Worker Mobility and UI Extensions*

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Abstract

We develop an equilibrium search model with a labor force participation decision, job-to-job transitions, and endogenous separations. The calibrated model perfectly matches the observed labor market flows in US data. We use the model to simulate the effects of an extension of unemployment insurance benefits to 99 weeks. The reform leads to a decrease in employment, an increase in the labor force participation and unemployment rate, while it leaves labor productivity roughly constant. Using a model-based decomposition, as well as comparisons with alternative simplified models, we show that modeling workers' participation decisions, job-to-job transitions, and endogenous separations together is crucial for a complete and accurate analysis of UI reforms.

Keywords: Labor Market Flows; Directed Search; Unemployment Insurance
JEL Classification: E24, J63, J64, J65, J68

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1 Introduction

In the US, only one quarter of new jobs are filled with unemployed workers. About 35% of hires are poached from other firms and another 40% are from workers not in the labor force. Despite this, few macroeconomic models of the labor market feature a labor force participation choice, and even fewer consider it together with job-to-job transitions and an endogenous job separation decision.[1] These features might be especially relevant for the positive analysis of unemployment insurance (UI) benefits. 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. In addition, a more generous UI system might affect the separation decision between workers and firms, as it makes unemployment more attractive relative to employment.

To better understand these trade-offs, we build upon Menzio and Shi (2011) and develop a search model with an endogenous labor force participation decision of workers. This extension makes it the first model in the literature featuring endogenous job creation by firms, job-to-job transitions, and endogenous separations in a search model with employment, unemployment, and out of the labor force (OLF) states. The calibrated model matches all observed labor market flows perfectly, which indicates that labor force participation choices, job-to-job transitions, and endogenous separations are important for a complete analysis of labor market dynamics. This unique combination of model elements allows us to comprehensively study the effects of an UI extension to 99 weeks. We find that the UI reform decreases employment and increases the labor force participation and unemployment rate. Since labor productivity stays roughly unchanged, the decline in employment leads to a decrease in overall output. Our main contribution is to show that disregarding flows in and out of the labor force, job-to-job transitions, and endogenous separations implies a significant bias in the analysis of UI reforms. In the model, the effects of UI extension 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; Domènech-Arumí and Vannutelli, 2022). Moreover, we show that in simpler models which abstract from endogenous separations or job-to-job transitions employment effectively does not respond to the UI extension, in contrast to empirical

[1] To the best of our knowledge, the only models that incorporate *both* endogenous participation decisions and job-to-job transitions are in Krusell et al. (2017, 2020). For a detailed comparison, see our literature review at the end of this section.

evidence.

In the 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 and family caring responsibilities, health, and disability shocks. 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. Successful matches start out with unknown productivity, which is subsequently revealed. Employed workers engage in job search and transition to more productive matches over time.

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, 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 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 monthly movements in and out of the labor force are very large, while there are many workers in 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 combination of home production with match-specific productivity. Workers in high quality matches have a higher home productivity threshold for separations 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 labor force participation, as typically these models are not flexible enough to match all flows.[2]

[2]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) does

Having shown that the model successfully replicates the US labor market dynamics, we proceed with the main goal of the paper: use the model to study the effects of a permanent UI benefits extension to 99 weeks.[3] More generous UI benefits significantly increase unemployment by about 14%. The increase in unemployment consists of roughly equal parts lower employment and more workers in the labor force. The employment to population ratio (E-Pop) decreases by 0.4%, whereas the labor force participation rate (LFPR) increases by 0.4%. As labor productivity is essentially unchanged, the lower employment rate leads to a 0.3% decline in output. Which channels account for these changes in the labor market? The three relevant margins of adjustment are the changes in the labor force participation decision, the separation decision, and the vacancy creation decision. First, in response to more generous UI, the home production threshold for participating in the labor force increases, which implies that more workers remain in the labor force. This reduces the flows from unemployment to OLF. Second, the match productivity threshold for separations increases, which in turn raises the separation rate. Third, as firms have to offer higher salaries in response to more generous benefits, vacancy creation declines, which reduces job-finding rates for unemployed and employed workers.

Does the inclusion of these three channels matter for the analysis of UI reforms? We proceed in two ways: first, using our calibrated model, we separately shut down the three decision margins to compute their quantitative importance. The main message of the first exercise is that the separation margin is much more important for the employment and unemployment responses than the changes in the job-finding probabilities, in line with recent empirical evidence (Lalive et al., 2011; Jäger et al., 2019; Hartung et al., 2020). Moreover, the participation margin is the main driver of the unemployment increase, as it incentivizes workers to stay in the labor force longer.[4] In the second exercise, we quantify the 99 weeks UI extension within simpler re-calibrated models, which do not feature endogenous separations, labor force participation, or job-to-job transitions. In the models without endogenous separations or job-to-job transitions, employment effectively does not respond to the UI extension, which contradicts the empirical evidence. Moreover, the response of the unemployment rate in the simplified models is half of the complete model. The model without endogenous separations also implies that job-to-job transitions remain practically unchanged in response to

not have enough degrees of freedom to account for the magnitude of several observed flows.

[3]We also contrast this reform to an equally expensive 19.5% increase of UI benefits while holding eligibility duration fixed in Appendix A.

[4]These findings also echo the results of Elsby et al. (2009) and Elsby et al. (2015) who highlight the importance of the separation and participation margin, respectively, for unemployment fluctuations.

UI extensions, since more workers in low quality matches stay in their jobs when benefits rise compared to the complete model. However, this contradicts the empirical evidence which shows that UI extensions significantly reduce job-to-job transitions. The model without labor force participation implies stronger employment reactions, as there is no dampening effect from the reduced flows from unemployment to OLF.[5] To sum up, these results highlight the importance of modeling endogenous separations, labor force participation, as well as job-to-job transitions together when analyzing UI benefit reforms.

This paper contributes to two strands of literature. The first 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. (2011, 2017, 2020), we endogenize the job creation decision of firms, making our model more suitable for the study of UI reforms. Cajner et al. (2021) enrich the framework of Krusell et al. (2011) with the life-cycle dimension and study UI benefits reforms. Next, Griffy and Masters (2022) also consider the effects of UI in a model with endogenous participation, but they do so in a random search framework without job-to-job transitions. Finally, 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.

Second, we contribute to the literature that 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), Nakajima (2012), and Rujiwattanapong (2021) who study the effects of UI reforms using equilibrium search models.[6] 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 and endogenous separations. For example, in a model without on-the-job search and without separations, Acemoglu and Shimer (1999) show that more generous UI makes workers pickier and may increase labor productivity. We show that including job-to-job transitions and endogenous separations counteracts this channel. Similarly, flows in and out of the labor force account for half of the unemployment response to more generous UI, highlighting the importance of modeling

[5] We provide suggestive empirical evidence that the flows from unemployment to OLF decline in response to UI benefit extensions in Section 5.2. The same conclusion was also obtained by the empirical work of Rothstein (2011), Farber and Valletta (2015), and Farber et al. (2015).

[6] 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.

this channel.

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 results along targeted and untargeted moments. In Section 5, we present the effects of more generous UI schemes on labor market stocks and flows, as well as empirical evidence to support our conclusions. Section 6 quantifies the importance of the various model channels and Section 7 concludes. Finally, the Appendix presents multiple robustness exercises with respect to different parameterizations, as well as the full transition path of the economy after the UI reforms.

2 The Model

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 differ in their home production h. 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. Employed workers do not engage in home production, which implies that h represents the home production forgone in order to be employed.

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 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. Our goal is not to explicitly model the different reasons why workers do not participate in the labor market, but rather build an equilibrium framework where worker flows are generated by economic decisions of agents.

The modeling details of UI benefits follow Mitman and Rabinovich (2015). The standard duration of unemployment benefits is six months in the United States. To obtain tractability, we model this in a stochastic fashion, assuming that UI benefits may expire at each month with a certain probability chosen to match the average duration of six months. Only workers with a previous employment spell receive unemployment benefits, whereas workers rejoining the labor force are not eligible. Finally, in the main body of the paper, we abstract from modeling the government's budget constraint to keep the model computationally tractable.[7]

[7]Adding a government budget constraint to the model would impose non-trivial computational burden,

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, as well as the expiration of 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 an efficiency that depends on their employment state. For the unemployed this efficiency is λ_u, whereas employed workers engage in on-the-job search with efficiency λ_e. The overall job-finding probability will not only depend on the matching efficiency λ_i, but also on which submarket the workers will search in, which is described in detail below. The different λ's reflect various factors for why employed and unemployed workers may not have the same efficiency in their job search, which include: differential callback and referral rates, differential treatment by recruiters, employed workers having a larger network of relevant connections, as well as being poached by other firms (Farber et al., 2019; Lester et al., 2021; Faberman et al., 2022). 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 efficiency λ_o.We label unemployed workers active searchers, and workers out of the labor force passive searchers.

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.[8] Workers are directing their search towards specific submarkets indexed by (x, h). These submarkets differ in terms of the meeting probability and the promised value of the job to the worker x. In submarket (x, h), firms offer workers of type h 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.[9] Intuitively, submarkets with high promised life-time utility will be visited by more workers. As a consequence, each submarket

since it requires solving a fixed point problem for taxes. In Appendix F, we show that introducing a tax on worker-firm matches to finance UI expenditure changes neither the baseline model results, nor the results from the policy reforms. The reason behind this is that UI expenditure are below 0.4 percent of GDP in the data, thus the tax rate required to finance it is too small to quantitatively affect our results.

[8]We assume that employed workers do not face search costs; that is, their productivity can be interpreted as labor productivity net of search costs.

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

(x, h) will have a different labor market tightness, as defined by the ratio of vacancies to job seekers, i.e. $\theta(x, h) = v(x, h)/u(x, h)$. Of course, the composition of job seekers varies across submarkets, as some submarkets are populated by employed, unemployed, or workers out of the labor force. Conditional on having the opportunity to search, a worker visiting submarket (x, h) faces a probability of meeting a vacancy of $p(\theta(x, h))$.

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, h) meets a worker with probability $q(\theta(x, h))$, where both $p(\cdot)$ and $q(\cdot)$ are twice differentiable, strictly monotone ($p(\cdot)$ is increasing and $q(\cdot)$ decreasing), and strictly concave functions such that $q(\theta(x, h)) = p(\theta(x, h))/\theta(x, h)$. 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 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.[10]

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. Actively searching unemployed workers forgo a fraction $(1 - \phi)$ of their home productivity. Additionally, they might be eligible for unemployment benefits of level $\bar{b}$.

2.1 Value Functions

We start with the problem of workers who are choosing which submarket to visit. 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).

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

The value of search consists of the probability of finding a job $p(\theta(x, h))$ times the capital gain from finding a job. This is given by the promised life-time utility x of the job, minus

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

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 with home production h and unemployment benefits $b \in \{0, \bar{b}\}$, facing the labor force participation decision.

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

The worker simply chooses to drop out of the labor force if its continuation value $N^o(h)$ is higher than the value of engaging in active job search $N^u(h, b)$. These value functions at the beginning of the production stage are presented in equations (3) and (4).

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

A worker that is currently not in the labor force enjoys flow utility of $\exp(h)$. Beginning of next period, shocks to home productivity realize. The expectation is taken over all possible future values of h'. Throughout the paper, we denote all variables in the next period with a prime. Next period, the worker again faces the decision to join or stay out of the labor force. Workers who rejoin the labor force are not eligible for UI benefits, thus the continuation value is the discounted expected value of equation (2), with $b = 0$. Workers engage in search next period with efficiency λ_o, which is valued $R(N(h', 0), h')$.

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

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

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

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

The match produces z units of output. At the beginning of next period, the new home pro-

duction h' is revealed and the match partners can decide to separate by setting $d = 1$. If the match is neither exogenously nor endogenously dissolved, it continues to the matching stage where the worker searches with efficiency λ_e. This opportunity is valued at $R(V(h', z), h')$. If the search is unsuccessful, the continuation value is $V(h', z)$.

