Article:

Kokonas, Nikolaos and Santos Monteiro, Paulo orcid.org/0000-0002-2014-4824 (2025) Equilibrium labor force participation and the business cycle. Economica. pp. 783-822. ISSN 1468-0335

https://doi.org/10.1111/ecca.12582

Equilibrium Labor Force Participation and the Business Cycle*

Nikolaos Kokonas†   Paulo Santos Monteiro‡

Abstract

We develop an equilibrium model of labor force participation to examine the labor market business cycle. The model remains agnostic about unemployment inflows and outflows, modeling these flows with a structural moving average representation derived from a factor-augmented VAR model. Estimating the augmented DSGE model on data for the United States, we identify the structural shocks and parameters driving business cycle fluctuations, avoiding misspecified job-finding and separation rates. Our results show that real wage rigidities play a minor role, labor force participation is mildly procyclical, and transitions between employment, unemployment, and non-participation are strongly cyclical.

Keywords: labor force participation, unemployment, business cycles.

JEL Classification: C50, E24, E32, J22, J64.

---

*We thank the Editor Wouter den Haan and three anonymous reviewers for comments that helped us improve the paper substantially. We are also grateful to Martin Ellison, Renato Faccini, Carlos Garriga, Pedro Gomes, Christian Haefke, Chris Martin, Franck Portier, Juan Rubio-Ramirez, Mike Wickens, Francesco Zanetti, and seminar participants at the Bank of England, Birkbeck, the Bank of Greece, the Federal Reserve Bank of St Louis, the Institute for Advanced Studies in Vienna, the University of Bath, the University of Durham, the University of Oxford, the University of St Andrews, the University of Sheffield, and the University of York for helpful comments.

†University of Bath

‡University of York

1 Introduction

Early macroeconomic models with frictional labor markets struggle to account for aggregate labor market volatility and conditional dynamics, often creating tension between matching unemployment volatility and other business cycle features, such as wage elasticity and the procyclicality of the opportunity cost of employment (Shimer, 2005, and Pissarides, 2009, and Chodorow-Reich and Karabarbounis, 2016). We propose a DSGE model that avoids the pitfalls of misspecifying the conditional dynamics of unemployment inflows and outflows by adopting an agnostic stance. Our model omits job creation and vacancy posting and instead imposes a structural time-series representation for the inflows and outflows, capturing labor market dynamics in response to structural shocks.

Although agnostic about job creation mechanisms, our model imposes equilibrium restrictions for how labor force participation evolves over the business cycle, with these restrictions driven by the interaction of inflows, outflows, and workers' intertemporal labor supply choices. This allows us to match gross worker flow dynamics across the three labor market states. Our approach highlights the volatility of individual flows into and out of the labor force – roughly equal to the volatility of flows between employment and unemployment – despite a relatively stable participation rate (Elsby et al., 2015, and Krusell et al., 2017).

We estimate the augmented DSGE model on data for the United States (US). Our main findings are threefold. First, we show that investment-specific technology shocks and labor market frictions, rather than TFP or exogenous expenditure shocks, are the primary drivers of business cycle volatility, particularly for unemployment and labor force participation. Given the minor role of TFP shocks, average labor productivity is largely acyclical. Moreover, although we estimate a large wage elasticity to productivity, this does not result in procyclical real wages because average productivity and unemployment are positively correlated under the shocks most responsible for business cycle fluctuations (the positive correlation between unemployment and labor productivity since the 1980s is also documented in Barnichon, 2010, and Galí and Van Rens, 2021). Thus, the limited wage movement over the cycle reflects this weak correlation rather than real wage rigidities.[1]

Second, our model finds that shock transmission occurs predominantly through changes in the job-finding rate, with fluctuations in real wages unimportant to explain cyclical changes in labor force participation. Third, the model accounts well for the mild procyclicality of labor force participation, often overstated in models featuring intertemporal substitution. Transitions into and out of non-participation from, in turn, employment and unemployment, produce offsetting forces that limit the cyclicality of participation. Moreover, recessions increase labor market churn (more job losses and transitions into unemployment), creating negative yet delayed effects on participation, since unemployed workers are less attached to the labor force (Elsby et al., 2019).

To make clear the advantages of our agnostic approach to modelling fluctuations in labor market frictions, in an additional exercise we contrast the predictions of our model with those of a fully specified DSGE model with matching frictions and endogenous job vacancy posting by the firms. In contrast to our agnostic model, the fully specified DSGE model produces counterfactual predictions with regards to the behavior of labor force participation and unemployment over the business cycle, exaggerating the volatility of participation (predicted to exceed the volatility of employment conditional on technology and expenditure shocks), and predicting a strong positive correlation between unemployment and labor force participation (thus, echoing the results by Ravn, 2006, and Veracierto, 2008, and Shimer, 2013, who also find the canonical DSGE model with endogenous labor force participation and search frictions produces these counterfactual predictions)

Our key methodological contribution is the use of an exogenous structural moving average (MA) representation to model unemployment inflows and outflows. This MA representation, derived from the impulse response functions of a factor-augmented VAR (FAVAR) model identified with external instruments, allows us to capture labor market dynamics without imposing potentially misspecified structural equations. This approach aligns with Christiano et al. (2005), who used an exogenous MA representation for monetary policy, and Cúrdia and Reis (2010), who introduced correlated disturbances using a stationary VARMA structure. Our approach also connects with Den Haan and Drechsel (2021), who added reduced-form disturbances to DSGE structural equations, but we maintain orthogonality between structural shocks while correlating them with job-finding and separation rates through the external MA representation.

Finally, our model offers insights into the measurement of the job-finding rate during the 2008 – 2009 Great Recession. Consistent with prior work (Shimer, 2012, and Elsby et al., 2011), we find substantial measurement errors in CPS data, resulting in an overestimation of long-term unemployment and a spurious decline in the job-finding rate. Using a Kalman filter, our model disentangles these measurement errors from the structural dynamics.

The rest of the paper is organized as follows. Section 2 presents the DSGE model, while Section 3 describes the FAVAR model for job-finding and separation rates. Section 4 discusses the estimation, Section 5 evaluates the model's ability to account for business cycles, focusing on labor force parcitipation. Section 6 concludes.

2 General equilibrium model

We consider an economy in which labor market adjustments occur along the extensive margin, and with three possible labor market states: "employment", "unemployment" and "out-of-the-labor-force", in turn, e, u and o. Adjustments along the extensive margin are determined by individuals' indivisible choice over labor force participation in frictional labor markets. To overcome the resulting non-convexity of the choice-set, we consider the Hansen (1985) and Rogerson (1988) lottery mechanism, but with individuals who purchase lotteries over participation instead of employment.

The formulation of the problem assumes that individuals are endowed with one unit of time each period and preferences over consumption, c, and leisure, ℓ, featuring internal habits in consumption, such that flow utility at date t is given by

$$\mathcal{U}_t = \begin{cases} \ln\left(c_t - \chi c_{t-1}\right) + v\left(\ell\right), & \text{if non-participant} \\ \ln\left(c_t - \chi c_{t-1}\right) + v\left(\ell\right) - \xi, & \text{if participant} \end{cases}, \tag{1}$$

where χc_{t-1} is the stock of habits in consumption, with $\chi \in (0,1)$, and $\xi > 0$ is the opportunity cost of labor market participation due to forgone home production, which is incurred irrespectively of whether the individual is employed or unemployed, and $v\left(\ell\right)$ is an increasing and concave function, with $v\left(1\right) = 0$. As in Hansen (1985) and Rogerson (1988), individuals purchase lotteries where with probability π they participate in the labor force and, thus, sacrifice utility ξ.

Still, there are frictional labor markets and, conditional on participation, an individual may either be employed or unemployed. An individual who participates in the labor market but begins period t without a job, finds employment with probability f_t. As in Blanchard and Galí (2010), and Michaillat (2012), newly hired workers at date t participate in production immediately, adding to the level of employment at date t. An employed individual sacrifices $\underline{h} \in (0,1)$ units of her endowment of time. Thus, the opportunity cost of participation has two components: ξ the cost of participation; and a second component, $v(1) - v(1 - \underline{h}) = -v(1 - \underline{h}) > 0$, incurred conditional on employment. We denote μ the marginal utility of consumption and in the remainder of this paper assume that $w_t > -v(1 - h_t)/\mu_t$ *almost surely* in the competitive equilibrium, where w_t is the wage rate. Thus, conditional on participation, unemployment is involuntary and any equilibrium with unemployment in this economy is not Pareto optimal.

Each job is destroyed with probability s_t. Upon destruction, an individual is allowed to choose between searching for another job or staying out of the labor force. If the existing job is not destroyed, then the individual continues with the existing employment relationship.

The timing of events is as follows: at the start of date t, individuals are randomly assigned to employment, unemployment, or leisure islands. Those on the employment island observe job status (retained or destroyed) before buying participation lotteries and deciding on search activity. Individuals on unemployment or leisure islands also buy participation lotteries first, then decide on search. State-contingent allocations are chosen before knowing the initial island assignment, with insurance provided by competitive firms making zero profit. At period's end, markets open for individuals to fulfill contracts, buy consumption and capital, and receive income.

2.1 Stand-in agent's problem

Time is discrete and the horizon is infinite, $t = 0, 1, 2, \ldots$; the measures of individuals that end date $t-1$ in employment, unemployment or out of the labor force, in turn, N_{t-1}, U_{t-1}, O_{t-1}, are all pre-determined variables. Agents face three salient sources of idiosyncratic risk: the outcome of the lottery over labor force participation, the risk of job loss conditional on employment, and the risk of not finding work conditional on labor force participation. However, as in Andolfatto (1996), Merz (1997) and Kokonas and Santos Monteiro (2021), despite the random matches and separations that occur in the labor market inducing different individual employment histories, this heterogeneity does not lead to wealth dispersion because of perfect insurance markets. In particular, since consumption and leisure are separable in the utility function and there are complete markets, all individuals enjoy the same level of consumption no matter their labor force status.[2]

This market structure yields a stand-in agent representation, with life-time utility given by

$$\mathbf{V} = \mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t \Big[\ln (c_t - \chi c_{t-1}) - \Omega N_{t-1}(1-s_t)\pi_{e,t} - \Psi_t \left(N_{t-1} s_t \pi_{s,t} + U_{t-1}\pi_{u,t} + O_{t-1}\pi_{o,t} \right) \Big], \quad (2)$$

with $\beta \in (0,1)$ the discount factor, and where

$$\Omega = \xi - v\left(1 - \underline{h}\right), \quad \text{and} \quad (3)$$

$$\Psi_t = \xi - v\left(1 - \underline{h}\right) f_t, \quad (4)$$

captures the opportunity cost of participation for each individual type; $\pi_{e,t}$, $\pi_{s,t}$, $\pi_{u,t}$, $\pi_{o,t} \in [0,1]$, are the probabilities of labor force participation at date t chosen by individuals that start date t, in turn, matched to a job that survives, a job that is destroyed, in unemployment, out of the labor force. The stand-in agent must choose state contingent allocations to maximize (2) subject to the budget constraint

$$c_t + x_t = r_t \iota_t k_t + w_t \Big[N_{t-1}(1-s_t)\pi_{e,t} + \left(N_{t-1} s_t \pi_{s,t} + U_{t-1}\pi_{u,t} + O_{t-1}\pi_{o,t} \right) f_t \Big] + \psi_t, \quad (5)$$

and the capital accumulation equation

$$k_{t+1}=V_t\left[1-\mathcal{S}\left(\frac{x_t}{x_{t-1}}\right)\right]x_t+\left(1-\delta\left(\iota_t\right)\right)k_t, \tag{6}$$

where x_t denotes investment, V_t is an investment specific technology shock (as in Justiniano et al., 2010), and k_{t+1} is the end of period capital stock holdings; $\mathcal{S}\left(\bullet\right)$ captures investment adjustment costs as in Christiano et al. (2005), with $\mathcal{S}\left(1\right)=\mathcal{S}'\left(1\right)=0$ and $S''\left(1\right)\equiv\kappa_x>0$; $\iota_t>0$ is capital utilization (equal to $\underline{\iota}$ in steady state); and $\delta\left(\iota_t\right)$ is capital depreciation, which is a strictly convex function in utilisation, with $\delta\left(\underline{\iota}\right)=\underline{\delta}\in(0,1)$, and $\underline{\iota}\left(\delta''/\delta'\right)\equiv\kappa_\iota>0$. In turn, w_t and r_t are the wage rate and the rental rate of capital, and ψ_t are the profits distributed by firms (net of lump-sum taxes and transfers).

In the remainder of this paper, it is assumed that individuals starting the period not in employment or in a job that is destroyed, always choose an interior solution for the probability of labor force participation: $\pi_{s,t},\pi_{u,t},\pi_{o,t}\in(0,1)$. The first-order conditions solving the stand-in agent's problem are

$$\mu_t=\frac{1}{c_t-\chi c_{t-1}}-\mathbf{E}_t\left[\frac{\beta\chi}{c_{t+1}-\chi c_t}\right], \tag{7}$$

$$\xi=\left[w_t\mu_t+v\left(1-h_t\right)\right]f_t, \tag{8}$$

$$\xi<\left[w_t\mu_t+v\left(1-h_t\right)\right], \tag{9}$$

$$\pi_{e,t}=1, \tag{10}$$

$$\mathcal{Q}_t=\beta\mathbf{E}_t\left[\frac{\left(1-\delta\left(\iota_{t+1}\right)\right)\mathcal{Q}_{t+1}+r_{t+1}\iota_{t+1}}{\mu_t/\mu_{t+1}}\right], \tag{11}$$

$$\delta'\left(\iota_t\right)=r_t, \tag{12}$$

$$1=\mathcal{Q}_tV_t\left[1-\mathcal{S}-\left(\frac{x_t}{x_{t-1}}\right)\mathcal{S}'\right]+\beta\mathbf{E}_t\left[V_{t+1}\left(\frac{x_{t+1}}{x_t}\right)^2\left(\frac{\mu_{t+1}}{\mu_t}\right)\mathcal{Q}_{t+1}\mathcal{S}'\right], \tag{13}$$

where conditions (8), (9) and (10) follow from assuming $\pi_{u,t}, \pi_{o,t}, \pi_{s,t} \in (0,1)$, and conditions (11), (12) and (13) are the standard intertemporal optimality conditions, with $\mathcal{Q}_t$ the marginal rate of substitution between installed capital and consumption. In particular, conditions (8) and (9) imply that individuals starting date t employed, and whose jobs are not destroyed, always choose to participate in the labor market, yielding condition (10).

2.2 Gross worker flows

The labor market evolves as follows

$$N_t = (1 - s_t)\, N_{t-1} + H_t f_t, \tag{14}$$

$$\Pi_t = (1 - s_t) N_{t-1} + H_t, \tag{15}$$

where N_t is the aggregate employment level, Π_t is the total labor force participation, with $u_t = 1 - (N_t/\Pi_t) = (U_t/\Pi_t) \in (0,1)$, the unemployment rate, and

$$H_t = \pi_{u,t} U_{t-1} + \pi_{o,t} O_{t-1} + \pi_{s,t} s_t N_{t-1}, \tag{16}$$

is the mass of members of the workforce searching for jobs at date t, either transiting from an existing job that was destroyed, or from unemployment and non-participation.

The model yields a matrix of gross flows across the three states of **E**mployment, **U**nemployment, and **O**ut of Labor Force, that result from individual optimal behaviour: [EE,EU,EO,UE,UU,UO,OE,OU,OO] $= [\phi_{ee}, \phi_{eu}, \phi_{eo}, \phi_{ue}, \phi_{uu}, \phi_{uo}, \phi_{oe}, \phi_{ou}, \phi_{oo}]$. The competitive equilibrium transition probabilities are given by

$$\begin{aligned}
&\phi_{ee,t} = (1-s_t) + \pi_{s,t} s_t f_t, && \phi_{ue,t} = \pi_{u,t} f_t, && \phi_{oe,t} = \pi_{o,t} f_t, \\
&\phi_{eu,t} = \pi_{s,t} s_t (1-f_t), && \phi_{uu,t} = \pi_{u,t} (1-f_t), && \phi_{ou,t} = \pi_{o,t} (1-f_t), \\
&\phi_{eo,t} = s_t (1-\pi_{s,t}), && \phi_{uo,t} = 1-\pi_{u,t}, && \phi_{oo,t} = 1-\pi_{o,t},
\end{aligned} \tag{17}$$

characterizing fully the equilibrium gross flows, conditional on an equilibrium sequence for the job-finding and separation rates $\{f_t, s_t\}$, and the participation choice by those not in employment at the end of date t, $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$. The model has the property that $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$ are not pinned down uniquely. Specifically, given the predetermined measures U_{t-1}, O_{t-1} and N_{t-1}, and an equilibrium realisation for H_t (which is uniquely determined), there exist multiple equilibrium solutions for $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$, each yielding identical aggregate allocations. Selecting two of the three elements in $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$, determines uniquely all gross flows. In Section 5, we show that this property of the model can be exploited to uncover the crucial role of flows $\phi_{uo,t}$ and $\phi_{eo,t}$ in determining the other gross worker flows. In particular, picking equilibrium realizations for $\pi_{u,t}$ and $\pi_{s,t}$ to match the UO and EO transitions, delivers a model that matches very well all other gross worker flows.

2.3 Search, labor services and wage bargaining

Labor services are an intermediate input sold to final good firms at price P_t. In turn, to produce labor services workers must be matched to intermediate firms in markets featuring search frictions. There is a continuum (with unit measure) of identical intermediate firms, each matched to several workers. As all intermediate firms are identical, we consider a representative intermediate good firm owned by the stand-in household and, hence, priced using the household's stochastic discount factor.

