The Ins and Outs of Unemployment in General Equilibrium*

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Abstract

We develop a general equilibrium business cycle model of the labor market which is agnostic about the determinants of unemployment inflows and outflows. To close the model we impose a moving average representation for the Ins and Outs, obtained from a structural factor augmented vector autoregression model. By estimating the augmented DSGE model, we learn about the structural parameters and shocks contributing to the business cycle, without miss-specified dynamics for the unemployment inflows and outflows. Real wage rigidities are not found to be important. Participation is nearly acyclical, but flows across employment, unemployment and non-participation are strongly cyclical.

Keywords: unemployment inflows and outflows, labor market, business cycles.
JEL Classification: C50, E24, E32, J22, J64.

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1 Introduction

The labor market in advanced market economies is characterized by high rates of worker flows across different jobs, and between employment, unemployment and non-participation. These worker flows hold the key to understand unemployment fluctuations over the business cycle, since a model that successfully accounts for the transitions between employment, unemployment and non-participation will also successfully match the unemployment volatility. Given the inability of macroeconomic models to account well for the aggregate labor market volatility (the unemployment volatility puzzle unveiled by Shimer, 2005), it is important to develop business cycle models that are able to match gross flows successfully. For example, a salient feature of gross worker flows, recently emphasized by Elsby et al. (2015) and Krusell et al. (2017), is that although the participation rate is relatively stable over the business cycle, the volatility of individual flows into and out of the labor force is of roughly the same magnitude as that of the flows between employment and unemployment. Therefore, to understand the dynamics of gross workers flows requires a model in which participation is endogenous but, at the same time, in which intertemporal substitution in labor supply does not exacerbate the procyclicality of participation.

In this paper we propose a tractable dynamic stochastic general equilibrium (DSGE) model of the business cycle that includes frictional labor markets and individual labor market transitions between three states: employment, unemployment and non-participation. Although ours is clearly not the first equilibrium business cycle model to include endogenous labor force participation, most existing studies adopt the large representative family assumption, whereby a stand-in family chooses the number of members to allocate between the three labor market states, thus pinning down net flows but leaving gross flows across each state undetermined (early examples, include: Ravn, 2006, and Veracierto, 2008, and Shimer, 2013). Instead, our approach adopts the indivisible labor supply set-up of Hansen (1985) and Rogerson (1988), with individuals who choose lotteries over labor force participation, have access to insurance contracts and experience heterogeneous employment histories. Although the model is extremely tractable, the focus on individual labor market choices yields a detailed characterization of gross worker flows.

Our main findings about the labor market business cycles are as follows. First, on the sources of volatility, the estimated model attributes a negligible role to TFP shocks and to exogenous expenditure shocks to explain business cycles and, in particular, unemployment volatility. Instead, investment specific technology shocks, and shocks to labor market frictions (orthogonal shocks to the finding rate and, to a lesser degree, job destruction shocks), are the predominant source of business cycle volatility. Second, on the transmission of shocks, we find that all three shocks transmit to the economy to a large extent by affecting the job finding rate. Although we allow for real wage rigidities, the estimated model assigns a large value to the real wage elasticity to changes in average labor productivity. Thus, real wage rigidities are not found to be important to explain unemployment dynamics. However, given the nature of the shocks which are found to be important to explain business cycles (in particular the finding rate shock and the investment specific shock), the real wage is found to be almost acyclical.

Our third important finding concerns the volatility of the labor force participation, and the gross flows underpinning those dynamics. In particular, the estimated model successfully accounts for the mild procyclicality of the labor force participation. This result is significant given the tendency for models featuring intertemporal substitution in frictional labor markets to deliver excessively procyclical participation and, thus, procyclical unemployment (a problem stressed by Ravn, 2006, and Shimer, 2013, for example). Underpinning the dynamics of labor force participation, we find that the transitions rates from employment and unemployment into non-participation are procyclical, indicating that in periods of high unemployment fewer workers exit the labor force. On the other hand, 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 (echoing Elsby et al., 2019, empirical characterization of the US labor market).