Successful matches initially start out with unknown quality, and we label this state as z_0. The value of these matches at the beginning of the production stage is given by

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

Just before production takes place, the productivity z of the match is revealed to both matching partners with probability α. Ex ante, in this case, the common continuation value is given by the expected continuation values of known z from equation (5). With probability $1 - \alpha$, the match continues with unknown productivity. In expectation, the match produces $\sum_z z f(z)$ units of output. The continuation value mirrors the one with known match quality, although the decisions agents take under unknown quality might be different.

Free entry on the firm side drives down the firm's expected gain from opening a vacancy in each submarket to its 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:

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

and $\theta(x, h) \geq 0$ with complementary slackness. This condition guarantees that the tightness function $\theta(\cdot, \cdot)$ is consistent with the firm's incentives to create vacancies. Moreover, equation (7) states that, if the vacancy-to-applicant ratio in submarket (x, h) is zero, the benefit of opening a vacancy must be larger than the cost (Menzio et al., 2016). 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 tight-

ness 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 process for the 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.[11]

Finally, the process for idiosyncratic home production shocks, h, follows a stochastic process. Each period, with probability p_h, agents draw a new h' from the distribution $\mathcal{U}([h - \Delta_h, h + \Delta_h])$. Thus, p_h governs the frequency and Δ_h the magnitude of home production shocks. With probability $1 - p_h$ the worker continues with their old home production h.[12] We discretize the process for h, using the method from Tauchen (1986), around a fixed common component $\bar{h}$, which determines the mean of the home production grid.[13]

We set a period in the model to be one month. Several model parameters are set exogenously and their values are presented in Table 1. The discount factor β is set to 0.996, consistent with a 5% annual interest rate. Moreover, we set the elasticity of the

[11] 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.

[12] We have calibrated the model with an AR(1) process for the home production shocks. The results are very similar and presented in Appendix G. 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.

[13] Since we are modeling a unit root process, 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. We assign all probability mass falling outside the grid to the boundaries.

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	1.27	Matching function elas.	Literature (see main text)
λ_e	1	Meeting intensity employed	Normalization
p_b	0.8329	Prob. of keeping UI benefits	Average eligibility duration of 26 weeks

Table 1: Externally Calibrated Parameters.

matching function, γ, to 1.27, which is the estimate reported by Den Haan et al. (2000). We normalize the search efficiency of employed workers λ_e to unity and calibrate endogenously the search efficiencies of workers who are unemployed and out of the labor force.[14] The monthly probability of a worker keeping UI benefits p_b is set to 0.8329 which yields on average the standard UI eligibility duration in the US of 26 weeks. Finally, we set the probability of learning the quality of a firm-worker match to one third per period. This 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 Appendix G, we show that our results also hold for different parameterizations. We conduct a sensitivity analysis with respect different levels of the learning speed α and the elasticity of the matching function γ.

The remaining 10 parameters are calibrated internally and their values are reported in Table 3. 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 from 1982 to 2016 in the US, reported by the OECD, as a target for the generosity of unemployment benefits.[15] Our model admits one normalization in either home production or labor productivity: we set $\bar{h}$ such that in equilibrium output is equal to one.

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.[16] Following Kudlyak and Lange (2018), we restrict our attention to

[14] λ_u and λ_o could in principle be larger than one, as long as the overall job-finding probability is below one, which is directly affected by the vacancy posting cost k.

[15] According to the OECD Public Unemployment Spending series, spending on unemployment benefits accounts for 0.4% of US GDP. 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. This moment choice is inconsequential for our results, see appendix G.

[16] The IPUMS database is made available by the Minnesota Population Center. Using the CPS data from

Transition Rates CPS 1982–2018			Benefits OECD and March CPS 1982-2018			Tenure Distribution CPS Job Tenure Suppl.		
Flow	Data	Model	Target	Data	Model	Years	Data	Model
JJ	0.021	0.021	b/GDP	0.004	0.004	≤ 1	0.229	0.286
EU	0.013	0.013				$(1, 3]$	0.227	0.183
EN	0.024	0.023				$(3, 9]$	0.273	0.261
UE	0.238	0.242				> 9	0.271	0.271
UN	0.214	0.215						
NE	0.063	0.063						
NU	0.039	0.039						

Table 2: Empirical Moments and Model Fit.

workers that have either four or eight interviews in CPS.[17] 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 aged 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, 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 together with the tenure distribution also inform the two parameters characterizing the home production process: p_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,

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 consistency check 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.

[17] Using workers with at least two consecutive interviews in CPS yields almost identical labor market flows.

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, $1-\phi$, 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.

The only parameter left to pin down is Δ_z, which governs the dispersion in 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.[18] 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. We begin with the choices of non-employed workers in Figure 1. First, there are two thresholds, h_b and h_n, above which UI eligible and non-eligible non-employed workers, respectively, drop out of the labor force (column 1 of Figure 1). For values of home production above these thresholds, workers prefer to stay OLF, but they accept employment opportunities when they arise, generating NE transitions. These 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

[18]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.

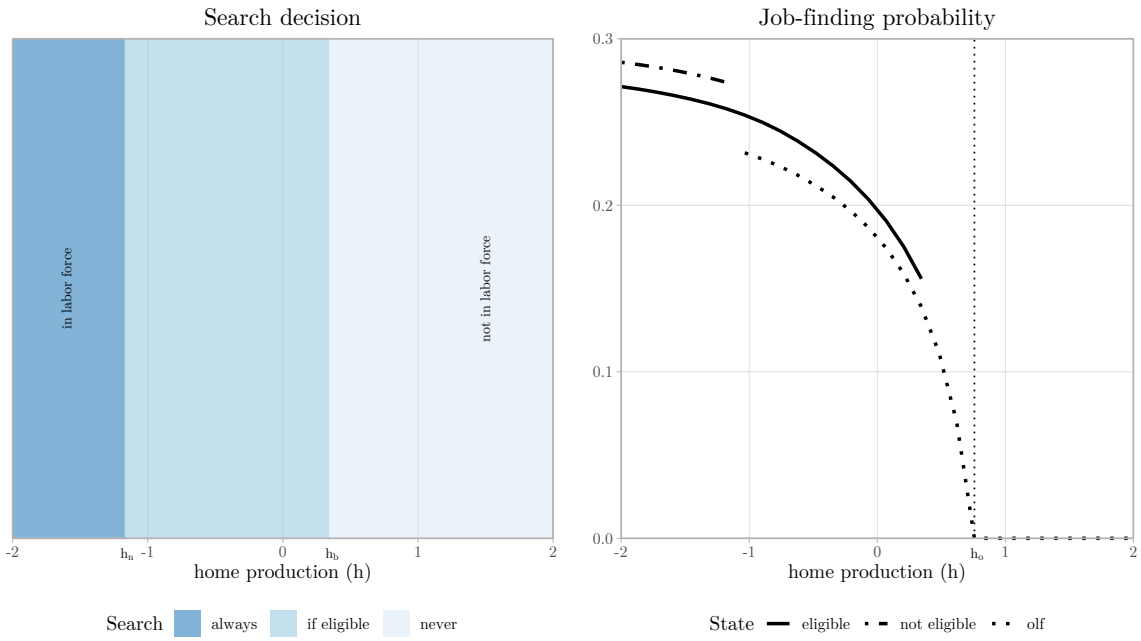


Figure 1: Search decision and job-finding probability for non-employed workers.

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 require levels of promised utilities which no firm is willing to offer; these workers stay jobless and inactive. Finally, job-finding rates are 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 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 unemployed workers who receive benefits are searching in submarkets with higher promised utility compared to non-eligible workers.[19]

[19]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 efficiencies $\lambda_u > \lambda_o$.

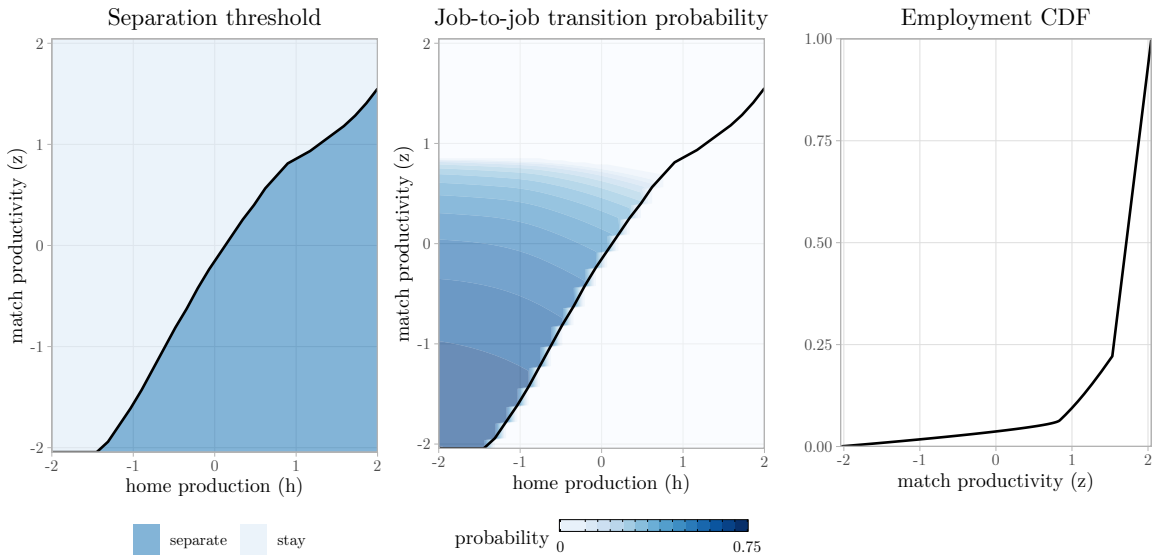


Figure 2: Separation threshold, job-to-job transition probability and employment CDF of employed workers.

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 workers 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 the 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 combination of match-specific productivity 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.[20] They are also decreasing in match-specific productivity, up to

[20]In addition, higher home production lowers the job-finding rate of employed workers because it raises

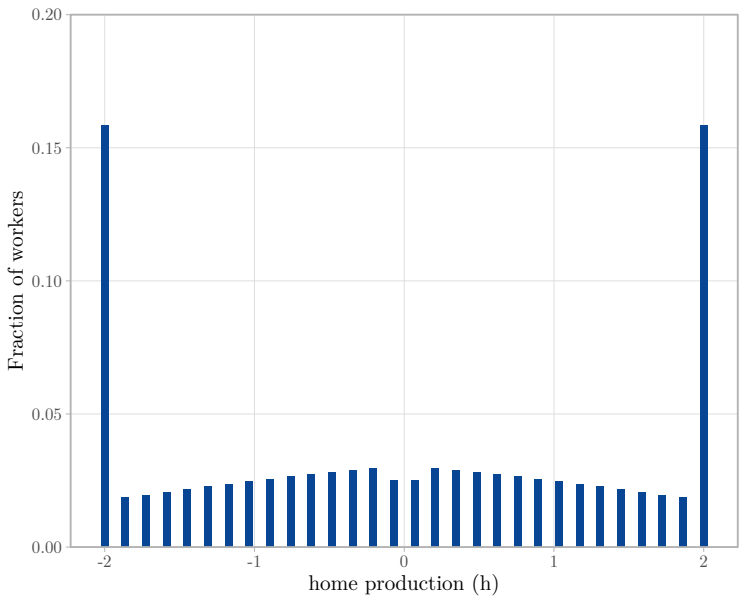


Figure 3: The distribution of workers across different home production levels in the model.

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 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 generates a negative correlation between job-tenure and job-to-job transitions in the model.

Given the importance of home production and match-specific productivity for the agents' behavior, we present two additional model features to better understand how these two forces interact. In Figure 3, we plot the distribution of workers across different home production levels in the model's stationary equilibrium. The home production process splits workers roughly into three large groups: a fraction with very low home production levels that exhibit high labor market attachment; a fraction with very high home production levels who stay OLF; and an intermediate group who account for the majority of labor market flows across states. The result that a parsimonious number of worker groups can account for the observed

the likelihood of *future* separations. This happens because the home production process is persistent in the calibrated model.

labor market flows is also found in other macro-labor frameworks (Hall and Kudlyak, 2019; Gregory et al., 2021; Ahn et al., 2023) and seems to paint a consistent picture of the US labor market dynamics.

