.594***
	(0.154)
Search intensity	0.343
	(0.356)
N	303
R^2	0.421

- Source: CPS. * p<0.05, ** p<0.01, *** p<0.001.
- Other control variables include race, education, gender, age (quartic), marital status, female and married, occupation, industry, recall expectation, potential UI exhaustion month, reason for unemployment, unemployment duration (quartic), previous job's tenure, previous job's weekly earnings, a linear time trend, a recession dummy, state fixed effects, and state unemployment rates.

B Stochastic model

B.1 Timing

1. Given u and z, the production takes place, and the maximum UI duration $\phi(u)$ is determined.
2. Workers optimally choose job search intensities (optimal job search censoring in case of current UI recipients).
3. Current worker-firm matches draw a new match quality m with probability λ.
4. Workers and unmatched firms meet via the matching function.
5. Aggregate productivity z' next period is realised.
6. Decisions regarding match separations and match formations are made.
7. u_B that remain unemployed exhaust UI with probability $\phi(u)$ if not meeting a firm, and with probability $\phi(u) + \big(1 - \phi(u)\big)\xi$ if a meeting has occurred.
8. Short-term unemployed workers become long-term unemployed workers with probability $d(u)$ for current UI recipients, and with probability d for non-UI recipients.
9. Unemployment for the next period, u', is realised.

B.2 Bellman equations

Let us define $\Omega \equiv \{z, e(m), u_{Bs}(m), u_{B\ell}(m), u_X, u_{Ns}, u_{N\ell}; \forall m\}$ as the set of state variables.[35] The value functions for current UI recipients with short- and long-unemployment

[35]Similar to the deterministic model, one variable, except for z, can be dropped from this set since the sum of all workers is normalised to unity.

duration ($Bs, B\ell$) and UI benefit $b(\tilde{m})$ are respectively

$$\begin{aligned} U_{Bs}(\tilde{m};\Omega) &= \max_{\gamma_{Bs}(\tilde{m};\Omega)} \quad b(\tilde{m}) + h - c\big(\gamma_{Bs}(\tilde{m};\Omega)\underline{s_B}\big) + \beta E_{m'\Omega'|\Omega}\Big[p_{Bs}\big(\gamma_{Bs}(\tilde{m};\Omega)\big)\max\Big\{W_{Bs(\tilde{m})}(m';\Omega'), \ldots \\ & \underbrace{\big(1-\phi(u)\big)(1-\xi)}_{\text{keep UI | meeting a firm}} \Big(\big(1-d(u)\big)U_{Bs}(\tilde{m};\Omega') + d(u)U_{B\ell}(\tilde{m};\Omega')\Big) + \underbrace{\big(\phi(u) + \big(1-\phi(u)\big)\xi\big)}_{\text{lose UI | meeting a firm}} U_X(\Omega')\Big\} \\ & +\Big(1 - p_{Bs}\big(\gamma_{Bs}(\tilde{m};\Omega)\big)\Big)\Big(\big(1-\phi(u)\big)\Big(\big(1-d(u)\big)U_{Bs}(\tilde{m};\Omega') + d(u)U_{B\ell}(\tilde{m};\Omega')\Big) + \phi(u)U_X(\Omega')\Big)\Big] \end{aligned} \tag{B.1}$$

$$\begin{aligned} U_{B\ell}(\tilde{m};\Omega) &= \max_{\gamma_{B\ell}(\tilde{m};\Omega)} \quad b(\tilde{m}) + h - c_X\big(\gamma_{B\ell}(\tilde{m};\Omega)\underline{s_B}\big) + \beta E_{m'\Omega'|\Omega}\Big[p_{B\ell}\big(\gamma_{B\ell}(\tilde{m};\Omega)\big)\max\Big\{W_{B\ell(\tilde{m})}(m';\Omega'), \ldots \\ & \underbrace{\big(1-\phi(u)\big)(1-\xi)}_{\text{keep UI | meeting a firm}} U_{B\ell}(\tilde{m};\Omega') + \underbrace{\big(\phi(u) + \big(1-\phi(u)\big)\xi\big)}_{\text{lose UI | meeting a firm}} U_X(\Omega')\Big\} \\ & +\Big(1 - p_{B\ell}\big(\gamma_{B\ell}(\tilde{m};\Omega)\big)\Big)\Big(\big(1-\phi(u)\big)U_{B\ell}(\tilde{m};\Omega') + \phi(u)U_X(\Omega')\Big)\Big] \end{aligned} \tag{B.2}$$

