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Unemployment Insurance Reforms in a Search Model with Endogenous Labor Force Participation*

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Abstract

This paper develops a life-cycle search model with a labor force participation decision of workers, job-to-job transitions and endogenous job creation to study unemployment insurance (UI) reforms. The calibrated model replicates the aggregate and life-cycle patterns of labor market flows from the Current Population Survey, as well as the worker labor market histories over four months. The model predicts that an UI extension to 99 weeks leads to a slight decrease in labor productivity, the employment to population ratio and the labor force participation rate, but to a non-trivial increase in the unemployment rate. An equally expensive increase in UI benefits, holding the eligibility duration unchanged, yields a smaller increase in the unemployment rate and a smaller decrease in the labor force participation rate. We show that disregarding the effect of flows in and out of the labor force and job-to-job transitions would significantly bias the response of the unemployment rate and labor productivity to UI reforms.

Keywords: Unemployment Insurance; Labor Market Flows; Directed Search
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1 Introduction

The provision of unemployment insurance (UI) benefits, together with their extension during economic downturns, constitute the most prominent policies to insure workers against joblessness. The effects of UI benefits have been studied extensively in labor economics, documenting that high levels of UI may worsen workers' job-finding prospects.[1] A recent literature explicitly models the firms' job creation response to UI extensions and uses structural models to obtain reliable counterfactual policy results.[2] The structural approaches have so far abstracted from workers' labor force participation decisions, as well as job-to-job transitions, which may have important implications for the analysis of UI reforms. On the one hand, more generous UI might improve workers' labor market outcomes as it incentivizes workers to stay in the labor force longer. On the other hand, firms may respond by creating fewer vacancies, which might be detrimental for labor productivity as fewer workers transition to high productivity jobs.

To address these challenges, we extend the life-cycle framework of Menzio, Telyukova, and Visschers (2016) by adding the labor force participation decision of workers. This extension makes this the first model in the literature featuring endogenous job creation by firms and job-to-job transitions in a three state model of the labor market. This unique combination allows us to comprehensively study the effects of an UI extension to 99 weeks and an equally expensive increase in UI benefits of 19%, while holding eligibility duration fixed at 6 months. We find that both UI reforms moderately reduce employment, the labor force participation rate (LFPR), GDP, and increase unemployment. These changes are mostly driven by changes in the separation rate and flows in and out of the labor force, as opposed to changes in the job-finding rate, consistent with the applied literature on UI extensions (Schmieder et al., 2016; Nekoei and Weber, 2017). The main difference between the two reforms is that the UI extension has a larger impact on the unemployment rate, because fewer unemployed workers drop out of the labor force.

Our main contribution is to show that disregarding the effect of flows in and out of the labor force and job-to-job transitions implies a significant bias in the analysis of UI reforms. Typically, in search models, more generous UI leads workers to become "pickier" and search

[1]See, among others, Schmieder and von Wachter (2016) and Tatsiramos and Van Ours (2014) for recent surveys of the microeconomic literature on the effects of UI benefits and Chodorow-Reich, Coglianese, and Karabarbounis (2019), Hagedorn, Karahan, Manovskii, and Mitman (2013), Hagedorn, Manovskii, and Mitman (2015), and Johnston and Mas (2018) for the aggregate effects.

[2]See Krause and Uhlig (2012), Nakajima (2012), Mitman and Rabinovich (2019) and Hartung et al. (2020).

for more productive jobs, which increases labor productivity. In our model with job-to-job transitions, labor productivity declines because fewer employed workers move on to more productive jobs due to depressed job creation. In addition, we show that flows in and out of the labor force account for up to a quarter of the employment response and up to one third of the unemployment response to more generous UI.

In our model, workers are heterogeneous in home production, which is subject to idiosyncratic shocks. These shocks capture in reduced form all changes to the relative return of market work compared to home production, such as child/family caring responsibilities, health, and disability shocks. In addition, workers age stochastically through a life-cycle, which also affects the value of home production. Non-employed workers choose whether to join the pool of unemployed or to drop out of the labor force. The unemployed give up a fraction of their home production in exchange for a higher job contact rate. To account for the large fraction of hires from out of the labor force, we assume that non-participating workers still contact jobs, but at a lower rate.[3] Successful matches start out with unknown productivity, which has to be learned over time. Employed workers engage in job search and transition to more productive matches over the life-cycle.

On the other side of the market, firms decide how many and what type of vacancies to open. Vacancies differ in the type of workers they hire and the promised utility they offer to workers, which gives rise to a segmented labor market. In each submarket, the frictional meeting process is modelled with a constant returns to scale matching function. Workers choose which type of vacancy to search for. This decision entails a trade-off, as high utility jobs attract more applicants but feature a lower job-finding probability. Workers with high home production or in high productivity matches search in submarkets with high promised utility but low job-finding rate. Finally, matches can be either endogenously or exogenously dissolved.

We calibrate the model targeting the average monthly labor market flows and the LFPR over the life cycle, in addition to the job tenure distribution. The tenure distribution provides information about the distribution of match-specific productivity, in addition to the labor force attachment of workers. This creates a tension in the calibration: the movements in and out of the labor force at a monthly frequency are very large, while there are many workers in stable jobs with long tenures. To account for the frequent movements in and out of the labor force requires a very volatile home production process, which would contradict the large mass of persistently employed workers. Our model overcomes this challenge with the interaction

[3] In CPS, 38.3% of new hires every month are from workers coming from out of the labor force.

between home production and match-specific productivity. Workers in high quality matches are "insulated" from home productivity shocks and remain employed for long periods of time. At the same time, the home production process has enough volatility for the model to match *all* labor market flows perfectly. This is not a trivial outcome in search models with a labor force participation margin, as typically these models are not flexible enough to match all flows.[4]

Any framework aiming to understand the aggregate effects of UI reforms should take into account the differences across workers' labor market attachment, since this heterogeneity is likely to affect the impact of UI policies. For example, Lalive (2008) and Tatsiramos (2010) have shown that old workers use UI as a bridge to retirement, and thus, might react differently to UI changes compared to prime age workers. Similarly, workers with strong labor market attachment respond less strongly to an increase in UI benefits compared to workers with lower attachment, such as secondary earners.[5] To gauge the model's ability to capture these aspects of worker heterogeneity, we examine its performance with respect to two sets of untargeted moments: the labor market flows over the life-cycle, and workers' four-month labor market histories identified from the CPS panel dimension (based on Kudlyak and Lange, 2017 and Hall and Kudlyak, 2019). We show that the labor market flows over the workers' life-cycle and the four-month labor market histories predicted by the model are close to the empirical ones. This shows that the model is consistent with rich heterogeneity in the labor market attachment of various workers, which makes it a suitable framework to study UI reforms.

We use the model to study the effects of an UI benefits extension to 99 weeks, a change implemented during the Great Recession in the United States, and contrast this reform to an equally expensive 19% increase of UI benefits while holding eligibility duration fixed. The 99 weeks extension leads to an increase in the unemployment rate by 19%, or a 1 percentage point increase, to a decline in the employment to population ratio by 2.1% and to a decrease in the LFPR by 1%. The declining employment rate is compounded by a decline in labor productivity, which leads to a decrease in GDP by 2.6%. The significant increase in the unemployment rate is driven mostly by changes in the separation rate and the flow out of the labor force, as opposed to changes in the job-finding probability. Thus, our model is

[4]For example, Garibaldi and Wasmer (2005) report that their model falls short in accounting for the magnitude of the UN and NU flows. Krusell et al. (2011) also report that the UN flow is too small and the UE flow is too large in their model compared to the data. Similarly, the model in Cairo et al. (2020) fails to account for the magnitude of several observed flows.

[5]For example, it has been shown that secondary earners change their behavior more often than primary earners over the business cycle; see Mankart and Oikonomou (2017).

consistent with two empirical findings on UI duration extensions. On the one hand, UI extensions have a small impact on the job-finding rate of unemployed workers (Schmieder et al., 2016; Nekoei and Weber, 2017). On the other hand, Hartung et al. (2020), studying a cut in UI eligibility duration in Germany, show that three quarters of the decline in the unemployment rate are due to lower separation rates into unemployment.

We further show that the UI extension leads to a decline in the labor force participation rate. This seems counterintuitive at first, because it is often argued that more generous UI benefits incentivize workers to stay longer in the labor force. Our model indeed estimates that flows from unemployment to out of the labor force (UN) would decline significantly by 17%, consistent with the empirical findings of Rothstein (2011) and Farber and Valletta (2015). The UI reform nevertheless leads to a decline in the LFPR rate. This occurs because the reservation productivity for staying in a match increases, which in turn increases the separation rate. Together with the reduced job-finding rates, this depresses the LFPR rate. Importantly, we show that disregarding the flows in and out of the labor force underestimates the effects of the reform on the unemployment rate by one third.

We contrast this change in the UI system with an equally expensive increase in UI benefits by 19%, holding UI eligibility duration constant at 6 months. This reform leads to similar employment effects, but to a 4% smaller increase in the unemployment rate (15% compared to 19%). The reason for this difference is that the UN flow declines more for the duration extension than for the benefit increase. This is driven by the small mass of unemployed workers who drop out of unemployment once benefits run out. Finally, the effects of both UI reforms on GDP and labor productivity are similar. With both policies, job-to-job transitions decline, implying fewer transitions to highly productive matches, which pulls average labor productivity down. Together with the lower employment rate, this leads to a decline in GDP of about 2.6%.

Although we make no claims about welfare, we believe that it is important to study the positive effects of more generous UI policies, as the policy debate often centers around the effects of these reforms on (un)employment and output.[6] Our framework shows that it is particularly important to account for the changes in *all* labor market flows to comprehensively understand the effects of UI benefit reforms. Specifically, we show it is important to account for the change in job-to-job transitions as it has a large impact on labor productivity. Another important result is that despite the drop in the UN transition rate, the LFPR

[6]The equilibrium of our directed search model is efficient, therefore it is not well suited for welfare comparisons.

ultimately declines after the UI reforms. The combination of lower job-finding with higher separation rates leads to an increase in the mass of unemployed workers. Overall, since there are more unemployed workers, the mass of workers dropping out of the labor force increases. In the end, the often heard argument that more generous UI benefits keep people in the labor force does not hold in our setting.

This paper contributes to two strands of literature. The first studies the aggregate effects of UI reforms. Recent contributions, among many others, include Chodorow-Reich et al. (2019), Hagedorn et al. (2013), Hagedorn et al. (2015), and Johnston and Mas (2018). Most closely related are Hartung et al. (2020), Krause and Uhlig (2012), Mitman and Rabinovich (2019), and Nakajima (2012) who study the effects of UI reforms using equilibrium search models.[7] An important difference with our work is that we consider a model with a labor force participation choice, as well as job-to-job transitions. In particular, more generous UI makes workers pickier and may increase labor productivity, as pointed out by Acemoglu and Shimer (1999). We show that including job-to-job transitions counteracts this channel. More generous UI reduces job-to-job transitions through lower job creation, which leads fewer workers climbing up the job ladder to more productive jobs, ultimately lowering labor productivity. Similarly, flows in and out of the labor force account for up to a quarter of the employment response and up to one third of the unemployment response to more generous UI.

Second, we contribute to the literature that develops search and matching models with an out of the labor force state, in the tradition of Pries and Rogerson (2009) and Garibaldi and Wasmer (2005). Compared to Krusell et al. (2010, 2011, 2017), we endogenize the job creation decision of firms, making our model more suitable for the study of UI reforms. Compared to Haefke and Reiter (2011) and Cairo et al. (2020), our model is flexible enough to match all the labor market flows perfectly and includes job-to-job transitions, although they go beyond our paper in studying the model's cyclical properties. Finally, we complement the work of Kudlyak and Lange (2018) and Hall and Kudlyak (2019) who exploit the panel dimension of CPS to identify heterogeneity in labor force profiles across workers. In our model, this heterogeneity is driven by economic choices, and, to the best of our knowledge, we are the first to compare model-generated four-month labor force histories with CPS data.

The rest of the paper is organized as follows. The next Section describes the model framework. Section 3 lays out the identification strategy and Section 4 presents the calibration

[7] Also related is the work of Costain and Reiter (2008) who highlight the link between labor market fluctuations and the responsiveness of unemployment to changes in UI benefits.

results along targeted and untargeted moments. In Section 5, we present the effects of more generous UI schemes on labor market stocks and flows. Section 6 concludes.

2 The Model

In this Section we lay out our model of worker flows over the life cycle. The model builds on the directed search framework of Menzio and Shi (2011) and Menzio, Telyukova, and Visschers (2016). Workers go through a life cycle and decide whether to participate in the labor market. They trade off the value of home production in exchange for market work. The labor market is frictional and segmented in submarkets. Firms choose how many and what type of vacancies to offer, and workers direct their search towards these type of vacancies.