Another way to see how home production and match-specific shocks influence different aspects of the model is the comparative statics exercise presented in Table 15 in Appendix C. The table contains the responses of labor market flows and the tenure distribution groups as percentage deviations from their steady state values when different model parameters increase by 1%. In particular, the dispersion of match-specific productivity shocks, Δz, mostly informs the job tenure distribution, as well as the job-to-job, EU, and EN flows. On the contrary, the frequency and dispersion of home production shocks, p_h and Δ_h respectively, mostly speak to the UN, NE, and NU flows. Intuitively, home production shocks determine the degree of workers' attachment to the labor market, while match-specific productivity shocks determine the behavior of strongly attached workers in terms of job-to-job transitions and separations, as well as the model-implied job tenure distribution. Having both of these forces in a common framework allows the model to accurately capture several important aspects of labor market dynamics.

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 16.3% 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.

To understand why the calibrated values of λ_u and λ_o are below the normalized value of $\lambda_e = 1$, it is important to note that employed and non-employed workers search for jobs in different submarkets. That is, the main job search decision for workers in the model is their submarket choice. In particular, employed workers search on average in submarkets with higher promised utility and lower job-finding rates than non-employed workers.[21] Since

[21] As shown in Figure 2, many employed workers are searching in submarkets with zero job-finding rates, hence they are effectively not searching for another job. In order for the model to generate enough job-to-job

Parameter	Description	Value
ϕ	Share of home production for unemployed	0.6010
λ_u	Meeting intensity unemployed	0.4614
λ_o	Meeting intensity out of labor force	0.3957
δ_0	Exogenous separation rate	0.0089
k	Per-period vacancy posting costs	1.0125
p_h	Prob. of home production shock	0.8409
Δ_h	Magnitude of home production shock	1.8728
Δ_z	Dispersion of match specific productivity	2.0442
$\bar{b}$	Unemployment benefits	0.2281
$\bar{h}$	Aggregate home production	-0.6640

Table 3: Internally Calibrated Parameters.

the overall job-finding rate is the product of λ_e and the submarket's specific meeting rate, employed workers meet less firms on average compared to non-employed workers. However, conditional on visiting the same submarket, employed workers would be more efficient in their search. This is consistent with the findings of Faberman et al. (2022) who document that the employed are more effective than the unemployed in job search.[22] Relatedly, to actively search for a job, unemployed workers sacrifice more than 40% of their home production value ($1 - \phi \approx 0.4$). This non-negligible utility cost of unemployment helps the model rationalize the observed labor force participation rate. Moreover, it is consistent with the empirical evidence regarding the large psychological and emotional costs experienced by unemployed individuals (Krueger and Mueller, 2011; Brand, 2015).

The calibration has important implications for the home production process. With probability $1 - p_h$, workers have the same home production level next period. This implies persistence for home production, which helps the model generate large groups with either very high or very low home production level. Nevertheless, p_h is estimated to be relatively large, which implies that there is also a large fraction of workers with intermediate levels

transitions and not overshoot the job-finding rates of the non-employed workers, λ_e has to be greater than λ_u and λ_o.

[22] A different interpretation of our calibration is based on poaching: employed workers are constantly available for job offers by other firms. The existence of professional recruiting services and online platforms, such as LinkedIn, has made poaching quite standard in modern labor markets. On the contrary, non-employed workers have to apply to jobs using more traditional means. This interpretation is also consistent with the empirical evidence of Faberman et al. (2022), who find that employed workers receive quite a lot job offers while not actively looking for a job.

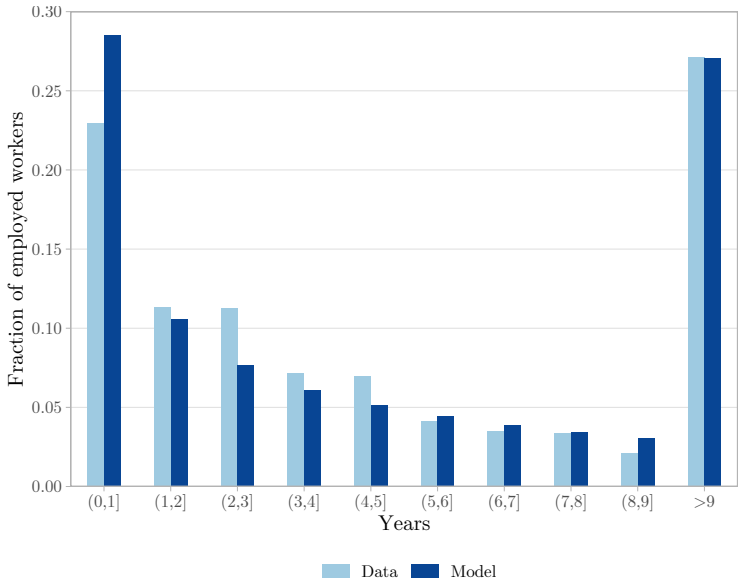


Figure 4: Job Tenure Distribution. Dark bars show the empirical tenure distribution in CPS, bright bars show the outcome of model simulations.

of home production. These features help the home production process roughly split the cross-section of workers into three major groups with differential labor market attachment, consistent with the US labor market dynamics (see Figure 3 in Section 4.1).

The model matches all targeted moments very closely, as can be seen in Table 2 and Figure 4. 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).[23] 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 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 flow is too small and the UE flow is too large in their model compared to the data.[24] On the contrary, our model can quantitatively account for all steady state flows. Furthermore, our model successfully

[23]As a robustness exercise, in Appendix G we present an alternative calibration, as well as policy counterfactuals, based on CPS flows that have been *de-NUNified*. That is, to control for measurement error in CPS, we follow Elsby et al. (2015) and recode particular labor market histories to avoid spurious transitions. For example, the history NUN has been recoded as NNN; the complete recoding scheme is available in Table 2 of Elsby et al. (2015). The results are fairly similar.

[24]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.

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, a small discrepancy 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.

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 several labor market moments which were not targeted in our calibration. The moments we chose are: the fractions of workers who performed a EU, EN, and UN transition for different reasons, as well as the labor market histories of workers across four consecutive months, as analyzed by Kudlyak and Lange (2017) and Hall and Kudlyak (2019). Both sets of moments are computed using the same CPS data set we used for computing the monthly labor market flows.

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 reasons behind labor market transitions lends credence to the model forces that move workers across labor market states. If the model mechanisms are empirically valid, then one has good reason to trust the model's counterfactual predictions about UI reforms. Second, we look at the four-month labor histories because they are measures of workers' labor market attachment. For example, 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. Workers with strong labor market attachment may respond differently to UI changes compared to workers with weak attachment. Hence, for the model to give reliable predictions about UI counterfactuals, it should capture that aspect of worker heterogeneity.

First, we begin with the reasons behind labor market transitions. In the CPS, unemployed and non-participating workers are asked about the reason they found themselves in this state in a particular month. The available reasons for unemployment are: job losers, temporary job has ended, job leavers, workers who re-entered unemployment, and workers who enter unemployment for the first time. Regarding the reasons for staying OLF, we

follow the standard practice and group the available options into the following categories: health related, retirement, family related, discouragement, attending school, and other reasons (e.g., transportation problems). In the model, there are four reasons for labor market transitions: innovations in home production, exogenous separations, learning match quality, and UI benefits expiration.

To make a meaningful comparison between model and data, we need to come up with a mapping between the model-based and the CPS categories. In terms of job separations, the model analogue of a job leaver is a worker who willingly separates due to a home production shock; a job loser is a worker who got hit by an exogenous separation; and a worker whose temporary job ended is a worker who separated due to learning that their match output is not high enough. Since we are focusing on EU flows, there should be no entrants performing this transition. Hence, we attribute these flows to measurement error and do not include them in model validation. In terms of transitions to non-participation, the model analogue of a worker who did not look for work due to school, family, health, or other reasons is a worker who got hit by a home production shock; and a discouraged worker is a worker who left the labor force due to losing UI eligibility.[25] Finally, we leave the category of retired non-participants in the data unassigned and do not use it for model validation.

Figure 5 provides a decomposition of the quantitative importance of each shock to EU, EN, and UN flows in the model and compares them with the corresponding transitions in the data. To perform the decomposition in the model, we assign each transition to a particular shock.[26] In the data, we split each transition into the categories of the final state and compute the fraction of each category.[27] The model does a good job mimicking the reasons behind labor market transitions in the data. In terms of job separations, the majority comes from exogenous shocks (job losers), while the role of home production (job leavers) and learning (temporary jobs ended) is relatively smaller. In terms of transitions to non-participation, the majority comes from home production shocks (school, health, family, other), while UI eligibility (discouragement) plays a more modest role. There results support the conclusion that the model mechanisms are empirically valid and the model can be trusted for policy

[25]Discouraged workers in the data have stronger attachment to the labor force than the other non-participants. This is also true for workers in the model who leave the labor force because their UI eligibility expired. Their relatively strong attachment is the reason we map these groups in the model and data.

[26]For the instances where two or more shocks occur at the same time, we describe the assignment in detail in Appendix D.

[27]Take EU transitions as an example: since there are four different unemployment categories, there are four different types of EU transitions (workers who moved from employment to unemployment and report they are job losers etc). We compute the fraction of each category according to the unemployment type reported by workers.

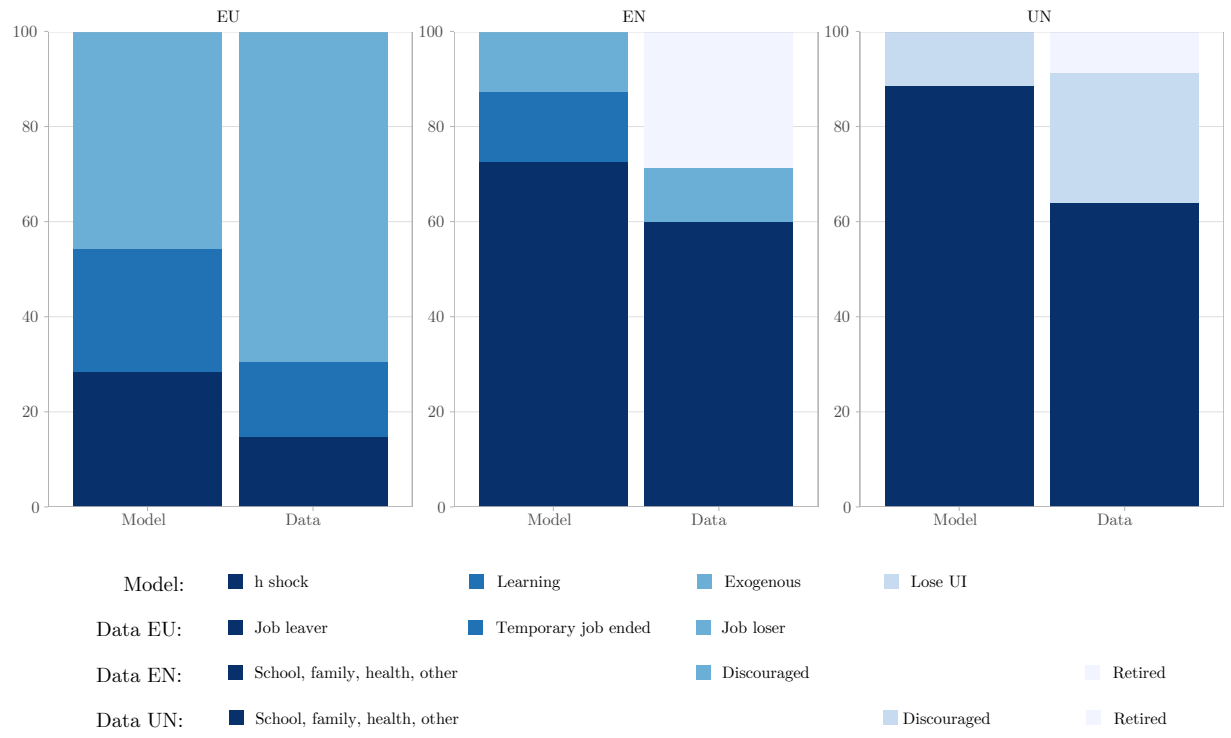


Figure 5: Decomposition of model flows across various channels and comparison with the corresponding transitions in CPS. The different colors correspond to the decision rules for workers of different types presented in Figures 1 and 2.

analysis.