Another important result concerns the measurement of the job finding rate during the 2008 – 2009 Great Recession. It is widely acknowledged that measurement and classification errors are pervasive in the CPS employment, unemployment, and unemployment duration data used to measure the unemployment inflow and outflow rates (Shimer, 2012). In particular, during the Great Recession, Elsby et al. (2011) argue that the long-term unemployed were overestimated because of classification errors (specifically, due to large inflows to unemployment at reported durations exceeding one month), causing a spurious excess decline in the observed job finding rate. Consistent with this hypothesis, our estimated DSGE model attributes an important role to measurement error in the job finding rate during this period, implying an overreporting of the decline in the measured job finding rate. Instead, the role of measurement in the remaining sample is much smaller. This finding suggests another important advantage of estimating a DSGE model to evaluate the unemployment Ins and Outs is the ability to disentangle the structural inflow and outflow rates from the measurement error using the likelihood Kalman filter.

Regarding its focus on gross workers flows over the business cycle, the work most closely related to ours is by Krusell et al. (2017), who also develop a heterogeneous agent model with search frictions and endogenous search effort. But there are two notable differences between our work and theirs. First, while Krusell et al. (2017) study an incomplete market economy, where labor market transitions are explained by labor market frictions and uninsurable idiosyncratic productivity shocks, we instead look at an economy with insurable idiosyncratic shocks. In our model, transitions are explained by labor market frictions in an economy with lotteries à la Hansen (1985) and Rogerson (1988). In particular, we combine the sequential randomization mechanism in Andolfatto (1996), with lotteries over labor force participation, to derive the stand-in agent representation and the gross worker flows between the three labor market states. The upshot is a model which is able to match gross worker flows remarkably well, and at the same time is very tractable, enabling estimation and simulation using standard methods.

The second important difference between the work by Krusell et al. (2017) and ours concerns the quantitative evaluation of the model's ability to explain the business cycle phenomena. The former look at very controlled deviations from the steady state equilibrium by changing the job finding and layoff rates to mimic a typical expansion or recession, but ignore general equilibrium adjustments of the labor demand and the wage rate. Recently, Krusell et al. (2020) extend Krusell et al. (2017) study, to allow for general equilibrium effects. However, both Krusell et al. (2017) and Krusell et al. (2020) are silent about which structural shocks are responsible for the fluctuations in labor market frictions. While omitting this is innocuous in a partial equilibrium framework, it matters greatly in general equilibrium which shocks cause movements in the unemployment inflow and outflow rates, since different shocks will impact labor demand and equilibrium wages differently. To understand how labor market frictions are affected by exogenous disturbances to productivity, relative prices and the resource constraints, we impose a structural moving average (MA) representation to capture the dynamics of the job finding and separation rate. This MA representation is obtained from the structural impulse response functions (IRF) of a factor augmented vector autoregression model (FAVAR), including the job finding and separation rates together with a vector of macroeconomic latent factors, and with the structural IRF identified using external instrumental variables as proxies for the shocks.

Another recent paper investigating labor market business cycles with a focus on gross flows is Cairo et al. (2019). This paper also investigates gross worker flows in a three-states labor market, using a complete markets' DSGE model featuring intertemporal substitution in labor supply. Differently to ours, their paper features a constant job destruction rate, and has no capital accumulation. Similar to the current paper, their estimated model is successful at obtaining a mildly procyclical labor force participation and also the main cyclical features of the underpinning transition rates. However, they require a very large degree of wage rigidity to avoid labor force participation turning excessively procyclical. Crucially, Cairo et al. (2019) only consider TFP shocks and, thus, average labor productivity is strongly procyclical in their model. Our model instead finds an important role for investment specific shocks and job finding rate shocks, which are associated with lower average labor productivity as employment rises. As an upshot, our findings are consistent with an acyclical real wage, but a large elasticity of wages to changes in average labor productivity (consistent with empirical evidence based on microdata by, for example, Pissarides, 2009, and Haefke et al., 2013).