2.1 The Environment

Time is discrete and the economy is populated with a unit mass of workers and a positive mass of firms to be determined in equilibrium. Workers stochastically age through a life cycle, which is modeled as A distinct stages of aging. Each period, a worker of age a reaches the next stage $a+1$ with probability p_a. After they aged through the last stage, workers exit the model and are replaced by an entering cohort of young agents.[8] In addition to age, workers are also heterogeneous in their home production. Home production is comprised of an idiosyncratic component h, which is subject to shocks, as well as an age-specific component $\bar{h}(a)$. In contrast to most of the search literature, workers' participation in the labor market entails an economic choice. They trade off their home production with the opportunity to earn a market wage.

The level of home production in our model should be thought of as the value of non-participation in the labor market relative to market work. Therefore, it is a reduced form way of capturing all the relevant reasons for not participating in the labor market. It comprises the value of goods and services produced at home, such as food preparation, child care, elderly care in addition to the value of leisure. But it also includes other important dimensions such as health shocks, or the value of getting education.[9] Our goal is not to explicitly model the different reasons why workers do not participate in the labor market, but rather build an

[8]The assumption of stochastic aging greatly simplifies the computational burden of the model. Since agents are risk-neutral, the assumption of stochastic aging compared to deterministic aging is inconsequential.

[9]Because the model admits one normalization on the production side, it does not matter whether we model health shocks as negative shocks to labor productivity, or as positive shocks to home productivity.

equilibrium framework where worker flows are generated by economic decisions of agents.

Periods are subdivided into six stages: realization of shocks, separation, matching, search, learning, and production. In the beginning of the period, all innovations to home productivity, aging shocks, as well as the expiration unemployment benefits are realized.

In the separation stage, these shocks might trigger endogenous separations for employed individuals. In addition, matches dissolve exogenously with probability δ_0.

The period continues with the matching stage. Workers participating in the labor market have the opportunity to search with a probability that depends on their employment state. For the unemployed this probability is λ_u, whereas employed workers engage in on-the-job search with probability λ_e. To account for the large amount of worker flows from out of the labor force directly to employment, we also allow workers not participating in the labor force to take part in the matching process with a probability λ_o.[10] We call search during unemployment active search, and passive search for out of the labor force (OLF) workers.

The labor market is frictional and search is a time-consuming process. While workers are unemployed, they have to forgo a fraction $1-\phi$ of their flow utility from home production to engage in active job search. Workers are directing their search towards specific submarkets indexed by (x, a, h). These submarkets differ in the terms of the meeting probability and the promised value of the job to the worker x. In submarket (x, a, h), firms offer workers of type (h, a) a contract with promised life time utility x to the worker. Workers are able to choose the submarket in terms of promised life time utility x, but are forced to search in the submarket for their respective type.[11] Intuitively, submarkets with high promised life-time utility will be visited by more workers. As a consequence, each submarket will have a different labor market tightness, as defined by the ratio of vacancies to job seekers, i.e. $\theta = v/u$. Conditional on having the opportunity to search, a worker visiting submarket (x, a, h) faces a probability of meeting a vacancy of $p(\theta(x, a, h))$.

Profit maximizing firms also choose how many vacancies to open in each submarket. Maintaining a vacancy costs k units of output per period. A vacancy in submarket (x, a, h) meets a worker with probability $q(\theta(x, a, h))$, where both $p()$ and $q()$ are twice differentiable, strictly increasing and strictly concave functions such that $q(\theta) = p(\theta)/\theta$. After a successful meeting, nature draws a match specific productivity z from the distribution $f(z)$. Matches are experience goods, and the idiosyncratic match productivity is unknown to both partners at the beginning. At the end of each matching stage, workers and firms in matches with

[10] In CPS, 38.3 % of all new hires involve workers from out of the labor force.

[11] This assumption will guarantee that the equilibrium is block-recursive, which reduces the computational burden of the model.

unknown z learn the productivity with probability α. The assumption that matches are experience goods is grounded in the observation that many matches are dissolved within a few months, and that most jobs have a specified trial period.[12]

After the matching stage, non-employed workers decide whether to actively search and join the pool of unemployed, or to drop out of the labor force. The period concludes with the production stage. Employed workers produce z units of output. Workers outside of the labor force produce according to their idiosyncratic productivity h times their age specific home productivity component $\bar{h}(a)$. Actively searching unemployed workers forgo a fraction $(1-\phi)$ of their home productivity. Additionally, they might be eligible for unemployment benefits of level $\bar{b}$. The eligibility criteria are modeled to capture the key elements of the US system. Only workers who lose their job are eligible for unemployment benefits. Although the unemployment insurance (UI) system varies from state to state, typically UI benefits expire after 6 months.

2.2 Value Functions

We start with the problem of workers who have the opportunity of searching. These workers face a trade-off between choosing a submarket with a high promised life-time utility but low job-finding rates, or lower paying jobs that are easier to come by. This maximization problem is described in equation (1).

$$R(V,a,h) = \max_{x} p(\theta(x,a,h))\,[x-V] \tag{1}$$

The value of search consists of the probability of finding a job $p(\theta(x,a,h))$ times the capital gain from finding a job. This is given by the promised life-time utility x of the job, minus the outside option of the searching worker V, which can be the value of employment or non-employment.

Next, equation (2) describes the problem of a non-employed worker in state a,h with unemployment benefits $b \in \{0,\bar{b}\}$, facing the labor force participation decision.

$$N(a,h,b) = \max\{N^u(a,h,b), N^o(a,h)\} \tag{2}$$

The worker simply chooses to drop out of the labor force if its continuation value $N^o(a,h)$ is higher than the value of engaging in active job search $N^u(a,h,b)$. These value functions

[12] According to CPS, 23 % of employed workers have job tenure less than a year.

at the beginning of the production stage are presented in equations (3) and (4).

$$N^o(a,h) = \exp(h + \bar{h}(a)) + \beta\mathbb{E}[N(a',h',0) + \lambda_o R(N(a',h',0),a',h')] \tag{3}$$

A worker that is currently not in the labor force enjoys flow utility of $\exp(h+\bar{h}(a))$. Beginning of next period, shocks to home productivity and age realize. The expectation is taken over all possible future values of h' and a'. Throughout the paper, we denote all variables in the next period with a prime. Next period, she again faces the decision to join or stay out of the labor force, thus the continuation value is the discounted expected value of equation (2). With probability λ_o she has the opportunity to search next period, which is valued $R(N(a',h',0),a',h')$.

Because unemployed workers have to spend a certain amount of time on search, they only receive a fraction ϕ of their total home productivity $\exp(h + \bar{h}(a))$ as flow payoff. In addition, workers receive unemployment benefits $b \in \{0, \bar{b}\}$, depending on their eligibility status. With probability λ_u, the worker is able to participate in the matching process, which entails a capital gain of $R(N(a',h',b'),a',h')$. Formally, the problem of an unemployed worker is presented below

$$N^u(a,h,b) = b + \phi\exp(h + \bar{h}(a)) + \beta\mathbb{E}\left[N(a',h',b') + \lambda_u R(N(a',h',b'),a',h')\right]. \tag{4}$$

Next, consider an employed worker of type (a,h) who is in a match with know quality z at the beginning of the production stage. The joint value of the match for the firm and the workers is given by

$$\begin{aligned} V(a,h,z) &= z \\ &\quad + \beta\mathbb{E}\left[\max_{d\in[\delta_0,1]}\left\{dN(a',h',\bar{b}) + (1-d)\left[\lambda_e R(V(a',h',z),a',h') + V(a',h',z)\right]\right\}\right]. \end{aligned} \tag{5}$$

The match produces z units of output. At the beginning of next period, the new values of h' and a' are revealed and the match partners can decide to separate by setting $d = 1$. If the match is neither exogenously nor endogenously dissolved, the match continues to the matching stage where the worker gets the opportunity to search with probability λ_e. This opportunity is valued at $R(V(a',h',z),a',h')$. If the search is unsuccessful, the continuation value is $V(a',h',z)$.

Successful matches initially start out with unknown quality. The value of these matches at the beginning of the production stage is given by

$$V(a,h,z_0) = \alpha \sum_z V(a,h,z)f(z) \ + (1-\alpha)\left(\sum_z zf(z) + \beta\mathbb{E}\left[\max_{d\in[\delta_0,1]}\left\{dN(a',h',\bar{b})\right.\right.\right.$$
$$\left.\left.\left. + \ (1-d)\left[\lambda_e R(V(a',h',z_0),a',h') + V(a',h',z_0)\right]\right\}\right]\right). \tag{6}$$

Just before production takes place, with probability α the productivity of the match is revealed. With probability $1-\alpha$, the match continues with unknown productivity. In expectation, the match produces $\sum_z zf(z)$ units of output. The continuation value mirrors the one with known match quality.

Free entry on the firm side drives down the firm's expected gain from opening a vacancy in each submarket to it's cost k. The gain is given by the job filling probability in the respective submarket, multiplied with the value of the job minus the amount promised to the worker:

$$k \geq q(\theta(x,a,h))\,(V(a,h,z_0) - x)\,. \tag{7}$$

This relationship pins down θ and hence the job-finding and job-filling probabilities for all submarkets in all states of the economy. Thus, firms and workers can form expectations about these objects without the knowledge of the distribution of matched and unmatched agents, giving rise to the block-recursive nature of the model (Menzio and Shi, 2011).

With all value functions described, we define the Block Recursive Equilibrium in this environment as in Menzio and Shi (2010, 2011) and Menzio et al. (2016):

Definition: A Block Recursive Equilibrium in this environment consists of a market tightness function θ, value functions V, N, N^u, N^o, a policy function for the participation decision of non-employed workers s, policy functions regarding the market to search in x^u, x^o, and policy functions for the firm-worker match, (d, x^e). These functions must satisfy the following conditions:

1. $V, N^u, N^o, N, s, x^o, x^u, x^e, d, \theta$ are independent of the distribution of agents across states.
2. θ satisfies the free entry condition $\forall\ (x,a,h)$ in equation (7)
3. s, x^u, x^o, x^e, d maximize the value functions V, N^u, N^o, N in equations (2)–(5).

The next Section discusses the calibration of the model.

3 Calibration

To calibrate the model, we have to specify a distribution of match-specific shocks, a functional form for the matching function, as well as the processes for the age profile and idiosyncratic shocks of home production. First, we assume that match-specific productivity z is drawn from a uniform distribution $\mathcal{U}([-\Delta_z, \Delta_z])$. Second, since the model is formulated in discrete time, we choose to work with the CRS matching function $M(u,v) = \frac{uv}{(u^{\gamma}+v^{\gamma})^{\frac{1}{\gamma}}}$, which yields well-defined job-finding and job-filling probabilities between 0 and 1.[13] Third, for the age profile of home production, we assume a linear spline with three different regimes:

$$\bar{h}(a) = \begin{cases} \frac{h_2-h_1}{a_1}(a-15)+h_1 & a \in [15, a_1] \\ \frac{h_3-h_2}{a_2-a_1}(a-a_1)+h_2 & a \in (a_1, a_2] \\ \frac{h_4-h_3}{64-a_1}(a-a_2)+h_3 & a \in (a_2, 64] \end{cases}$$

These regimes capture the behavior of labor force participation over the life cycle: it increases for young workers, plateaus during prime age, and decreases as workers get older. The process is characterized by six parameters: a_1 and a_2 are the age cutoffs at which the home production regime changes, while $h_1 - h_4$ determine the unconditional levels of home production at ages $15, a_1, a_2$, and 64, respectively. Finally, the process for idiosyncratic home production shocks, h, follows a random walk $h' = h + \sigma_h \epsilon_h$, where σ_h represents the probability a shock ϵ_h occurs, with $\epsilon_h \sim \mathcal{U}([-\Delta_h, \Delta_h])$.[14] We calibrate Δ_h and discretize the process for h using the method from Tauchen (1986).[15]

We set a period in the model to be one month. Several model parameters are set exogenously. The discount factor β is set to 0.996, consistent with a 5% annual interest rate. Moreover, we set the elasticity of the matching function, γ, to 0.6, which lies between the estimates reported by Den Haan et al. (2000) and Hagedorn and Manovskii (2008). We normalize the search intensity of employed workers to unity; we calibrate endogenously the search intensities of workers who are unemployed and out of the labor force. The monthly probability of a worker keeping UI benefits is set to 0.8329 which yields an average eligibility

[13] We use u to denote the measure of job seekers in a particular submarket. This may consist of employed, unemployed or individuals out of the labor force.