where ξ is the probability of losing the UI eligibility after rejecting a job offer. It is useful to note that $d(u)$ governs the rate at which a current UI recipient becomes a long-term unemployed worker with a lower search efficiency whilst continuing to collect UI. $d(u)$ is zero except for when the UI duration is extended, i.e., when $u \geq \bar{u}$. In which case, $d(u)$ takes the value of 1/6 (the same as the value of ϕ). This is because the standard UI duration is 6 months in the model and the definition of long-term unemployment is those who are unemployed for more than 6 months.

The Bellman equations for former UI recipients (X), short-term non-UI recipients (Ns), and long-term non-UI recipients ($N\ell$) are, respectively:

$$\begin{aligned} U_X(\Omega) &= \max_{s_X(\Omega)} \quad h - c_X\big(s_X(\Omega)\big) + \beta E_{m'\Omega'|\Omega}\Big[p_X(\Omega)\underbrace{\max\{W_X(m';\Omega'), U_X(\Omega')\}}_{\text{job formation/rejection decision}} \\ & \quad +\big(1-p_X(\Omega)\big)U_X(\Omega')\Big] \end{aligned} \tag{B.3}$$

$$\begin{aligned} U_{Ns}(\Omega) &= \max_{s_{Ns}(\Omega)} \quad h - c\big(s_{Ns}(\Omega)\big) + \beta E_{m'\Omega'|\Omega}\Big[p_{Ns}(\Omega)\underbrace{\max\{W_{Ns}(m';\Omega'), \bar{U}_N(\Omega')\}}_{\text{job formation/rejection decision}} \\ & \quad +\big(1-p_{Ns}(\Omega)\big)\bar{U}_N(\Omega')\Big] \end{aligned} \tag{B.4}$$

$$\begin{aligned} U_{N\ell}(\Omega) &= \max_{s_{N\ell}(\Omega)} \quad h - c_X\big(s_{N\ell}(\Omega)\big) + \beta E_{m'\Omega'|\Omega}\Big[p_{N\ell}(\Omega)\underbrace{\max\{W_{N\ell}(m';\Omega'), U_{N\ell}(\Omega')\}}_{\text{job formation/rejection decision}} \\ & \quad +\big(1-p_{N\ell}(\Omega)\big)U_{N\ell}(\Omega')\Big] \end{aligned} \tag{B.5}$$

where $\bar{U}_N(\Omega') \equiv (1-d)U_{Ns}(\Omega') + dU_{N\ell}(\Omega')$. d governs the rate at which short-term non-UI recipients (Ns) become long-term non-UI recipients ($N\ell$). With the model's monthly frequency, d is set to 1/6 representing that the average duration of short-term non-UI recipients is 6 months.

The Bellman equation for an employed worker whose current match quality is m and previous period's employment status and associated benefit level is $j \in \{E(\tilde{m}), Bs(\tilde{m}), B\ell(\tilde{m}), X, Ns, N\ell\}$ is

$$\begin{aligned} W_j(m;\Omega) \quad = \quad & \max_{s_E(m;\Omega)} \quad w_j(m;\Omega) - c_E\big(s_E(m;\Omega)\big) + \beta E_{\Omega'|\Omega}\Bigg[\\ & (1-\delta)(1-\lambda)\Big[\Big(1 - p_E(m;\Omega)\big(1-F(m)\big)\Big)W_{E(m)+}(m;\Omega') \\ & + p_E(m;\Omega)\big(1-F(m)\big)E_{m'|m'>m}[W_{E(m)+}(m';\Omega')]\Big] \\ & +(1-\delta)\lambda E_{m'}\Big[\Big(1 - p_E(m;\Omega)\big(1-F(m')\big)\Big)W_{E(m)+}(m';\Omega') \\ & + p_E(m;\Omega)\big(1-F(m')\big)E_{m''|m''>m'}[W_{E(m)+}(m'';\Omega')]\Big] \\ & +\delta\Big((1-\psi)U_{Bs}(m,\Omega') + \psi U_{Ns}(\Omega')\Big)\Bigg] \end{aligned} \tag{B.6}$$

where $W_{E(m)+}(m';\Omega') \equiv \max\{W_{E(m)}(m';\Omega'), (1-\psi)U_{Bs}(m;\Omega') + \psi U_{Ns}(\Omega')\}$ represents the worker's options whether to stay employed or become unemployed. $W_{E(m)+}(m;\Omega')$ and $W_{E(m)+}(m'';\Omega')$ are analogously defined.