Second, the labor histories of workers in the model are also broadly consistent with the four-month histories reported in CPS (Figure 6). There are two relevant comparisons shown in Figure 6: 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 6, 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 perfectly capture.

To get a better sense of the model's fit, we implement the second comparison shown in Figure 6: 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 out of the labor force, and "quite a lot" for workers starting in unemployment (the two models are very close for workers starting in employment). The fact that the model considerably improves upon the prediction of the mechanical approach for

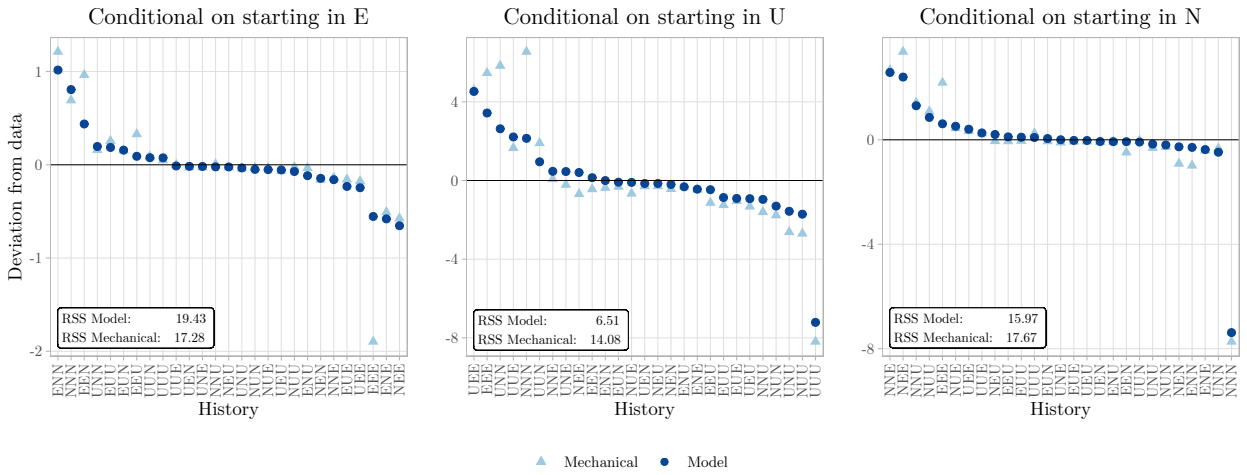


Figure 6: Difference between simulated and observed frequencies of four-months labor market histories in CPS. Mechanical frequencies are constructed by multiplying the monthly transition probabilities from CPS. The histories are sorted by the model deviations. RSS denotes the sum of squared percentage deviations.

unemployed workers is especially useful for our analysis of UI benefit reforms. The differential labor force attachment, due to home production shocks, together with the differential value of employment, due to match-specific productivity shocks, are the model ingredients responsible for 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. Intuitively, 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

	Baseline	99 weeks UI	
Moment	Value	Value	Pct. Change
E-Pop	0.712	0.709	-0.418%
LFPR	0.753	0.756	0.401%
U-Rate	0.055	0.062	14.082%
GDP	1.005	1.002	-0.326%
GDP/L	1.413	1.414	0.092%

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.

degrees of attachment behave very differently in the labor market.[28] As shown in Figure 6, the combination of home production and match-specific productivity shocks in the model captures a substantial amount of this panel dimension. In particular, our model performs much better than the mechanical one for several histories, such as EEEU, EEEE, and EEEN. The implication is that the model 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. In our main analysis, we focus on an extension of UI benefits from 26 weeks to 99 weeks, but we also discuss an equally expensive 19.5% increase in UI benefits while keeping the duration at 26 weeks in Appendix A. Our main analysis focuses on a comparison between steady states, but we also present the transition paths in Appendix E. The next subsection presents the aggregate effects the UI policy reform and explains how changes in agents' policy functions generate the results. Section 6 will then quantify which model channels are the main driving forces behind the aggregate effects.

5.1 Aggregate Effects of UI Extensions

Table 4 shows the effects of the 99-week extension on employment, labor force participation, unemployment rate, GDP, and labor productivity.[29] More generous UI benefits significantly increase unemployment by about 14%. The increase in unemployment originates to roughly equal parts from lower employment and more workers searching for jobs. The employment to population ratio (E-Pop) decreases by 0.4%, whereas the LFPR increases by 0.4%. As labor productivity is essentially unchanged, the lower employment rate leads to a 0.3% decline in output.

We also conducted a number of sensitivity checks of our results with respect to various parameters, as well as other calibration choices. In Appendix G, we show that using different values for the learning parameter α or for the elasticity of the matching function γ, using an alternative target for the levels of UI benefits, adding a life-cycle to the model, using de-nunified labor market flows, or using an AR(1) process for labor productivity does not change the policy results significantly. Moreover, in Appendix F we show that our main conclusions are robust to imposing a tax on match output to finance UI benefits. The reason behind this is that expenditures on UI benefits constitute only 0.4 percent of GDP, thus the distortionary effects of tax changes due to UI benefit reforms are quantitatively not important.

In order to understand how the effects of the UI reform come about, we study the responses of the underlying labor market flows. These responses are driven by two forces: (i) behavioral changes by firms and workers through changes in their policy functions, which are reported in Figure 7, and (ii) compositional changes in the pools of employed, unemployed, and out of the labor force workers across different 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) fixed to the pre-reform level. The behavioral change can be also thought of as the change on impact along the transition path (see Appendix E). On impact, the distribution has not changed yet. Over time, the distribution converges to the new steady state, and so do the flows, which then are a combination of behavioral and compositional changes.

The UI reform affects agents' policy functions along three relevant margins. More gen-

[28] 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.

[29] Notice that in all figures we compute percentage changes before rounding the numbers.

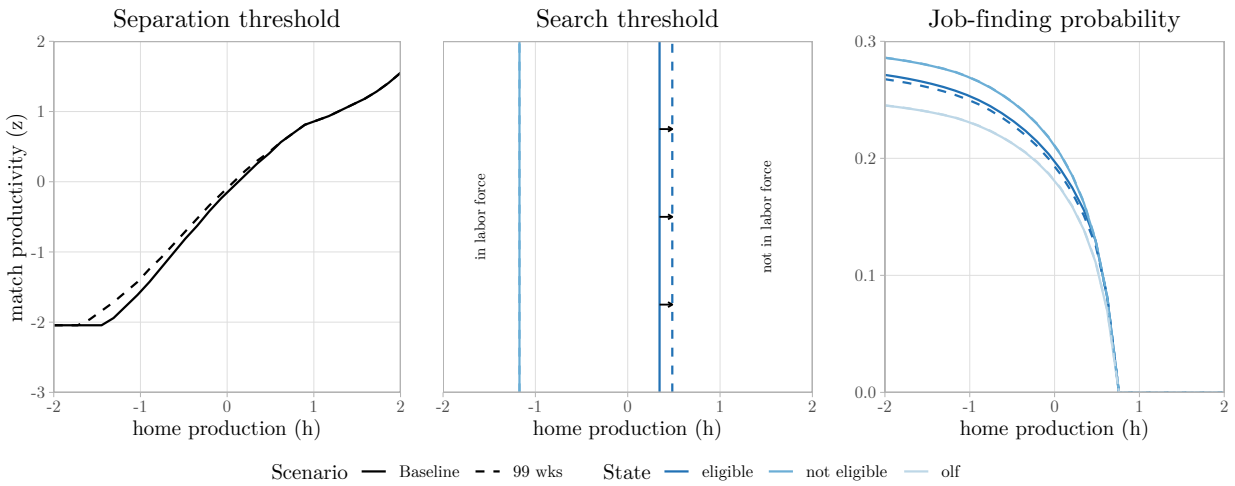


Figure 7: Policy functions and job-finding probability under different UI policies.

erous UI leads to: (i) a higher reservation productivity for viable matches (left column of Figure 7), (ii) a higher reservation home production to exit the labor market (middle column), and (iii) lower job-finding probabilities (right column). This can also be seen in the flow results of Table 5. How do these changes in the policy functions translate into the overall changes in labor market flows?

The UI reforms affect the UN flow 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 only search while receiving unemployment benefits. In the case of extended UI benefits, the probability of an UI expiration declines, which leads to a significant reduction (-14%) in the UN rate. This decline in the UN rate changes the composition of unemployed and OLF states. Workers transitioning from unemployment to OLF have a higher home production 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. First, workers entering the labor force are not eligible for UI benefits and thus the direct behavioral effect of extended UI benefits is close to zero for the NE and NU flows. However, because high h workers have a lower propensity to enter the labor force, and the overall higher home production level in the pool of out of the labor force workers leads to a decline in the NE and NU rate.

	Baseline	99 weeks UI		
	Value	Value	Overall Change	Behavioral Change
JJ	0.021	0.020	-3.631%	-3.032%
EU	0.013	0.015	14.377%	15.849%
EN	0.023	0.022	-4.523%	-4.362%
UE	0.242	0.231	-4.368%	-0.853%
UN	0.215	0.184	-14.599%	-12.466%
NE	0.063	0.062	-1.822%	0.226%
NU	0.039	0.037	-4.327%	-0.017%

Table 5: Effects of more generous UI benefits on labor market flows. The table reports how flows respond to a 99 weeks UI extension.

Next, we move to the UE, EU, and EN rates. The post-reform job-finding rate declines because of two reasons. First, the unemployment pool after the reforms consists of workers with higher home production and, as a result, lower job-finding probabilities; this puts a downward pressure on UE flows. Second, the UE rate declines because firms have to offer higher value jobs in response to more generous UI benefits, which depresses vacancy creation. The higher reservation threshold for match specific productivity leads to fewer viable matches, and thus to more separations. Due to the extended UI benefits, the unemployment state is now more attractive, thus conditional on separation, more workers choose unemployment over out of the labor force, as can be seen by the increase reservation home production in the middle panel of Figure 7. This leads to an increase in EU flows and a decrease in EN flows.

In addition, the overall higher separation rates lower the return of opening new vacancies, 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 job-to-job transition rates. One the one hand, the lower job-to-job transition rates lead to fewer workers climbing up the match specific productivity ladder, which tends to lower labor productivity. On the other hand, the higher reservation productivity puts upward pressure on labor productivity. In the end, the effect of the UI extension on labor productivity is ambiguous, but the calibration implies that labor productivity is essentially unchanged after the UI reform. This is in contrast to models without job-to-job transitions, where the higher reservation productivity unambiguously leads to higher labor productivity (Acemoglu and Shimer, 1999). This result would be missed by a

framework without an explicit role for job-to-job transitions and endogenous separations.

In Appendix A, we contrast these results to an alternative UI reform. We compute the effects of a 19.5% increase in the level of UI benefits while keeping the duration at 26 weeks. This increase has the same budgetary costs as the 99 weeks extension. Overall, the effects of the two policy changes are very similar. The only major difference is the effect on UN, which declines significantly less compared to the benefit extension. This is because some workers only remain in the labor force while receiving UI benefits, thus the UN rate declines more with extended benefits.

5.2 Empirical Evidence

To evaluate the empirical plausibility of our model, we need to compare its results with the responses of labor market flows to UI reforms in the data. Before proceeding, we should highlight that the following comparison between the model and the empirical estimates is only indicative for a number of reasons. First, the empirical UI reforms are usually short-lived extensions, while the reforms studied in the model are permanent expansions. Second, the UI extensions usually take place in recessions, whereas the reforms in the model take place in steady state. Nevertheless, we believe that confronting the model results with the empirical estimates is a useful exercise that can show whether the model is qualitatively consistent with the data.