[14] We have calibrated the model with an AR(1) process for the home production shocks and the results are very similar. As we explain later, it is important that the home production process has persistence; simple iid shocks would not allow us to match the labor market flows.

[15] Since we are modeling a random walk, we have to impose ex ante bounds for the values of h in the calibration process. We assume that h can take values in a $[-2, 2]$ grid.

Parameter	Value	Description	Target
α	0.3333	Prob. of learning	Average learning duration of 3 months
β	0.996	Discount factor	5% real interest rate
γ	0.6	Matching function elas.	Literature (see main text)
λ_e	1	Search intensity employed	Normalization
p_b	0.8329	Prob. of keeping UI benefits	Average eligibility duration of 26 weeks
p_a	0.0167	Aging Probability	Average lifecyle of 50 years with 10 age groups

Table 1: Externally Calibrated Parameters

duration 26 weeks in the model, the standard UI duration in the US. Moreover, we choose to have 10 age groups and an average career length of 50 years. This implies an average group length of 5 years, which we achieve by setting the aging probability p_a equal to 0.0167. Finally, we set the probability of learning the quality of a firm-worker match to one third per period. This number implies a modest level of learning frictions, since workers and firms learn their match quality in three months on average, very close to the parameterization of Menzio et al. (2016). In the appendix Section C, we show that our results also hold for different parameterizations. We conduct sensitivity analysis with respect to both higher and lower levels of the learning speed α and the elasticity of the matching function γ.

The remaining 15 parameters are calibrated internally. We choose a set of identifying moments from US data to inform these model parameters. To begin with, the choice of the identifying moment for the flow value of unemployment benefits $\bar{b}$ is straightforward. We use the the long run average of the ratio of unemployment benefit expenses over GDP in the US as reported by the OECD as a target for the generosity of unemployment benefits.[16][17]

For most of the remaining identifying moments, our main data source is the Current Population Survey (CPS) obtained from Integrated Public Use Microdata Series (IPUMS) from 1982 to 2018.[18] Following Kudlyak and Lange (2018), we restrict our attention to

[16] According to the OECD Public Unemployment Spending series, spending on unemployment benefits accounts for 0.67% of US GDP.

[17] We also consider an alternative target, where we exclude capital income from GDP, since capital is missing in our model, and target UI expenditures over labor income instead. The choice of moment is inconsequential for our results, see Appendix C.

[18] The IPUMS database is made available by the Minnesota Population Center. Using the CPS data from IPUMS compared to NBER has an important advantage: individual ids are fully linked over time. They are meticulously constructed by Rivera Drew et al. (2014) with a procedure that improves upon the standard procedure of Madrian and Lefgren (2000) usually employed in the literature. As a result, all variables of interest are harmonized over time. We also performed the standard sanity test of checking whether sex, race and age are consistent within individual records. There were few ids that did not have consistent demographics, which we dropped from the sample.

Transition Rates CPS 1982–2018			UI System OECD			Tenure Distribution CPS Job Tenure Suppl.			LFPR CPS 1982–2018		
Flow	Data	Model	Target	Data	Model	Years	Data	Model	Age	Data	Model
JJ	0.021	0.020	b/GDP	0.007	0.007	≤ 1	0.229	0.257	15–19	0.460	0.465
EU	0.013	0.013				$(1, 3]$	0.227	0.190	20–24	0.754	0.750
EN	0.024	0.024				$(3, 9]$	0.273	0.287	25–29	0.830	0.832
UE	0.238	0.236				> 9	0.271	0.266	30–34	0.834	0.854
UN	0.214	0.212							35–39	0.840	0.859
NE	0.063	0.063							40–44	0.847	0.858
NU	0.039	0.039							45–49	0.835	0.847
									50–54	0.796	0.786
									55–59	0.709	0.704
									60–64	0.518	0.540

Table 2: Empirical Moments and Model Fit

workers that have either four or eight interviews in CPS. The calculation of labor force histories is possible only for these workers and we want to use the same sample for both targeted and untargeted moments. We consider workers between 16 and 64 and we treat the data set as a large cross-section. That is, we pool all observations together before computing averages.

The identification strategy for the parameters describing labor market frictions is standard. The transition rates between employment, unemployment, and out of the labor force (OLF), as well as the job-to-job transition rate inform the search friction parameters λ_u and λ_o, the flow cost of vacancy creation k, the exogenous separation rate δ_0, and the cost of active job searching $1 - \phi$.

These transition rates also inform the two parameters characterizing the home production process: σ_h, capturing the likelihood of a shock, and Δ_h, capturing the shock's magnitude. Intuitively, the mapping between the data moments and the model parameters works as follows. The flows from unemployment and OLF to employment pin down λ_u and λ_o, respectively. The cost of vacancy creation, k, determines the overall scale of job-finding probabilities from all states; since we normalized λ_e to unity, the remaining job-to-job transition rate informs k. δ_0 is linked to the flow from employment to unemployment. The cost of active searching, ϕ, directly affects the transition from OLF to unemployment. Finally, the flows from employment and unemployment to non-participation inform the home production process: the former speaks to the magnitude of shocks, since large shocks are required to move employed workers to the OLF state instead of unemployment. The volatility of the process affects the latter flow, as frequent shocks drive unemployed workers OLF before they find a job and transition to employment.

To identify the six parameters governing the home production profile over the life-cycle, we target the labor force participation rate for ten age groups over the life cycle. It is important to notice that we do not include the age profiles for any transition rates in the calibration targets. On the contrary, the predictions of the model regarding flows over the life-cycle will be used to gauge model performance.

The only parameter left to pin down is Δ_z, which governs the dispersion in the match specific productivity. To identify Δ_z, we target the job tenure distribution, which we compute using the CPS Job Tenure supplement, also available in IPUMS.[19] The job tenure distribution is informative about the match-specific productivity distribution because the survival probability of a match strongly depends on z. Workers in low z matches have a higher probability of moving to unemployment, looking for another job or even leaving the labor force after learning the match productivity. Therefore, the dispersion of match specific productivities affects the fraction of jobs surviving over time and consequently, the tenure distribution informs the range of shocks Δ_z. A similar identification strategy has been applied in Menzio and Shi (2011). The values of all empirical calibration targets are summarized in Table 2.

4 Results

4.1 Worker and Firm Behavior

In this Section, we provide intuition for worker and firm behavior in equilibrium. Figures 1, 2 and 3 contain various pieces of relevant information across three specific age groups: young, prime-age and old workers. These categories correspond to groups 1, 5 and 10 of the ten age groups we used to calibrate the model. In Appendix B, we provide the results for all age groups. An important result is that workers of different ages have different behavior; the decision rules, however, have the same qualitative features across age groups, and we start with those.

We start by explaining the choices of non-employed workers in Figure 1. First, there are two thresholds, h_b and h_n, above which non-employed workers stop active searching (column 1 of Figure 1). Specifically, jobless workers with home production levels greater than h_b (h_n) stop active searching if they are UI eligible (non-eligible). For these values of home production workers prefer to stay OLF than actively search for a job, but they accept employment opportunities when found, giving rise to NE transitions. These workers

[19]The Job Tenure supplement was conducted in 1983, 1987, and every two years from 1996 to 2018. We compute the tenure moments by pooling all observations and treating it as a large cross-section, similar to what we did with the monthly CPS.

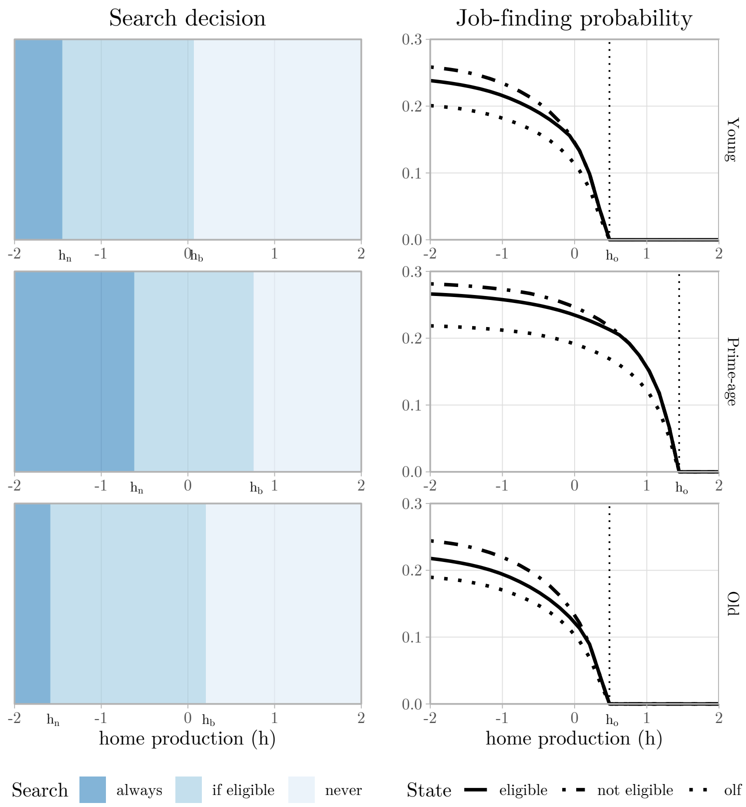

Figure 1: Search decision and job-finding probability for different age groups of non-employed workers.

prefer to enjoy the full value of their home production over higher future job-finding rates. Second, for values of home production lower than the h_n threshold, workers join the labor force and actively look for jobs. When OLF workers are hit by shocks driving them below this threshold, they perform a NU transition; symmetrically, when non-eligible unemployed workers are hit by shocks driving them over h_n, they perform a UN transition.

Moreover, there is a home production threshold h_o above which the probability of finding a job is zero (column 2 of Figure 1). Workers with these home production levels search in submarkets in which the promised utility is so high that firms do not create any vacancies; these workers stay jobless and inactive. Finally, the slope of job-finding rates is decreasing in home production; here is the intuition for that. Workers have to be compensated with at least the value of their outside option in equilibrium, otherwise they would not accept the job (see equation 1). This implies that the higher the level of a worker's home production, the higher has to be the promised utility the firm offers to the worker. At the same time, free entry of firms implies that firms have to be indifferent between submarkets (see equation

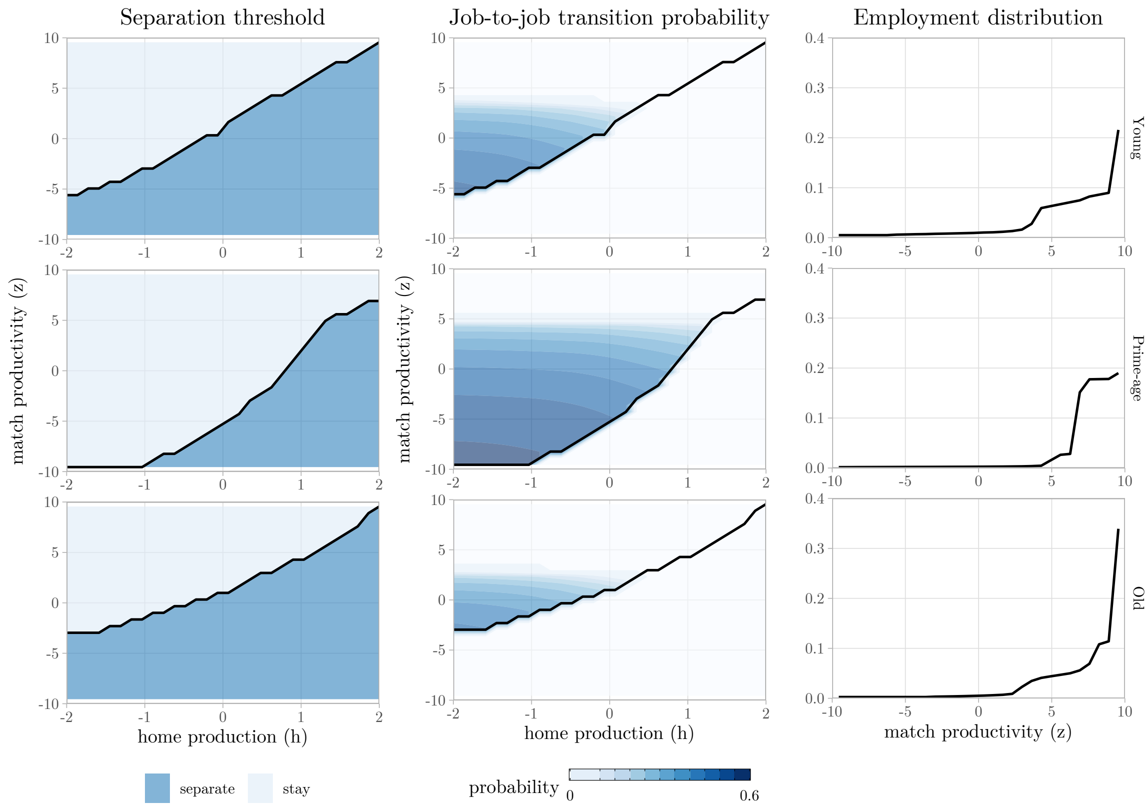

Figure 2: Separation threshold, job-to-job transition probability and employment distribution for different age groups of employed workers.