The capital value of a job, $\mathbf{J}_t$, must satisfy the following Bellman equation:

$$\mathbf{J}_t = \mathbf{S}_t + \beta \mathbf{E}_t \left[\frac{\mu_{t+1}}{\mu_t} (1 - s_{t+1}) \mathbf{J}_{t+1} \right]. \tag{18}$$

Condition (18) states that the capital value of a job is equal to its current profit flow, $\mathbf{S}_t = P_t \underline{h} - w_t$, plus an expected, discounted, future capital value: with probability $1 - s_{t+1}$ the job is still active next period and consequently the capital value is $\mathbf{J}_{t+1}$.

The capital value will be determined by the wage contract negotiated with the worker. Employers and workers bargain over the overall wage, w_t. To determine the wage w_t, workers play a bilateral, non-cooperative bargaining game with the stand-in intermediate firm that yields the wage rate

$$w_t = \zeta P_t \underline{h} + A_t \mathcal{B}, \tag{19}$$

with $\zeta \in (0, 1)$ and $\mathcal{B} > 0$. Any profits from the intermediate sector are distributed to the stand-in household. In Appendix B we show how (19) is the outcome of an alternating offer bargaining protocol (AOB) à la Rubinstein (1982). Following Hall and Milgrom (2008) and Christiano et al. (2016), we assume that as the bargaining takes place, the worker receives a flow benefit while the job's output depreciates. Notice that this specification moderates the response of the real wage to changes in the price P_t, thus allowing for endogenous real wage rigidities.[3]

We do not model vacancy creation by firms. Instead, vacancies are assumed to be exogenous *manna from heaven*, non-produced and non-storable and, therefore, the model leaves the job-finding rate f_t undetermined (in Section 5 we discuss an alternative version of the model with endogenous vacancy posting). From the perspective of the stand-in intermediate firm, employment evolves exogenously according to the motion equation

$$N_t = (1 - s_t) N_{t-1} + \mathbf{M}(1, \Theta_t) H_t, \\ = (1 - s_t) N_{t-1} + f_t H_t. \tag{20}$$

2.4 Market clearing and equilibrium conditions

Production, consumption and investment take place at the end of each period. The stand-in final good firm combines aggregate capital services $\iota_t K_t$ and aggregate labor services N_t, as follows

$$Y_t = Z_t (\iota_t K_t)^{\alpha} (A_t N_t \underline{h})^{1-\alpha}, \\ = C_t + X_t + E_t, \tag{21}$$

with $\alpha \in (0,1)$ and where Z_t is the transitory component of TFP; $A_t = \mathcal{G}^t A_0$ is a deterministic trend. The final good serves three purposes: aggregate consumption, C_t; investment, I_t; and exogenous spending E_t (financed by lump-sum taxes). The equilibrium factor prices are given by

$$P_t = (1 - \alpha)(Y_t / N_t \underline{h}), \tag{22}$$

$$\iota_t r_t = \alpha (Y_t / K_t). \tag{23}$$

Combining conditions (8), (19) and (22) yields the labor participation condition

$$\xi = \underbrace{\left\{ \Big[\zeta (1 - \alpha)(Y_t / N_t) + A_t \mathcal{B} \Big] \mu_t + v (1 - \underline{h}) \right\}}_{\text{worker's surplus}} f_t, \tag{24}$$

requiring non-employed workers to choose their participation probability to equate the cost of participation, ξ, to the expected benefit of participation. The latter is given by the worker's surplus multiplied by the probability of finding work conditional on participation, f_t, and the worker's surplus is the difference between the real wage and the opportunity cost of employment conditional on participation. In the absence of participation costs, ξ, individuals only forgo leisure conditional on employment, and condition (24) is analogous to that obtained in Hansen (1985) canonical indivisible labor model augmented with search frictions as in Andolfatto (1996).

Two observations are important in interpreting condition (24). First, the job-finding rate appears as a wedge in the intratemporal choice between consumption and leisure (the labor market wedge). Fluctuation in labor market frictions leads to volatility in the labor market wedge. Therefore, employment and consumption may increase simultaneously even in the absence of productivity shocks, supported by an improvement in the job-finding rate (resolving the Barro and King, 1984, challenge). Second, unlike what happens in the "large family" model with endogenous participation (as in Ravn, 2006, and Shimer, 2013, for example), the worker's surplus in the participation condition (24), does not include an asset value of employment. Our model has this feature because we adopt the same full insurance market structure as in Andolfatto (1996). In particular, there's a distinction between job and worker flows. The first is determined by the job-separation and job-finding processes, while workers' flows are determined exogenously by what Andolfatto (1996) calls a game of "musical chairs", whereby the entire workforce is shuffled randomly across employment and non-employment (see Appendix A for a detailed explanation).

The goods market's clearing conditions are given by $\widetilde{c}_t = \widetilde{C}_t$, $\widetilde{i}_t = \widetilde{I}_t$, $\widetilde{k}_t = \widetilde{K}_t$, where the notation $\widetilde{Y}_t$ denotes the stationary version of Y_t, given by (Y_t/A_t). Combining these conditions with the optimality conditions (7) – (13), equation (19), the production function (21), and the factor demand equations (22) and (23), yields the following equilibrium conditions

$$\bar{\mu}_t \equiv A_t \mu_t = \frac{1}{\widetilde{C}_t - (\chi/\mathcal{G})\,\widetilde{C}_{t-1}} - \mathbf{E}_t \left[\frac{\beta\chi}{\mathcal{G}\widetilde{C}_{t+1} - \chi\widetilde{C}_t} \right], \tag{25}$$

$$\xi = \left[\zeta\,(1-\alpha)\left(\widetilde{Y}_t/N_t\right) + \mathcal{B} - \frac{v\,(1-\underline{h})}{\bar{\mu}_t} \right] f_t \bar{\mu}_t, \tag{26}$$

$$\mathcal{Q}_t = \beta \mathbf{E}_t \left[\frac{(1-\delta(\iota_{t+1}))\,\mathcal{Q}_{t+1} + \alpha\widetilde{Y}_{t+1}/\widetilde{K}_{t+1}}{\mathcal{G}\,(\bar{\mu}_t/\bar{\mu}_{t+1})} \right], \tag{27}$$

$$\delta'(\iota_t) = \alpha\widetilde{Y}_t/\left(\iota_t\widetilde{K}_t\right), \tag{28}$$

$$1 = \mathcal{Q}_t V_t \left[1 - \mathcal{S} - \mathcal{G}\left(\frac{\widetilde{X}_t}{\widetilde{X}_{t-1}}\right)\mathcal{S}' \right] + \beta\mathcal{G}\mathbf{E}_t \left[\left(\frac{\mathcal{Q}_{t+1}V_{t+1}}{\bar{\mu}_t/\bar{\mu}_{t+1}}\right)\left(\frac{\widetilde{X}_{t+1}}{\widetilde{X}_t}\right)^2 \mathcal{S}' \right], \tag{29}$$

$$\widetilde{Y}_t = Z_t \left(\iota_t\widetilde{K}_t\right)^{\alpha} (N_t\underline{h})^{1-\alpha}, \tag{30}$$

$$\widetilde{Y}_t = C_t + \widetilde{X}_t + \widetilde{E}_t, \tag{31}$$

$$\mathcal{G}\widetilde{K}_{t+1} = V_t\,(1-\mathcal{S})\,\widetilde{X}_t + (1-\delta_t)\,\widetilde{K}_t, \tag{32}$$

where $\mathcal{G} > 1$ is the gross growth rate of A_t along the deterministic balanced growth path (BGP) equilibrium described in Appendix D, and with $\hat{z}_t = \log(Z_t/\underline{Z})$, $\hat{v}_t = \log(V_t/\underline{V})$ and $\hat{e}_t = \log(E_t/\underline{E})$, in turn, the total factor productivity (TFP) shock, the shock to the relative price of investment, and an exogenous expenditure (E) shock, following exogenous stochastic processes given by

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \sigma_z \epsilon_t^z, \tag{33}$$

$$\hat{v}_t = \rho_v \hat{v}_{t-1} + \sigma_v \epsilon_t^v, \tag{34}$$

$$\hat{e}_t = \rho_e \hat{e}_{t-1} + \sigma_e \epsilon_t^e, \tag{35}$$

with $\rho_x \in (-1,1)$ and $\sigma_x > 0$ for $x \in \{z, v, e\}$.

Notice that the system of equilibrium conditions is block-recursive. Specifically, given the job-finding rate f_t, the system (25) to (32) determines the equilibrium dynamics for the set of variables $\left\{\bar{\mu}_t, \widetilde{C}_t, \widetilde{X}_t, \widetilde{Q}_t, \iota_t, \widetilde{K}_t, \widetilde{N}_t, \widetilde{Y}_t\right\}$, independently of the job-separation rate, s_t. Thus, shocks to the job-separation rate only affect the business cycle dynamics for these macroeconomic aggregates conditional on their impact on the job-finding rate, f_t. Subsequently, we obtain the mass of job seekers, $\widetilde{H}_t$, from equation (16), which, in turn, determines the participation rate and the unemployment rate. Finally, as it stands the model is underdetermined, since s_t and f_t, are not pinned down by the equilibrium conditions. To close the general equilibrium model we augment the list of equilibrium conditions with structural IRFs for the job-finding and separation rate, obtained from an estimated FAVAR model. This is described in the next Section.

3 Structural MA for the Ins and Outs

The literature is split over the roles of the inflows into and outflows away from unemployment – the Ins and Outs. A popular approach, since the work of Hall (2005b) and Shimer (2005, 2012), is to emphasize the importance of the cyclical fluctuations in the outflows from unemployment, and assume an acyclical job-separation rate. Instead, other influential studies assign a leading role to endogenous job destruction (see, for example, Den Haan et al., 2000, and Fujita and Ramey, 2009). In Figure 1, the quarterly job-separation and job-finding probabilities are represented. The job-finding and separation rates are obtained using the methodology by Elsby et al. (2010) and Shimer (2012), who calculate monthly transition rates based on the Current Population Survey (CPS) with the corresponding quarterly outflows and inflows computed as three-months averages (see Appendix F for details on how these series are obtained).

[Figure 1 about here.]

Figure 1 reveals the substantial volatility at business cycle frequencies in the job-finding rate, but it also suggests upshifts in the job-separation during most recessions. At any rate, the unemployment inflow rate does not appear to be entirely acyclical. Therefore, we propose a very general and non-committal characterization of the cyclical behavior of hires and separations, and assume the following factor augmented vector autoregression (FAVAR) model for the joint dynamics of the job-finding rate, the job-separation rate, and the macroeconomic conditions

$$\begin{bmatrix} \hat{s}_t \\ \hat{f}_t \\ \hat{m}_t \end{bmatrix} = \sum_{i=0}^{p} \mathbf{A}_i \begin{bmatrix} \hat{s}_{t-i} \\ \hat{f}_{t-i} \\ \hat{m}_{t-i} \end{bmatrix} + \eta_t, \tag{36}$$

where the endogenous variables $\hat{s}_t$ and $\hat{f}_t$ are the cyclical components of, in turn, the job-separation and finding rates, and $\hat{m}_t$ is a vector with $\mathtt{k} = \mathtt{n} - 2$ latent factors capturing macroeconomic conditions. Thus, the matrices $\mathbf{A}_i$, for $i = 1, \ldots p$, are each $\mathtt{n} \times \mathtt{n}$ square matrices of coefficients, and $\eta_t = \mathbf{B}\mathcal{E}_t$ is the vector of reduced form residuals. We assume $\mathtt{n} = 5$ and the random vector $\mathcal{E}_t = \left[\epsilon_t^z, \epsilon_t^v, \epsilon_t^e, \epsilon_t^s, \epsilon_t^f\right]'$ contains the DSGE structural macroeconomics shocks with diagonal covariance matrix $\mathbf{I}_5$, the 5-dimensional identity matrix. The structural shocks ϵ_t^z, ϵ_t^v, ϵ_t^e are as in Section 2. We also include two additional shocks, ϵ_t^s and ϵ_t^f which are, in turn, a separation and finding rate shock.

The model (36) is a FAVAR model (Bernanke et al., 2005), estimated in two steps: principal components extract latent factors, then an augmented VAR is estimated. IRFs for any series in the dataset are obtained via factor projections. Using rich information helps avoid non-fundamental representations (see Giannone and Reichlin, 2006). If the system in (36) is stationary, it admits an infinite moving-average representation of the form

$$\begin{bmatrix} \hat{s}_t \\ \hat{f}_t \\ \hat{m}_t \end{bmatrix} = \sum_{i=0}^{\infty} \mathbf{D}_i \mathbf{B} \mathcal{E}_{t-i}, \tag{37}$$

with $\mathbf{D}_i = \sum_{j=1}^{p} \mathbf{A}_j \mathbf{D}_{i-j}$, obtained recursively from $\mathbf{A}_i$, for $i > 0$, and where $\mathbf{D}_0 = \mathbf{I}_5$ and $\mathbf{D}_i = \mathbf{0}$ for $i < 0$. To identify the structural IRFs one needs to obtain the $\mathtt{n} \times \mathtt{n}$ matrix $\mathbf{B}$.

For the purpose of completing the DSGE model developed in the previous sections, we are interested in particular in the first two equations in the system (37), representing the job-finding and separation rates as a function of the history of structural shocks, as follows

$$\begin{bmatrix} \hat{s}_t \\ \hat{f}_t \end{bmatrix} = \sum_{i=0}^{\infty} \mathbf{d}_i \mathbf{B} \mathcal{E}_{t-i}, \tag{38}$$

with $\mathbf{d}_i$ corresponding to the first two rows of the matrix $\mathbf{D}_i$. This system yields the structural IRFs for the job-finding and separation rates. Of course, it is not feasible to consider the infinite dimensional moving-average representation in (38). Thus, in practice we consider a truncated version of the IRFs, given by

$$\begin{bmatrix} \hat{s}_t \\ \hat{f}_t \end{bmatrix} = \sum_{i=0}^{\tau} \mathbf{d}_i \mathbf{B} \mathcal{E}_{t-i}, \tag{39}$$

and conjecture this to be an appropriate approximation as long as the sequence $\{\mathbf{D}_i\}_{i=0}^{\tau}$ converges to zero as τ approaches infinity, so that the effects of the shocks are transitory. The latter is true for any stationary VAR model.

Under some regularity conditions (see Fernández-Villaverde et al., 2007, for a careful treatment of this issue), the IRF of the VAR are a good approximations to the IRFs of the unknown true economic model. The latter is unknown, insofar as the DSGE developed in the previous section does not impose any restrictions on the conditional dynamics for the job-finding and separation rates. In turn, the MA in (39) describes the evolution of the job-separation and job-finding rates, conditional on the exogenous structural shocks. Thus, we may legitimately use these IRFs without violating any cross-equation restrictions imposed by the model.

Based on this result, the approach that we follow in the remainder of this paper is to complete the underdetermined DSGE model developed in Section 2 with the system of equations in (39). To ensure that the DSGE model matches the empirical conditional dynamics of the job-finding and separation rates we calibrate the coefficients in the matrix $\mathbf{B}$ using parameters obtained based on external instruments (as explained next). Finally, in Section 4, we estimate the remaining parameters of the augmented DSGE model using conventional bayesian methods.

3.1 Identification and estimation of the structural MA model

Our purpose in this section is to obtain estimates for the matrices $\mathbf{d}_i$, for $i = 1, \ldots, p$, and $\mathbf{B}$, to recover the structural MA model for the job-finding and separation rates. We estimate the model in (36) using US quarterly time-series covering 1948:Q1–2018:Q3. The macroeconomic variables included in the vector $\hat{m}_t$ are real per capita gross domestic product (GDP), real per capita consumption, real per capita investment, the unemployment rate, labor force participation rate, total factor productivity (TFP), the relative price of investment, and exogenous shocks to government expenditure. All series are taken in log levels and detrended using the method in Hamilton (2018). Details about the data used and its treatment are provided in Appendix F.

We select the lag-order in the system (36) to be $p = 4$, with the resulting residuals exhibiting no serial correlation. The coefficients in $\mathbf{A}_i$, $i = 1 \ldots, p$, are estimated using the ordinary least squares (OLS) method, which also yields the reduced form residuals $\eta_t = \mathbf{B}\mathcal{E}_t$. To identify the matrix $\mathbf{B}$ and, thus, obtain the structural IRF, we follow the proxy SVAR methodology developed by Stock and Watson (2012) and Mertens and Ravn (2013). The approach uses instrumental variables to capture a subset of structural shocks in the SVAR, along with a short-run restriction to ensure invertibility. Specifically, we obtain instruments for the TFP shock, the investment-specific (IS) shock, and the exogenous expenditure (EE) shock. To identify the i^{th} shock, the instrument z_t must meet certain conditions.

1. $\mathbf{E}\left(z_t\mathcal{E}_t^i\right) = \psi \neq 0,\ \forall\, t$;

2. $\mathbf{E}\left(z_t\mathcal{E}_t^s\right) = 0,\ \forall\, t$ and $s \neq i$.

The first condition establishes the instrument relevance, and the second its exogeneity. In turn, the instrumental variables used are: the innovations to the Fernald (2014) utilization adjusted TFP measure, to instrument for the TFP shock; the innovations to the relative price of investment, to instrument for the IS shock; and the Ramey (2011) narrative measure of defense expenditure shocks, to instrument for the EE shock. By imposing an additional "short-run" zero restriction, the three instruments allow us to identify all five shocks and, thus, all the elements of the matrix $\mathbf{B}$. The implementation of the instrumental variable method is explained carefully in Appendix G.

[Figure 2 about here.]