We follow Farber et al. (2015) (which combines the methodologies developed in Rothstein 2011 and Farber and Valletta 2015) and focus on the UI reforms that took place during and after the Great Recession in the US. Farber et al. (2015) estimated the effect of UI reforms on the UE and UN transition probabilities using cross-state and temporal variation in UI provision (since different states changed their UI policies at different times and using different eligibility criteria). We merge their UI reforms data set (with information about UI provision across different states from 2004 to 2014) with our CPS sample and consider the effects of UI reforms on all labor market transition probabilities, as well as labor market stocks, building upon their methodology.

The main dependent variable of interest in Farber et al. (2015) are the exit rates from unemployment. This allows them to use workers' unemployment duration as the UI eligibility criterion and compare different individuals to estimate the effect of UI reforms on the UE and UN rates. Since we are interested in all labor market flows, we have to consider individuals in all labor market states, not only unemployment. Hence, unemployment duration cannot be used as the eligibility criterion and we cannot make individual-level comparisons. We

Flow	Marginal Effect	Stock	Marginal Effect
JJ	-.0000018	E	-.0002282**
	(.0000107)		(.000071)
EU	-.0000153	U	.0002289***
	(.00000804)		(.0000405)
EN	-.0000011	N	-.0001091
	(.00000962)		(.0000601)
UE	-.00000375		
	(.00000841)		
UN	-.0000366*		
	(.0000156)		
NE	.00000829		
	(.00000977)		
NU	-.0000524**		
	(.0000171)		

Table 6: Estimated average marginal effects of UI reforms. The table presents the average marginal effect of an extra week of UI availability on labor market flows and stocks. The marginal effects are based on the estimated coefficients of UI availability measured in weeks included in a logit model (see the text for other controls). Standard errors are clustered at the state level and are reported in parentheses.

make state-level comparisons which estimate how much a particular flow changed in a state after the implementation of a UI reform in the Farber et al. (2015) data set.

Our dependent variables of interest are the observed monthly labor market transitions and stocks. The latent variable is modeled as:

$$y^*_{ist} = X_{ist}\beta + Z_{st}\lambda + UI_{st}\delta + \omega_s + \psi_t + \epsilon_{ist}$$

Building upon Farber et al. (2015), we estimate a logit model of the observed labor market outcomes, include several controls (ω_s is state and ψ_t is month-year fixed effect; Z_{st} includes a cubic in the monthly seasonally adjusted state unemployment rate and a cubic in the 3-month annualized payroll employment growth rate; X_{ist} includes indicators for five education groups, three race categories, female, married, as well as an age polynomial), and cluster the standard errors at the state level. Table 6 contains the estimated marginal effects δ of an extra week of UI availability on the monthly probability an individual performs a particular labor market transition or is in a particular labor market state. The presentation of results

in Table 6 follows the presentation of Table 1 on p. 175 in Farber et al. (2015).

In terms of results, the first thing to notice is that even though we only use state-level variation, our estimates for UE and UN transitions are consistent with the results of Farber et al. (2015): an extra week of UI benefits has an insignificant effect on the job-finding probability but a significant negative effect on the labor force exit probability.[30] Moreover, we uncover a significant negative effect on the probability of employment and a significant negative effect on the probability of unemployment. These two effects seem to cancel each other out and the effect on the probability of labor force participation is insignificant.[31] Finally, we also find a significant negative effect on the NU transition probability. To sum up, all the estimates above are in accordance with the model's predictions.

The estimates for the job-to-job transitions and separations are not precisely estimated and we cannot rule out zero effects at conventional 95% confidence levels. Put differently, our estimates are consistent with both large negative and large positive effects, since both are within the confidence intervals. The literature, however, has provided several high-quality measurements for these two channels. First, several papers, employing different data sets and approaches, document a significant negative effect of UI extensions on job-to-job transitions in line with our model. Burgess and Low (1998), Light and Omori (2004), and Gutierrez (2016, 2019) show this using a control function approach, while Britto (2016) and Grindaker (2022) employ a regression kink design. Second, several papers report a significant positive effect of UI extensions on worker separations in line with our model. Lalive et al. (2011) and Jäger et al. (2019) make this point with data from Austria, Hartung et al. (2020) from Germany, Albanese et al. (2020) from Italy, and Grindaker (2022) from Norway. In total, the model implications are in accordance with the empirical correlations produced by our logit specification, as well as the estimates produced by several empirical papers in the literature.

[30] This finding is consistent with other recent papers that employ causal research designs; see, for example, Schmieder et al. (2016), Nekoei and Weber (2017), and Domènech-Arumí and Vannutelli (2022).

[31] The empirical literature has also produced mixed evidence regarding the effects of UI extensions on labor force participation. On the one hand, Hagedorn et al. (2019) and Conway (2022), focusing on the 2013 UI reductions across states, find a significant positive effect on labor force participation. On the other hand, Figura and Barnichon (2014), using UI reforms data from multiple historical episodes, document quite small effects on the participation rate.

6 The Importance of Participation, Separations, and Job-to-Job Flows for UI Extensions

The goal of this section is to highlight the importance of endogenous labor force participation, separations, and job-to-job transitions for a complete analysis of UI policies. In other words, we aim to show that structural models that do not incorporate these features provide biased characterizations for at least some implications of UI reforms. We proceed in two steps: first, using our calibrated model, we shut down individual policy function changes to compute the quantitative importance of different model channels. Second, we quantify the 99 weeks UI extension within simpler models which do not feature endogenous separations, labor force participation, or job-to-job transitions. Both approaches show that incorporating these three channels is crucial for a complete understanding of UI reforms.

6.1 The Contribution of Different Model Channels

One of the key contributions of this paper is to study the effects of UI reforms 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). Importantly, our model also incorporates endogenous separations and job-to-job transitions. In this section, we evaluate the quantitative contributions of these mechanisms for the economy's response to UI reforms.

The UI reform changes agents' policy functions, leading to both behavioral and compositional effects (see Section 5.1). Taken together, the behavioral and compositional changes originate from three distinct margins of adjustment. First, the separation margin, i.e. the reservation productivity for viable matches, changes. Second, we define the participation margin as the adjustment in the home productivity threshold for participating in the labor market. Moreover, there is an additional effect in the participation margin due to the benefits extension: because the probability of UI expiration declines, fewer workers lose UI eligibility, which in turn affects labor market stocks and flows. Third, we define the matching margin as the sum of adjustments due to changes in vacancy creation and changes in the submarket search decisions of employed and non-employed workers. We use our model to disentangle the contribution of each one of these channels to the aggregate effects of UI reforms. To do so, we compute the total effects of changing each margin from pre- to post-reform one by one, while holding all other margins fixed at their pre-reform levels.

Table 7 reports the contribution of each individual channel on aggregate stocks, while

	99 weeks UI				
Values	E-Pop	LFPR	U-Rate	GDP	GDP/L
Separation margin	-0.39%	-0.16%	4.04%	-0.31%	0.08%
Participation margin	-0.00%	0.53%	9.12%	-0.00%	0.00%
Matching margin	0.00%	0.02%	0.25%	0.01%	0.01%
Total effect	-0.42%	0.40%	14.08%	-0.33%	0.09%

Table 7: Contribution of individual channels to the aggregate UI reform effects. The table shows the effect of moving individual policy functions from pre to post-reform level, while holding all other policy functions fixed at pre-reform level.

	99 weeks UI						
Values	JJ	EU	EN	UE	UN	NE	NU
Separation margin	-3.71%	6.59%	-0.19%	-0.13%	-0.71%	0.17%	0.37%
Participation margin	-0.02%	7.77%	-4.32%	-3.50%	-13.32%	-2.10%	-4.41%
Matching margin	0.10%	0.03%	-0.02%	-0.50%	-0.08%	0.20%	-0.06%
Total effect	-3.63%	14.38%	-4.52%	-4.37%	-14.60%	-1.82%	-4.33%

Table 8: Contribution of individual channels to the aggregate UI reform effects. The table shows the effect of moving individual policy functions from pre to post-reform level, while holding all other policy functions fixed at pre-reform level.

Table 8 reports the decomposition results for labor market flows. In all cases, the individual effects sum up approximately to the total effect, indicating that interaction effects between the channels play a limited role. The change in the separation threshold has the largest single impact on employment and GDP, while the participation margin plays an important role for the reaction of the unemployment rate and LFPR. The matching margin plays a modest role. This is due to the fact that the job-finding rates decline by a large part because of compositional changes in the unemployment pool, as can be seen in Table 5. These compositional changes in turn are driven by the participation margin, as can be seen in Table 8. The finding that the separation margin is quantitatively important for the effects of UI reforms is in line with several empirical studies conducted in various settings (Lalive et al., 2011; Jäger et al., 2019; Hartung et al., 2020).

Based on the limited importance of the matching margin for labor market stocks, one may conclude that modeling job-to-job transitions is not necessary for a comprehensive un-

derstanding of UI reforms. This conclusion, however, would be premature. A model without job-to-job transitions might imply a different distribution of match specific productivity. On the one hand, employed workers would not be able to transition to higher productivity jobs. On the other hand, workers are less likely to accept low productivity jobs after productivity is revealed. This, in turn, can affect the model responsiveness to UI changes. We will come back to this point in Section 6.2.

Last but not least, the changing participation margin is quantitatively important for the aggregate effects of UI reforms. First, the participation margin counteracts the drop in LFPR due to the separation margin. Second, and perhaps more importantly, it alone accounts for two thirds of the unemployment rate response. This highlights the importance of taking the labor force participation decision explicitly into account when considering changes to the UI system.

6.2 Comparison of Alternative Model Specifications

The goal of this section is to evaluate whether models that do not contain endogenous separations, labor force participation, and job-to-job transitions miss important aspects of UI reforms. The reason for this exercise is that the majority of structural equilibrium models used to evaluate UI reforms in the literature typically abstracts from one or more of these channels. Our aim is to quantify the extent to which these simplifying assumptions produce biased implications vis-a-vis the complete model that contains all endogenous worker mobility features. To perform this exercise, we proceed in the following steps. First, we simplify our model by separately excluding the labor force participation choice, endogenous separations, and job-to-job transitions. Then, we re-calibrate the simpler models to make them consistent with the same data as the complete model, and use them to evaluate the effects of the 99 weeks UI extension. The empirical fit of all models is presented in Table 19 in Appendix H.[32] Finally, we compare the labor market implications of the simpler models triggered by the UI extension with those of the complete model.

We begin by excluding endogenous separations which implies that jobs terminate only at the exogenous rate δ_0. Taking away the ability to dissolve a match eliminates the separation margin in the model. Although the simplified model still manages to match most observed labor market flows, it predicts only half of the observed EN transition rate. Moreover, the

[32]In general, the calibration of all simpler models is successful, in the sense that the models reproduce the relevant flows and tenure distribution. The only exception is that the model without endogenous separations underestimates the EN flow and struggles with aspects of the tenure distribution.

	Baseline	99 weeks UI	
Moment	Value	Value	Pct Change
Full Model			
E-Pop	0.712	0.709	-0.418%
LFPR	0.753	0.756	0.401%
U-Rate	0.055	0.062	14.082%
GDP	1.005	1.002	-0.326%
GDP/L	1.413	1.414	0.092%
Model without endogenous separations			
E-Pop	0.795	0.794	-0.080%
LFPR	0.828	0.830	0.263%
U-Rate	0.040	0.043	8.173%
GDP	1.008	1.007	-0.162%
GDP/L	1.269	1.268	-0.082%
Model without labor force participation			
E-Pop	0.947	0.941	-0.596%
LFPR	1.000	1.000	0.000%
U-Rate	0.053	0.059	10.631%
GDP	1.000	0.997	-0.304%
GDP/L	1.056	1.059	0.294%
Model without job-to-job transitions			
E-Pop	0.712	0.712	-0.023%
LFPR	0.759	0.762	0.477%
U-Rate	0.061	0.065	7.679%
GDP	1.004	1.005	0.031%
GDP/L	1.410	1.410	0.053%

Table 9: Effects of more generous UI benefits in various models. The table reports how labor market stocks, GPD, and labor productivity respond to a 99 weeks UI extension in models with different features.

model predicts an essentially unchanged E-Pop and a much smaller change in the unemployment rate, which again confirms the importance of the separation margin for the impact of UI reforms (Table 9). Even though separations are exogenous (and, thus, unchanged), the EU rate still declines with the UI extension. This happens because, conditional on a separation, more generous UI raises the incentives to remain unemployed rather than to drop out of the labor force. However, as can be seen in Table 10, without the option to terminate a match the EU response is only one third of the complete model.