7). This means that in submarkets in which they offer high promised utilities, firms have to be compensated with higher vacancy filling rates. To achieve this outcome, firms open less vacancies in submarkets featuring workers of high home production. Put differently, tightness and job-finding probability is a decreasing function of home productivity, as can be seen in column 2 of Figure 1. This argument also explains why firms open less vacancies for unemployed workers who receive benefits relative to those who do not receive benefits.[20]

Next, we explain the behavior of employed workers in Figure 2. An important aspect of the model for these workers is the interaction of match-specific and home production shocks. This interaction is manifested in how employed workers endogenously separate from jobs: as can be seen in column 1 of Figure 2, there is a match-specific productivity threshold $\underline{z}(h)$ which is increasing in the worker's home production level. In other words, employed work-

[20]Since workers OLF have the same outside option as non-eligible unemployed workers, they choose the same submarket with the same tightness. The difference in job-finding probabilities in column 2 of Figure 1 arises only due to the different search intensities $\lambda_u > \lambda_o$.

ers with high home production levels stay employed only if they are employed in matches with high match-specific productivity. The existence of match-specific productivity implies a natural persistence mechanism in our model: workers in high quality matches are "insulated" from home production shocks and remain employed for long periods of time. On the other hand, workers in low quality matches may quit when hit by a relatively small home production shock and immediately try to find a new job. This heterogeneous behavior along the match-specific productivity dimension helps the model generate both a persistent state of employment with many long-tenure matches and many high-frequency worker movements in and out of employment.

The interaction between match-specific and home production shocks is also crucial for the job-finding rates of employed workers, as column 2 of Figure 2 makes clear. Naturally, job-finding rates are decreasing in home production due to the logic we outlined for non-employed workers. They are also decreasing in match-specific productivity, up to a point at which employed workers stop searching because the promised value in their current job is higher than the expected value of a new match. An implication of this is that the most employed workers are in high productivity matches, as shown in column 3 of Figure 2. Here is the intuition for why job-finding rates for employed workers are decreasing in match-specific productivity. Workers employed in matches of low productivity are eager to leave their jobs for better ones. Therefore, they search in submarkets with higher job-finding rates and lower promised values compared to workers in high value matches who are pickier. Finally, this mechanism leads to the observed negative correlation between job-tenure and job-to-job transitions.

So far we have abstracted from the effect of aging on labor market behavior; however, as workers become older, their labor market behavior changes. There are two main forces that differentiate the behavior of younger and older workers compared to the prime-age ones. First, due to the U-shape of the age-specific part of the home productivity process, young and old workers have higher levels of home production. This, as a result, lowers their labor force attachment. Second, as workers age, the expected remaining duration of their lifetime becomes shorter. Since the exogenous probability a match will dissolve is higher, the value of matching with an older worker is lower for the firms. This force reduces the job-finding rate of old workers, lowering their low labor force attachment even more.

The effects of these two forces can be seen in both Figures 1 and 2. Focusing on non-employed workers, the home production thresholds h_o, h_b and h_n first increase then decrease again, mirroring the U-shape home production profile. In other words, young and old workers

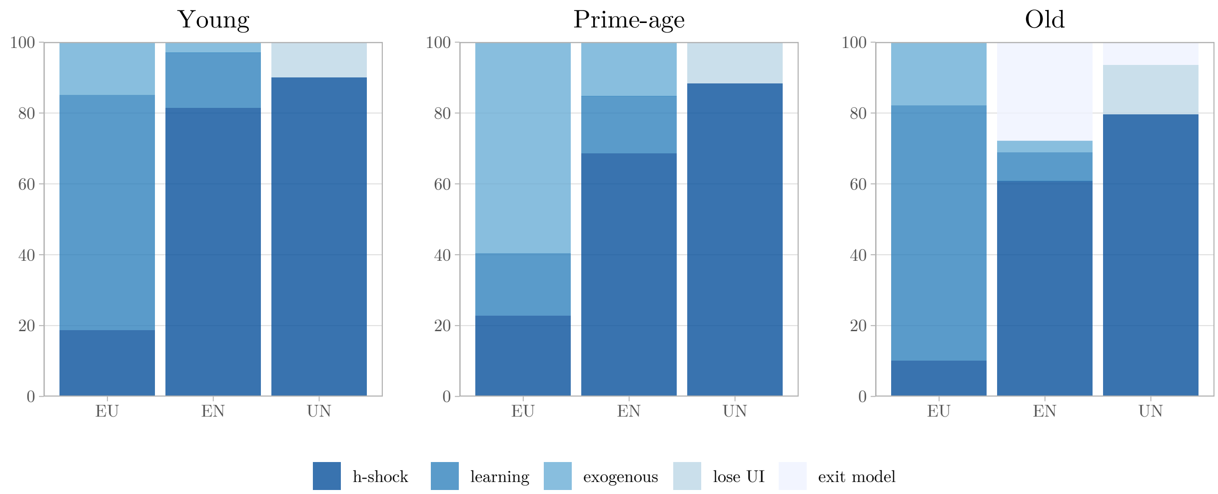

Figure 3: Decomposition of flows for different age groups across various model channels.

with only very low levels of home production stay in the labor force, especially if they are not eligible for UI. Notice that the threshold for non-eligible workers, h_n, moves more than the threshold for the eligible ones, h_b. Moreover, the h_b shift is less pronounced for old workers. Due to shorter expected duration of a match, UI becomes more important for the decision to stay in the labor force. This is consistent with the evidence that older workers may use UI benefits as a bridge to retirement; see Lalive (2008) and Tatsiramos (2010). Correspondingly, the h_n shift is more pronounced for old workers. For young workers, participating in the labor force has relatively high returns due to potential movements up the job ladder, while old workers do not have the time to wait for those.

Turning to Figure 2, young and old employed workers are pickier than prime-age ones. Their age-specific home production levels are higher, implying a higher reservation match productivity. Moreover, older people have lower job-to-job transition probabilities, since the expected value of a match is lower. Finally, with respect to the the employment distribution, the share of old workers in the best matches is over 30%, as opposed to around 20% for both young and prime-age workers. Since good matches need time to be found, older workers are employed in better matches. Interestingly, there is a non-trivial share of old workers in average quality matches, with z close to 5. Since job-finding probabilities are lower, older workers in average matches stay there longer. These results are consistent with the observed employment prospects of older workers who very often are employed in either high level long tenure positions or in entry level jobs for short durations.

Finally, Figure 3 provides a decomposition of various channels contributing to EU, EN, and UN flows. On the one hand, home production shocks are the most important factor behind EN and UN transitions across all ages. The quantitative importance of benefits expiration for UN flows is limited. On the other hand, the relative importance of factors contributing to EU are different across age groups. Exogenous separations play a major role for prime-age workers, while learning is the most important factor for the young and old ones. Compared to a model without learning, our model predicts more EU and UE flows. Given that young and old workers are pickier, this has a particularly strong impact on them. This makes the model predict high EU and UE rates of young workers, as in the data. Unfortunately, it also makes the model overstate the EU and the unemployment rate of old workers.

4.2 Targeted Moments

The values of all calibrated parameters are summarized in Table 3. A few comments on the most important features of the parameterization follow. When eligible, unemployed workers receive around 23.6% of the average worker productivity as unemployment benefits. In our model, b does not include the value of home production, as in most models without an out of the labor force state, which explains its relatively low value. The very low value of the exogenous separation rate δ_0 implies that the vast majority of separations taking place in the model are endogenous outcomes of firm-worker decisions. This is in contrast to models without home production shocks, which often rely on high levels of exogenous job destruction rates to match the empirically observed separation rates.

The values of λ_u and λ_o imply that unemployed and OLF workers sample job opportunities with a 46% and 58% lower probability than employed workers, respectively (λ_e is normalized to one). This implies that search frictions are more severe for non-employed than for employed workers. To make the model consistent with the observed job-to-job transition rate, the calibration implies that employed workers sample job offers more often than non-employed workers. This is consistent with Faberman et al. (2017) who find that employed workers generate more job offers than non-employed workers in line with our calibration. However, in line with the data, their job-finding rate is lower as they are more selective than non-employed workers.

To actively search for a job, unemployed workers sacrifice more than 60% of their home production value. This sizeable utility cost of unemployment helps the model rationalize the observed LFPR and the strong persistence of the OLF state. Moreover, it is consistent with the empirical evidence regarding the large psychological and emotional costs experienced

Parameter	Description	Value
ϕ	Share of home production for unemployed	0.3848
λ_u	Search intensity unemployed	0.5352
λ_o	Search intensity not in labor force	0.4157
δ_0	Exogenous separation rate	0.0072
k	Per-period vacancy posting costs	1.2521
σ_h	Prob. of home production shock	0.9999
Δ_h	$\epsilon_h \sim \mathcal{U}([-\Delta_h, \Delta_h])$	1.5175
Δ_z	$z \sim \mathcal{U}([-\Delta_z, \Delta_z])$	9.5532
$\bar{b}$	Unemployment benefits	1.7971
a_1	Second age knot for $\bar{h}(a)$-spline	21.5924
a_2	Third age knot for $\bar{h}(a)$-spline	47.4494
h_1	Home production at age 15	1.8145
h_2	Home production at age a_1	0.8140
h_3	Home production at age a_2	0.9093
h_4	Home production at age 64	1.3118

Table 3: Internally Calibrated Parameters

by unemployed individuals (Krueger and Mueller (2011) and Brand (2015)).[21] It is also important to notice the implications of the calibration for the home production process. Although it is persistent, since it is a random walk, shocks are drawn very often (σ_h is estimated to be very large). The states of employment and OLF are very persistent in CPS, with a large mass of workers never leaving the state they begin in; the persistence of the random walk allows the model to capture this. At the same time, there are large flows among labor market states at monthly frequencies, with many workers changing their labor market status from month to month; the fact that home production shocks are drawn very often makes the model consistent with this fact. Finally, the values of home production over the life-cycle have a U-shape, which enables the model to match the inverse U-shape profile of labor force participation found in the data.

The model matches all the targeted moments very closely, as can be seen in Table 2 and Figures 4 and 5. First, the average transition rates in the steady state of the model are very close to the average monthly transition rates of our CPS sample (Table 2). Comparing our results with the results of other three-state models of the labor market reveals that matching the average flows is not a trivial outcome but a rather a success of the model. For example, Garibaldi and Wasmer (2005) report that their model falls short in accounting for the magnitude of the UN and NU flows. Krusell et al. (2011) also report that the UN

[21]It is also consistent with the fact that around 25% of eligible individuals do not take up UI benefits, implying that there are non-trivial unemployment costs; see Auray et al. (2019) and Auray and Fuller (2020).

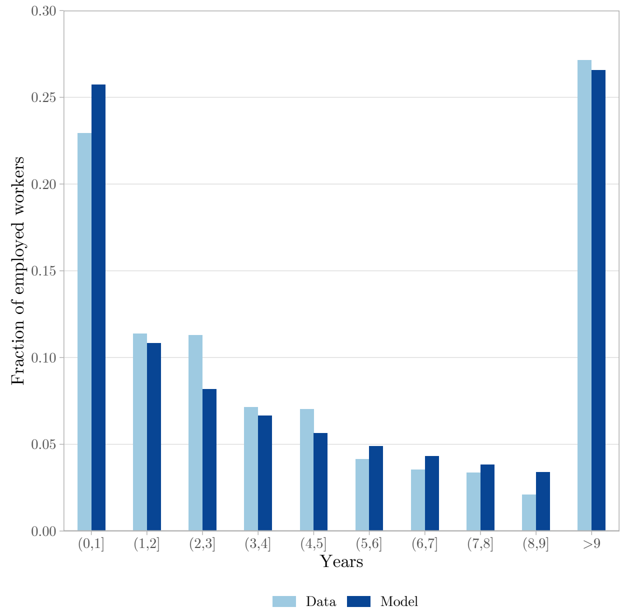

Figure 4: Job Tenure Distribution. Dark bars show the empirical tenure distribution in CPS, bright bars show the outcome of model simulations.

flow is too small and the UE flow is too large in their model compared to the data.[22] On the contrary, our model can quantitatively account for all steady state flows. Furthermore, our model successfully matches the job-to-job transition rate, a flow usually not targeted in other three-state models of the labor market with the exception of Krusell et al. (2017).