Methodologically, our approach is related to the work by Cúrdia and Reis (2010), and Den Haan and Drechsel (2020). The latter, introduce additional disturbances with associated reduced-form coefficients to the DSGE structural equations, which do not impose additional cross-equation restrictions. The former allow for correlated disturbances by modeling the structural shocks from a DSGE as a covariance stationary VARMA model. Unlike Den Haan and Drechsel (2020), we maintain that the exogenous structural shocks are orthogonal while introducing correlation between the disturbances and the job finding and separation rates (both observable variables) using an auxiliary structural MA representation external to the DSGE model.

Importantly, since the DSGE model is underdetermined, leaving the job finding and separation dynamics unspecified (hence, exogenous), the structural MA representation for the job finding and separation rates do not violate any cross-equation restrictions imposed by the equilibrium model (this feature is, thus, similar to Den Haan and Drechsel, 2020). Thus, our approach to combine the structural MA and DSGE models is different from Del Negro and Schorfheide (2004) seminal DSGE-VAR method of eliciting priors for a reduced form VAR based on a more parsimonious DSGE model. In particular, unlike theirs, our approach does not confront model miss-specification directly. In a recent paper, Drautzburg (2020) extends the DSGE-VAR framework by substituting the reduced form VAR with a structural proxy-VAR and, thus, imposes, causal inference on impulse response functions (IRF). We also identify structural IRF based on a proxy VAR, but only for variables which are exogenous in the DSGE model (the job finding and separation rates).

Finally, our approach is also related to Caldara et al. (2014), who show how to represent the propagation of shocks originating in sectors that are not included in the baseline DSGE using an auxiliary VAR model. We follow their approach by modeling the dynamics of the job finding and separation rates with an auxiliary MA model. However, we differ from Caldara et al. (2014) as we allow for the job finding and separation rates to affect the transmission of structural shocks that are part of the underlying DSGE model. In particular, the forecast errors from the FAVAR used to model the job finding and separation rates are spanned by the space of structural shocks, that include a total factor productivity shock, an investment specific shock, an exogenous expenditure shock, a job destruction shock and a job finding shock.

The rest of the paper is organized as follows. Section 2 develops the general equilibrium business cycle model. Section 3 describes the structural FAVAR model used to model the joint dynamics of the job finding and separation rates. Section 4 considers the estimated augmented DSGE model, and Section 5 evaluates its ability to account for labor market business cycles and, in particular, the observed gross labor market flows. Finally, 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 that purchase lotteries played over labor market 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

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

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 $v(\ell)$ is an increasing and concave function, with $v(1) = 0$. 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 sequel 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.

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), despite the random matchings 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.[1]

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

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

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

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

[1] In Appendix A we show how this aggregation result is obtained.

budget constraint

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

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; $\mathcal{S}(\bullet)$ captures investment adjustment costs as in Christiano et al. (2005), with $\mathcal{S}(1) = \mathcal{S}'(1) = 0$ and $S''(1) \equiv \kappa_x > 0$; $\iota_t > 0$ is capital utilization (equal to $\underline{\iota}$ in steady state); and $\delta(\iota_t)$ is capital depreciation, which is a strictly convex function in utilisation, with $\delta(\underline{\iota}) = \underline{\delta} \in (0,1)$, and $\underline{\iota}(\delta''/\delta') \equiv \kappa_\iota > 0$. 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).[2]

In the sequel, 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

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

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

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

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

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

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

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

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

[2] As explained in the sequel, final good firms in this economy are perfectly competitive and do not earn profit rents, but recruiting firms do earn profit rents given the existence of labor market search frictions.

that individuals starting date t employed, and whose jobs are not destroyed, always choose to participate in the labor market, yielding condition (10).[3]

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 employment, unemployment, and non-participation, that result from individual optimising behaviour. The competitive equilibrium transition probabilities are given by

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

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, $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$. In the system (17), the transition probability $\phi_{ee,t}$ has two distinct components, which are $(1 - s_t)$ and $\pi_{s,t} s_t f_t$. The first component, $(1 - s_t)$, yields the probability of an individual who starts the period employed in a given job to remain at the same job at the end of the period, while the second term, $\pi_{s,t} s_t f_t$, yields the probability of a laid-off worker to transit to another job within the same period.