	Baseline	99 weeks UI	
Moment	Value	Value	Pct Change
Full Model			
JJ	0.021	0.020	-3.631%
EU	0.013	0.015	14.377%
EN	0.023	0.022	-4.523%
UE	0.242	0.231	-4.368%
UN	0.215	0.184	-14.599%
NE	0.063	0.062	-1.822%
NU	0.039	0.037	-4.327%
Model without endogenous separations			
JJ	0.025	0.025	-0.009%
EU	0.011	0.011	4.672%
EN	0.012	0.012	-4.056%
UE	0.241	0.231	-4.072%
UN	0.215	0.191	-11.174%
NE	0.058	0.057	-2.117%
NU	0.039	0.038	-3.579%
Model without labor force participation			
JJ	0.022	0.020	-5.181%
EU	0.013	0.014	8.986%
UE	0.235	0.230	-2.074%
Model without job-to-job transitions			
EU	0.017	0.018	5.946%
EN	0.020	0.019	-4.850%
UE	0.238	0.232	-2.768%
UN	0.221	0.196	-11.421%
NE	0.061	0.060	-2.292%
NU	0.039	0.037	-4.432%

Table 10: Effects of more generous UI benefits in various models. The table reports how labor market flows respond to a 99 weeks UI extension in models with different features.

The muted response of separations in the simplified model also affects the implications of the UI extension for job-to-job transitions. Since separations do not increase, there are more low quality matches preserved relative to the full model. Workers in these matches are the ones who engage in job-to-job transitions more intensely. As these are preserved in the model without endogenous separations, the job-to-job transition rate is essentially not affected

by the UI extension. This contradicts several empirical papers documenting a significant negative effect of UI extensions on job-to-job transitions, an implication missing in the model without endogenous separations.[33] To sum up, the model without endogenous separations underestimates the response of EU and job-to-job flows, and, as a result, underestimates the response of the unemployment rate by half compared to the full model. In addition, employment is essentially unchanged, which is in contradiction with the empirical evidence presented in Table 6.

Next, we exclude the labor force participation choice from the model. To implement this, we remove home production shocks, set $\phi = 1$, and re-calibrate $\bar{h}$ to normalize the economy's GDP to 1. In terms of model channels, this exercise removes the participation margin from the model. In terms of quantitative implications, the model without endogenous participation underestimates the response of the unemployment rate and overestimates the response of the employment to population ratio and aggregate productivity (Table 9). Intuitively, without the participation margin all workers have very strong labor market attachment. As a result, workers separate from their jobs and transition to new matches less often when benefits expand (see the response of EU and job-to-job flows in Table 10). Furthermore, in the full model more generous UI also incentivizes workers to stay in the labor force, as the decline in UN rate shows, which is consistent with the empirical evidence in Farber et al. (2015) and Table 6. This in fact dampens the E-Pop decline triggered by the UI extension. This force is missing in the simplified model, which leads to a larger decline in employment and a lower increase in the unemployment rate. Moreover, in the absence of any heterogeneity in home production, the separation margin is even stronger and the benefits extension raises aggregate productivity much more than in the full model. To sum up, the model without endogenous participation underestimates the response of the EU flow and the unemployment rate, while it overestimates the response of employment, job-to-job transitions, and aggregate productivity relative to the full model.

Finally, we consider a model without job-to-job transitions by setting $\lambda_e = 0$ and using all other moments except the job-to-job transitions as targets in the calibration. In the full model, workers stay in low productivity matches after learning the match productivity, because of the opportunity to move to a better job. In the model without job-to-job transitions, since the opportunity of improving upon the current match is missing, the low productivity matches do not survive after match quality is revealed.[34] Thus, the pool of

[33]The main references are Burgess and Low (1998), Light and Omori (2004), Gutierrez (2016, 2019), Britto (2016), and Grindaker (2022).

[34]The average labor productivity between the two models is still very similar. This is due to the fact

employed workers is more insulated to changes in UI benefits. Hence, the separation margin is muted, which in turn explains the muted employment response. Consequently, the model without job-to-job transitions predicts a essentially unchanged E-Pop and GDP, as well as a much smaller increase in the unemployment rate. This is clearly at odds with the empirical evidence, which shows a decline in employment in response to UI extensions (see Table 6). To sum up, the separation margin rests on both endogenous separations and job-to-job transitions to be operative in the complete model. As a result, the model without job-to-job transitions underestimates the response of the E-Pop, unemployment rate, GDP, as well as the response of the EU flow relative to the full model.

To recap the main point of this section, the evidence presented points towards the importance of having endogenous separations, labor force participation, as well as job-to-job transitions together when analyzing UI benefit reforms.

7 Conclusion

In this paper, we develop an equilibrium search model featuring *all* labor market flows, as well as endogenous job creation by firms and endogenous separations, and use it to perform a positive analysis of UI policies. Compared to the previous literature, our model includes job-to-job transitions, a labor force participation and job separation decision, all of which play an important role for a complete analysis of UI reforms. The first source of heterogeneity in the model is home production, which changes over time due to workers' 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 and the job tenure distribution. To gauge the empirical validity of the model, we compare its performance with two sets of untargeted

that although without job-to-job transitions there are fewer low productivity jobs, workers cannot transition to the very high productivity matches through job-to-job transitions. Thus, the two forces cancel out, and average labor productivity is not affected much.

empirical moments, also from CPS: the fractions of workers who performed a EU, EN, and UN transition for different reasons, as well as the workers' four-month labor market histories. The model successfully replicates all targeted moments and performs very well in comparison with the untargeted statistics, showing it is reliable laboratory to study the positive effects of UI reforms.

We use the model to quantitatively study the effects of extended UI benefits. The model predicts that the 99 weeks extension leads to a increase in the unemployment rate, which is both due to lower employment and a higher LFPR. Labor productivity stays roughly constant after the reform. Our main contribution is to highlight the importance of flows in and out of the labor force, job-to-job transitions, and endogenous separations for a complete analysis of UI policies. We do so in two ways: first, we use our model to quantify the importance of these channels for the effects of the 99 weeks extension. Second, we show that simplified models without the OLF state, endogenous separations, and job-to-job transitions have counter-factual implications when analyzing the same UI extension as the baseline model.

To sum up, the main message of our paper is that structural analyses that do not incorporate job-to-job transitions, flows in and out of the labor force, as well as endogenous separations decisions would produce biased implications when used to study UI reforms. Models without the OLF state would overestimate the drop in employment and underestimate the rise in unemployment due to the benefits extension. Models without endogenous separations or job-to-job transitions would overestimate the increase in labor productivity and underestimate the drop in employment due to the UI reform. These cautionary notes should be relevant for modelers and policy-makers alike.

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A Comparison to more generous UI benefits

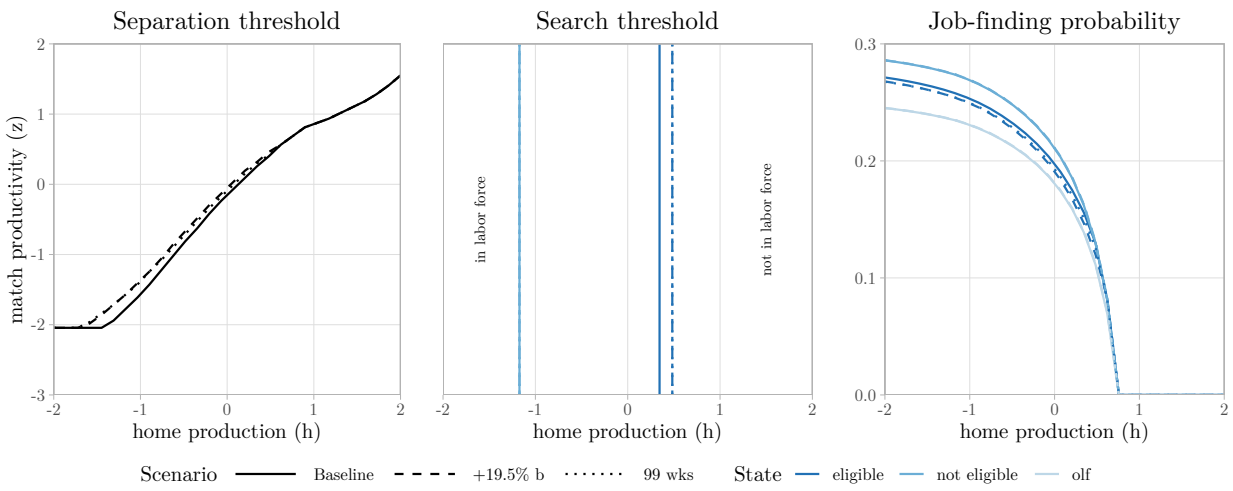


Figure 8: Policy functions and job-finding probability under different UI policies.

	Baseline	UI +19.5%		99 weeks UI	
Moment	Value	Value	Pct. Change	Value	Pct. Change
E-Pop	0.712	0.708	-0.441%	0.709	-0.418%
LFPR	0.753	0.753	0.071%	0.756	0.401%
U-Rate	0.055	0.060	8.845%	0.062	14.082%
GDP	1.005	1.002	-0.335%	1.002	-0.326%
GDP/L	1.413	1.414	0.107%	1.414	0.092%

Table 11: 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 19.5% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

	Baseline		UI +19.5%			99 weeks UI		
	Value		Value	Overall Change	Behavioral Change	Value	Overall Change	Behavioral Change
JJ		0.021	0.020	-4.192%	-3.494%	0.020	-3.631%	-3.032%
EU		0.013	0.015	15.670%	17.406%	0.015	14.377%	15.849%
EN		0.023	0.022	-4.742%	-4.362%	0.022	-4.523%	-4.362%
UE		0.242	0.235	-2.576%	-0.580%	0.231	-4.368%	-0.853%
UN		0.215	0.214	-0.779%	-3.459%	0.184	-14.599%	-12.466%
NE		0.063	0.063	-0.146%	0.331%	0.062	-1.822%	0.226%
NU		0.039	0.039	-0.553%	-0.021%	0.037	-4.327%	-0.017%

Table 12: Effects of more generous UI benefits on labor market flows. The table reports how flows respond to a 99 weeks UI extension and an 19.5% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

	UI +19.5%				
Values	E-Pop	LFPR	U-Rate	GDP	GDP/L
Separation margin	-0.46%	-0.19%	4.67%	-0.36%	0.09%
Participation margin	0.01%	0.23%	3.71%	0.01%	0.00%
Matching margin	0.01%	0.02%	0.27%	0.02%	0.01%
Total effect	-0.44%	0.07%	8.85%	-0.33%	0.11%
	99 weeks UI				
Values	E-Pop	LFPR	U-Rate	GDP	GDP/L
Separation margin	-0.39%	-0.16%	4.04%	-0.31%	0.08%
Participation margin	-0.00%	0.53%	9.12%	-0.00%	0.00%
Matching margin	0.00%	0.02%	0.25%	0.01%	0.01%
Total effect	-0.42%	0.40%	14.08%	-0.33%	0.09%

Table 13: Contribution of individual channels to the aggregate UI reform effects. The table shows the effect of moving individual policy functions from pre to post-reform level, while holding all other policy functions fixed at pre-reform level.