With regard to the second calibration target, namely the job tenure distribution, the model-implied distribution is very close to the empirical one (Figure 4). The model slightly overestimates the fraction of workers with tenure less than a year and slightly underestimates the fraction of workers with tenure between two and three years. These small discrepancies are commonly found in other models in the literature using the job tenure distribution to inform match specific shocks; see Menzio and Shi (2010) for a prominent example. We should highlight that the calibration targets include only four summary groups from the tenure distribution (see Table 2); the good performance of the model for the ten detailed groups in Figure 5 serves as another source of external validation.

Various calibration features imply a persistent employment state, which helps the model produce a realistic job tenure distribution. Exogenous separations are very improbable and

[22]The model of Krusell et al. (2011) can actually match the UE rate well, but this parameterization of the model implies a steady state unemployment rate of over 10%. The richer model of Krusell et al. (2017), with which our model shares many common elements, was the first model in the literature to quantitatively account for all observed labor market flows.

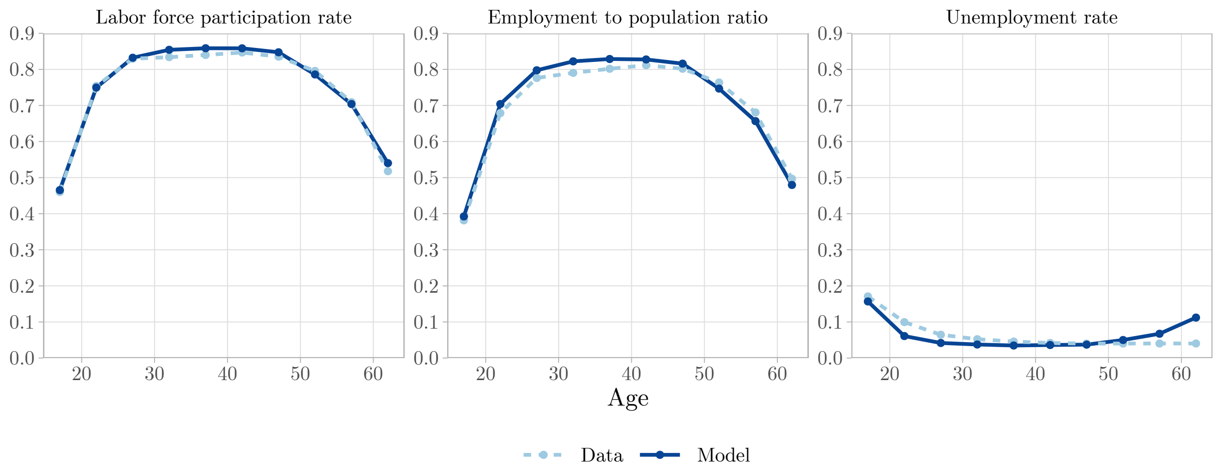

Figure 5: Age profile of LFPR, employment to population ratio and the unemployment rate in the model and CPS. The LFPR is a targeted moment, employment to population ratio and the unemployment rate by age is untargeted.

learning the quality of a match is completed in three months on average. Moreover, the majority of workers are employed in high-value matches. Home production is very persistent as explained above, implying that the opportunity cost of employment for most workers in good matches stays low for a while. Finally, employed workers sample job opportunities often ($\lambda_e = 1$) but only workers in low value matches are interested in moving to a new job. Taken together, all these model elements imply that a large fraction of workers stay in the same job for long tenures in the model, as in the data.

Finally, the model produces a realistic age profile for labor force participation (Figure 5). There is a slight discrepancy for prime age and older workers, which may well be expected since the model does not include schooling or retirement. The successful matching of the age profile of labor force participation is reassuring for our use of age profiles of worker flows as evaluation tests of the model. It implies that the model has the potential to generate realistic transitions across labor market states over the life-cycle, while being consistent with the aggregate stocks found in the data. Again, it is important to highlight that we have not included the age profile of any flows in the calibration targets, and that the model without the life-cycle component can successfully match all monthly flows. The age profiles of various worker flows will be used only as evaluation tests of the empirical validity of the model.

4.3 Untargeted Moments

The goal of this Section is to show that our model is a reliable laboratory for analyzing the effects of different unemployment insurance policies. To achieve this goal, we present the predictions of the model for a series of labor market moments which were not targeted in our calibration. The moments we chose are: i) the paths of the employment to population (E-Pop) ratio and the unemployment rate over the life-cycle; ii) the paths of all worker flows over the life-cycle; and, iii) the labor market histories of workers across four consecutive months in CPS, as analyzed by Kudlyak and Lange (2017) and Hall and Kudlyak (2019).

Our choices of untargeted moments are guided by the fact that we want to use the model to study changes in the provision of UI benefits. First, looking at the E-Pop ratio and the unemployment rate is natural, since we want to make sure that the model is consistent with all important labor market stocks. The impact of UI on labor market stocks is an important part of the policy debate, hence it is crucial for the calibrated model to replicate those. Second, we look at labor market flows over the life-cycle and the four-month labor histories because they are measures of workers' labor market attachment. Workers with strong labor market attachment may respond differently to UI changes compared to workers with weak attachment. For example, Lalive (2008) and Tatsiramos (2010) show that in countries in which UI can be used as a bridge to early retirement, unemployment for older workers is an absorbing state. Similarly, Kudlyak and Lange (2017) and Hall and Kudlyak (2019) find that a worker's labor market history preceding a given month is a strong predictor of the conditional probability of a move from non-employment to employment in that month. Hence, for the model to give reliable predictions to UI counterfactuals, it should capture these aspects of worker heterogeneity.

The untargeted moments generated by the model are close to the empirical ones, showing that the model is a reliable laboratory for the study of UI policies. First, as shown in Figure 5, the model-implied E-Pop ratio and unemployment rate follow closely their empirical counterparts over the life-cycle. The model slightly overestimates (underestimates) the unemployment rate for older (younger) workers. These small differences between the model and the data can be attributed to forces we do not explicitly model. Older individuals, for example, may have accumulated assets which ease their transition out of the labor force just before retirement, while they still actively look for jobs in the model.

Second, the model-implied paths of worker flows over the life-cycle are very close to the empirical ones (Figure 6). For many flows, such as the JJ, UE, and NE flows, the paths are almost identical to the data. This is particularly important because some of these flows have

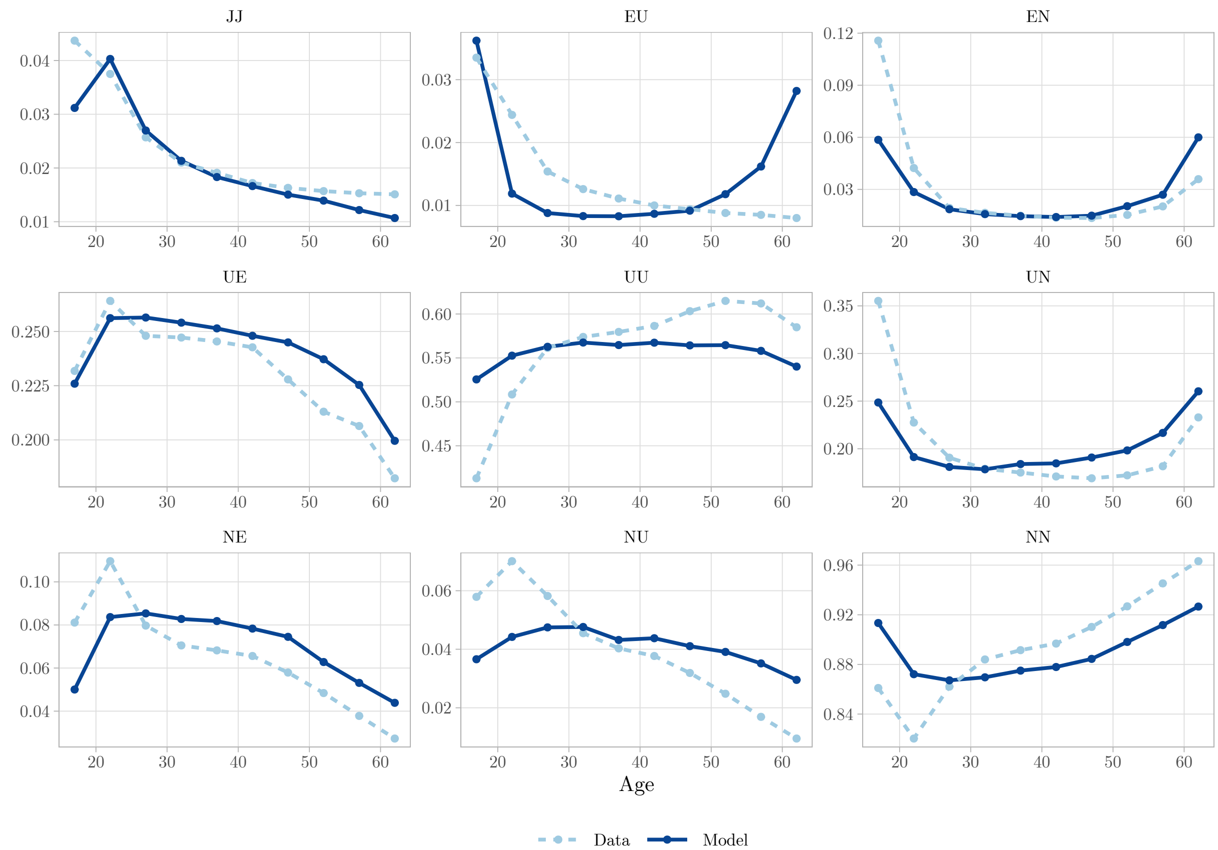

Figure 6: Age profile of flows in CPS compared to model simulations. The life-cycle profile of flows is untargeted.

not been studied by the UI literature, while our structural framework seems appropriate to do so. For most other flows, such as UN and EN, the model delivers the right shape and levels similar to the data. Given that the only targeted life-cycle moment is the LFPR, this result is a non-trivial success of the model, showing that it can predict realistic worker movements across multiple untargeted dimensions. As explained earlier, the age dimension is especially important because it provides information about how older workers may be differentially affected by UI policies compared to prime-age or younger workers. It is worth repeating, however, that the absence of schooling and retirement from the model does not allow us to capture some aspects of the life-cycle flows. For example, the model does not capture the level of NE flows for young workers (which in the data comes from workers' schooling decisions) and overestimates the EU flows for older workers (while in the data these workers leave the labor force as retired).

Third, the labor histories of workers in the model are broadly consistent with the four-

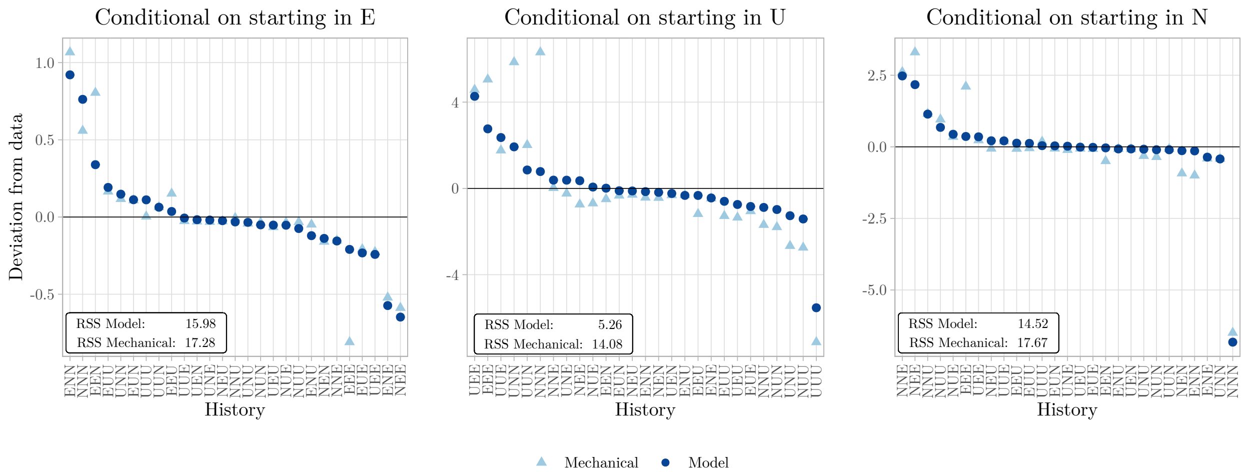

Figure 7: Difference between simulated and observed frequencies of four-months labor market histories in CPS. Mechanical frequencies are constructed by multiplying the monthly transition probabilities from CPS. The histories are sorted by the model deviations. RSS denotes the sum of squared percentage deviations.

month histories reported in CPS (Figure 7). There are two relevant comparisons shown in Figure 7: the first is between the model-implied fractions of various four-month worker histories and the fraction of these histories in the data. As can be seen in Figure 7, for most four-month histories the deviations of model predictions from the data are almost zero. However, there are few histories that the model is not able to capture.