[3] Multiple equilibria exist for $\pi_{u,t}$, $\pi_{o,t}$ and $\pi_{s,t}$; however, aggregate consumption, investment and employment allocations are identical across different equilibria. Moreover, assuming the existence of an interior solution with $\pi_{u,t}, \pi_{o,t}, \pi_{s,t} \in (0, 1)$, the symmetric equilibrium where $\pi_{u,t} = \pi_{o,t} = \pi_{s,t}$ is always implementable, although empirically it is not the most salient.

The model has the following property: the gross worker flows are indeterminate. Specifically, given the predetermined measures U_{t-1}, O_{t-1} and N_{t-1}, and an equilibrium realisation for H_t (which is pinned down uniquely), there exist multiple equilibrium solutions for $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$, each yielding identical aggregate allocations. The upshot, is that $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$ must be obtained from an extrinsic mechanism (sunspots) to resolve the indeterminacy. Selecting two of the three elements in $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$, determines uniquely two of the three gross flows in $\{\phi_{uo,t}, \phi_{oo,t}, \phi_{eo,t}\}$. Thus, allowing us to test the model's performance for the remaining seven gross flows. In Section 5, we argue that this property of the model allow us to uncover the crucial role of flows $\phi_{uo,t}$ in determining the variation in the unemployment rate.

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 C 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.

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.[4] From the perspective of the stand-in intermediate firm employment evolves exogenously according to the motion equation

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

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

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

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 market participation condition

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

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

[4] This modelling approach is similar to that followed by Şahin et al. (2014), who also represent unfilled vacancies as following an exogenous stochastic process. As they explain in their paper, this is equivalent to a model with endogenous vacancy posting and an elasticity of the cost of creating vacancies which is infinitely large. See Appendix B for an interpretation of this approach.

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 lead 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.[5]

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

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

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

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

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

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

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

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

[5] 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 workers 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. The upshot is that the probability of starting date $t+1$ in employment is N_t and is taken as given by the stand-in agent. Thus, there is no asset value of employment in the participation condition (24). The "musical chairs" device is an artificial mechanism to construct a recursive equilibrium (see Appendix A for full details). But the same allocation can be achieved with an Arrow-Debreu formulation contingent on sunspots (Kokonas and Monteiro, 2019).

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

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 (2005) 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: quarterly job separation and finding probabilities in logs, US (1948:1 – 2018:4)

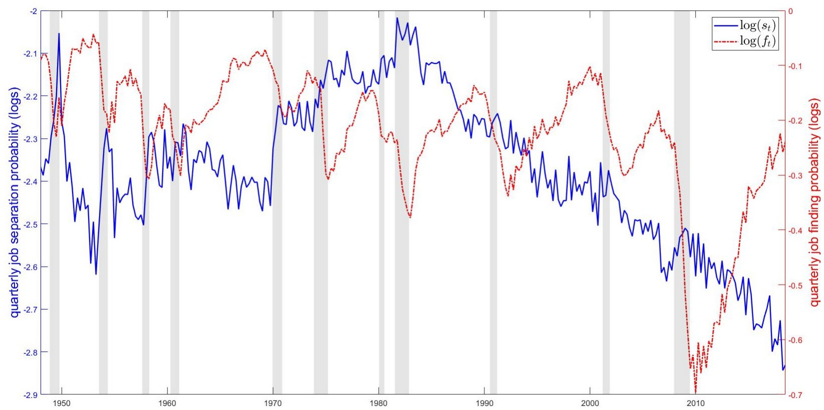


Figure 1 reveals the substantial volatility at business cycle frequencies in the job finding rate, but it also suggests upshifts in the job separation during most recessions. At any rate, the unemployment inflow rate does not appear to be entirely acyclical. Therefore, we propose a very general and non-committal 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 $i = 1, \dots p$, 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.

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 $\mathbf{B}$.[6]

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 $\{\Phi_i\}_{i=0}^{\tau}$ 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 general equilibrium model.