In Figure 2, we plot the IRF corresponding to the percentage responses of the job-finding and separation rates to a one standard deviation innovation to each structural shock. An improvement in TFP is found to lower mildly the job-separation rate on impact, but the effect vanishes immediately. In contrast, the TFP shock lowers the job-finding rate sharply during the first four quarters following the shock, with a modest subsequent increase. The increase in the job-finding rate reaches a maximum of 0.5 percent after roughly two years. The overall short-term impact on the labor market of a TFP shock is, therefore, protracted and is contractionary on impact. Instead, we obtain an immediate and persistent expansionary impact on the labor market following a positive IS shock (a negative innovation to the relative price of investment). The job-separation is found to fall substantially on impact. The job-finding rate increases strongly, reaching its peak of 1 percent after a year, with the positive effect subsiding after roughly three years.[4] The effect of the exogenous expenditure shock on the labor market is mildly expansionary, with the job-separation falling and the job-finding rate increasing modestly after a positive expenditure shock. At any rate, the effect of government spending shocks on the job-finding and separation rates appear expansionary (echoing Monacelli et al., 2010).

Finally, we examine job-finding and separation shocks. The latter is identified by imposing a zero short-run restriction, assuming the separation shock has no immediate effect on the job-finding rate. Both shocks significantly impact unemployment inflows and outflows. Notably, job-separation shocks lower the job-finding rate, with the strongest effects occurring about a year after the shock. This interplay between inflows and outflows plays a crucial role in labor market dynamics. Our job-finding shock is not a matching efficiency shock, which implies a counterfactual positive vacancy-unemployment correlation (Furlanetto and Groshenny, 2016). Instead, it captures shocks – like, for example, risk premium shock as in Kehoe et al. (2023) – that reduce vacancies relative to unemployment.

4 Estimation of the augmented DSGE model

We consider the system of equations given by the log-linear approximation to the equilibrium model around the deterministic steady state as described in Appendix E, augmented with the two structural MA representations in (39). The coefficients of these two equations are set to the values estimated in Section 3, thereby ensuring that the augmented DSGE model is entirely consistent with the conditional dynamics of the job-finding and separation rates. Thus, the model is calibrated to exactly match the IRF in Figure 2. We set the truncation parameter in equation (39) to $\tau = 20$, since in Figure 2 it is apparent that after five years the impact of the shocks on the job-finding and separation rates have almost entirely vanished.

The rest of the model is estimated with Bayesian methods (details about the estimation method are provided in Appendix H). The model is estimated on quarterly US data spanning 1948:q1 until 2018:q3, using seven macroeconomic time-series: real per capita output, real per capita consumption, real per capita investment, employment, the unemployment rate, the job-separation rate, and the job-finding rate. Since we have five structural shocks and seven observed time series, we assume measurement error in the observation equations for the job-separation and job-finding rates. Including measurement error in the observation equations for the job-separation and finding rates is partially motivated by the well-documented problems of measurement and time-aggregation in the CPS series used to obtain the inflow and outflow rates (Shimer, 2012).

[Table 1 about here.]

4.1 Parameter restrictions and steady state gross flows

Not all model parameters are estimated; we calibrate some to match key secular features of macroeconomic time series, following standard practice (see, for example, Christiano et al., 2016). The calibrated parameters and their targets are detailed in Table 1. We pay particular attention to calibrating the parameters that shape steady-state gross labor market flows: $\left(\underline{f}, \underline{s}, \underline{\pi} s, \underline{\pi} u, \underline{\pi} o\right)$. As explained in Section 2, for a given participation rate $\underline{\Pi}$, the participation rates of different groups not in employment ($\underline{\pi} s$, $\underline{\pi}_u$, $\underline{\pi}_o$) are not fully determined by equilibrium conditions, allowing us to set them to target specific gross worker flows.

From the system (17), the steady state transition probabilities are given by

$$\begin{aligned}
&\underline{\phi_{ee}} = (1-\underline{s}) + \underline{\pi}_s \underline{s}\, \underline{f}, && \underline{\phi_{ue}} = \underline{\pi}_u\, \underline{f}, && \underline{\phi_{oe}} = \underline{\pi}_o\, \underline{f}, \\
&\underline{\phi_{eu}} = \underline{\pi}_s \underline{s} \left(1-\underline{f}\right), && \underline{\phi_{uu}} = \underline{\pi}_u \left(1-\underline{f}\right), && \underline{\phi_{ou}} = \underline{\pi}_o \left(1-\underline{f}\right), \\
&\underline{\phi_{eo}} = \underline{s}\left(1-\underline{\pi}_s\right), && \underline{\phi_{uo}} = 1-\underline{\pi}_u, && \underline{\phi_{oo}} = 1-\underline{\pi}_o.
\end{aligned} \tag{40}$$

To set the average job-finding rate, $\underline{f}$, we use monthly CPS gross flows data aggregated to the quarterly frequency (Gomes, 2015), yielding $\underline{f} = \underline{\phi_{ue}}/\left(1-\underline{\phi_{uo}}\right) = 0.738$. Similarly, the job-separation rate, $\underline{s}$, is set using CPS data as $\underline{s} = \underline{\phi_{eu}}/\left(1-\underline{f}\right) + \underline{\phi_{eo}} = 0.190$, with $\underline{\pi}_s = 1 - \underline{\phi_{eo}}/\underline{s} = 0.547$. The transition probability from unemployment to non-participation is matched by setting $\underline{\pi}_u = 1 - \underline{\phi_{uo}} = 0.624$. Finally, we set $\underline{\pi}_o = 0.255$ to match the historical average participation rate of 71.0% for individuals aged 16 to 64, our target for aggregate participation, $\underline{\Pi}$. Although we do not use it as a target, the calibration yields and unemployment rate in steady state equal to 6.32%, very close to the historical average unemployment rate in the US. Table 2 shows that our model closely matches empirical gross flows, comparable to richer incomplete markets models (Krusell et al., 2017).

[Table 2 about here.]

4.2 Estimated parameters prior selection

The remaining parameters are estimated by maximizing the posterior density of the DSGE model over the vector of observables. The estimated parameters include the autocorrelation coefficients and volatility parameters of the structural shocks and the following structural parameters: $\kappa_\xi \equiv \xi/\underline{\Psi} \in (0,1)$, that controls the cost of labor force participation; $\chi \in (0,1)$, the habit formation parameter; $\kappa_x \equiv \mathcal{S}'' > 0$, the elasticity of adjustment costs to changes in investment; $\kappa_w \equiv (1 - \mathcal{B}/\underline{w}) \in (0,1)$, controlling the degree of wage rigidity; and $\kappa_\iota \equiv \delta' / (\delta' + \underline{\iota}\delta'') \in (0,1)$, the elasticity of the capital utilisation rate to changes in the return to capital. The choice of priors for each parameter is reported in Table 3. The prior distributions chosen for χ, κ_ξ and κ_w is the Beta distribution, as all three parameters have support on the interval $(0,1)$, and for κ_x the prior distribution imposed is the Gamma to guarantee positiveness.

4.3 Posterior estimates of the parameters

Columns 3–5 of Table 3 present the posterior mode, standard deviation, and 80% credible set for each parameter, estimated using the Metropolis-Hastings algorithm. The marginal posterior densities are significantly tighter than the prior distributions, indicating strong parameter identification. The MH algorithm appears well-tuned, as indicated by an acceptance rate of roughly 30%, within the recommended range to obtain efficient sampling of the parameter space. Furthermore, the standard MCMC convergence diagnostics indicate the convergence of the chains, confirming that the posterior distribution has been fully explored.

[Table 3 about here.]

The estimated persistence of the three serially correlated exogenous shocks – TFP, IS, and EE – is 0.833, 0.810, and 0.737, respectively. These values are notably lower than the typical persistence estimates above 0.9 commonly found in the DSGE literature. This lower persistence suggests that our model relies more heavily on internal propagation mechanisms. A key driver of this is the dynamic response of the job-finding rate to shocks, captured through the structural moving average process in equation (39).

We now turn to the estimated structural parameters that govern this internal propagation. In particular, we focus on two parameters from the intratemporal labor participation condition for the non-employed: κ_ξ and κ_w. These play central roles in the transmission of shocks through the labor market. The parameter κ_ξ captures how shocks propagate via the job-finding rate, while κ_w governs real wage rigidity by determining the elasticity of wages with respect to average labor productivity.

Starting with κ_ξ, the posterior mode is estimated at 0.277. The parameter is well identified, as indicated by the tight posterior distribution. To better understand its role, recall that κ_ξ enters the log-linear equilibrium condition, as follows

$$\underbrace{-\hat{\mu}_t + (1-\kappa_\xi)\hat{f}_t}_{\text{cyclical component of the opportunity cost}} = \underbrace{\kappa_w\left(\hat{y}_t - \hat{n}_t\right) + \hat{f}_t}_{\text{effective wage rate}}, \tag{41}$$

that corresponds to the log-linearized version of equation (24), the intratemporal condition relevant for the labor participation choice of the non-employed. The left-hand side of equation (41) gives the cyclical component of the opportunity cost of employment in terms of consumption, while the right-hand side denotes the "effective real wage": that is, the real wage adjusted for fluctuations in the job-finding rate. If κ_ξ is zero, labor market participants only forgo utility when employed, and $\kappa_\xi \hat{f}_t$ drops from equation (41). In this case, fluctuations in opportunity cost offset those in the effective wage, reducing our framework to the standard RBC model with indivisible labor supply.

Equation (41) highlights two channels affecting participation: returns to market work, driven by the cyclical effective wage rate $\hat{w}_t + \hat{f}_t$, and the opportunity cost of employment, $(1 - \kappa_\xi)\hat{f}_t$. Thus, the net effective wage, incorporating opportunity cost, simplifies to $\hat{w}_t + \kappa_\xi \hat{f}_t$, with participation fluctuations driven by the net wage. Accordingly, equation (41) gives:

$$-\hat{\mu}_t = \underbrace{\kappa_w (\hat{y}_t - \hat{n}_t) + \kappa_\xi \hat{f}_t}_{\text{net effective wage rate}}, \tag{42}$$

where the right-hand side of (42) denotes the net effective wage rate. Note that the cyclical behavior of the marginal utility of wealth, and hence of consumption, is pinned down by the cyclical behavior of the net wage rate.

The parameter κ_w, which governs the elasticity of the real wage to changes in labor productivity, has a posterior mode of $\kappa_w = 0.502$, indicating a strong wage response to productivity changes. This aligns with findings by Pissarides (2009) and Haefke et al. (2013) using micro-level data, showing that new hires' wages are volatile. Since κ_w is identified from (42), the labor supply condition for non-employed individuals, this result supports the evidence of volatile wages for newly hired workers.

The habits persistence parameter, $\chi = 0.015$, is negligible compared to other studies, while the cost of changing investment elasticity, $\kappa_x = 8.497$, is slightly lower than typical values but remains well-identified. The inverse elasticity of capital utilization, $\kappa_\iota = 0.806$, aligns with prior research. These findings suggest that the model's internal propagation relies less on habits and adjustment costs, with adjustments in the job-finding rate driving shock persistence, as shown in the following sections.

In the I we report and interpret the impulse response functions (IRF) for the estimated DSGE model, and compare these to the IRF obtained using the structural FAVAR in Section 3.

5 Labor market business cycles

This section examines the quantitative implications of our estimated model for worker flows across labor market states during the business cycle. We first analyze the contribution of each structural shock to the labor market business cycles, and the ability of our agnostic model to capture fluctuations in macroeconomic aggregates and labor market flows. Next, we compare the predictions of our proposed augmented DSGE model, agnostic about inflows and outflows, with an alternative model featuring endogenous vacancy creation and an equilibrium job-finding rate. This comparison highlights how imposing a misspecified model for unemployment outflows can bias estimates of structural parameters and shocks shaping the labor market cycle. Finally, we discuss the role of measurement error in unemployment inflows and outflows through the lens of the estimated DSGE model.

5.1 Variance decompositions

Our goal is to develop a model that captures labor market dynamics, particularly unemployment, labor force participation, and the gross worker flows that drive them. The equilibrium dynamics depend on how the real wage and job-finding rate behave over the business cycles, and this is influenced by the structural shocks contributing to business cycle volatility. We therefore analyze the contribution of each shock using forecast error variance (FEV) decompositions.

[Figure 3 about here.]

Figure 3a shows the FEV decomposition for output, consumption, real wages, and employment across different horizons. At short horizons, the job-finding rate shock dominates output and consumption, while the investment-specific (IS) shock becomes more influential at medium and long horizons. Real wage volatility is entirely driven by TFP shocks, and consumption is influenced by the IS shock primarily through the job-finding rate. Employment volatility is initially explained by TFP shocks but increasingly by job-finding rate and IS shocks over time.

Figure 3b decomposes the job-separation and job-finding rates, labor participation, and unemployment rate. The IS shock accounts for around 40% of job-separation rate volatility, while job-finding rate fluctuations are mainly driven by labor market frictions and the IS shock, with minimal contribution from TFP shocks. Over longer horizons, non-technology shocks largely explain unemployment volatility. These findings align with the Shimer puzzle (Shimer, 2005), where technology shocks alone cannot account for labor market volatility. The model assigns a critical role to shocks affecting the job-finding rate, particularly IS and job-separation shocks, consistent with Fujita and Ramey (2009), where the job-separation shock primarily impacts the job-finding rate.

For labor force participation, TFP shocks explain the bulk of volatility at short horizons, while the contribution of the IS shock rises over time. Persistent shocks to the job-finding rate, however, have limited impact on participation, suggesting a weak connection between job-finding rate fluctuations and labor force participation. This statement can be made precise by calculating the elasticity of participation to a permanent change in the job-finding rate. This elasticity around the steady state is equal to

$$\eta = \kappa_\xi - \frac{\underline{s}/\underline{f}}{1 - \underline{s} + \underline{s}/\underline{f}},$$

where κ_ξ, is the contribution of the opportunity cost channel to the substitution effect which appears in condition (42), while the second term is the income effect from a permanent change in the finding rate. Substitute $\kappa_\xi = 0.277$ (see Table 3) and $\underline{s} = 0.19$, $\underline{f} = 0.738$ (see Table 1) into the elasticity formula, so that $\eta = 0.036$, which is negligibly small.

5.2 Employment, unemployment and participation

Next, we look at the model's ability to match the cyclical movements of the main macroeconomic variables, placing particular emphasis on the cyclical behavior of the labor market stock variables: employment, unemployment, and participation. Table 4 shows second-order moments of the key macroeconomic aggregates, including their correlation with unemployment, correlation with output and the relative volatilities.

The key result is the weak cyclicality of the labor force participation, consistent with the data. Labor force participation is less volatile than employment, its correlation with output is 64.2%, and the correlation with unemployment is near zero, consistent with the nearly acyclical labor force participation found empirically.

This result is of particular importance because DSGE models with endogenous participation and intertemporal substitution in labor supply often yield a labor force participation which is too procyclical and more volatile than employment, and thus imply a procyclical unemployment rate. In a pioneering contribution, Ravn (2006) labeled the tendency for intertemporal substitution in frictional labor markets to lead to excessively procyclical participation and, thus, procyclical unemployment, the "consumption-tightness" puzzle. Models in Veracierto (2008), Shimer (2013), and Krusell et al. (2020) generate highly procyclical participation and volatile participation rates, often leading to acyclical or procyclical unemployment. The latter matches our findings more closely when both TFP and friction shocks are included. The latter study can generate less procyclical movements in the participation rate and countercyclical unemployment, only if both TFP and labor market frictions shocks are included, echoing some of our findings.

[Table 4 about here.]

Our model also assigns an important role to intertemporal substitution in labor supply, but obtains an acyclical labor force participation. This result follows from the predominant role attributed to job-finding and investment specific shocks to explain unemployment dynamics, and the labor force participation condition (24). Both these shocks raise the job-finding rate and, for a given labor force participation, raise employment and lower the real wage. On the other hand, the higher job-finding rate raises the return to participation. Overall, the fall in the real wage and the higher job-finding rate are offsetting forces. The upshot is a weak labor force participation response, and also a nearly acyclical real wage despite the large estimated wage elasticity in response to productivity shocks. A real wage nearly acyclical is consistent with the empirical evidence on US business cycles (Stock et al., 1999).

Naturally the upshot of matching well the acyclical labor force participation rate and imposing data consistent unemployment inflows and outflows is that we account well for the unemployment rate business cycle dynamics. In particular, unemployment is strongly countercyclical and roughly an order of magnitude more volatile than output (consistent with the Okun's relationship). The model also accounts well for the correlation of the unemployment inflows and outflows with output and the unemployment rate, offering support to the general equilibrium restrictions implied by the augmented DSGE model. Overall, the model captures well the business cycle phenomena, in terms of the second order moments of the main macroeconomic aggregates, such as output, consumption, investment and employment.

5.3 Cyclical properties of gross flows

We can use our model to understand how the dynamics of labor force participation are shaped by the various gross flows (what Elsby et al., 2019, call the flow origin of participation). Both empirically and in our model, the OO flow is acyclical and is the least volatile of all gross flows, indicating that the dynamics of labor force participation are shaped by the EO and UO flows. Both these transition rates are procyclical in the model indicating that in periods of high unemployment fewer workers exit the labor force. At the same time it also exhibits a mildly procyclical participation rate. Based on this feature of gross flows, Elsby et al. (2019) argue that labor market churn explains the dynamics of labor force participation. Churn refers to the flows between unemployment and employment. Unemployed workers are more likely to exit the labor force compared to employed workers. In recessions, more workers transit from employment to unemployment (churn) as indicated by the correlation between unemployment and the EU transition rate, which is 0.784 in the model (matching the data almost exactly). Subsequently these newly unemployed workers are more likely to exit the labor force, thus applying dynamic negative forces on labor force participation.

[Table 5 about here.]

Similarly, the correlation between unemployment and the OU flow is 0.706, suggesting unemployment might increase in recessions as more individuals enter the labor force through unemployment, instead of entering the labor force through employment (the OE transition rate is procyclical in both the model and the data). Once again, as unemployed workers are more likely to exit the labor force compared to employed workers, this leads to subsequent reductions in labor force participation.