To get a better sense of the model's fit, we implement the second comparison shown in Figure 7: we compare the model's performance with the worker histories implied by the mechanical projection of the CPS monthly transition rates. This comparison can tell us how much more information about workers' prospects the model carries over the information contained in the aggregate month-to-month transition rates. The answer is "a non-trivial amount" for workers starting in employment and out of the labor force, and "quite a lot" for workers starting in unemployment. The fact that the model considerably improves upon the prediction of the mechanical approach for unemployed workers is especially useful for our approach, since unemployed workers are the main target of UI benefits. The directed search protocol helps the model generate this improvement. Workers in the same labor market state but with different outside options face different probabilities to leave this state, which helps the model account for various histories. For example, some OLF workers have much higher home production than others; the former will be the ones mostly staying in this state over time (performing histories such as NNNN), while the latter will be transitioning across labor market states (performing histories such as NENU).

It is important to understand why the four-month histories are of particular importance for our study. Following workers over time provides a panel dimension, which is lost when one considers only monthly transition rates. As Kudlyak and Lange (2018) and Hall and Kudlyak (2019) emphasize, this panel dimension provides important information about the underlying worker heterogeneity, which may be important for the analysis of UI benefits. In intuitive terms, the observed monthly worker flows are the result of some workers changing labor market state often and some workers changing status rarely. The four-month histories shed light to how many workers of each type are present in the workforce. Importantly, this information is also indicative of a worker's labor market attachment; to see this, compare a worker with EEEE versus NNNN history. It is well-known that workers with different degrees of attachment behave very differently in the labor market.[23] As shown in Figure 7, our model captures a substantial amount of this panel dimension, implying that it is consistent with the underlying worker heterogeneity that may be important for the effects of UI policies.

5 Policy Exercises

We next use the model as a laboratory to study the effects of an increase in UI benefits on the labor market. These effects have been controversially discussed by the general public as well as the academic literature. Using our equilibrium model, we evaluate the effects of two different changes in the UI system. We study an extension of UI benefits from 26 weeks to 99 weeks, mimicking the extension that took place in the US during the Great Recession and after the Dot-Com Bubble recession. We contrast this policy change with an equally expensive increase of UI benefits of 19.4%, while keeping the duration eligibility at 26 weeks.

Table 4 shows the effects of the two reforms on employment, labor force participation, unemployment rate, GDP, and labor productivity. Both reforms lead to decline in the E-Pop ratio of 2.1%. This, together with a slight reduction in productivity leads to a 2.5% decline in output across both scenarios. The difference between the two policies lies in the response of the unemployment rate, which rises by 19% for the UI benefits duration extension, and by 15% for the increase in UI benefits. The stronger increase in the unemployment rate is not due to fewer jobs, but because more workers are kept in the labor force with the UI

[23] As an example along these lines, Mankart and Oikonomou (2017) show that second earners change their labor market behavior more often than primary earners over the business cycle.

	Baseline	UI +19%		99 weeks UI	
Moment	Value	Value	Pct. Change	Value	Pct. Change
E-Pop	0.707	0.692	-2.124%	0.692	-2.153%
LFPR	0.750	0.740	-1.248%	0.742	-1.019%
U-Rate	0.057	0.065	14.780%	0.067	19.077%
GDP	5.396	5.258	-2.563%	5.256	-2.597%
Labor Prod.	7.631	7.597	-0.449%	7.597	-0.453%

Table 4: Effects of more generous UI benefits. The table reports how labor market stocks, GPD and labor productivity respond to a 99 weeks UI extension and an 19.4% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

extension to 99 weeks. While it is sometimes argued that more generous UI benefits lead to an increase in the LFPR, we find the opposite. In both scenarios the LFPR declines slightly by about 1% to 1.2%. We also conduct a number of sensitivity analysis of our results with respect to the parameters we set before the calibration. Table 8 in the appendix shows that these results are robust to various different parameterizations.[24]

In order to understand how these changes come about, we have to study the responses of the underlying labor market flows. These changes are themselves driven by two forces: (1) behavioral changes by firms and workers through changes in their policy functions, which are reported in Figure 8, and (2) compositional changes in the pool of employed, unemployed, and out of the labor force workers across different age and home production levels. Table 5 presents the overall percentage changes of labor market flows. In addition, it reports the behavioral changes only, which are the changes induced solely by policy function changes, while holding the distribution of agents across the states space (z, h, a) fixed to the pre-reform level.

Overall, both reforms have very similar effects on policy functions. More generous UI leads to a higher reservation productivity for viable matches (left column of Figure 8), a higher reservation home productivity to exit the labor market (middle column), and lower job-finding probabilities (right column) across all age groups.[25] That policy functions react similarly can be also seen in Table 5. Focusing on the behavioral changes, which holds the the distribution of agents over (z, h, a) fixed, both reforms have a similar impact on flows, with

[24] We use both higher and lower levels of the learning speed α, and the elasticity of the matching function γ. In addition, instead of using UI expenditures over GDP as the target for UI benefits, we use UI expenditures over labor income in the data. This essentially implies higher UI benefits, and we show that our findings are also robust with respect to this change.

[25] Figure 9 in the appendix shows the policy function for all ages

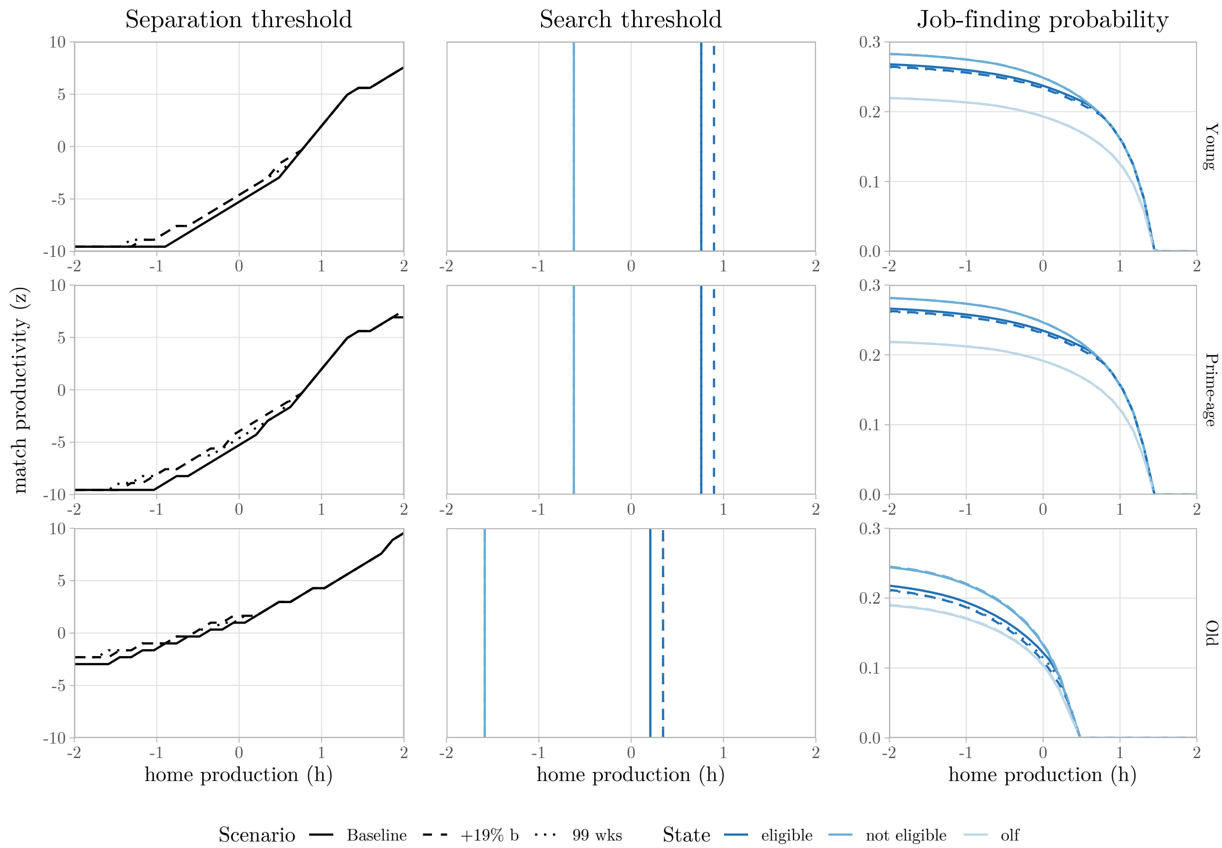

Figure 8: Policy functions and job-finding probability under different UI policies by age groups.

the exception of the UN rates, which declines much more with the 99 weeks UI extension.

The policy affects UN flows through two forces. First, large enough positive shocks to home production lead unemployed workers to drop out of the labor force. Because of the change in the search threshold, active search now covers a larger range of h values. Thus, the probability of receiving a high enough shock to leave the labor force declines, which reduces the UN flow. Second, some workers are only searching while they receive unemployment benefits. In the case of extended UI benefits, the probability of an UI expiration declines, which leads to a significant reduction (-16%) in the UN rate. The decline in the UN rate changes the composition of unemployed and OLF workers. Workers transitioning from U to N have a higher h compared to unemployed workers and a lower h compared to OLF workers. Thus, the declining UN rate leads to an unemployment and out of the labor force pool with higher home production.

These compositional changes affect the flows into the labor force, NE and NU. Because

	Baseline	UI +19%			99 weeks UI		
Moment	Value	Value	Overall Change	Behavioral Change	Value	Overall Change	Behavioral Change
JJ	0.020	0.020	-2.473%	-4.842%	0.020	-2.337%	-4.844%
EU	0.013	0.016	22.621%	23.452%	0.015	17.813%	19.189%
EN	0.024	0.024	0.979%	16.071%	0.025	3.418%	18.053%
UE	0.236	0.231	-2.191%	-0.619%	0.227	-3.680%	-1.053%
UN	0.212	0.208	-1.837%	-3.931%	0.176	-16.652%	-10.775%
NE	0.063	0.063	-0.327%	0.398%	0.062	-1.519%	0.298%
NU	0.039	0.038	-0.793%	-0.036%	0.037	-4.896%	-0.035%

Table 5: Effects of more generous UI benefits on labor market flows. The table reports how flows respond to a 99 weeks UI extension and an 19.4% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

high h workers have a lower propensity to enter the labor force, the overall higher home production in the pool of out of the labor force workers leads to a decline in the NE and NU rates. This effect is stronger for the UI extension to 99 weeks, as it has a larger effect on the UN flows. The behavioral effect of the UI reform on these flows is very muted, as workers entering the labor force are not eligible for UI benefits.

The job-finding rate declines because of two reasons. First, the unemployment pool consists now of more workers with high home production and thus low job-finding probabilities, which puts a downward pressure on UE flows. Second, it declines because firms have to offer higher value jobs in response to higher UI benefits, which depresses vacancy creation.

Under both UI reforms, the separation rates increase. The higher reservation threshold in match specific productivity leads to fewer z jobs being viable, and thus to more separations and higher EU flows. Abstracting from compositional changes, the same force would lead to an increase in EN flows. But because UI reforms affect older workers more, the pool of employed workers shifts towards prime age workers with a stronger labor force attachment. This compositional change undoes the behavioral effect, and overall the EN rate only marginally changes.

In addition, the higher overall separation rate also makes opening new vacancies more risky, as fewer of these jobs survive the revelation of the match specific productivity. This depresses the job-finding rates for unemployed and employed workers even further, which can be seen by the decrease in both UE and EE rates. The lower job-to-job transition rate also explains the decrease in labor productivity. Even though the reservation productivity is now

	UI +19%			99 weeks UI		
Values	E-Pop	LFPR	U-Rate	E-Pop	LFPR	U-Rate
EU	-1.69%	-0.96%	12.44%	-1.34%	-0.76%	9.81%
EN	-0.21%	-0.19%	0.38%	-0.74%	-0.66%	1.33%
UE	-0.18%	-0.10%	1.35%	-0.31%	-0.18%	2.28%
UN	0.08%	0.11%	0.62%	0.74%	1.10%	5.95%
NE	-0.07%	-0.06%	0.12%	-0.32%	-0.28%	0.57%
NU	-0.04%	-0.05%	-0.29%	-0.22%	-0.33%	-1.83%
EN/NE/UN/NU	-0.24%	-0.19%	0.83%	-0.56%	-0.20%	6.02%
Total Effect	-2.12%	-1.25%	14.78%	-2.15%	-1.01%	19.07%

Table 6: Effects of individual flows on labor market stocks. The table reports how labor market stocks respond if individual flows are changed from the baseline level to post-reform level, while holding all other flows fixed, using the system of equations in (8). An UI extension to 99 weeks and a 19.4% increase in UI benefits holding duration fixed is considered. Both UI policy changes imply the same budgetary costs.

higher, fewer workers climb up the match specific productivity ladder, which depresses labor productivity. This is in contrast to models without job-to-job transitions, where the higher reservation productivity leads to higher labor productivity (Acemoglu and Shimer, 1999). This highlights the importance of including job-to-job transitions in models that analyze UI reforms.