The Bellman equation for a matched firm with a worker whose current match quality is m and previous period's employment status is $j \in \{E(\tilde{m}), Bs(\tilde{m}), B\ell(\tilde{m}), X, Ns, N\ell\}$ is

$$\begin{aligned} J_j(m;\Omega) \quad = \quad & mz - w_j(m;\Omega) - \tau(\Omega) + \beta E_{\Omega'|\Omega}\Bigg[\ldots \\ & (1-\delta)(1-\lambda)\Big[\Big(1 - p_E(m;\Omega)\big(1-F(m)\big)\Big)J_{E(m)+}(m;\Omega')\Big] \\ & +(1-\delta)\lambda E_{m'}\Big[\Big(1 - p_E(m;\Omega)\big(1-F(m')\big)\Big)J_{E(m)+}(m';\Omega')\Big] \\ & +\delta V(\Omega')\Bigg] \end{aligned} \tag{B.7}$$

where $J_{E(m)+}(m';\Omega') \equiv \max\{J_{E(m)}(m';\Omega'), V(\Omega')\}$ represents the matched firm's options whether to stay matched or become unmatched. $J_{E(m)+}(m;\Omega')$ is analogously defined.

Lastly, the Bellman equation for an unmatched firm with a vacancy is

$$\begin{aligned} V(\Omega) \quad = \quad & -\kappa + \beta q(\Omega) E_{\Omega'|\Omega}\Bigg[\sum_m \zeta_E(m;\Omega)(1-F(m))E_{m'|m'>m}[J_{E(m)+}(m';\Omega')] \\ & + \sum_m \zeta_{Bs}(m;\Omega)E_{m'}[J_{Bs(m)+}(m';\Omega')] + \sum_m \zeta_{B\ell}(m;\Omega)E_{m'}[J_{B\ell(m)+}(m';\Omega')] \\ & + \sum_{j\in\{X,Ns,N\ell\}} \zeta_j(\Omega)E_{m'}[J_{j+}(m';\Omega')]\Bigg] \end{aligned} \tag{B.8}$$

$$\begin{aligned}
\text{where} \qquad \zeta_E(m) &= \frac{(1-\lambda)s_E(m)e(m) + \lambda f(m)\sum_m s_E(m)e(m)}{s} \\
\zeta_{Bs}(m) &= \frac{\gamma_{Bs}(m)\underline{s_B}u_{Bs}(m)}{s} \\
\zeta_{B\ell}(m) &= \frac{\gamma_X\gamma_{B\ell}(m)\underline{s_B}u_{B\ell}(m)}{s} \\
\zeta_X &= \frac{\gamma_X s_X u_X}{s} \\
\zeta_{Ns} &= \frac{s_{Ns}u_{Ns}}{s} \\
\zeta_{N\ell} &= \frac{\gamma_X s_{N\ell}u_{N\ell}}{s} \\
s &= \sum_m \Big((1-\lambda)s_E(m)e(m) + \lambda f(m)\sum_m s_E(m)e(m)\Big) \\
&\quad + \sum_m \Big(\gamma_{Bs}(m)\underline{s_B}u_{Bs}(m) + \gamma_X\gamma_{B\ell}(m)\underline{s_B}u_{B\ell}(m)\Big) \\
&\quad + \gamma_X s_X u_X + s_{Ns}u_{Ns} + \gamma_X s_{N\ell}u_{N\ell}
\end{aligned}$$

Note that the free entry condition implies $V(\Omega) = 0, \forall\Omega$.