5.4 Confronting the agnostic model with a fully specified DSGE

Next, we compare the predictions of our proposed augmented DSGE model, agnostic about inflows and outflows, with an alternative model featuring endogenous vacancy creation and an equilibrium job-finding rate. This comparison highlights how imposing a misspecified model for unemployment outflows can bias estimates of structural parameters and shocks shaping the labor market cycle. The alternative (fully specified) model with endogenous vacancy creation is outlined in Appendix C.

To model the endogenous vacancy creation process, we follow Şahin et al. (2014) and introduce a convex cost of vacancy posting. Following Şahin et al. (2014) we include a shock to the matching function to capture the job-finding rate shock. Finally, we model the job-separation as an exogenous moving average determined by a single shock, that is independent of technology, expenditure, and matching efficiency shocks. We estimate the alternative model with endogenous vacancy creation and contrast the predictions of this estimated model with those of the agnostic DSGE model.

Our main findings are shown in Figures 6 and 7 and Table 6. The estimated model with endogenous vacancies yields a very low elasticity of the real wage to productivity changes (κ_w), with the posterior distribution concentrated near 0.1 (the imposed lower bound). This suggests that wage rigidities are necessary to achieve a sufficiently volatile job-finding rate, consistent with the Shimer puzzle and prior literature (Hall, 2005a, and Ljungqvist and Sargent, 2017). However, such explanations conflict with the observed procyclicality of the opportunity cost of employment (Chodorow-Reich and Karabarbounis, 2016).

The alternative model also produces predictions that conflict with the observed cyclical behavior of labor force participation, unemployment, and consumption (Table 6). Specifically, it predicts a strongly positive correlation between participation and unemployment (0.151), excessive consumption volatility relative to output (1.122), and unrealistically low real wage volatility (0.055). These results align with known issues in models combining endogenous participation and search frictions, as highlighted by Ravn (2006) and Veracierto (2008). The model's flaws stem from dominant wealth effects during expansions. As labor earnings rise with eased frictions, low wage elasticity (κ_w) keeps wages acyclical, reducing the incentive to search for work. This leads to falling participation rates during booms, causing the model to predict a counterfactual positive correlation between unemployment and participation.

In conclusion, imposing a misspecified model for unemployment inflows and outflows overstates the role of wage rigidities and incorrectly predicts a positive correlation between unemployment and participation.

5.5 Measurement error

The measurement of unemployment outflows relies on monthly transitions of workers across labor market states but is subject to substantial error due to factors like classification errors, time aggregation issues, and sample attrition (Shimer, 2012). A key advantage of combining the structural MA representation (identified with external instruments) and the DSGE model is that it allows for the inclusion of measurement error in the observation equations. This enables the likelihood Kalman filter to produce smoothed job-finding rates free from such errors.

[Figure 4 about here.]

Figure 4 compares the measured and smoothed job-finding rates. The most notable feature is the significant measurement error during the 2008 Great Recession, as documented by Elsby et al. (2011). During this period, the job-finding rate was biased downward due to classification errors, with some individuals misreporting their unemployment duration as long-term. This misreporting, more pronounced during the recession, reflected the return of inactive workers to the labor force, consistent with the countercyclicality of the OU gross flow.

The empirical job-finding rate shows a significant drop during 2008-2009, but the model's smoothed series corrects this spurious reduction. The model's success in capturing gross flows during the 2008 recession reflects the milder decline in the job-finding rate during this time. It is reassuring that the measurement issue is most pronounced during 2008 – 2009, suggesting that unemployment exits are measured more accurately for the majority of the sample.

6 Conclusion

We develop a general equilibrium business cycle model with frictional labor markets and endogenous labor force participation, incorporating a structural MA representation for job-finding and separation rates identified using external instruments from a FAVAR model. This approach ensures the model aligns with the empirical dynamics of labor market flows, avoiding the pitfalls of misspecification and enabling accurate estimates of the macroeconomic shocks driving unemployment fluctuations.

Despite allowing for real wage rigidities, we estimate a large elasticity of real wages to labor productivity, aligning with micro-level evidence. Moreover, although intertemporal substitution in labor supply is strong, the participation rate remains only mildly procyclical due to the dominance of job-finding rate and investment-specific shocks. These shocks raise the probability of finding employment while reducing labor productivity, leading to only mild shifts in labor force participation.

The model also captures the cyclical nature of transitions across employment, unemployment, and non-participation, despite the nearly acyclical participation rate. In recessions, more workers join the labor force through unemployment (instead of employment), and also more workers lose their jobs and become unemployed. Since unemployed workers are more likely to exit the labor force, this heightened labor market churn applies dynamic negative forces on labor force participation during recessions, and yields a weakly procyclical participation rate.

We demonstrate how an estimated DSGE model can be consistent with recent empirical findings on labor market flows (Elsby et al., 2015, 2019). Our agnostic approach to modeling unemployment flows, using external instruments, can be extended to include other shocks, such as monetary or financial shocks, yielding insights into both business cycle dynamics and the effects of policy interventions on labor market outcomes.

Notes

[1]Ellington et al. (2024) use a time-varying parameter VAR with DSGE-based sign restrictions to show that real wages respond more to productivity shocks than to other shocks. Like us, they find that averaging across all shocks overstates real wage rigidity and its role in explaining unemployment volatility.

[2]Following Hansen (1985), individuals choose lotteries over participation rather than employment. Conditional on participating, they may be unemployed due to frictions. Despite differing labor market histories, all consume equally, allowing a representative agent formulation (See Merz, 1997, for an early characterization of how to construct a market structure similar to Hansen, but in which there is involuntary unemployment and search frictions). In Appendix A we show how this aggregation result is obtained.

[3]Given the assumed bargaining protocol, the outside option of workers affects only the bargaining out-of-equilibrium (as a threat point), but not the equilibrium wage. Thus, the real wage cyclicality is controlled by the cyclicality of the marginal product of labor, P_t.

[4]The result that the job-finding rate falls on impact following a positive TFP shock is not new in the literature. Balleer (2012) and Canova et al. (2012) also exploit a structural VAR model for the job-finding and separation rates and, like us, includes a measure of TFP and the relative price of investment. Both papers identify the structural productivity shocks based on long-run restrictions, and similarly to us find that the job-finding rate falls conditional on a neutral technology shock and increases conditional on an investment-specific shock. Christiano et al. (2016) report similar results.

References

Andolfatto, D. (1996). Business cycles and labor-market search, *American Economic Review* **86**(1): 112–132.

Balleer, A. (2012). New evidence, old puzzles: Technology shocks and labor market dynamics, *Quantitative economics* **3**(3): 363–392.

Barnichon, R. (2010). Productivity and unemployment over the business cycle, *Journal of Monetary Economics* **57**(8): 1013–1025.

Barro, R. J. and King, R. G. (1984). Time-separable preferences and intertemporal-substitution models of business cycles, *Quarterly Journal of Economics* **99**(4): 817–839.

Bernanke, B. S., Boivin, J. and Eliasz, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach, *Quarterly Journal of Economics* **120**(1): 387–422.

Blanchard, O. and Galí, J. (2010). Labor markets and monetary policy: A New Keynesian model with unemployment, *American Economic Journal: macroeconomics* **2**(2): 1–30.

Born, B., Peter, A. and Pfeifer, J. (2013). Fiscal news and macroeconomic volatility, *Journal of Economic Dynamics and Control* **37**(12): 2582–2601.

Canova, F., Lopez-Salido, D. and Michelacci, C. (2012). The Ins and Outs of Unemployment: An Analysis Conditional on Technology Shocks, *The Economic Journal* **123**(569): 515–539.

Chahrour, R., Chugh, S. K. and Potter, T. (2023). Anticipated productivity and the labor market, *Quantitative Economics* **14**(3): 897–934.

Chernozhukov, V. and Hong, H. (2003). An MCMC approach to classical estimation, *Journal of Econometrics* **115**(2): 293–346.

Chodorow-Reich, G. and Karabarbounis, L. (2016). The cyclicality of the opportunity cost of employment, *Journal of Political Economy* **124**(6): 1563–1618.

Christiano, L. J., Eichenbaum, M. and Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy, *Journal of Political Economy* **113**(1): 1–45.

Christiano, L. J., Eichenbaum, M. S. and Trabandt, M. (2016). Unemployment and business cycles, *Econometrica* **84**(4): 1523–1569.

Christiano, L. J., Trabandt, M. and Walentin, K. (2011). Introducing financial frictions and unemployment into a small open economy model, *Journal of Economic Dynamics and Control* **35**(12): 1999–2041.

Cooley, T. F. and Prescott, E. C. (1995). Economic growth and business cycles, *Frontiers of business cycle research* **1**.

Cúrdia, V. and Reis, R. (2010). Correlated disturbances and us business cycles, *Technical report*, National Bureau of Economic Research.

Del Negro, M. and Schorfheide, F. (2008). Forming priors for DSGE models (and how it affects the assessment of nominal rigidities), *Journal of Monetary Economics* **55**(7): 1191–1208.

Den Haan, W. J. and Drechsel, T. (2021). Agnostic structural disturbances (asds): Detecting and reducing misspecification in empirical macroeconomic models, *Journal of Monetary Economics* **117**: 258–277.

Den Haan, W. J. and Kaltenbrunner, G. (2009). Anticipated growth and business cycles in matching models, *Journal of Monetary Economics* **56**(3): 309–327.

Den Haan, W. J., Ramey, G. and Watson, J. (2000). Job destruction and propagation of shocks, *American Economic Review* **90**(3): 482–498.

Ellington, M., Martin, C. and Wang, B. (2024). Revisiting real wage rigidity, *Journal of Money, Credit and Banking* **56**(2-3): 613–626.

Elsby, M., Hobijn, B., Karahan, F., Koşar, G. and Şahin, A. (2019). Flow origins of labor force participation fluctuations, *AEA Papers and Proceedings*, Vol. 109, pp. 461–64.

Elsby, M. W., Hobijn, B. and Sahin, A. (2010). The labor market in the great recession, *Brookings Papers on Economic Activity: Spring 2010* .

Elsby, M. W. L., Hobijn, B. and Şahin, A. (2015). On the importance of the participation margin for labor market fluctuations, *Journal of Monetary Economics* **72**: 64–82.

Elsby, M. W. L., Hobijn, B., Şahin, A., Valletta, R. G., Stevenson, B. and Langan, A. (2011). The labor market in the great recession – an update to september 2011 [with comment and discussion], *Brookings Papers on Economic Activity* pp. 353–384.

Fernald, J. (2014). A quarterly, utilization-adjusted series on total factor productivity, *Technical report*, Federal Reserve Bank of San Francisco.

Fernández-Villaverde, J., Rubio-Ramirez, J. and Sargent, T. (2007). The ABC (and D) of strucutual VARs, *American Economic Review* **97**(3): 1021–1026.

Fujita, S. and Ramey, G. (2009). The cyclicality of separation and job finding rates, *International Economic Review* **50**(2): 415–430.

Furlanetto, F. and Groshenny, N. (2016). Mismatch shocks and unemployment during the great recession, *Journal of Applied Econometrics* **31**(7): 1197–1214.

Galí, J. and Van Rens, T. (2021). The vanishing procyclicality of labour productivity, *The Economic Journal* **131**(633): 302–326.

Giannone, D. and Reichlin, L. (2006). Does information help recovering structural shocks from past observations?, *Journal of the European Economic Association* **4**(2-3): 455–465.

Gomes, P. (2015). The importance of frequency in estimating labour market transition rates, *IZA Journal of Labor Economics* **4**(1): 6.

Gomme, P., Ravikumar, B. and Rupert, P. (2011). The return to capital and the business cycle, *Review of Economic Dynamics* **14**(2): 262–278.

Gomme, P. and Rupert, P. (2007). Theory, measurement and calibration of macroeconomic models, *Journal of Monetary Economics* **54**(2): 460–497.

Haefke, C., Sonntag, M. and Van Rens, T. (2013). Wage rigidity and job creation, *Journal of monetary economics* **60**(8): 887–899.

Hall, R. E. (2005a). Employment fluctuations with equilibrium wage stickiness, *American Economic Review* **95**(1): 50–65.

Hall, R. E. (2005b). Job loss, job finding, and unemployment in the us economy over the past fifty years, *NBER macroeconomics annual* **20**: 101–137.

Hall, R. E. and Milgrom, P. R. (2008). The limited influence of unemployment on the wage bargain, *American Economic Review* **98**(4): 1653–1674.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter, *Review of Economics and Statistics* **100**(5): 831–843.

Hansen, G. D. (1985). Indivisible labor and the business cycle, *Journal of Monetary Economics* **16**(3): 309–327.

Justiniano, A., Primiceri, G. E. and Tambalotti, A. (2010). Investment shocks and business cycles, *Journal of Monetary Economics* **57**(2): 132–145.

Kehoe, P. J., Lopez, P., Midrigan, V. and Pastorino, E. (2023). Asset prices and unemployment fluctuations: A resolution of the unemployment volatility puzzle, *The Review of Economic Studies* **90**(3): 1304–1357.

Kehoe, T. J., Levine, D. K. and Prescott, E. C. (2002). Lotteries, sunspots, and incentive constraints, *Journal of Economic Theory* **107**(1): 39–69.

Kokonas, N. and Santos Monteiro, P. (2021). Aggregation in economies with search frictions, *Journal of Mathematical Economics* **96**.

Krusell, P., Mukoyama, T., Rogerson, R. and Şahin, A. (2017). Gross worker flows over the business cycle, *American Economic Review* **107**(11): 3447–76.

Krusell, P., Mukoyama, T., Rogerson, R. and Şahin, A. (2020). Gross worker flows and fluctuations in the aggregate labor market, *Review of Economic Dynamics* **37**: S205–S226.

Ljungqvist, L. and Sargent, T. J. (2017). The fundamental surplus, *American Economic Review* **107**(9): 2630–2665.

Lunsford, K. G. (2015). Identifying structural VARs with a proxy variable and a test for a weak proxy, *Technical report*, Federal Reserve Bank of Cleveland, Working Paper no. 15-28.

Mertens, K. and Ravn, M. O. (2013). The dynamic effects of personal and corporate income tax changes in the United States, *American Economic Review* **103**(4): 1212–47.

Merz, M. (1997). A market structure for an environment with heterogeneous job-matches, indivisible labor and persistent unemployment, *Journal of Economic Dynamics and Control* **21**(4-5): 853–872.

Michaillat, P. (2012). Do matching frictions explain unemployment? Not in bad times, *American Economic Review* **102**(4): 1721–1750.

Monacelli, T., Perotti, R. and Trigari, A. (2010). Unemployment fiscal multipliers, *Journal of Monetary Economics* **57**(5): 531–553.

Mortensen, D. T. and Pissarides, C. A. (1994). Job creation and job destruction in the theory of unemployment, *Review of Economic Studies* **61**(3): 397–415.

Pissarides, C. A. (2009). The unemployment volatility puzzle: Is wage stickiness the answer?, *Econometrica* **77**(5): 1339–1369.

Prescott, E. C. and Townsend, R. M. (1984). General competitive analysis in an economy with private information, *International Economic Review* **25**(1): 1–20.

Ramey, V. A. (2011). Identifying government spending shocks: It's all in the timing, *Quarterly Journal of Economics* **126**(1): 1–50.

Ravn, M. O. (2006). The consumption-tightness puzzle [with comments], *NBER International Seminar on Macroeconomics*, JSTOR, pp. 9–63.

Rogerson, R. (1988). Indivisible labor, lotteries and equilibrium, *Journal of Monetary Economics* **21**(1): 3–16.

Rubinstein, A. (1982). Perfect equilibrium in a bargaining model, *Econometrica: Journal of the Econometric Society* pp. 97–109.

Şahin, A., Song, J., Topa, G. and Violante, G. L. (2014). Mismatch unemployment, *American Economic Review* **104**(11): 3529–64.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies, *American Economic Review* **95**(1): 25–49.

Shimer, R. (2012). Reassessing the Ins and Outs of unemployment, *Review of Economic Dynamics* **15**(2): 127–148.

Shimer, R. (2013). Job search, labor-force participation, and wage rigidities, *Advances in Economics and Econometrics: Volume 2, Applied Economics: Tenth World Congress*, Vol. 50, Cambridge University Press, p. 197.

Stock, J. H. and Watson, M. W. (2012). Disentangling the channels of the 2007/09 recession, *Brookings Papers on Economic Activity: Spring 2012* p. 81.

Stock, J. H., Watson, M. W. et al. (1999). Business cycle fluctuations in us macroeconomic time series, *Handbook of Macroeconomics* **1**: 3–64.

Veracierto, M. (2008). On the cyclical behavior of employment, unemployment and labor force participation, *Journal of Monetary Economics* **55**(6): 1143–1157.

Appendix

A Musical chairs and lotteries

The purpose of this section is to derive the stand-in agent representation (2)–(5), obtained by combining an exogenous randomisation mechanism with lotteries over labor force participation. This exogenous randomisation is analogous to the "musical chairs" assumption in Andolfatto (1996), and allows us to specify the problem of the stand-in agent in recursive form. In fact, Merz (1997) has also used a similar randomisation device as Andolfatto (1996) to decentralise the constrained optimum in a two-state labor market. In Kokonas and Santos Monteiro (2021) we show that this hybrid model with musical chairs and lotteries has solid microfoundations. Specifically, it corresponds to an economy with complete markets and date zero trading (Arrow-Debreu markets), where individuals trade according to the realisation of public signals (sunspots) prior and after the realisation of idiosyncratic shocks, along the lines of Prescott and Townsend (1984) and Kehoe et al. (2002).