One of the key contributions of this paper is to study the effects of an UI reform while explicitly taking into account the response of the labor force participation margin, which is typically abstracted from in the literature (Nakajima, 2012; Hagedorn et al., 2013; Mitman and Rabinovich, 2015). In order to understand which labor market flow change has a significant impact on employment and unemployment, we adopt a stock-flow approach used in Elsby et al. (2015) and Kroft et al. (2016). The evolution of the three labor market stocks are a function of all the six labor market flows:

$$\begin{bmatrix} e_t \\ u_t \\ n_t \end{bmatrix} = \begin{bmatrix} 1 - EN_t - EU_t & UE_t & NE_t \\ EU_t & 1 - UE_t - UN_t & NU_t \\ EN_t & UN_t & 1 - NE_t - NU_t \end{bmatrix} \begin{bmatrix} e_{t-1} \\ u_{t-1} \\ n_{t-1} \end{bmatrix} \tag{8}$$

Using this system, we compute counterfactual steady state stocks by setting single flows from their pre-reform level to the post-reform levels, while holding all other flows fixed to the pre-reform level. Table 6 presents how the specific flow contributed to the overall change in the E-Pop, LFPR, and unemployment rate. For both reforms, the change in the separation rate has the largest single impact on employment, LFPR and the unemployment rate. Its change by itself generates between half (99 weeks extension) and over 80% (benefit increase) of the total response in the labor market stocks to the UI reforms. This is in line with recent evidence in Hartung et al. (2020), which shows that lower separation rates into unemployment accounted for 76% of declining unemployment after the Hartz reforms, which cut eligibility duration in Germany.

The effects of jointly moving all flows in and out of the labor force to their post-reform levels is of particular interest, as these are usually abstracted from in the literature. For the UI benefit extensions, the flows in and out of the labor force do not play an out-sized role, but nevertheless explain about 10% of the labor market stock responses. This is in contrast to the UI extension to 99 weeks, where the flows in and out of the labor force are important drivers and account for a quarter of the employment response, and a third of the unemployment change. This highlights the importance of taking flows in and out of the labor force into account when considering changes to the UI system.

6 Conclusion

The goal of this paper is to analyze the positive effects of unemployment insurance (UI) reforms on labor market flows and stocks. To do so, we develop an equilibrium life-cycle search model featuring *all* labor market flows, as well as endogenous job creation by firms. Importantly, compared to the previous literature, our model includes job-to-job transitions and a labor force participation decision, both of which play an important role for the analysis of UI reforms. The first source of heterogeneity in the model is home production, which changes over time due to workers' aging and idiosyncratic shocks. Workers with high levels of home production tend to stay out of the labor force, while workers with low levels of home production engage in active jobs search as unemployed. On the other side of the market, firms create jobs with different characteristics directed to workers with different outside options. The second source of heterogeneity in the model is match-specific productivity: job-worker matches differ with respect to the output produced. Moreover, matches start out with unknown productivity, which is learned over time. The opportunity of finding a better match incentivizes employed workers to look for jobs and transition to more productive matches over time.

We calibrate the model to a set of empirical moments from CPS. Our calibration targets include the aggregate labor market flows, the job tenure distribution, as well as the profile of labor force participation over the life-cycle. To gauge the empirical validity of the model, we compare its performance with two sets of untargeted empirical moments, also from CPS: the labor market flows over the life-cycle, and the four-month labor market histories of workers. The model successfully replicates all targeted moments and predicts very realistic profiles for most life-cycle flows and worker labor market histories, showing it is reliable laboratory to study the positive effects of UI reforms.

The central contribution of the paper is to use the model to study the effects of two UI benefits reforms: an extension of UI benefits to 99 weeks, as well as an equally expensive 19% benefits increase, while the eligibility duration is held constant. The model predicts that the 99 weeks extension leads to a slight decrease in the employment to population ratio and the labor force participation rate, but to a significant increase in the unemployment rate. The equally expensive increase in benefits yields a smaller increase in the unemployment rate and a smaller decrease in the labor force participation rate. Both reforms have similar effects on GDP, labor productivity, and job-to-job transitions. Importantly, we show that disregarding the effect of job-to-job transitions and flows in and out of the labor force would significantly underestimate the response of labor productivity and the unemployment rate to UI reforms, respectively.

To be more specific, our exercise yields two important policy-relevant messages. First, based on the results of previous studies, commentators have argued that more generous UI benefits would reduce workers' exit from the labor force. We show that despite this being true in our model, taking into account the response of all flows, the LFPR actually declines. Second, as Acemoglu and Shimer (1999) point out, more generous UI makes workers pickier and may increase labor productivity. In our model, this result does not hold: more generous UI reduces job-to-job transitions through lower job creation, which leads fewer workers climbing up the job ladder to more productive jobs, ultimately lowering labor productivity. To conclude, we argue that any successful framework studying the effects of UI reforms should take the response of job-to-job transitions and the participation decision of workers into account.

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A Computational Appendix

We solve for the equilibrium of the model using the following procedure:

First, we discretize the continuous distribution for productivity as well as the continuous process for home production. For the idiosyncratic productivity, z, we use 30 equally spaced grid points between $-\Delta_z$ and Δ_z. Furthermore, we define an additional 31st state which denotes the case that the match-specific productivity is still unknown. We approximate the continuous process for idiosyncratic home production, h, by defining 30 points on an equally spaced grid between -2 and 2 and using the Tauchen method to assign transition probabilities between these grid points. As discussed in the main text, these bounds are necessary as we model a random walk which is unbounded. Additionally, we evaluate the spline for home production by age, $\bar{h}(a)$, for 10 age groups. Along this dimension, agents can transition at most one step each period with probability 0.0167. Lastly, we keep track of the eligibility status b for unemployed agents. In total, an agent can be in one of $30 \times 10 \times (31 + 2 + 1) = 10,200$ states.

Second, we solve for the policy functions given the free entry condition using value function iteration. This algorithm can be executed with low computational cost as the optimal submarket and the associated job-finding probability can be solved in closed-form. Additionally, we use the independence of the various shocks to simplify the computation of the expected value next period.

Third, given the optimal decision of the agents and the job-finding probabilities, we compute the steady state. Not that we assume that agents entering the model draw their first state from the stationary distribution. Since the transition matrix is relatively large (10,200 $\times$ 10,200), this step is computational expensive. We alleviate this problem by exploiting the sparsity of the matrix and solve for the eigenvector associated to the largest eigenvalue. Since we need to repeat this procedure many times, we employ an iterative solver for finding the eigenvector and solve the model in C++.

To calibrate the model, we use the method of simulated moments and minimize the relative distance between the data target and the model moment. This makes the moment conditions unit free and, hence, we use an identity weighting matrix. The problem can then be described as finding the global minimum of a 15-dimensional function with an unknown functional form. As this problem is notoriously hard to solve, we use the Matlab global optimization solver "particle swarm" with 200 particles and restart this algorithm over 300 times with random initial particles. Finally, we choose the best model among all these repetitions.