B.3 Wages and surpluses

As in the deterministic model, wages are still negotiated every period between a worker and a firm via Nash bargaining. A worker whose last-period employment status is $j \in \{E(\tilde{m}), Bs(\tilde{m}), B\ell(\tilde{m}), X, Ns, N\ell\}$ receives a wage

$$w_j(m;\Omega) \quad = \quad \text{argmax} \Big(WS_j(m;\Omega)\Big)^{\mu}\Big(J_j(m;\Omega)\Big)^{(1-\mu)} \tag{B.9}$$

where $\mu \in (0,1)$ denotes the worker's bargaining power, $(1-\mu)$ denotes the firm's bargaining power, and WS_j denotes the surplus from being employed for a worker with the last-period status j. The total surplus of a match is split between a worker and a firm according to their respective bargaining powers. Let $S_j(m;\Omega)$ denote a total surplus of a match between a firm and a worker whose last-period status is j. We have

$$\begin{aligned}
S_j(m;\Omega) &= WS_j(m;\Omega) + J_j(m;\Omega) \\
WS_j(m;\Omega) &= \mu S_j(m;\Omega) \\
J_j(m;\Omega) &= (1-\mu)S_j(m;\Omega)
\end{aligned}$$

The surplus of a worker with the last-period status $j \in \{E(\tilde{m}), Bs(\tilde{m}), B\ell(\tilde{m}), X, Ns, N\ell\}$ can be summarised as follows

$$
\begin{aligned}
WS_{E(\tilde{m})}(m;\Omega) &= W_{E(\tilde{m})}(m;\Omega) - \big((1-\psi)U_{Bs}(\tilde{m};\Omega) + \psi U_N(\Omega)\big) \\
WS_{Bs(\tilde{m})}(m;\Omega) &= W_{Bs(\tilde{m})}(m;\Omega) - \big((1-\phi(u))(1-\xi)\bar{U}_B(\tilde{m};\Omega) + \phi(u)U_X(\Omega)\big) \\
WS_{B\ell(\tilde{m})}(m;\Omega) &= W_{Bs(\tilde{m})}(m;\Omega) - \big((1-\phi(u))(1-\xi)U_{B\ell}(\tilde{m};\Omega) + \phi(u)U_X(\Omega)\big) \\
WS_X(m;\Omega) &= W_X(m;\Omega) - U_X(\Omega) \\
WS_{Ns}(m;\Omega) &= W_{Ns}(m;\Omega) - \bar{U}_N(\Omega) \\
WS_{N\ell}(m;\Omega) &= W_{N\ell}(m;\Omega) - U_{N\ell}(\Omega)
\end{aligned}
$$

where $\bar{U}_B(\tilde{m};\Omega) \equiv (1-d(u))U_{Bs}(\tilde{m};\Omega) + d(u)U_{B\ell}(\tilde{m};\Omega)$. It is useful to recall that $d(u)$ is $1/6$ when $u \geq \bar{u}$ and zero otherwise. Recall also that $\bar{U}_N(\Omega) \equiv (1-d)U_{Ns}(\Omega) + dU_{N\ell}(\Omega)$ where $d \equiv 1/6$.

B.4 Optimal job search intensity and censoring

Given the worker's Bellman equations, we can find the first order derivatives to obtain the optimal job search intensity and/or censoring. The first order conditions for workers of type $j \in \{E(m), Bs(m), B\ell(m), X, Ns, N\ell\}$ are as follows

$$
\begin{aligned}
c'_E\big(s_E(m;\Omega)\big) &= -\beta(1-\delta)M\big(1,\theta(\Omega)\big)E_{\Omega'|\Omega}\Big[\ldots \\
&\quad (1-\lambda)\big(1-F(m)\big)\Big(WS_{E(m)+}(m;\Omega') - E_{m'|m'>m}[WS_{E(m)+}(m';\Omega')]\Big) \\
&\quad +\lambda E_{m'}\Big[\big(1-F(m')\big)(WS_{E(m)+}(m';\Omega') - E_{m''|m''>m'}[WS_{E(m)+}(m'';\Omega')])\Big]\Big]
\end{aligned}
\tag{B.10}
$$

$$
c'\big(\gamma_{Bs}(m;\Omega)\big) = \beta M\big(1,\theta(\Omega)\big)E_{m'\Omega'|\Omega}\Big[\max\{WS_{Bs(m)}(m';\Omega'),0\} - \xi\big(1-\phi(u)\big)\bar{US}_B(m,\Omega')\Big]
\tag{B.11}
$$