The economy is populated by a continuum of individuals of unit measure. There is a distinction between job and worker flows in the model. Individuals are distributed across three states or "islands": the employment "island"; the unemployment "island"; and the leisure "island". The mass of individuals on each "island" at the start of date t is, respectively, N_{t-1}, U_{t-1} and O_{t-1}, where N_{t-1} denotes the mass of employed individuals at the end of $t-1$, U_{t-1} denotes the mass of unemployed individuals at the end of $t-1$, and O_{t-1} denotes the mass of non-participants at the end of $t-1$. At the beginning of date t, individuals are allocated randomly across islands, $\imath \in \mathcal{L} \in \{e, u, o\}$. Figures 5a and 5b show the sequence of events conditional on the musical chairs' randomisation. Specifically, individuals assigned to the employment island ($\imath = e$)

observe the realisation of the idiosyncratic shock $\kappa \in \{e_s, e_{ns}\}$, where $\kappa = e_s$ denotes separation (s) with probability s, and $\kappa = e_{ns}$ denotes no separation (ns) with $1-s$; subsequently they buy lotteries over labor force participation, and engage (or not) in search activity. Individuals assigned to the unemployment or leisure island ($\imath \in \{u, o\}$) buy lotteries over labor force participation and then engage (or not) in search activity.

Individuals choose state-contingent allocations before knowing in which island they will be allocated initially, and there exist insurance opportunities for every possible randomization contingency. Insurance contracts are provided by competitive firms that make zero profits in equilibrium. We focus on separating equilibria where firms offer different prices to different types and insurance is actuarially fair. The price of an insurance contract is denoted by q and the quantity bought is denoted by y. At the end of each period, spot markets open, where individuals execute contacts, buy consumption and capital, and receive capital and labor income. To simplify presentation, and without loss of generality, we abstract from aggregate risk, habit formation, capital adjustment costs and fluctuations in time endowment. Moreover, we abstract from time subscripts and formulate individual decisions recursively—subscripts "−1" denote past values and superscripts " $'$ " denote future values.

[Figure 5 about here.]

The Bellman equation characterising the problem solved by each individual is

$$\mathbf{V}(K,k) = \max_{c,\pi,y,k'} \Big\{ N_{-1}\left[s v_{e_s} + (1-s) v_{e_{ns}}\right] + U_{-1} v_u + O_{-1} v_o \Big\}, \tag{43}$$

with

$$v_{e_{ns}} = -\pi_e \Omega + \pi_e \left[\ln\left(c_{e_{ns},e}\right) + \beta \mathbf{V}\left(K', k'_{e_{ns},e}\right)\right] + (1-\pi_e)\left[\ln\left(c_{e_{ns},o}\right) + \beta \mathbf{V}\left(K', k'_{e_{ns},o}\right)\right],$$

$$v_{e_s} = -\pi_s \Psi + f\pi_s \left[\ln\left(c_{e_s,e}\right) + \beta \mathbf{V}\left(K', k'_{e_s,e}\right)\right] + (1-f)\,\pi_s \left[\ln\left(c_{e_s,u}\right) + \beta \mathbf{V}\left(K', k'_{e_s,u}\right)\right]$$
$$+ (1-\pi_s)\left[\ln\left(c_{e_s,o}\right) + \beta \mathbf{V}\left(K', k'_{e_s,o}\right)\right],$$

$$v_u = -\pi_u \Psi + f\pi_u \left[\ln\left(c_{u,e}\right) + \beta \mathbf{V}\left(K', k'_{u,e}\right)\right] + (1-f)\,\pi_u \left[\ln\left(c_{u,u}\right) + \beta \mathbf{V}\left(K', k'_{u,u}\right)\right]$$
$$+ (1-\pi_u)\left[\ln\left(c_{u,o}\right) + \beta \mathbf{V}\left(K', k'_{u,o}\right)\right],$$

$$v_o = -\pi_o \Psi + f\pi_o \left[\ln\left(c_{o,e}\right) + \beta \mathbf{V}\left(K', k'_{o,e}\right)\right] + (1-f)\,\pi_o \left[\ln\left(c_{o,u}\right) + \beta \mathbf{V}\left(K', k'_{o,u}\right)\right]$$
$$+ (1-\pi_o)\left[\ln\left(c_{o,o}\right) + \beta \mathbf{V}\left(K', k'_{o,o}\right)\right].$$

Subscripts denote (personal) labor market states (however, notation with respect to the participation probabilities and the opportunity cost of employment is consistent with the main text). The first subscript denotes the assignment of the randomisation induced by musical chairs, that is, e_s denotes pre-existing jobs that destroyed with probability s, e_{ns} denotes pre-existing jobs that survived with probability $1-s$, u denotes unemployment and o denotes out of labor force (non-participation). The second subscript denotes the labor market state of an individual at the end of the period, following the outcome of the lottery over participation and the search process. To simplify exposition, we denote labor market transitions with the pair $(\tilde{\imath}, \jmath)$, with $\tilde{\imath} \in \{e_s, e_{ns}, u, o\}$ and $\jmath \in \{e, u, o\}$; $\tilde{\imath}$ denotes the assignment induced by the musical chairs' randomisation and the realisation of idiosyncratic shocks and $\jmath$ the assignment induced by the lottery over participation and the outcome of the search process.

Participation in the labor market entails a fixed disutility cost ξ and, in the event of employment, individuals incur an additional disutility cost, $v\,(1-\underline{h})$, where $\underline{h}$ is the amount of time devoted to employment. The opportunity cost of participation for each type is

$$\Psi = \xi - v\,(1-\underline{h})\,f,\;\; \Omega = \xi - v\,(1-\underline{h}).$$

The flow budget constraint for each pair $(\tilde{\imath}, \jmath)$ is

$$c_{\tilde{\imath},\jmath} + k'_{\tilde{\imath},\jmath} + \sum_{\tilde{\imath}} \sum_{\jmath} q_{\tilde{\imath},\jmath} y_{\tilde{\imath},\jmath} = Rk + w\mathbb{1}_{\jmath} + y_{\tilde{\imath},\jmath}, \tag{44}$$

where $\mathbb{1}_{\jmath}$ is an indicator function which equals 1 if $\jmath = e$ and zero otherwise.

Actuarially fair insurance and strict concavity of the instantaneous utility function imply

$$c_{\tilde{\imath},\jmath} = c, \tag{45}$$

for all pairs $(\tilde{\imath}, \jmath)$. Optimality with respect to k' requires

$$c_{\tilde{\imath},\jmath}^{-1} = \beta \mathbf{V}_{k'}(K', k'_{\tilde{\imath},\jmath}); \tag{46}$$

$\mathbf{V}_{k'}(\cdot)$ denotes the derivative of the value function with respect to k'. Combining (A.3) and (A.4), yields

$$k'_{\tilde{\imath},\jmath} = k', \tag{47}$$

for all pairs $(\tilde{\imath}, \jmath)$; moreover, (A.5) implies that $K = k$.

The individual's consolidated decision reduces to

$$\begin{gathered}
\mathbf{V}\left(k\right) = \max_{c,k',\pi} \Big\{ \ln(c) - \Omega N_{-1}(1-s)\pi_e - \Psi\left(N_{-1}s\pi_s + U_{-1}\pi_u + O_{-1}\pi_o\right) + \beta \mathbf{V}\left(k'\right) \Big\}, \\
s.t. \\
c + k' = Rk + w\Big[N_{-1}(1-s)\pi_e + \left(N_{-1}s\pi_s + U_{-1}\pi_u + O_{-1}\pi_o\right) f\Big], \\
\pi \in [0,1].
\end{gathered} \tag{48}$$

The consolidated decision of the individual is similar to the one in the main text. We restrict attention to an interior equilibrium with the following characteristics:

$\pi_u^*, \pi_o^*, \pi_s^* \in (0,1)$. Then, it follows that $\pi_e^* = 1$ is the optimal response of an individual assigned to the employment island and whose job survives with probability $1-s$.

B Wage bargaining

Bilateral bargaining between each worker and the representative intermediate firm takes place period by period. It follows a simple version of the alternating offer bargaining (AOB) protocol, with a finite number of rounds as in Rubinstein (1982). Similar to Hall and Milgrom (2008) and Christiano et al. (2016), we assume that as the bargaining takes place, the worker receives a flow benefit while the job's output depreciates. Each period a bargaining game with two rounds takes place: in the first round, the firm makes an offer; if the offer is accepted, the game ends and production takes place; else, the game moves to the second round, where the worker makes a take-it-or-leave-it offer.

The period surplus obtained by the firm if an agreement is reached at date t is given by

$$\mathbf{S}_t = P_t \underline{h} - w_t. \tag{49}$$

The capital value of a job satisfies the following Bellman equation:

$$\mathbf{J}_t = \mathbf{S}_t + \beta \mathbf{E}_t \left[\frac{\mu_{t+1}}{\mu_t} \left(1 - s_{t+1}\right) \mathbf{J}_{t+1} \right]. \tag{50}$$

We assume that if an agreement is not reached at round 2, the match will not be productive at date t, but the job will still be in place at date $t+1$ with probability $1 - s_{t+1}$, which is taken as given by the worker and the firm. The bargaining outcome relies on assumptions about off-equilibrium behavior. We assume that if no agreement is reached at time t, the job becomes dormant but survives, retaining the value of an active job. This separates the durability of the job from that of the match and implies that wages depend on flow surpluses, not their present value (Den Haan and Kaltenbrunner, 2009, and Chahrour et al., 2023, see). As a result, the job's capital value $\mathbf{J}$ is well defined, even without a vacancy creation/free entry condition.

Given discounting, in equilibrium the game will end with an agreement reached in round 1. In particular, consider a firm that makes a wage offer, $w_{1,t}$, in round 1. The firm sets $w_{1,t}$ as low as possible subject to the worker not rejecting it. Thus, the wage offer satisfies the following indifference condition

$$w_{1,t} = \max\left\{-\frac{v(1-\underline{h})}{\mu_t}, w_{2,t} + A_t\mathcal{B}\right\}, \tag{51}$$

with $\mathcal{B} > 0$. If the worker is indifferent between accepting and rejecting an offer, she accepts it. Therefore, an accepted wage offer made by the firm must be at least as large as the opportunity cost of employment, $-v(1-\underline{h})/\mu$, and at the same time no less than the worker's disagreement payoff given by the value of the counteroffer made by the worker in round 2. The disagreement payoff has two components: the benefit that the worker receives by rejecting the firm's offer, $A_t\mathcal{B}$, and the value of the wage the worker chooses to counteroffer, $w_{2,t}$. The former is assumed proportional to A_t to guarantee that the wage rate grows at a constant rate in the BGP equilibrium. We assume (and verify in equilibrium) that the disagreement payoff exceeds the opportunity cost of employment and, thus, the worker's surplus is positive.

To see why the game ends in round 1, consider next the problem of a worker who makes a take-it-or-leave-it offer $w_{2,t}$ in round 2, the last round. The firm's flow surplus if it accepts the worker's counter offer in round 2 is given by

$$\mathbf{S}_{2,t} = \zeta P_t\underline{h} - w_{2,t}. \tag{52}$$

The worker makes the highest possible offer in round 2 sub-game perfect equilibrium, subject to the firm not rejecting it. The upshot is a counteroffer that satisfies the following indifference condition

$$w_{2,t} = \zeta P_t \underline{h}. \tag{53}$$

Going backward, in the round 1 sub-game perfect equilibrium, the firm offers

$$w_{1,t} = \max \left\{ -\frac{v(1-\underline{h})}{\mu_t}, \zeta P_t \underline{h} + A_t \mathcal{B} \right\}, \tag{54}$$

where we assume $P_t \underline{h} > \zeta P_t \underline{h} + A_t \mathcal{B} > -v\left(1-\underline{h}\right)/\mu_t$ *almost surely* in the competitive equilibrium; as an upshot, $w_{1,t} = \zeta P_t \underline{h} + A_t \mathcal{B}$, and the worker accepts this offer.

The game ends in the first round, with $w_t = w_{1,t}$, and the firm obtains the flow surplus

$$\mathbf{S}_t = (1-\zeta) P_t \underline{h} - A_t \mathcal{B}. \tag{55}$$

Finally, the equilibrium capital value of a job is given by

$$\mathbf{J}_t = (1-\zeta) P_t \underline{h} - A_t \mathcal{B} + \mathbf{E}_t \left[\beta \frac{\mu_{t+1}}{\mu_t} (1 - s_{t+1}) \mathbf{J}_{t+1} \right]. \tag{56}$$

C Alternative (complete) model with endogenous vacancies

As we did not specify the process by which vacancies are created by recruiting firms, the model is underdetermined and it is possible to close the model with the system in (39). In this Appendix, we present an alternative (complete) model, which is fully specified, in the sense that it includes endogenous vacancy posting by the intermediate firms. This allows us to compare the incomplete but agnostic DSGE model to a more familiar benchmark with endogenous vacancy posting by firms and an equilibrium job-finding rate.

[Figure 6 about here.]

[Table 6 about here.]

We model vacancy posting in a way that is similar to Şahin et al. (2014). In particular, suppose each period the stand-in intermediate good firm posts vacancies at cost

$$\mathcal{K}_t = \underline{\nu}\kappa A_t \left[\left(\frac{\nu_t}{\underline{\nu}} \right)^{1+\varsigma} - 1 \right], \tag{57}$$

expressed in units of final output, with $\varsigma > 0$, the elasticity of the vacancy creation cost, and $\underline{\nu} > 0$ the level of vacancies in the balanced growth path steady state equilibrium. Following the canonical Mortensen and Pissarides (1994) search and matching framework, the total number of matches between unfilled vacancies and workers searching for jobs, $\mathbf{m}_t$, is determined by a constant returns to scale (CRS) matching function

$$\mathbf{m}_t = \exp\left(\hat{m}_t\right) \mathbf{M}\left(H_t, \nu_t\right) = \exp\left(\hat{m}_t\right) H_t^{\mathbf{z}} \nu_t^{1-\mathbf{z}}, \tag{58}$$

where H_t is the mass of job seekers defined in (16), ν_t is the mass of vacancies, and

$$\hat{m}_t = \rho_m \hat{m}_{t-1} + \sigma_m \epsilon_t^m, \tag{59}$$

is a matching efficiency shock. Accordingly, the vacancy-filling probability and job-finding probability each period are, in turn, given by

$$\mathtt{vf}_t = \exp\left(\hat{m}_t\right) \mathbf{M}\left(1/\Theta_t, 1\right), \tag{60}$$

$$f_t = \exp\left(\hat{m}_t\right) \mathbf{M}\left(1, \Theta_t\right), \tag{61}$$

with $\Theta_t = \nu_t / H_t$, the labor market tightness. The equilibrium condition determining the optimal posting of vacancies by intermediate firms is

$$\left(1+\varsigma\right) \kappa A_t \left(\frac{\nu_t}{\underline{\nu}}\right)^{\varsigma} = \mathtt{vf}_t \mathbf{J}_t, \tag{62}$$

which requires the marginal cost of an additional vacancy to be equal to the value of a filled vacancy, $\mathbf{J}_t$, multiplied by the probability of filling the vacancy, $\mathtt{vf}_t$.

Finally, the feasibility condition for the extended model must now include a term that captures the output cost of posting vacancies and is given by

$$\widetilde{C}_t + \widetilde{X}_t + \widetilde{E}_t + \widetilde{\mathcal{K}}_t = \widetilde{Y}_t. \tag{63}$$

Table 6 shows the set of business cycle statistics implied by the alternative estimated model with endogenous vacancies.

D Balanced growth path equilibrium

Let $\underline{X}$ denote the steady state of $\widetilde{X}$. The following equations uniquely characterize the steady state of the model

$$\left(\underline{K}/\underline{Y}\right) = \left[\frac{\alpha}{\mathcal{G}/\beta - (1-\delta)}\right], \tag{64}$$

$$\left(\underline{C}/\underline{K}\right) = \left(\underline{Y}/\underline{K}\right) - \left(\underline{X}/\underline{K}\right) - \left(\underline{E}/\underline{K}\right), \tag{65}$$

$$\underline{V} = 1, \tag{66}$$

$$(\underline{X}/\underline{K}) = \mathcal{G} - (1-\delta)\,, \tag{67}$$

$$(\underline{L}/\underline{N}) = \underline{h}, \tag{68}$$

$$(\underline{K}/\underline{N}) = (1/\underline{h})\,(\underline{K}/\underline{Y})^{1/(1-\alpha)}\,, \tag{69}$$

$$\underline{N} = (1-\underline{u})\,\underline{\Pi}, \tag{70}$$

$$\underline{H} = \left(\underline{s}/\underline{f}\right)\underline{N}, \tag{71}$$

$$\underline{O} = 1 - \underline{\Pi}, \tag{72}$$

$$\underline{U} = \underline{u}\,\underline{\Pi}, \tag{73}$$

$$\underline{u} = \frac{\underline{s}(1-\underline{f})}{\underline{f}(1-\underline{s})+\underline{s}} \tag{74}$$

E Log-linear Equilibrium Conditions

Let $\hat{x} \equiv \ln\left(\widetilde{X}/\underline{X}\right)$ denote the variable $\widetilde{X}$ in log-deviation from steady state. The log-linearized equilibrium conditions (around the deterministic steady state) are given by

$$(\mathcal{G}-\chi\beta)\,(\mathcal{G}-\chi)\,\hat{\mu}_t = \chi\beta\mathcal{G}\mathbf{E}_t\Big(\hat{c}_{t+1}\Big) - \left(\mathcal{G}^2+\chi^2\beta\right)\hat{c}_t + \chi\mathcal{G}\hat{c}_{t-1}, \tag{75}$$

$$-\hat{\mu}_t = \kappa_w\,(\hat{y}_t - \hat{n}_t) + \kappa_\xi \hat{f}_t, \tag{76}$$

$$\begin{aligned}(\mathcal{G}/\beta)\left[\hat{\mathcal{Q}}_t - \mathbf{E}_t\,(\hat{\mu}_{t+1}-\hat{\mu}_t)\right] = \alpha\,(\underline{Y}/\underline{K})\,\mathbf{E}_t\left(\hat{y}_{t+1} - \hat{k}_{t+1} - \hat{\iota}_{t+1}\right)&\\ + (1-\underline{\delta})\mathbf{E}_t\left(\hat{\mathcal{Q}}_{t+1}\right),&\end{aligned} \tag{77}$$

$$\hat{\iota}_t = \kappa_\iota\left(\hat{y}_t - \hat{k}_t\right), \tag{78}$$

$$\mathcal{G}^2\kappa_x\,(\hat{x}_t - \hat{x}_{t-1}) = \hat{\mathcal{Q}}_t + \hat{\upsilon}_t + \mathcal{G}^2\beta\kappa_x\mathbf{E}_t\,(\hat{x}_{t+1}-\hat{x}_t)\,, \tag{79}$$

$$\hat{y}_t = \alpha\left(\hat{\iota}_t + \hat{k}_t\right) + (1-\alpha)\,\hat{n}_t + z_t, \tag{80}$$

$$\left(\underline{C}/\underline{K}\right)\hat{c}_t + \left(\underline{X}/\underline{K}\right)\hat{x}_t + \left(\underline{E}/\underline{K}\right)\hat{e}_t = \left(\underline{Y}/\underline{K}\right)\hat{y}_t, \tag{81}$$

$$\mathcal{G}\hat{k}_{t+1} = \left(\underline{X}/\underline{K}\right)\left(\hat{x}_t + \upsilon_t\right) + \left(1-\underline{\delta}\right)\hat{k}_t - \alpha\left(\underline{Y}/\underline{K}\right)\hat{\iota}_t, \tag{82}$$

$$\underline{u}\hat{u}_t = \left(1-\underline{u}\right)\left(\hat{\pi}_t - \hat{n}_t\right), \tag{83}$$

$$\hat{n}_t = \left(1-\underline{s}\right)\hat{n}_{t-1} + \underline{s}\left(\hat{h}_t + \hat{f}_t - \hat{s}_t\right). \tag{84}$$

Above, we use the definitions

$$\kappa_\xi \equiv \xi/\underline{\Psi}_{uo} \in (0,1), \tag{85}$$

$$\kappa_x \equiv \mathcal{S}'' > 0, \tag{86}$$

$$\kappa_w \equiv \left(1 - \mathcal{B}/\underline{w}\right) \in (0,1), \tag{87}$$

$$\kappa_\iota \equiv \delta'/\left(\delta' + \underline{\iota}\delta''\right) \in (0,1). \tag{88}$$

As explained in the main text, the system of equilibrium conditions is underdetermined. The model is closed, by assuming that the joint dynamics of the job-finding and separation rates are governed by the system (39). This completes the log-linear equilibrium model.