B Policy Functions for all Age Groups

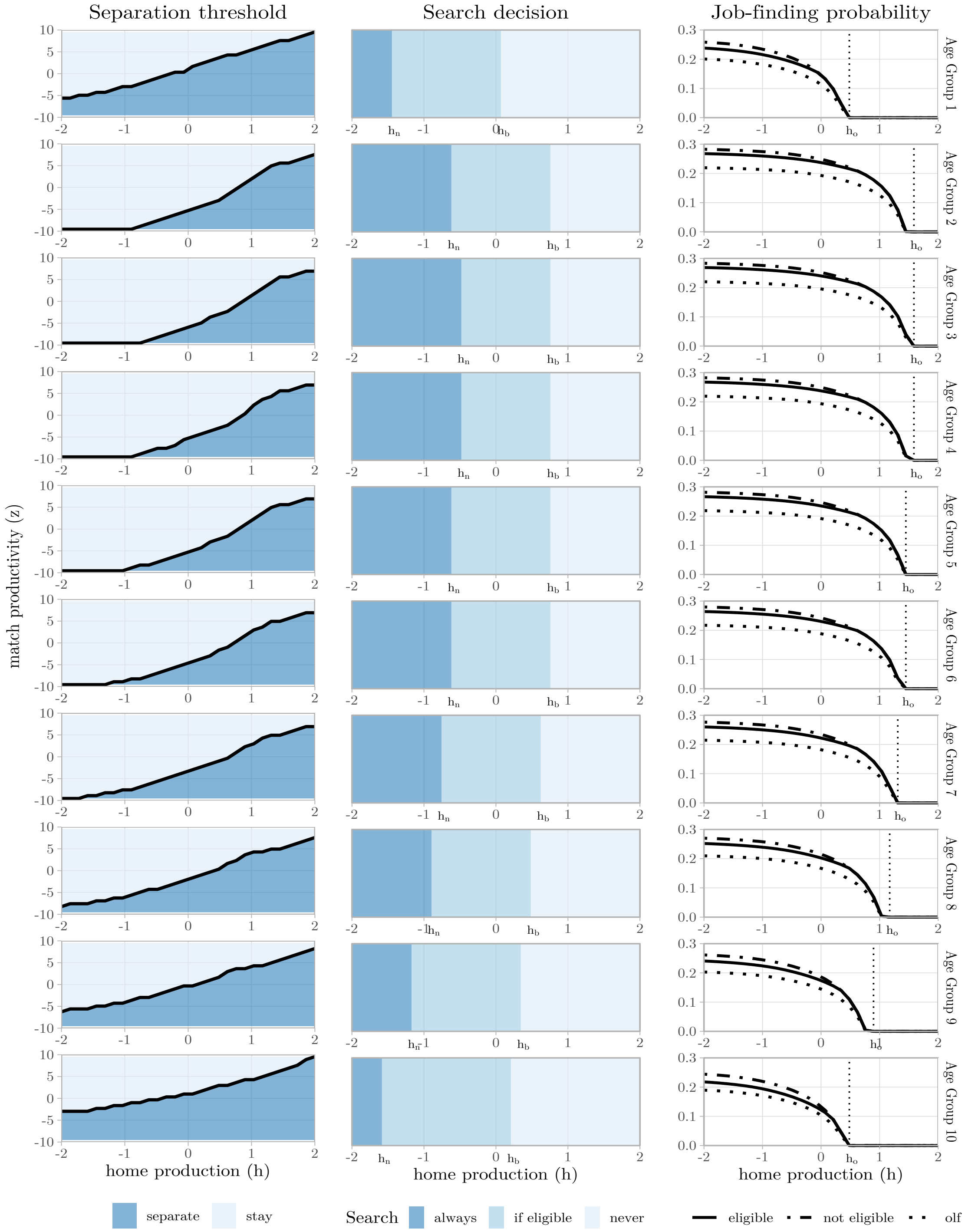

Figure 9: Policy functions for all age groups

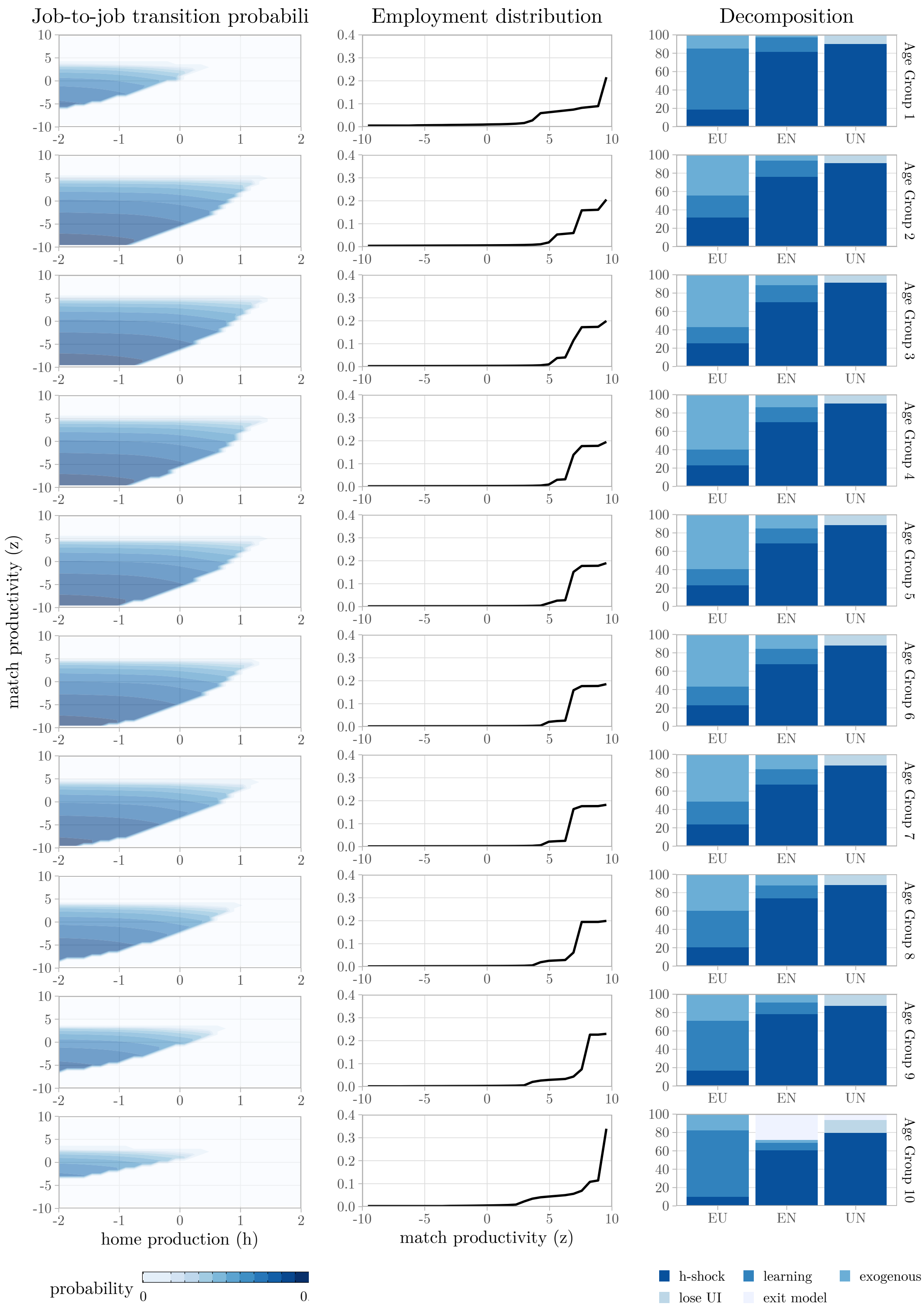

Figure 10: Job-to-job transition probabilities, employment distribution, and decomposition for all age groups

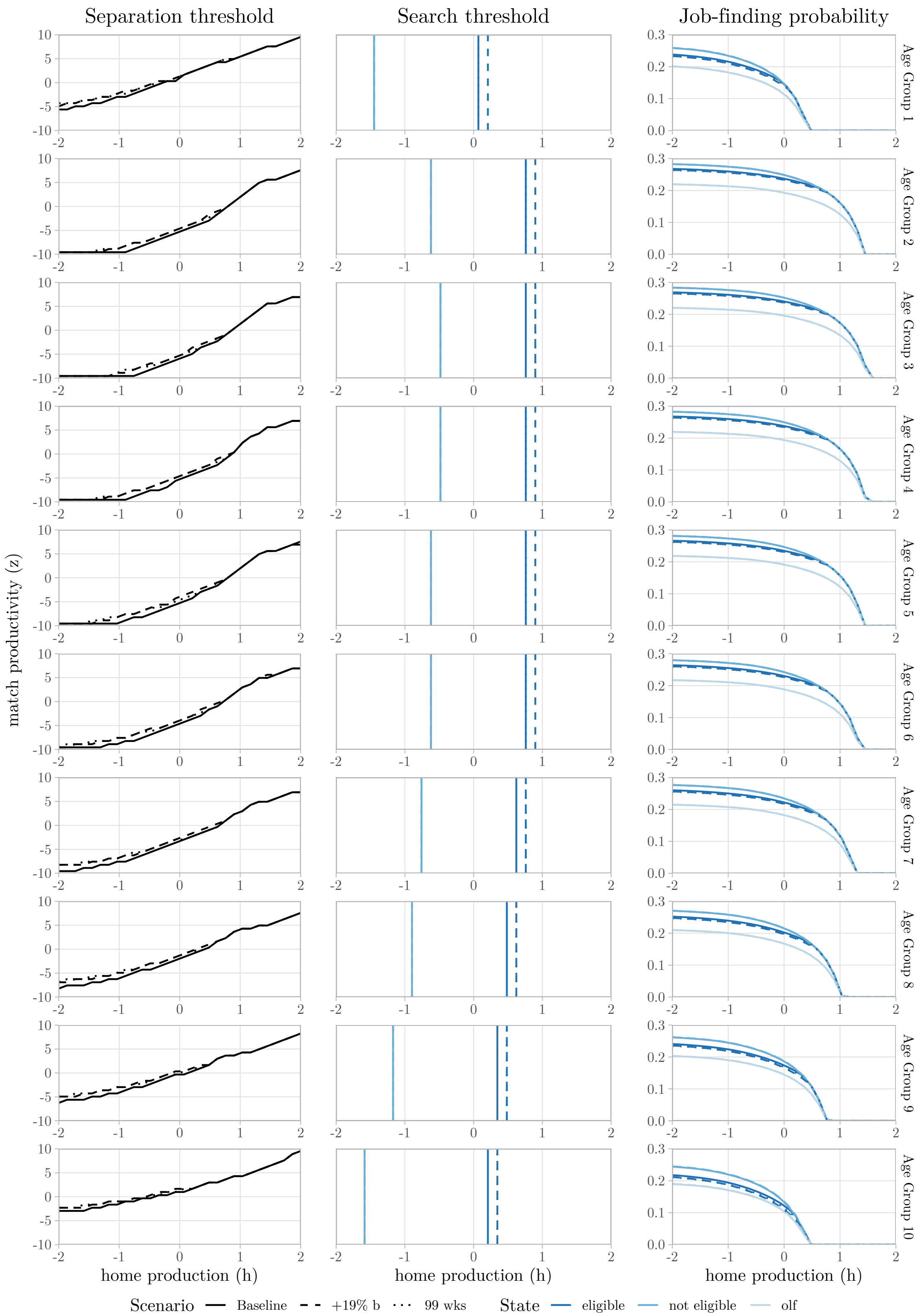

Figure 11: Policy functions across the scenarios for all age groups

C Robustness Exercises

To gauge the robustness of our results with respect to the exogenously set parameters, we re-calibrate the model with different values for the learning parameter α and for the elasticity of the matching function γ. We use two different values for α, one which implies a shorter duration until agents learn their productivity ($\alpha = 1/2$) and one implying a longer duration ($\alpha = 1/6$). Regarding the elasticity of the matching function, we set γ to 0.407 or 1.27 which are taken from Hagedorn and Manovskii (2008) and Den Haan et al. (2000), respectively. Finally, we also consider an alternative target for the level of UI benefits, where we exclude capital income from GDP, since capital is missing in our model. We target UI expenditures over labor income instead, which we compute as UI expenditure / (0.66*GDP).

Table 7 reports the model fit while Table 8 shows the effect of a more generous UI system. All alternative calibrations imply very similar results compared to our baseline calibration, expect for the case where we let agents learn their match-specific productivity after 6 months on average ($\alpha = 1/6$). In this calibration, the labor force participation rate as well as average labor productivity increase slightly. However, this specification has the worst overall data fit with a squared sum of relative deviations twice as high as the other calibrations. Taken together, we conclude that these calibrations support the robustness of our results.

Target	Data	Baseline	$\alpha = 1/6$	$\alpha = 1/2$	$\gamma = 0.407$	$\gamma = 1.27$	b/GDP: 150%
				Transition Rates			
Flow							
JJ	0.021	0.020	0.020	0.021	0.021	0.021	0.021
EU	0.013	0.013	0.013	0.013	0.013	0.013	0.013
EN	0.024	0.024	0.023	0.024	0.024	0.023	0.024
UE	0.238	0.236	0.240	0.233	0.231	0.241	0.236
UN	0.214	0.212	0.216	0.213	0.200	0.217	0.212
NE	0.063	0.063	0.062	0.063	0.064	0.062	0.063
NU	0.039	0.039	0.038	0.038	0.038	0.038	0.038
				UI System			
b/GDP	0.007	0.007	0.007	0.007	0.007	0.007	0.010
				Tenure Distribution			
Years							
≤ 1	0.229	0.257	0.283	0.241	0.258	0.256	0.255
$(1, 3]$	0.227	0.190	0.181	0.197	0.188	0.191	0.189
$(3, 9]$	0.273	0.287	0.264	0.292	0.280	0.288	0.288
> 9	0.271	0.266	0.273	0.270	0.274	0.265	0.268
				LFPR			
Age							
15–19	0.460	0.465	0.460	0.460	0.461	0.470	0.459
20–24	0.754	0.750	0.764	0.756	0.752	0.750	0.753
25–29	0.830	0.832	0.825	0.842	0.849	0.832	0.831
30–34	0.834	0.854	0.857	0.837	0.871	0.855	0.853
35–39	0.840	0.859	0.870	0.844	0.847	0.859	0.860
40–44	0.847	0.858	0.886	0.855	0.843	0.857	0.857
45–49	0.835	0.847	0.854	0.819	0.833	0.849	0.848
50–54	0.796	0.786	0.793	0.794	0.810	0.796	0.783
55–59	0.709	0.704	0.718	0.709	0.734	0.707	0.704
60–64	0.518	0.540	0.523	0.536	0.513	0.527	0.538

Table 7: Model fit for various calibrations

	Baseline	UI +19%		99 weeks UI	
Moment	Value	Value	Pct Change	Value	Pct Change
		Main Calibration			
E-Pop	0.707	0.692	-2.124%	0.692	-2.153%
LFPR	0.750	0.740	-1.248%	0.742	-1.019%
U-Rate	0.057	0.065	14.780%	0.067	19.077%
GDP	5.396	5.258	-2.563%	5.256	-2.597%
Labor Prod.	7.631	7.597	-0.449%	7.597	-0.453%
		$\alpha = 1/6$			
E-Pop	0.714	0.710	-0.523%	0.711	-0.364%
LFPR	0.755	0.759	0.493%	0.760	0.672%
U-Rate	0.054	0.064	17.599%	0.064	17.915%
GDP	4.728	4.710	-0.395%	4.718	-0.217%
Labor Prod.	6.623	6.632	0.129%	6.633	0.148%
		$\alpha = 1/2$			
E-Pop	0.702	0.689	-1.902%	0.689	-1.952%
LFPR	0.745	0.738	-0.975%	0.740	-0.678%
U-Rate	0.058	0.067	15.288%	0.070	20.961%
GDP	5.746	5.621	-2.171%	5.619	-2.209%
Labor Prod.	8.180	8.158	-0.274%	8.159	-0.262%
		$\gamma = 0.407$			
E-Pop	0.707	0.690	-2.436%	0.694	-1.794%
LFPR	0.751	0.740	-1.444%	0.746	-0.651%
U-Rate	0.059	0.068	16.088%	0.070	18.393%
GDP	5.238	5.081	-2.981%	5.132	-2.016%
Labor Prod.	7.407	7.366	-0.559%	7.390	-0.227%
		$\gamma = 1.270$			
E-Pop	0.709	0.702	-1.077%	0.701	-1.104%
LFPR	0.750	0.748	-0.327%	0.749	-0.131%
U-Rate	0.055	0.062	12.990%	0.064	16.819%
GDP	5.537	5.461	-1.382%	5.459	-1.408%
Labor Prod.	7.808	7.784	-0.309%	7.784	-0.308%
		$b/GDP : 150\%$			
E-Pop	0.706	0.688	-2.573%	0.687	-2.721%
LFPR	0.749	0.739	-1.293%	0.741	-1.053%
U-Rate	0.057	0.069	21.586%	0.073	28.054%
GDP	5.626	5.463	-2.894%	5.457	-3.013%
Labor Prod.	7.966	7.940	-0.329%	7.942	-0.300%

Table 8: Effects of more generous UI benefits across the calibrations. The table reports how flows and stocks respond to a 99 weeks UI extension and an 19.4% increase in UI benefits holding duration fixed. For the baseline calibration, both UI changes imply the same budgetary costs.