$$
c'_X\big(\gamma_{B\ell}(m;\Omega)\big) = \beta\gamma_X M\big(1,\theta(\Omega)\big)E_{m'\Omega'|\Omega}\Big[\max\{WS_{B\ell(m)}(m';\Omega'),0\} - \xi\big(1-\phi(u)\big)US_{B\ell}(m,\Omega')\Big]
\tag{B.12}
$$

$$
c'_X\big(s_X(\Omega)\big) = \beta\gamma_X M\big(1,\theta(\Omega)\big)E_{m'\Omega'|\Omega}\Big[\max\{WS_X(m';\Omega'),0\}\Big]
\tag{B.13}
$$

$$
c'\big(s_{Ns}(\Omega)\big) = \beta M\big(1,\theta(\Omega)\big)E_{m'\Omega'|\Omega}\Big[\max\{WS_{Ns}(m';\Omega'),0\}\Big]
\tag{B.14}
$$

$$
c'_X\big(s_{N\ell}(\Omega)\big) = \beta\gamma_X M\big(1,\theta(\Omega)\big)E_{m'\Omega'|\Omega}\Big[\max\{WS_{N\ell}(m';\Omega'),0\}\Big]
\tag{B.15}
$$

where $\bar{US}_B(m,\Omega') \equiv (1-d(u))US_{Bs}(m,\Omega') + d(u)US_{B\ell}(m,\Omega') - US_X(\Omega')$ and $US_{B\ell}(m,\Omega') \equiv US_{B\ell}(m,\Omega') - US_X(\Omega')$.

B.5 Transition equations

Employment The mass of employed agents in t with match quality m, $e_t(m)$, evolves as follows

$$\begin{aligned} e_{t+1}(m) &= (1-\delta)(1-\lambda)(1-p_{e,t}(m)+p_{e,t}(m)F(m))e_t(m)\mathbb{1}\{S_{e(m),t+1}(m)>0\} \\ &+(1-\delta)(1-\lambda)f(m)\int_{m'<m} p_{e,t}(m')e_t(m')\mathbb{1}\{S_{e(m'),t+1}(m)>0\}dm' \\ &+(1-\delta)\lambda f(m)\int_{m'}(1-p_{e,t}(m')+p_{e,t}(m')F(m))e_t(m')\mathbb{1}\{S_{e(m'),t+1}(m)>0\}dm' \\ &+(1-\delta)\lambda F(m)f(m)\int_{m'} p_{e,t}(m')e_t(m')\mathbb{1}\{S_{e(m'),t+1}(m)>0\}dm' \\ &+f(m)\int_{\tilde{m}} u_{Bs,t}(\tilde{m})p_{Bs,t}(\tilde{m})\mathbb{1}\{S_{Bs(\tilde{m}),t+1}(m)>0\}d\tilde{m} \\ &+f(m)\int_{\tilde{m}} u_{B\ell,t}(\tilde{m})p_{B\ell,t}(\tilde{m})\mathbb{1}\{S_{B\ell(\tilde{m}),t+1}(m)>0\}d\tilde{m} \\ &+f(m)u_{X,t}p_{X,t}\mathbb{1}\{S_{X,t+1}(m)>0\} \\ &+f(m)u_{Ns,t}p_{Ns,t}\mathbb{1}\{S_{Ns,t+1}(m)>0\} \\ &+f(m)u_{N\ell,t}p_{N\ell,t}\mathbb{1}\{S_{N\ell,t+1}(m)>0\} \end{aligned} \tag{B.16}$$

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

Job separations The job separation probability of employed workers with match quality m at the beginning of period t and m' at the end of period t, and the average job separation probability are respectively

$$\begin{aligned} \rho_t^{EU}(m,m') &= \begin{cases} \delta & \text{if } S_{e(m),t+1}(m')>0, \\ 1 & \text{otherwise} \end{cases} \\ \rho_t^{EU} &= \left(\delta \int\int_{\{(m,m'):S_{e(m),t+1}(m')>0\}} e_t^{post}(m,m')dm\, dm' \right. \\ &\left. + \int\int_{\{(m,m'):S_{e(m),t+1}(m')\leq 0\}} e_t^{post}(m,m')dm\, dm' \right)/e_t \end{aligned}$$