Finally, in the version of the model with endogenous vacancies considered in Appendix C, the following additional log-linear equilibrium conditions are obtained

$$\hat{\mathbf{j}}_t = \kappa_j\left(\hat{y}_t - \hat{n}_t\right) + \beta\mathcal{G}\left(1-\underline{s}\right)\mathbf{E}_t\left(\hat{\mathbf{j}}_{t+1} + \hat{\mu}_{t+1} - \hat{\mu}_t - \frac{\underline{s}}{1-\underline{s}}\hat{s}_{t+1}\right), \tag{89}$$

$$\hat{\mathtt{vf}}_t = \hat{m}_t + \mathtt{z}\left(\hat{h}_t - \hat{\nu}_t\right), \tag{90}$$

$$\hat{f}_t = \hat{m}_t + \left(1-\mathtt{z}\right)\left(\hat{\nu}_t - \hat{h}_t\right), \tag{91}$$

$$\varsigma\hat{\nu}_t = \hat{\mathtt{vf}}_t + \hat{\mathbf{j}}_t, \tag{92}$$

where

$$\kappa_j \equiv (1 - \beta\mathcal{G}(1 - \underline{s})) \frac{(1-\zeta)(\underline{W} - \mathcal{B})}{(1-\zeta)(\underline{W} - \mathcal{B}) - \zeta\mathcal{B}} = \frac{(1 - \beta\mathcal{G}(1 - \underline{s}))(1-\zeta)\kappa_w}{\kappa_w - \zeta}, \quad (93)$$

and with equations (89) to (92), corresponding, in turn, to conditions (56), (57), (60), (61), and (62), in log-linear form, and where we have that $\kappa_j \geq 0$, given that the condition $\mathcal{S} = (1-\zeta) P_t \underline{h} - A_t \mathcal{B} > 0$, imposed in Appendix B, requires $\kappa_w > \zeta$.

F Data

The DSGE model is estimated on quarterly US data spanning 1948:q1 until 2018:q3. In particular, we estimate the DSGE model on seven macroeconomic time-series: real per capita output (GDP), real per capita consumption, real per capita investment, the employment to population ratio, the unemployment rate, the job-separation rate, and the job-finding rate. Furthermore, the resource constraint corresponding to the model with vacancy posting costs, equation (63)

The data sources are as follows:

- Population – Civilian Noninstitutional Population, Thousands of Persons, Quarterly, Not Seasonally Adjusted (source: St Louis FRED);

- Nominal GDP – Gross Domestic Product, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (source: St Louis FRED);

- GDP deflator – Gross Domestic Product: Implicit Price Deflator, Index 2009=100, Quarterly, Seasonally Adjusted (source: St Louis FRED);

- Total nominal Consumption – obtained as the sum of: Personal Consumption Expenditures: Nondurable Goods, Billions of Dollars, Quarterly, Seasonally

Adjusted Annual Rate, Personal Consumption Expenditures: Services, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate, and Personal Consumption Expenditures: Durable Goods, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (source: St Louis FRED);

- Investment – Gross Private Domestic Investment, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (source: St Louis FRED);
- Unemployment rate – Civilian Unemployment Rate, Percent, Quarterly, Seasonally Adjusted (source: St Louis FRED);
- Employment – All Employees: Total Nonfarm Payrolls, Thousands of Persons, Quarterly, Seasonally Adjusted (source: St Louis FRED);

In addition, to construct the job-finding rate and the job-separation rate series, we follow the methodology developed in the methodology by Elsby et al. (2010) and Shimer (2012), who calculate monthly transition rates based on the Current Population Survey (CPS) with the corresponding quarterly outflows and inflows computed as three-months averages.

The data series used in these calculations are as follows:

- Unemployed for less than 5 weeks aged 16 and over, seasonally adjusted (source and series ID: BLS - LNS13008396); This series displays a discontinuous decline following the CPS redesign in 1994, due to a change in the way unemployment duration was recorded. To correct for this we follow Elsby et al. (2010) and rescale the series by a factor of 1.1549;
- Unemployment level of workers aged 16 and over, seasonally adjusted (source and series ID: BLS - LNS13000000);

- Labor force Series title: Civilian labor force Level 16 years and over, seasonally adjusted (source and series ID: BLS - LNS11000000).

The monthly job-finding probability is computed using the formula

$$f_\tau^{\text{monthly}} = 1 - \left(\frac{U_\tau - U_\tau^{< 5 \text{ weeks}}}{U_\tau} \right), \tag{94}$$

where U_τ is total unemployment in month $\tau = 1, \ldots 3$ (within quarter t), and $U_\tau^{< 5 \text{ weeks}}$ is the number of unemployed for less than 5 weeks. The hazard rate is then obtained as $\tilde{f}_\tau = - \ln \left(1 - f_\tau^{\text{monthly}}\right)$. Next, the job-separation hazard rate is obtained as the solution to the difference equation

$$U_{\tau+1} = \Pi_\tau \left(\frac{\tilde{s}_\tau}{\tilde{s}_\tau + \tilde{f}_\tau} \right) + \Pi_\tau \left[U_\tau - \left(\frac{\tilde{s}_\tau}{\tilde{s}_\tau + \tilde{f}_\tau} \right) \right] e^{-\left(\tilde{s}_\tau + \tilde{f}_\tau\right)}, \tag{95}$$

with Π_t the size of the labor force at date t (assumed constant within two consecutive months). Finally, the quarterly job-separation and job-finding probability are obtained from the monthly hazard rates, as follows:

$$s_t = \sum_{\tau=1}^{3} \frac{1 - \exp\left(-3\tilde{s}_\tau\right)}{3}, \tag{96}$$

$$f_t = \sum_{\tau=1}^{3} \frac{1 - \exp\left(-3\tilde{f}_\tau\right)}{3}. \tag{97}$$

The resulting time series for the unemployment inflows and outflows (in logs) are plotted in Figure 1, and essentially extend the equivalent series in Elsby et al. (2010) and Shimer (2012), until 2018:q3.

The instrumental variables used in the Proxy VAR to identify the TFP shock, the IS shock and the EE shock are, in turn: the innovations to the Fernald (2014) utilization adjusted TFP measure, to instrument for the TFP shock; the innovations to the relative price of investment, to instrument for the IS shock (Relative Price of Investment Goods, Index 2009=1, Quarterly, Seasonally Adjusted – source: St Louis FRED); and the Ramey (2011) narrative measure of defense expenditure shocks, to instrument for the EE shock.

Finally, the quarterly gross flows data used in Section 5 are obtained from Gomes (2015) who calculates quarterly gross flows based on the CPS longitudinal data. The gross flows data sample spans 1976:q1 until 2011:q2.

G Structural IRF identification

In Section 4 we compare the estimated impulse response functions (IRF) from the DSGE to those obtained from a structural VAR model. The structural VAR model is identified using a combination of "short-run" zero restrictions and external instruments, following the methodology by Stock and Watson (2012) and Mertens and Ravn (2013). In what follows we explain carefully how this method is implemented, following the approach in Lunsford (2015).

The $n \times 1$ vector of macroeconomic time-series $h_t = \left[\hat{s}_t, \hat{f}_t, \hat{m}_t'\right]'$ is assumed to follow a reduced-form VAR model with p lags of the form

$$h_t = \sum_{i=1}^{p} \mathbf{A}_i h_{t-i} + \eta_t, \tag{98}$$

where η_t denotes the reduced form errors. The corresponding structural shocks are given by $\mathcal{E}_t$ such that $\eta_t = \mathbf{B}\mathcal{E}_t$, with $\mathbf{B}$ an $n \times n$ square matrix, $\mathbf{E}\left(\mathcal{E}_t\mathcal{E}_t'\right) = \mathbf{I}_n$ the n-dimensional identity matrix and, thus, $\mathbf{E}\left(\eta_t\eta_t'\right) = \mathbf{BB}'$, the covariance matrix of the reduced form errors. Suppose we have an instrument z_t for the structural shock $\mathcal{E}_t^1$ that satisfies the two conditions:

1. $\mathbf{E}\left(\mathcal{E}_t^1 z_t\right) = \psi \neq 0$;

2. $\mathbf{E}\left(\mathcal{E}_t^s z_t\right) = 0,\ \forall\ s \neq 1$.

Let $\mathbf{B}^\bullet$ denote the first column of $\mathbf{B}$, so that $\mathbf{B} = [\mathbf{B}^\bullet, \mathbf{B}^{\bullet\bullet}]$. Then, from the two conditions above, we have that $\mathbf{E}\left(\eta_t z_t\right) = \mathbf{B}^\bullet \psi$. We further assume that $\mathbf{B}$ is invertible, with the upshot that $\mathbf{B}^{-1}\mathbf{B}^\bullet = [1, 0 \ldots 0]' \equiv \mathbf{i}$. Making use of these conditions we obtain identification of ψ up to a sign (which we assume is known), as follows

$$
\begin{aligned}
\left(\mathbf{B}\mathbf{B}'\right)^{-1} &= \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1}, \\
\psi \mathbf{B}^{\bullet\prime} \left(\mathbf{B}\mathbf{B}'\right)^{-1} \mathbf{B}^\bullet \psi &= \mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right), \\
\psi \mathbf{i}'\mathbf{i} \psi &= \mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right), \\
\psi &= \operatorname{sign}\left(\psi\right) \sqrt{\mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right)}.
\end{aligned} \tag{99}
$$

This in turn yields identification of the vector $\mathbf{B}^\bullet$, as follows

$$
\mathbf{B}^\bullet = \operatorname{sign}\left(\psi\right) \mathbf{E}\left(\eta_t z_t\right) \left\{ \sqrt{\mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right)} \right\}^{-1}, \tag{100}
$$

and, thus, of the corresponding structural IRF.

H DSGE estimation

The model is estimated on quarterly US data spanning 1948:q1 until 2018:q3. In particular, we estimate the DSGE model on seven macroeconomic time-series: real per capita output (GDP), real per capita consumption, real per capita investment, the employment to population ratio, the unemployment rate and the job-separation rate and the job-finding rate. Since we have five structural shocks, we assume the existence of measurement error in the observation equations for the job-separation and job-finding rates, denoted me_t^s and me_t^f.

The variables are all included in log levels and detrended by applying Hamilton (2018) method, who recommends defining the cyclical component of quarterly time series as the two-year ahead forecast error with the forecast obtained based on four lags of the variable. The corresponding measurement equations are

$$100\times\begin{bmatrix}\log(\text{GDP})_t-\mathbf{P}_{t-h}\left(\log(\text{GDP})_t\mid\log(\text{CONS})_{t-h-i}\right)\\ \log(\text{CONS})_t-\mathbf{P}_{t-h}\left(\log(\text{CONS})_t\mid\log(\text{CONS})_{t-h-i}\right)\\ \log(\text{INV})_t-\mathbf{P}_{t-h}\left(\log(\text{INV})_t\mid\log(\text{INV})_{t-h-i}\right)\\ \log(\text{EMP})_t-\mathbf{P}_{t-h}\left(\log(\text{EMP})_t\mid\log(\text{EMP})_{t-h-i}\right)\\ \log(\text{UNP})_t-\mathbf{P}_{t-h}\left(\log(\text{UNP})_t\mid\log(\text{UNP})_{t-h-i}\right)\\ \log(\text{S})_t-\mathbf{P}_{t-h}\left(\log(\text{S})_t\mid\log(\text{S})_{t-h-i}\right)\\ \log(\text{F})_t-\mathbf{P}_{t-h}\left(\log(\text{F})_t\mid\log(\text{F})_{t-h-i}\right)\end{bmatrix}=100\times\begin{bmatrix}\hat{y}_t\\ \hat{c}_t\\ \hat{x}_t\\ \hat{n}_t\\ \hat{u}_t\\ \hat{s}_t\\ \hat{f}_t\end{bmatrix}+\begin{bmatrix}0\\ 0\\ 0\\ 0\\ 0\\ me_t^s\\ me_t^f\end{bmatrix},\quad(101)$$

for $i=0,\ldots,3$, and with $\hat{y}_t$ given by $\ln\left(\widetilde{Y}/\underline{Y}\right)$, the variable $\widetilde{Y}$ in log deviation from its steady state; the projection $\mathbf{P}_{t-h}\left(x_t|x_{t-h-i}\right)$ is the univariate forecast at date $t-h$ of variable x_t based on the lags $x_{t-h},\ldots x_{t-h-3}$, the projection suggested by Hamilton (2018) to obtain the cyclical component of quarterly macroeconomic time-series.

To improve the ability of the estimated model to match the second-order moments of the data, we update the selection of priors following the endogenous priors procedure developed in Del Negro and Schorfheide (2008) and Christiano et al. (2011). This procedure is based on Bayesian learning, and it is implemented by multiplying the initial priors by a large sample approximation to the likelihood function for the target second-order moments obtained from a "pre-sample" data. The large sample approximation to the likelihood function is a Laplace approximation (Chernozhukov and Hong, 2003), obtained using MCMC (see the technical appendix in Christiano et al., 2011, for a description of the method). However, as we do not have a "pre-sample", we follow Christiano et al. (2011) and Born et al. (2013) in obtaining the target second order moments from the same sample as that used to estimate the model.

The estimation is done with Dynare. The posterior is evaluated using the Metropolis-Hasting MCMC algorithm. The Hessian resulting from the optimization procedure was used for defining the transition probability function that generates the new proposed draw. In particular, we consider 5 MH chains, with 10,000 draws per chain, and keeping the last 50% of the draws. The acceptance rate for each chain is around 30%.

[Figure 7 about here.]

I DSGE estimated impulse response functions

In this Section, we report the model's estimated impulse response functions (IRF), and compare these to the IRF obtained using the structural FAVAR in Section 3.

In Figures 8 to 10b, we consider the responses of output, consumption, investment, employment, unemployment rate, real wage, and capacity utilization to a one standard deviation innovation to each of the five structural shocks (ϵ^z, ϵ^v, ϵ^e, ϵ^f, ϵ^s), and compare them to the estimated IRF based on the FAVAR model. The shaded areas represent 95% confidence intervals for the FAVAR impulse response functions. Despite not targeting the IRF in the estimation, the estimated model does very well in matching the conditional business cycle dynamics. In each Figure, we also plot the IRF for the job-separation and job-finding rate. But for these latter two sets of IRF, the match with the FAVAR based analog is exact, since the model is calibrated to match the conditional dynamics of unemployment inflows and outflows.

In Figure 8, we examine the adjustment following a TFP shock. The model matches the conditional dynamics of all variables well, though the employment response is too strong initially. Consistent with the FAVAR model, the investment response is protracted and hump-shaped. The model also captures the responses of consumption and output, with consumption showing a strong, persistent rise as higher TFP and capital utilization boost output, despite a drop in employment. The employment decline is driven by a sharp fall in the job-finding rate, reducing the return to participation.

[Figure 8 about here.]

[Figure 9 about here.]

In Figure 9a, the model matches the conditional dynamics of the investment-specific (IS) shock, ϵ^v, well, with responses generally within the 95% confidence interval of the FAVAR model. Both consumption and employment rise on impact, driven by an increase in the job-finding rate. With more participants finding jobs, employment increases, lowering the real wage, though this is partially offset by higher capital utilization. As the job-finding rate rises, the effective real wage also increases, leading to higher consumption. This effective wage channel helps the model capture the positive correlation between consumption and investment after an IS shock.