	UI +19.5%						
Values	JJ	EU	EN	UE	UN	NE	NU
Separation margin	-4.31%	7.77%	-0.31%	-0.21%	-0.56%	0.21%	0.44%
Participation margin	-0.01%	7.76%	-4.35%	-1.71%	0.00%	-0.64%	-0.89%
Matching margin	0.13%	0.04%	-0.02%	-0.63%	-0.05%	0.30%	-0.09%
Total effect	-4.19%	15.67%	-4.74%	-2.58%	-0.78%	-0.15%	-0.55%
	99 weeks UI						
Values	JJ	EU	EN	UE	UN	NE	NU
Separation margin	-3.71%	6.59%	-0.19%	-0.13%	-0.71%	0.17%	0.37%
Participation margin	-0.02%	7.77%	-4.32%	-3.50%	-13.32%	-2.10%	-4.41%
Matching margin	0.10%	0.03%	-0.02%	-0.50%	-0.08%	0.20%	-0.06%
Total effect	-3.63%	14.38%	-4.52%	-4.37%	-14.60%	-1.82%	-4.33%

Table 14: Contribution of individual channels to the aggregate UI reform effects. The table shows the effect of moving individual policy functions from pre to post-reform level, while holding all other policy functions fixed at pre-reform level.

B 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 200 equally spaced grid points between $-\Delta_z$ and Δ_z. Furthermore, we define an additional 201st 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. Lastly, we keep track of the eligibility status b for unemployed agents. In total, an agent can be in one of $30 \times (201 + 2 + 1) = 6,120$ 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. Since the transition matrix is relatively large (6,120 $\times$ 6,120), 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[35]. The problem can then be described as finding the global minimum of a 10-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 200 times with random initial particles. Finally, we choose the best model among all these repetitions.

[35]Each tenure cell is weighted by 0.25 to account for the fact that the tenure distribution has to inform one moment.

C Model parameter elasticity

	JJ	EU	EN	UE	UN	NE	NU	Ten1Y	Ten2-3Y	Ten4-9Y	Ten10Y
Δ_z	1.81%	-3.63%	-2.05%	0.87%	-0.15%	1.85%	-1.40%	-0.24%	-0.29%	0.19%	0.26%
$1-p_h$	0.11%	-0.16%	-0.12%	0.02%	-0.13%	-0.08%	-0.27%	-0.01%	0.04%	0.01%	-0.02%
Δ_h	-0.50%	0.73%	0.80%	-0.46%	3.38%	2.85%	-8.33%	0.14%	-0.28%	-0.09%	0.14%

Table 15: Percentage responses of labor market flows and the tenure distribution to 1% increases in various model parameters.

D Details about flow decomposition

This section provides the details regarding the decomposition of Figure 5.

Let $\Phi_U(h,\bar{b})$ denote the distribution of unemployed workers across home production level h and unemployment eligibility $\bar{b}$ at the end of the period. Let $p_{trans}(h',\bar{b}'|h,\bar{b})$ denote the probability of being in state $(h',\bar{b}')$ after the realization of shocks (the first stage of the period) conditional on being in state $(h,\bar{b})$ at the end of the previous period. Finally, let $p_{job}(h,\bar{b})$ denote the probability of finding a job. Then, the UN rate can be written as

$$UN = \sum_{h,\bar{b}} \Phi_U(h,\bar{b}) \sum_{h',\bar{b}'} p_{trans}(h',\bar{b}'|h,\bar{b})(1-p_{job}(h',\bar{b}'))1_{N^o(h')>N^u(h',\bar{b}')}$$

This allows to decompose the transition rate into two components:

$$UN = UN_{\text{lose UI}} + UN_{\text{h-shock}}$$

with

$$
\begin{aligned}
UN_{\text{lose UI}} &= \sum_{h,\bar{b}} \Phi_U(h,\bar{b}) 1_{N^o(h)>N^u(h,0)} 1_{\bar{b}=b} \\
&\quad \times \sum_{h',\bar{b}'} p_{trans}(h',\bar{b}'|h,\bar{b})(1-p_{job}(h',\bar{b}'))1_{\bar{b}'=0} 1_{N^o(h')>N^u(h',\bar{b}')} \\
UN_{\text{h-shock}} &= \sum_{h,\bar{b}} \Phi_U(h,\bar{b}) 1_{N^o(h)\not>N^u(h,0)} 1_{\bar{b}=b} \\
&\quad \times \sum_{h',\bar{b}'} p_{trans}(h',\bar{b}'|h,\bar{b})(1-p_{job}(h',\bar{b}'))1_{\bar{b}'=0} 1_{N^o(h')>N^u(h',\bar{b}')} \\
&\quad + \sum_{h,\bar{b}} \Phi_U(a,h,\bar{b}) 1_{\bar{b}=0} \sum_{h',\bar{b}'} p_{trans}(h',\bar{b}'|h,\bar{b})(1-p_{job}(h',\bar{b}'))1_{N^o(a',h')>N^u(h',\bar{b}')}
\end{aligned}
$$

$UN_{\text{lose UI}}$ represents the workers who (1) were eligible and lost eligibility, (2) prefer N after losing eligibility, (3) would also have preferred N in the previous period if they had not been eligible. Hence, it represents exactly those workers who left U to N in response to a loss in eligibility, since eligibility was the sole reason to remain in U. Symmetrically, $UN_{\text{h-shocks}}$ represents the workers, who satisfy (2) and (3) but not (4). That is, it contains all workers who were not eligible in the previous and current period and decided to leave the labor force in response to seeing the new h.

A similar logic applies to EN and EU transitions. However, instead of losing eligibility, workers might learn their productivity or exogenously separate. To describe these flows, let $d(h,z)$ denote the (chosen) probability of separation, which can either arise with probability one if the value from non-employment is higher than the value of working, or with exogenous probability δ_0 otherwise. Additionally, let $\Phi_E(h,z)$ denote the distribution of employed workers across h and z. Then, the EU rate can be written as

$$
EU = \sum_{h,z} \Phi_E(h,z) \sum_{h'} p_{trans}(h'|h) d(h',z) 1_{N^o(h')<N^u(h',b)}
$$

Similar to before, this rate can be decomposed into three components

$$
EU = EU_{\text{exogenous}} + EU_{\text{h-shock}} + EU_{\text{learning}}
$$

with

$$
\begin{aligned}
EU_{\text{exogenous}} &= \sum_{h,z} \Phi_E(h,z) \sum_{h'} p_{trans}(h'|h)\delta_0 1_{N^o(h')<N^u(h',b)} \\
EU_{\text{h-shock}} &= \sum_{h,z} \Phi_E(h,z) 1_{d(h,z)<1} \sum_{h'} p_{trans}(h'|h)(1-\delta_0) 1_{d(h',z)=1} 1_{N^o(h')<N^u(h',b)} \\
EU_{\text{learning}} &= \sum_{h,z} \Phi_E(h,z) 1_{d(h,z)=1} \sum_{h'} p_{trans}(h'|h)(1-\delta_0) 1_{d(h',z)=1} 1_{N^o(h')<N^u(h',b)}
\end{aligned}
$$

First, to perform an EU transition instead of an EN transition, the worker must prefer N over U while being eligible. Second, independently of the idiosyncratic state of the worker, with probability δ_0 she is exogenously separated and counted in $EU_{\text{exogenous}}$. Third, to disentangle the remaining part $(1-\delta_0)$ from endogenous separations, we consider if the worker would have preferred to leave employment even before the new shock h' hit. If not, then endogenous separation was triggered by h' which we label as "h-shock". If yes, then we know that the worker just learned her (low) match-specific productivity, as she would have otherwise separated in the stage before. Hence, we count these transitions as "learning".

An analogous decomposition can be done for the EN rate with the two differences that workers can now exit and that they need to prefer N over U after separation. In this case, the EN rate is

$$
EN = \sum_{h,z} \Phi_E(h,z) \sum_{h'} p_{trans}(h'|h) d(h',z) 1_{N^o(h')>N^u(h',b)}
$$

with the decomposition of

$$
EN = EN_{\text{exogenous}} + EN_{\text{h-shock}} + EN_{\text{learning}}
$$

and

$$
\begin{aligned}
EN_{\text{exogenous}} &= \sum_{h,z} \Phi_E(h,z) \sum_{h'} p_{trans}(h'|h)\delta_0 1_{N^o(h')>N^u(h',b)} \\
EN_{\text{h-shock}} &= \sum_{h,z} \Phi_E(h,z) 1_{d(h,z)<1} \sum_{h'} p_{trans}(h'|h)(1-\delta_0) 1_{d(h',z)=1} 1_{N^o(h')>N^u(h',b)} \\
EN_{\text{learning}} &= \sum_{h,z} \Phi_E(h,z) 1_{d(h,z)=1} \sum_{h'} p_{trans}(h'|h)(1-\delta_0) 1_{d(h',z)=1} 1_{N^o(h')>N^u(h',b)}
\end{aligned}
$$

E Transition Paths

Figures 9 and 10 present the transition paths for labor market flows and stocks following the two UI reforms described in the main text. The shock is an unexpected permanent change of UI generosity which occurs at period 0 (when the economy is at the steady state with the previous level of unemployment benefits). We plot the transition paths from the old to the new steady state.

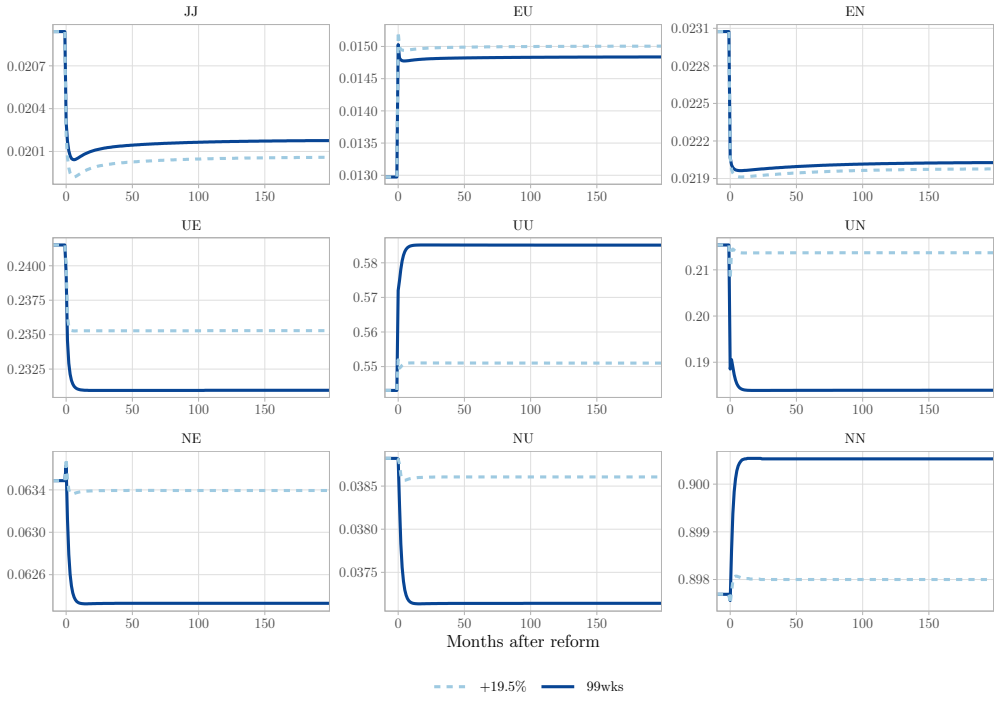


Figure 9: Transition paths of flows for a permanent change in the UI system.