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

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

Job findings The job finding probability for unemployed workers of status $j \in \{Bs(\tilde{m}), B\ell(\tilde{m}), X, Ns, N\ell\}$ and the average job finding probability are respectively

$$
\begin{aligned}
\rho^{EU}_{j,t} &= \int \rho^{EU}_{j,t}(m) f(m) dm \\
\rho^{EU}_{t} &= \frac{\int_{\tilde{m}} u_{Bs,t}(\tilde{m}) \rho^{UE}_{Bs(\tilde{m}),t} d\tilde{m} + \int_{\tilde{m}} u_{B\ell,t}(\tilde{m}) \rho^{EU}_{B\ell(\tilde{m}),t} d\tilde{m} + \sum_{k \in \{X,Ns,N\ell\}} u_{k,t} \rho^{EU}_{k,t}}{\int_{\tilde{m}} u_{Bs,t}(\tilde{m}) d\tilde{m} + \int_{\tilde{m}} u_{B\ell,t}(\tilde{m}) d\tilde{m} + u_{X,t} + u_{Ns,t} + u_{N\ell,t}} \\
\text{where} \quad \rho^{EU}_{j,t}(m) &= \begin{cases} p_{j,t} & \text{if } S_{j,t+1}(m) > 0, \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
$$

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

$$
\begin{aligned}
\rho^{EE}_{t}(m) &= (1-\delta)\Big((1-\lambda) p_{e,t}(m)(1-F(m)) E_{m'>m}[\mathbb{1}\{S_{e,t+1}(m,m') > 0\}] \\
&\quad + \lambda \int_{m'} p_{e,t}(m) f(m')(1-F(m')) E_{m''>m'}[\mathbb{1}\{S_{e,t+1}(m,m'') > 0\}] dm' \Big) \\
\rho^{EE}_{t} &= \frac{\int_m \rho^{EE}_t(m) e_t(m) dm}{e_t}
\end{aligned}
$$

Unemployment The mass of unemployed workers of status $j \in \{Bs(\tilde{m}), B\ell(\tilde{m}), X, Ns, N\ell\}$ as well as the total unemployment rate evolve respectively as follows

$$
\begin{aligned}
u_{Bs,t+1}(\tilde{m}) &= (1-d(u_t))\Big(\underbrace{(1-\phi(u_t))(1-p_{Bs,t}(\tilde{m}))u_{Bs,t}(\tilde{m})}_{\text{unmatched, not losing UI}} + \underbrace{\chi_{Bs,t}(\tilde{m})(1-\phi(u_t))(1-\xi)p_{Bs,t}(\tilde{m})u_{Bs,t}(\tilde{m})}_{\text{bad match, not losing UI}} \Big) \\
&\quad + \underbrace{(1-\psi)\int_{m'} \rho^{EU}_t(\tilde{m},m') e_t(\tilde{m},m') dm'}_{\text{destroyed match, not losing UI}} \qquad \text{(B.17)} \\
u_{B\ell,t+1}(\tilde{m}) &= \underbrace{(1-\phi(u_t))(1-p_{B\ell,t}(\tilde{m}))u_{B\ell,t}(\tilde{m})}_{\text{unmatched, not losing UI}} + \underbrace{\chi_{B\ell,t}(\tilde{m})(1-\phi(u_t))(1-\xi)p_{B\ell,t}(\tilde{m})u_{B\ell,t}(\tilde{m})}_{\text{bad match, not losing UI}} \\
&\quad + d(u_t)\Big(\underbrace{(1-\phi(u))(1-p_{Bs,t}(\tilde{m}))u_{Bs,t}(\tilde{m}) + \chi_{Bs,t}(\tilde{m})(1-\phi_t)(1-\xi)p_{Bs,t}(\tilde{m})u_{Bs,t}(\tilde{m})}_{\text{losing search efficiency}} \Big) \qquad \text{(B.18)} \\
u_{X,t+1} &= \int_{\tilde{m}} \Big(\underbrace{\phi(u_t)(1-p_{Bs,t}(\tilde{m}))u_{Bs,t}(\tilde{m})}_{\text{unmatched, losing UI}} + \underbrace{\chi_{Bs,t}(\tilde{m})\Big(\phi(u_t) + (1-\phi(u_t))\xi\Big)p_{Bs,t}(\tilde{m})u_{Bs,t}(\tilde{m})}_{\text{bad match, losing UI}} \Big) d\tilde{m} \\
&\quad + \int_{\tilde{m}} \Big(\underbrace{\phi(u_t)(1-p_{B\ell,t}(\tilde{m}))u_{B\ell,t}(\tilde{m})}_{\text{unmatched, losing UI}} + \underbrace{\chi_{B\ell,t}(\tilde{m})\Big(\phi(u_t) + (1-\phi(u_t))\xi\Big)p_{B\ell,t}(\tilde{m})u_{B\ell,t}(\tilde{m})}_{\text{bad match, losing UI}} \Big) d\tilde{m} \\
&\quad + (1-\rho^{UE}_{X,t})u_{X,t} \qquad \text{(B.19)} \\
u_{Ns,t+1} &= (1-d)(1-\rho^{UE}_{Ns,t})u_{Ns,t} + \underbrace{\psi \rho^{EU}_t e_t}_{\text{destroyed match, losing UI}} \qquad \text{(B.20)} \\
u_{N\ell,t+1} &= (1-\rho^{UE}_{N\ell,t})u_{N\ell,t} + d\ \underbrace{(1-\rho^{UE}_{Ns,t})u_{Ns,t}}_{\text{losing search efficiency}} \qquad \text{(B.21)} \\
u_{t+1} &= \int_{\tilde{m}} u_{Bs,t+1}(\tilde{m}) d\tilde{m} + \int_{\tilde{m}} u_{B\ell,t+1}(\tilde{m}) d\tilde{m} + u_{X,t+1} + u_{Ns,t+1} + u_{N\ell,t+1} \qquad \text{(B.22)}
\end{aligned}
$$