Next, Figure 9b shows that the model also matches well the macroeconomic dynamics conditional on expenditure shocks, ϵ^e. The model yields positive but very small cumulative employment multipliers conditional on an expenditure shock. This follows from the conditional response of the job-finding and separation rates being close to zero, consistent with empirical findings in the literature (Monacelli et al., 2010).

In Figures 10a and 10b, we examine shocks to labor market frictions. Figure 10a shows the response to a job-separation shock. Due to the block-recursive structure of the model, job-separation shocks, ϵ^s, affect consumption, investment, and employment through their impact on the job-finding rate. As shown in the bottom panels, a positive job-separation shock persistently lowers the job-finding rate, though its initial effect is restricted to be zero. This reduction leads to a prolonged decline in consumption, investment, and output, closely matching the FAVAR-estimated IRF. The model also captures the employment and unemployment dynamics, though it slightly overestimates the unemployment rate response.

Lastly, following a shock to the job-finding rate the model matches the response of all the macroeconomic aggregates, even if it overestimates the response of consumption. Interestingly, the qualitative response of several of the macroeconomic aggregates following an investment-specific shock and a job-finding rate shock is very similar (in turn, Figures 9a and 10b), suggesting an analogous propagation mechanism.

[Figure 10 about here.]

J Model implied gross flows

Using the gross flows in the system (17), we obtain the transition probabilities

$$\phi_{eo,t} = s_t \left(1 - \pi_{s,t}\right) \tag{102}$$

$$\phi_{uo,t} = \left(1 - \pi_{u,t}\right), \tag{103}$$

$$\phi_{oo,t} = \left(1 - \pi_{o,t}\right). \tag{104}$$

Since $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$ are not pinned down uniquely in equilibrium (recall the discussion in Section 2), it follows that we can pick values for any two elements in $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$ to exactly match two of the above gross flows. Given these, the equilibrium value for the third transition probability is uniquely determined from condition (16). All other flows are uniquely determined in equilibrium and, thus, our model provides restrictions for the labor market transitions that can be confronted with the data.

The literature looking at gross worker flows has struggled to match the UO transition rate. Therefore, in our analysis we pick realizations for $\pi_{u,t}$ to match UO exactly. We also choose $\pi_{s,t}$ to match the EO gross flows. Thus, it becomes clear that the equilibrium model is entirely consistent with the UO and EO flows. But to test the model's fit we must subsequently look at the the remaining gross flows generated in equilibrium: EE, EU, UE, UU, OE, OU and OO. In particular, we compute the correlation between the gross flows filtered values (obtained from the likelihood Kalman filter) and their empirical counterparts, and compute relevant second order moments. As detailed next, the model is able to match well the cyclical properties of gross flows.

Figure 11 shows all transition probabilities, and Table 5 reports their standard deviations and correlations with unemployment. The model's generated gross flows have high correlations with the data, and the relative volatilities and correlations with unemployment are similar. Notably, the model matches the EU and UE flows well, with correlations of 75% and 60%, respectively, aligning with findings from Elsby et al. (2015) that these flows account for two-thirds of unemployment variation. The model also captures the spikes in all flows, particularly during the 2008 recession.

List of Tables

Table 1: Calibrated Parameters (time unit of model: quarterly)

Ξ	Value	Target (and source)
α	0.283	capital's income share of 28.3% (Gomme and Rupert, 2007);
$\mathcal{G}$	1.005	annualized quarterly per capita real GDP growth of 1.84% (BEA, 1948:q1–2018:q4);
δ	0.014	annual investment/capital ratio of 7.6% (Cooley and Prescott, 1995);
β	0.992	annual rate of return on capital of 5.16% (Gomme et al., 2011);
$\underline{\mathrm{E}}/\underline{\mathrm{Y}}$	0.200	government spending income share of 20% (Christiano et al., 2016);
$\underline{f}$	0.738	quarterly gross worker flows (based on Gomes, 2015, calculations on CPS data);
$\underline{s}$	0.190	quarterly gross worker flows (based on Gomes, 2015, calculations on CPS data);
$\underline{\pi}_s$	0.547	quarterly gross worker flows (based on Gomes, 2015, calculations on CPS data);
$\underline{\pi}_u$	0.624	quarterly gross worker flows (based on Gomes, 2015, calculations on CPS data);
$\underline{\pi}_o$	0.255	civilian labor participation rate (16 to 64 year) of 71.0% (BEA, 1948:q1–2018:q4);

Table 2: Steady state gross flows (data and baseline model)

	$\underline{\phi}_{ee}$	$\underline{\phi}_{eu}$	$\underline{\phi}_{eo}$
Data	0.887	0.027	0.086
Model	0.887	0.027	0.086
	$\underline{\phi}_{ue}$	$\underline{\phi}_{uu}$	$\underline{\phi}_{uo}$
Data	0.460	0.164	0.376
Model	0.460	0.164	0.376
	$\underline{\phi}_{oe}$	$\underline{\phi}_{ou}$	$\underline{\phi}_{oo}$
Data	0.139	0.044	0.817
Model	0.188	0.067	0.745

Table 3: Prior and Posterior Distributions

Parameter	Prior distribution (mean; st.d.)	Post mode	Post st.d.	80% c.i.
κ_ξ	beta (0.500; 0.100)	0.277	0.003	[0.273 , 0.281]
χ	beta (0.500; 0.100)	0.015	0.004	[0.011 , 0.022]
κ_w	beta (0.800; 0.100)	0.502	0.016	[0.483 , 0.523]
κ_ι	beta (0.500; 0.100)	0.806	0.014	[0.785 , 0.823]
κ_x	gamma (10.000; 0.500)	8.497	0.078	[8.393 , 8.594]
ρ_z	beta (0.500; 0.050)	0.833	0.016	[0.810 , 0.851]
ρ_v	beta (0.500; 0.050)	0.810	0.004	[0.805 , 0.815]
ρ_g	beta (0.500; 0.050)	0.737	0.015	[0.717 , 0.755]
$100 \times \sigma_z$	inverse-gamma (0.1; 0.5)	0.970	0.027	[0.938 , 1.007]
$100 \times \sigma_v$	inverse-gamma (0.1; 0.5)	3.300	0.052	[3.236 , 3.369]
$100 \times \sigma_g$	inverse-gamma (0.1; 0.5)	2.380	0.056	[2.306 , 2.451]
$100 \times \sigma_s$	inverse-gamma (0.1; 0.5)	1.650	0.022	[1.625 , 1.682]
$100 \times \sigma_f$	inverse-gamma (0.1; 0.5)	1.200	0.024	[1.171 , 1.231]

Note: The 80% credible intervals reported correspond to the 1^{st} and 9^{th} deciles of each marginal posterior density. The posterior is evaluated using the Metropolis-Hasting MCMC algorithm. In particular, we consider 5 Metropolis-Hasting chains, with 10,000 draws per chain.

Table 4: Cyclical behavior of macroeconomic variables

	correlation with unemployment rate		correlation with output		std deviation relative to output	
variable	data	model	data	model	data	model
consumption	−0.660	−0.918	0.834	0.632	0.615	0.701
	(−0.899 ; −0.421)	[−0.924 ; −0.912]	(0.710 ; 0.959)	[0.620 ; 0.643]	(0.527 ; 0.703)	[0.688 ; 0.711]
investment	−0.618	−0.346	0.835	0.898	3.025	3.907
	(−0.835 ; −0.401)	[−0.357 ; −0.336]	(0.687 ; 0.982)	[0.895 ; 0.900]	(2.461 ; 3.588)	[3.840 ; 3.976]
real wage	−0.178	0.163	0.384	−0.013	0.700	0.208
	(−0.415 ; 0.059)	[0.147 ; 0.178]	(0.150 ; 0.619)	[−0.054 ; 0.026]	(0.534 ; 0.866)	[0.193 ; 0.223]
employment	−0.718	−0.676	0.746	0.925	0.649	1.086
	(−0.914 ; −0.522)	[−0.685 ; −0.666]	(0.594 ; 0.897)	[0.916 ; 0.934]	(0.515 ; 0.783)	[1.074 ; 1.098]
participation	−0.194	0.002	0.410	0.642	0.305	0.801
	(−0.413 ; 0.025)	[−0.012 ; 0.017]	(0.183 ; 0.636)	[0.628 ; 0.655]	(0.224 ; 0.385)	[0.787 ; 0.815]
separation rate	0.672	0.729	−0.389	−0.503	2.418	3.605
	(0.504 ; 0.840)	[0.723 ; 0.734]	(−0.626 ; −0.153)	[−0.511 ; −0.495]	(1.786 ; 3.051)	[3.564 ; 3.646]
finding rate	−0.802	−0.956	0.772	0.629	2.615	2.562
	(−1.000 ; −0.562)	[−0.957 ; −0.956]	(0.566 ; 0.978)	[0.620 ; 0.638]	(1.859 ; 3.370)	[2.531 ; 2.594]
unemployment	1	1	−0.736	−0.667	7.137	10.911
			(−0.914 ; −0.559)	[−0.676 ; −0.658]	(6.070 ; 8.204)	[10.795 ; 11.026]

Note: In square brackets we report the 80% credible intervals for the second moments. The 80% credible intervals reported correspond to the 1^{st} *and* 9^{th} *deciles of each marginal posterior density. The posterior is evaluated using the Metropolis-Hasting MCMC algorithm. In particular, we consider 5 Metropolis-Hasting chains, with 10,000 draws per chain. In curly brackets, we report the 99% confidence intervals for the empirical (data) second moments, constructed using the GMM method with Heteroskedasticity and Autocorrelation Consistent (HAC) variance estimators, following the Newey-West procedure.*

Table 5: Cyclical behavior of gross flows (in sample)

	std deviation relative to unemployment rate			correlation with unemployment rate		
gross flow	data		model	data		model
EE	0.022	(0.017 ; 0.028)	0.039	−0.713	(−1.000 ; −0.410)	−0.787
EU	0.643	(0.514 ; 0.773)	1.527	0.785	(0.526 ; 1.000)	0.784
EO	0.205	(0.114 ; 0.297)	0.245	0.027	(−0.287 ; 0.341)	−0.248
UE	0.323	(0.280 ; 0.366)	0.290	−0.844	(−1.000 ; −0.660)	−0.475
UU	0.923	(0.688 ; 1.157)	0.832	0.781	(0.498 ; 1.000)	0.743
UO	0.169	(0.100 ; 0.238)	0.202	−0.432	(−0.777 ; −0.087)	−0.499
OE	0.227	(0.170 ; 0.285)	0.470	−0.689	(−0.991 ; −0.386)	−0.319
OU	0.573	(0.440 ; 0.706)	0.854	0.706	(0.373 ; 1.000)	0.710
OO	0.020	(0.012 ; 0.029)	0.121	−0.068	(−0.337 ; 0.200)	−0.138

Note: The model moments correspond to the in sample moments of the filtered variables over the period 1976:1 and 2011:2, which corresponds to the period over which we measure the empirical gross flows. The empirical time series of gross flows are detrended using the method in Hamilton (2018). In curly brackets, we report the 99% confidence intervals for the empirical (data) second moments, constructed using the GMM method with Heteroskedasticity and Autocorrelation Consistent (HAC) variance estimators, following the Newey-West procedure.

Table 6: Cyclical behavior of macroeconomic variables – Model with endogenous vacancies

	correlation with unemployment rate		correlation with output		std deviation relative to output	
variable	data	model	data	model	data	model
consumption	−0.660	−0.974	0.834	0.715	0.615	1.122
	(−0.899 ; −0.421)	[−0.975 ; −0.973]	(0.710 ; 0.959)	[0.699 ; 0.729]	(0.527 ; 0.703)	[1.104 ; 1.140]
investment	−0.618	−0.217	0.835	0.730	3.025	3.236
	(−0.835 ; −0.401)	[−0.235 ; −0.198]	(0.687 ; 0.982)	[0.721 ; 0.740]	(2.461 ; 3.588)	[3.099 ; 3.371]
real wage	−0.178	−0.204	0.384	0.064	0.700	0.055
	(−0.415 ; 0.059)	[−0.222 ; 0.185]	(0.150 ; 0.619)	[0.040 ; 0.088]	(0.534 ; 0.866)	[0.053 ; 0.058]
employment	−0.718	−0.580	0.746	0.874	0.649	1.104
	(−0.914 ; −0.522)	[−0.594 ; −0.564]	(0.594 ; 0.897)	[0.863 ; 0.887]	(0.515 ; 0.783)	[1.081 ; 1.124]
participation	−0.194	0.151	0.410	0.420	0.305	0.910
	(−0.413 ; 0.025)	[0.134 ; 0.169]	(0.183 ; 0.636)	[0.396 ; 0.451]	(0.224 ; 0.385)	[0.887 ; 0.931]
separation rate	0.672	0.701	−0.389	−0.617	2.418	3.025
	(0.504 ; 0.840)	[0.691 ; 0.710]	(−0.626 ; −0.153)	[−0.624 ; −0.608]	(1.786 ; 3.051)	[2.968 ; 3.082]
finding rate	−0.802	−0.977	0.772	0.721	2.615	2.754
	(−1.000 ; −0.562)	[−0.978 ; −0.976]	(0.566 ; 0.978)	[0.705 ; 0.735]	(1.859 ; 3.370)	[2.707 ; 2.805]
unemployment	1	1	−0.736	−0.750	7.137	11.529
			(−0.914 ; −0.559)	[−0.762 ; −0.736]	(6.070 ; 8.204)	[11.329 ; 11.735]

Note: In square brackets we report the 80% credible intervals for the second moments. The 80% credible intervals reported correspond to the 1^{st} *and* 9^{th} *deciles of each marginal posterior density. The posterior is evaluated using the Metropolis-Hasting MCMC algorithm. In particular, we consider 5 Metropolis-Hasting chains, with 10,000 draws per chain. In curly brackets, we report the 99% confidence intervals for the empirical (data) second moments, constructed using the GMM method with Heteroskedasticity and Autocorrelation Consistent (HAC) variance estimators, following the Newey-West procedure.*

List of Figures

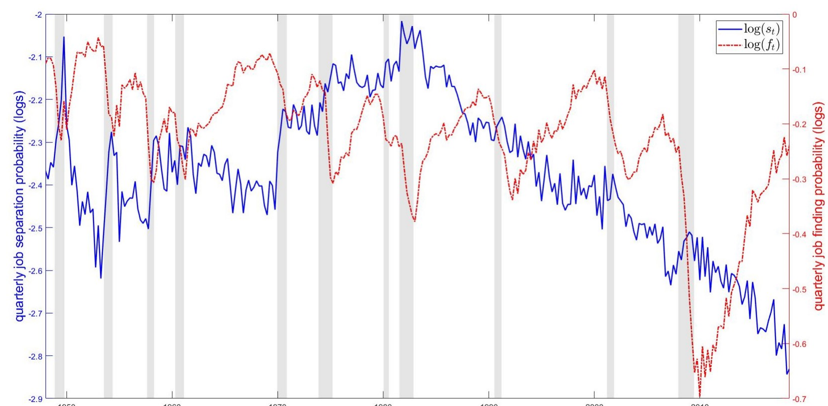


Figure 1: quarterly job-separation and finding probabilities (logs)

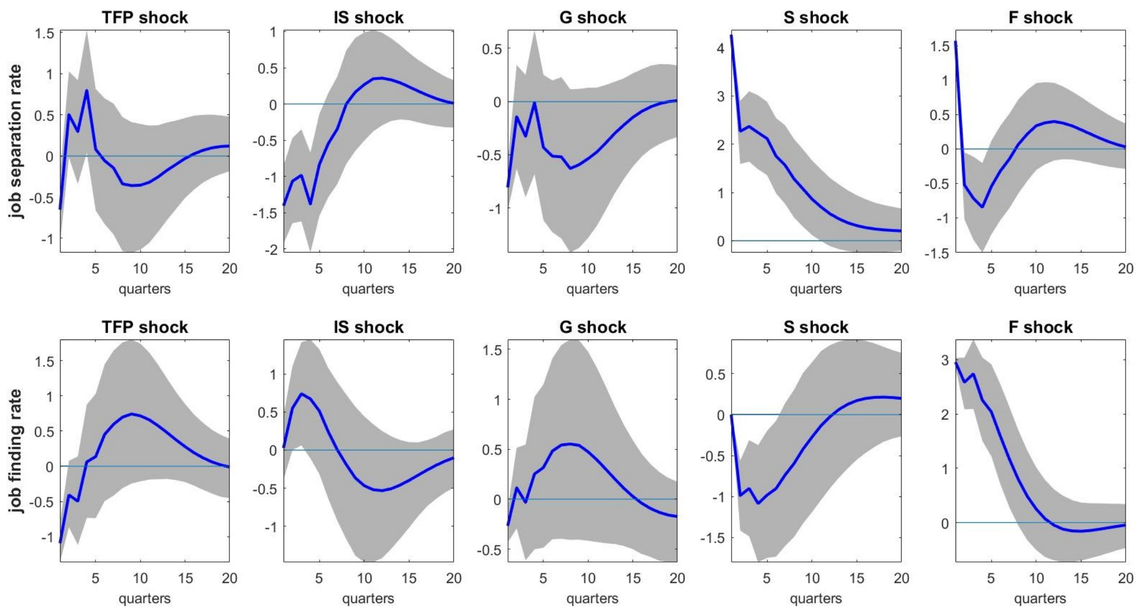
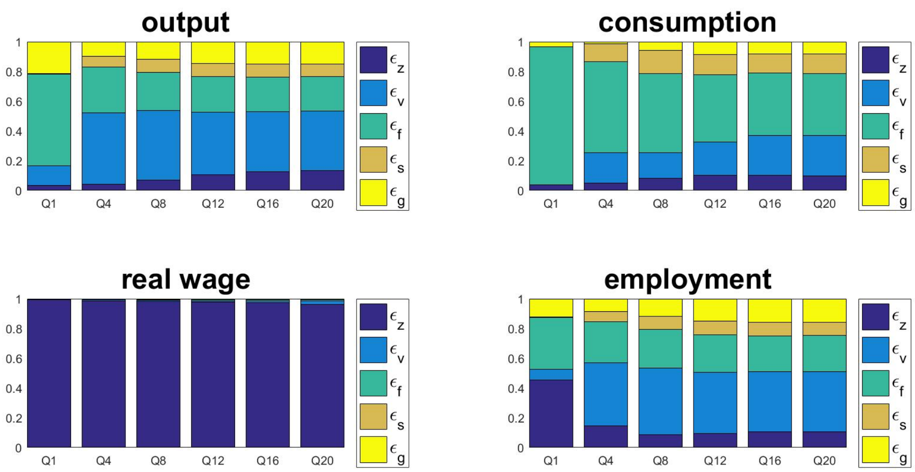
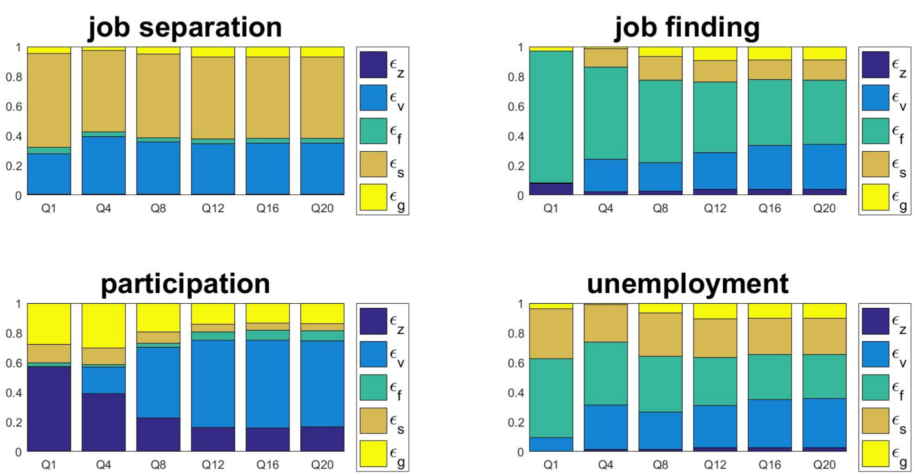