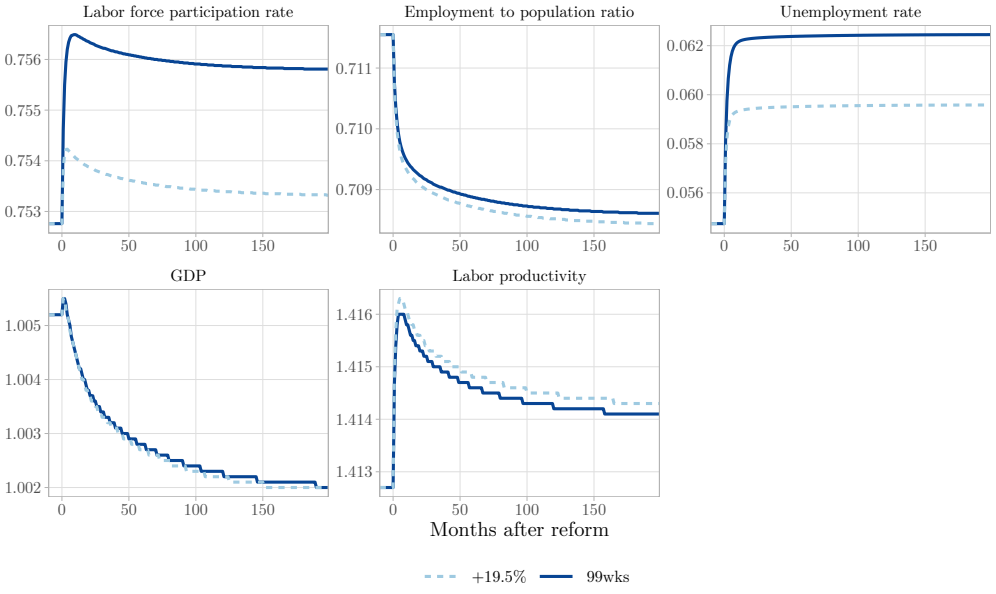


Figure 10: Transition paths of stocks for a permanent change in the UI system.

F Fully-Financed UI System

In the main body of the paper, we make the simplifying assumption that UI benefits are not explicitly financed by the government. Without this assumption, we would need to solve an additional fixed point problem for finding the tax rate that balances the government budget, rendering our calibration strategy impossible. In this appendix, we gauge the robustness of our main results with respect to this assumption. To do so, we perform the following exercise: given the calibrated parameters, we solve for the equilibrium lump-sum tax on the output of a firm-worker match that equates the total cost of the unemployment insurance system to the total tax revenue.[36]

Table 16 compares the baseline model, as well as the effects of the two reforms, to their counterparts with a fully-financed UI system. Regarding the local deviation from the baseline model, we see very small changes. This is not surprising: total UI costs are 0.4% of GDP in the US, implying a tax rate of 0.45% in terms of average labor output. This small tax leads to a minor reduction in the value of a match, which makes employment less attractive, therefore decreasing E-Pop and LFPR slightly. The same observation is true for both reforms. We view our main conclusions as robust to this extension, since the implied tax rates are very small and the main message of our results does not change.

[36]Note that in this exercise the two reforms do not lead to the same budgetary costs anymore.

		Baseline	UI +19.5%		99 weeks UI	
Moment	Tax	Value	Value	Pct. Change	Value	Pct. Change
E-Pop	No	0.712	0.708	-0.441%	0.709	-0.418%
	Yes	0.709	0.705	-0.639%	0.705	-0.625%
LFPR	No	0.753	0.753	0.071%	0.756	0.401%
	Yes	0.748	0.748	-0.044%	0.751	0.327%
U-Rate	No	0.055	0.060	8.845%	0.062	14.082%
	Yes	0.053	0.058	10.720%	0.062	17.072%
GDP	No	1.005	1.002	-0.335%	1.002	-0.326%
	Yes	0.997	0.990	-0.725%	0.990	-0.733%
Labor Prod.	No	1.413	1.414	0.107%	1.414	0.092%
	Yes	1.407	1.405	-0.087%	1.405	-0.109%

Table 16: Effects of more generous UI benefits. The table reports how labor market stocks, GDP and labor productivity respond to a 99 weeks UI extension and an 19.5% increase in UI benefits holding duration fixed.

G 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.[37] 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 is taken from Den Haan et al. (2000). 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).

Finally, we consider robustness regarding de-nunification, using an AR(1) process for home production, and using a life-cycle model. For the latter, we assume that workers age stochastically and transition across 10 age groups (each covering 5 years) before leaving the model. To capture the different trade-offs along the age-dimension in a reduced form way, we model $\bar{h}$ as a spline, taking on different values across the age groups. Finally, we assume that the oldest workers receive pension benefits if they do not participate in the labor market. To discipline these additional parameters, we target the transition rates of all age groups as well as average retirement payment to workers between 60 and 64 over GDP per person.

Table 17 reports the model fit while Table 18 shows the effect of a more generous UI system. Focusing on the increase in the eligibility duration, all alternative calibrations imply qualitatively the same effects. Quantitatively, the implied responses of the baseline calibration is close to the median response across this set of model specifications. The largest deviations from the baseline results are implied by the AR(1) specification, $\gamma = 0.407$, and the $\alpha = 1/2$ models. However, these models also imply the worst data fit. Interestingly, the model targeting the flows using denunification yields very similar results. Taken together, we conclude that these calibrations support the robustness of our results.

[37] While we restart the global minimization algorithm over 800 times for the baseline calibration, we repeat the procedure over 200 times for each robustness exercise.

Target	Data	Baseline	$\alpha =$ 1/6	$\alpha =$ 1/2	$\gamma =$ 0.407	b/GDP= 0.7%	De-NUN	AR(1)	Life-Cycle
				Transition Rates					
Flow									
JJ	0.021	0.021	0.021	0.020	0.021	0.020	0.020	0.020	0.032
EU	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.011
EN	0.024	0.023	0.023	0.024	0.024	0.023	0.023	0.022	0.021
UE	0.238	0.242	0.245	0.241	0.230	0.240	0.249	0.244	0.242
UN	0.214	0.215	0.215	0.215	0.202	0.214		0.232	0.198
NE	0.063	0.063	0.063	0.063	0.065	0.064	0.063	0.064	0.040
NU	0.039	0.039	0.039	0.039	0.038	0.039		0.039	0.028
UN*	0.132						0.133		
NU*	0.022						0.022		
				UI System and GDP					
b/GDP	0.004	0.004	0.004	0.004	0.004	0.007	0.004	0.004	0.005
GDP	1.000	1.005	1.002	1.004	1.016	1.001	1.002	1.003	1.441
				Tenure Distribution					
Years									
≤ 1	0.229	0.286	0.309	0.269	0.284	0.286	0.072	0.280	0.279
$(1, 3]$	0.227	0.183	0.173	0.195	0.177	0.187	0.257	0.208	0.218
$(3, 9]$	0.273	0.261	0.238	0.278	0.248	0.273	0.188	0.295	0.287
> 9	0.271	0.271	0.280	0.258	0.292	0.254	0.285	0.217	0.217

Table 17: Model fit for various calibrations. $*$ denotes flows after de-nunification. For the life-cycle model the table reports aggregate flows which are not directly targeted.

	Baseline	UI +19.5%		99 weeks UI	
Moment	Value	Value	Pct Change	Value	Pct Change
		Main Calibration			
E-Pop	0.712	0.708	-0.441%	0.709	-0.418%
LFPR	0.753	0.753	0.071%	0.756	0.401%
U-Rate	0.055	0.060	8.845%	0.062	14.082%
GDP	1.005	1.002	-0.335%	1.002	-0.326%
Labor Prod.	1.413	1.414	0.107%	1.414	0.092%
		$\alpha = 1/6$			
E-Pop	0.713	0.712	-0.105%	0.712	-0.140%
LFPR	0.753	0.758	0.637%	0.760	0.962%
U-Rate	0.054	0.061	13.034%	0.064	19.298%
GDP	1.002	1.001	-0.078%	1.001	-0.122%
Labor Prod.	1.406	1.406	0.027%	1.406	0.019%
		$\alpha = 1/2$			
GDP	0.707	0.702	-0.737%	0.702	-0.680%
E-Pop	0.748	0.748	-0.075%	0.750	0.245%
LFPR	0.055	0.061	11.384%	0.064	15.853%
U-Rate	1.004	0.999	-0.532%	0.999	-0.494%
Labor Prod.	1.420	1.423	0.207%	1.422	0.188%
		$\gamma = 0.407$			
E-Pop	0.707	0.698	-1.328%	0.697	-1.402%
LFPR	0.751	0.749	-0.175%	0.749	-0.167%
U-Rate	0.058	0.069	18.837%	0.069	20.170%
GDP	1.016	1.001	-1.503%	1.000	-1.559%
Labor Prod.	1.436	1.434	-0.177%	1.434	-0.159%
		$b/GDP = 0.7\%$			
E-Pop	0.711	0.703	-1.078%	0.702	-1.270%
LFPR	0.752	0.752	0.037%	0.753	0.104%
U-Rate	0.055	0.065	19.258%	0.068	23.726%
GDP	1.001	0.993	-0.827%	0.992	-0.992%
Labor Prod.	1.409	1.412	0.254%	1.413	0.281%
		De-NUN			
E-Pop	0.712	0.707	-0.664%	0.706	-0.766%
LFPR	0.750	0.751	0.128%	0.752	0.312%
U-Rate	0.051	0.058	14.780%	0.061	20.070%
GDP	1.002	0.997	-0.487%	0.996	-0.580%
Labor Prod.	1.408	1.410	0.178%	1.410	0.188%
		AR(1)			
E-Pop	0.720	0.717	-0.461%	0.718	-0.288%
LFPR	0.759	0.763	0.586%	0.767	1.135%
U-Rate	0.051	0.061	19.442%	0.064	26.279%
GDP	1.003	1.000	-0.325%	1.001	-0.181%
Labor Prod.	1.393	1.395	0.136%	1.395	0.108%
		Life-Cycle			
E-Pop	0.663	0.661	-0.309%	0.661	-0.304%
LFPR	0.699	0.701	0.264%	0.702	0.441%
U-Rate	0.051	0.056	10.669%	0.058	13.849%
GDP	1.441	1.438	-0.232%	1.438	-0.227%
Labor Prod.	2.173	2.174	0.077%	2.174	0.078%

Table 18: 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 19.5% increase in UI benefits holding duration fixed. For the baseline calibration, both UI changes imply the same budgetary costs.

H Fit of Alternative Models

This section explains the calibration strategy of the simplified alternative models described in Section 6.2.

In the first simplified model, we shut down endogenous separations. Since this specification generates the same moments and contains the same set of parameters as our baseline model, we use the same calibration strategy. The fit of this model is presented in the fourth column of Table 19. This specification matches most targets quite well, but cannot generate the large flows from employment to OLF, as well as enough matches with long tenures.

The second simplified model abstracts from the labor force participation decision. Since this leads to dropping all flows in and out of the labor force as potential targets, we can no longer identify the home production process. Hence, we assume that all workers have the same level of (aggregate) home production identified by the GDP target. This specification is able to match all remaining targets very well, as shown in the fifth column of Table 19.

For the final alternative, we set $\lambda_e = 0$ thereby ruling out job-to-job transitions and excluding the corresponding empirical target. As presented in the last column of Table 19, the model fits the data decently. The largest deviations is the tenure distribution, since now the h-process is solely responsible for generating short tenures on top of matching the OLF flows.

Target	Data	Baseline	No endogenous separations	No LF participation/ h heterogeneity	No JJ
			Transition Rates		
Flow					
JJ	0.021	0.021	0.025	0.022	–
EU	0.013	0.013	0.011	0.013	0.017
EN	0.024	0.024	0.012	–	0.020
UE	0.238	0.238	0.241	0.235	0.238
UN	0.214	0.214	0.215	–	0.221
NE	0.063	0.063	0.058	–	0.061
NU	0.039	0.039	0.039	–	0.039
			GDP and UI System		
GDP	1.000	1.005	1.008	1.000	1.004
b/GDP	0.004	0.004	0.004	0.004	0.004
			Tenure Distribution		
Years					
≤ 1	0.229	0.286	0.358	0.218	0.210
$(1, 3]$	0.227	0.183	0.290	0.182	0.180
$(3, 9]$	0.273	0.261	0.286	0.324	0.297
> 9	0.271	0.271	0.066	0.276	0.313

Table 19: The Fit of Alternative Models.