where $\chi_{Bs,t}(\tilde{m}) \equiv \int \mathbb{1}\{S_{Bs(\tilde{m}),t+1}(m) \leq 0\} f(m)dm$ denotes the rate the newly formed matches consisting of $u_{Bs}(\tilde{m})$ are not viable. $\chi_{B\ell,t}(\tilde{m})$ is analogously defined.

B.6 UI finance

The government's UI budget is balanced every period. Particularly, unemployment benefits are financed via lump-sum tax (τ_t) paid by matched firms:

$$\tau_t(1 - u_t) = \sum_{j \in \{Bs, B\ell\}} \sum_{\tilde{m}} u_{j,t}(\tilde{m}) b(\tilde{m}) \tag{B.23}$$

where $u_{j,t}(\tilde{m})$ is the number of (insured) unemployed workers of type $j \in \{Bs, B\ell\}$ whose UI benefit is $b(\tilde{m})$.

B.7 Equilibrium definition

A recursive competitive equilibrium is characterised by the value functions $\{W_j(m;\Omega), U_j(\Omega), J_j(m;\Omega), V(\Omega)\}$, market tightness $\theta(\Omega)$, effective search policy $\tilde{s}_j(\Omega)$ and wage functions $w_j(m;\Omega)$ for $j \in \{E(\tilde{m}), Bs(\tilde{m}), B\ell(\tilde{m}), X, Ns, N\ell\}$, such that, given the initial distribution of workers, the government's policy $\{\tau(\Omega), \phi(\Omega)\}$ and the law of motion for z:

1. Value functions and the market tightness satisfy the Bellman equations for workers and firms, and the free entry condition (namely, equations (B.1), (B.2), (B.3),(B.4),(B.5), (B.6), (B.7), and (B.8)),
2. Search decisions satisfy the FOCs for the optimal search intensity (namely, equations (B.10), (B.11), (B.12), (B.13), (B.14), and (B.15)),
3. Wage functions satisfy the FOCs for the Nash bargaining rule (equation (B.9)),
4. UI's budget constraint is satisfied every period (equation (B.23)), and
5. The distribution of workers evolves according to the transition equations (namely, equations (B.16), (B.17), (B.18), (B.19), (B.20), (B.21),and (B.22)), consistent with the utility-maximising behaviour of agents.