Figure 2: structural IRF of the job-finding and separation rates

Note: *The Figure plots the percentage responses of the job-finding and separation rates to a 1 standard deviation innovation shock. The VAR includes $p = 4$ lags. The shaded areas are 95% confidence intervals computed using bootstrap with 10,000 replications.*



(a) Forecast error variance decomposition of main aggregates



(b) Forecast error variance decomposition of inflows and outflows

Figure 3: Forecast error variance decomposition for (a) main aggregates and (b) inflows and outflows.

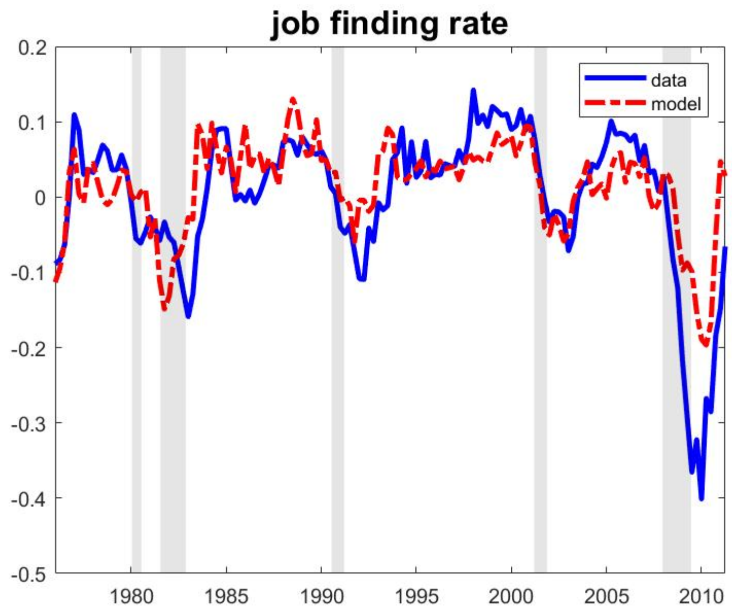
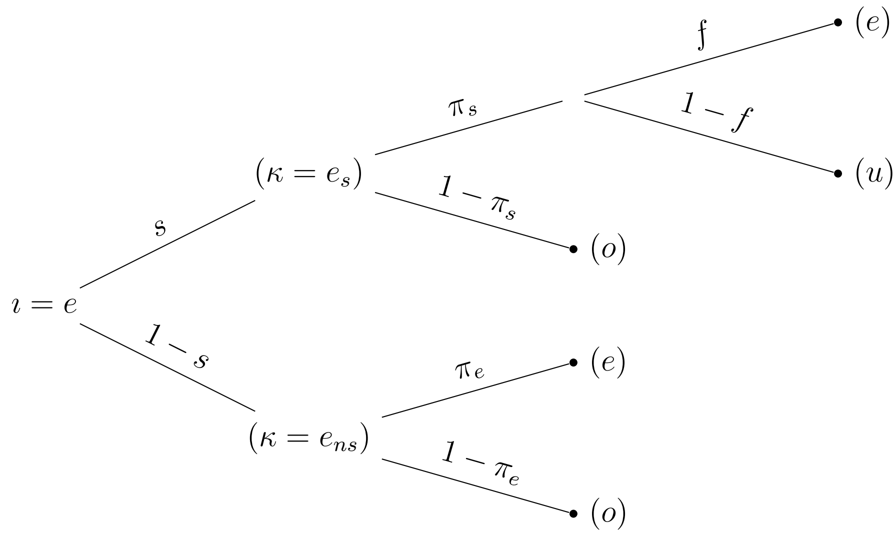
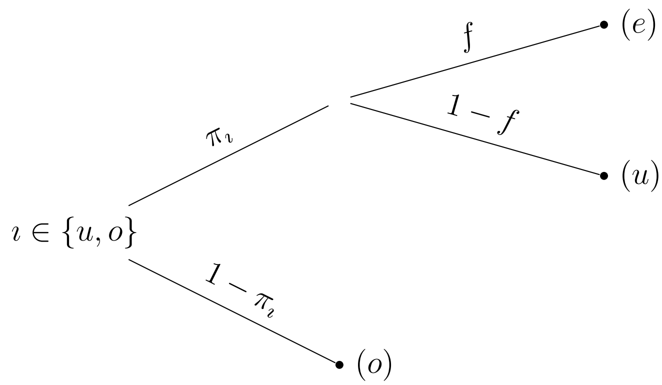


Figure 4: Ins and Outs

(data — and in-sample model fit - -)



(a) Sequence of events conditional on $\imath = e$



(b) Sequence of events conditional on $\imath \in \{u, o\}$

Figure 5: Sequence of events conditional on musical chairs' randomisation

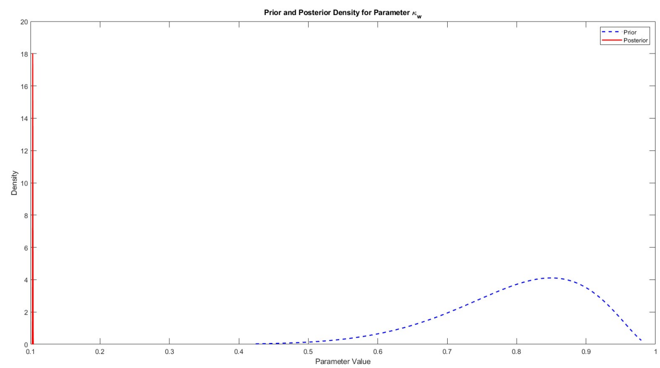


Figure 6: Estimation of κ_w – model with endogenous vacancies

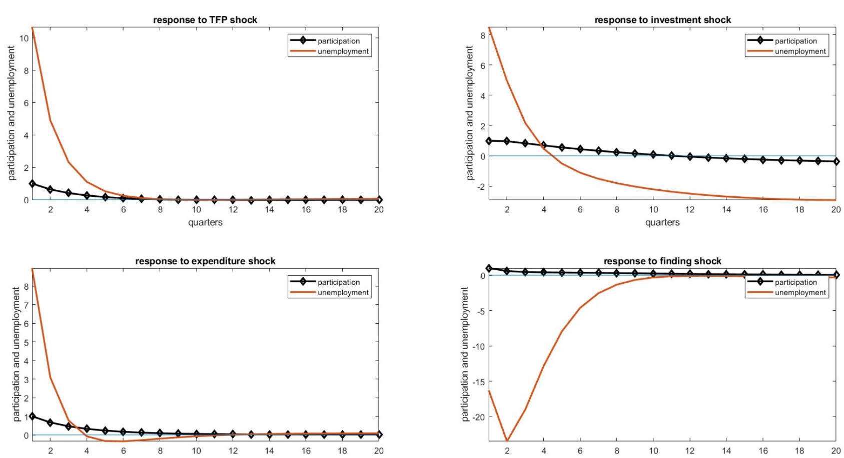


Figure 7: IRF of participation and unemployment conditional on each structural shock causing participation to increase on impact 1%

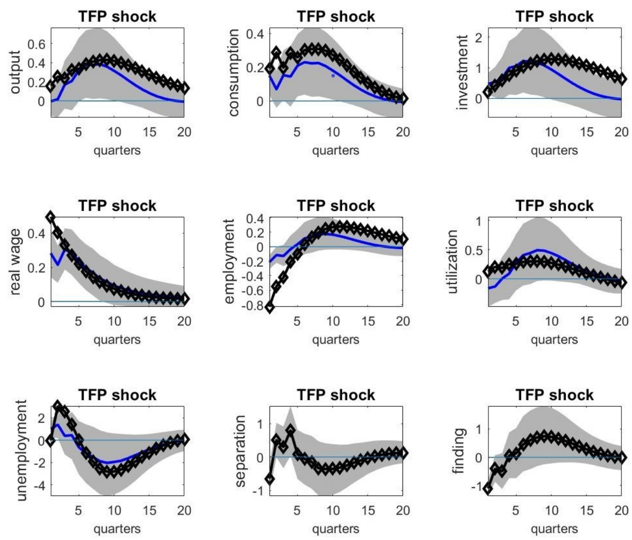
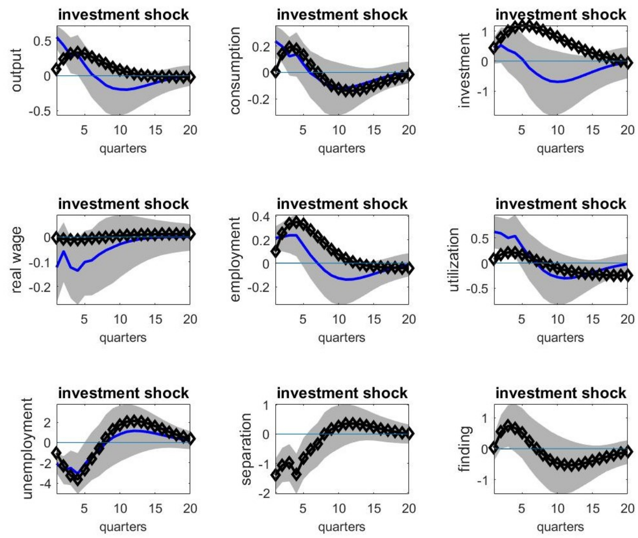
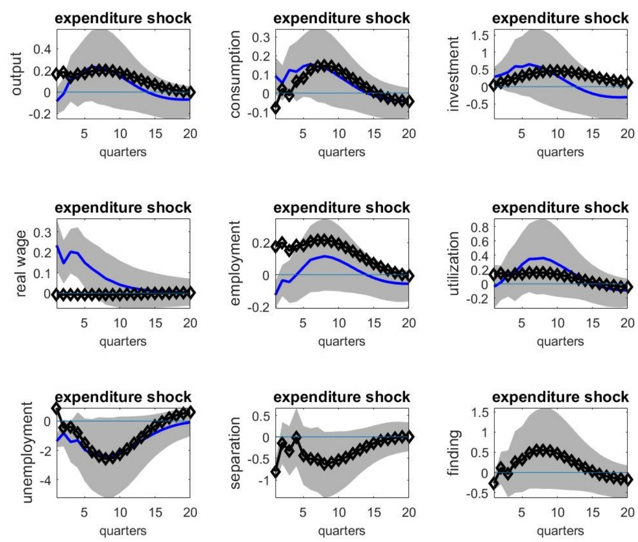


Figure 8: IRF to TFP shock: model and SVAR

Note: *The Figure plots the percentage responses of each variable to a one standard deviation TFP shock. The black line with diamond squares represents the DSGE model and the blue full line the VAR model. The VAR includes* $p = 4$ *lags. The shaded areas are 95% VAR confidence intervals computed using bootstrap with 10,000 replications.*

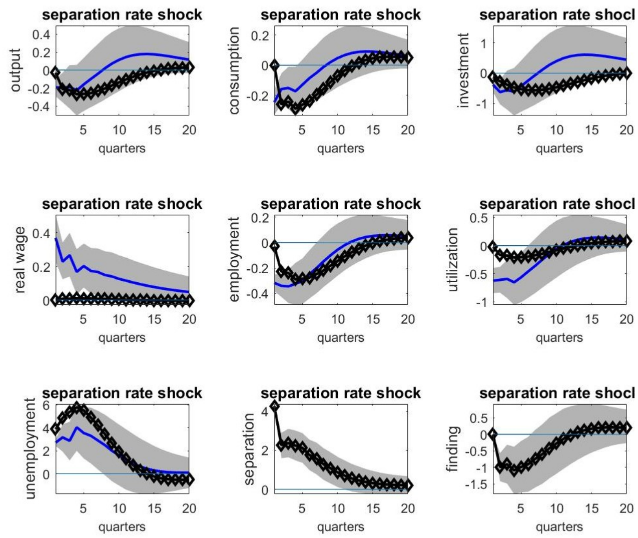


(a) IRF to investment-specific shock: model and SVAR

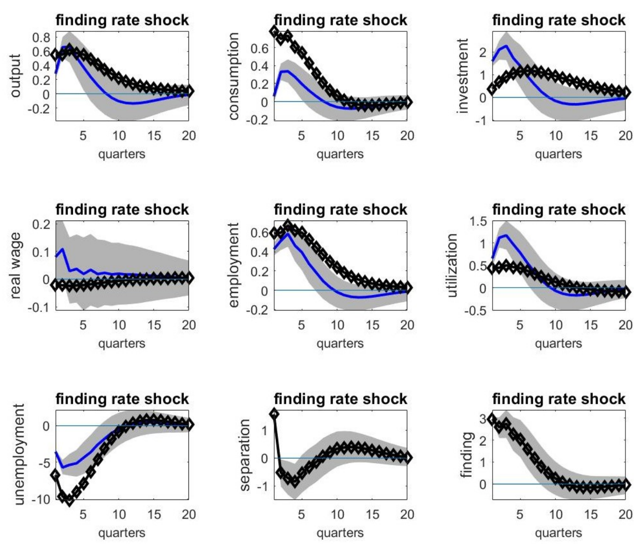


(b) IRF to expenditure shock: model and SVAR

Figure 9: IRFs to investment-specific (panel a.) and expenditure (panel b.) shocks: model vs. SVAR.



(a) IRF to job-separation shock: model and SVAR



(b) IRF to job-finding shock: model and SVAR

Figure 10: IRFs to separation (panel a.) and finding shock (panel b.) shocks : model vs. SVAR.

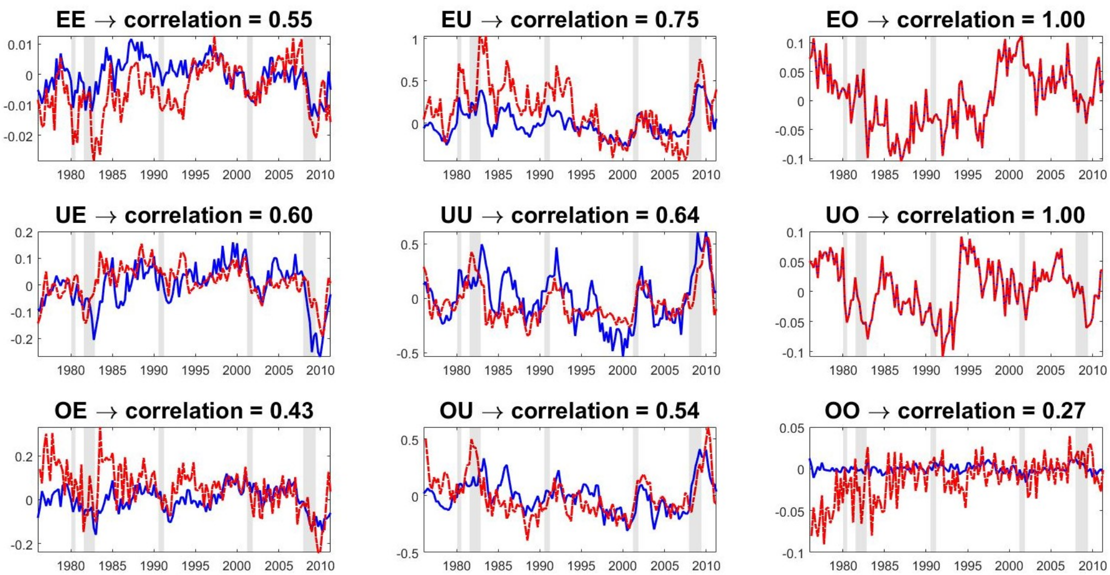


Figure 11: Baseline scenario: gross worker flows

(data — and in-sample model fit - -)