Based on this result, the approach that we follow in the sequel is to complete the underdetermined DSGE model developed in Section 2 with the system of equations in (39). To ensure that the

[6] The model represented by equation (36) is a FAVAR model as proposed by Bernanke et al. (2005). The model can be estimated using a simple two-step procedure. In the first step, the latent factors $\hat{m}_t$ are obtained as the first $\mathtt{k}$ principal components of $\mathcal{X}_t$, which is a $\mathtt{q}$ dimensional vector of observable macroeconomic time-series forming the information set. In the second step, the augmented VAR model is estimated. With the FAVAR method, the IRFs can be constructed for any variable in $\mathcal{X}_t$, the information set, using the projection $\mathcal{X}_t = \Lambda \left[\hat{s}_t,\, \hat{f}_t,\, \hat{m}_t'\right]'$, where Λ is a $\mathtt{q} \times \mathtt{n}$ matrix of factor loadings. By using a large informational data-set, the FAVAR model is better suited to avoid non-fundamental representations and, thus, enabling the identification of the structural shocks (see Giannone and Reichlin, 2006, for a careful explanation of this issue).

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.[7]

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 relies on the use of instrumental variables that contain information about a subset of the structural shocks in the SVAR, and an additional short-run restriction rendering the SVAR invertible. In particular, we obtain an instrumental variables for, in turn, the TFP shock, the investment specific (IS) shock, and the exogenous expenditure (EE) shock. To identify the i^{th} shock an instrumental variable, z_t, must satisfy the conditions

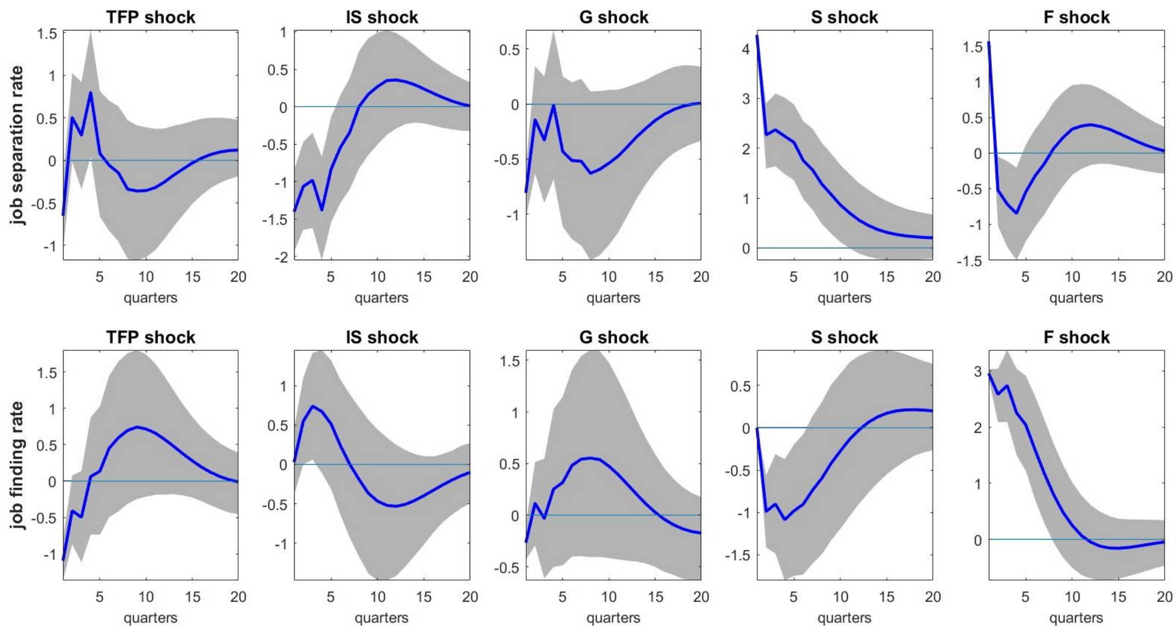
1. $\mathbf{E}\left(z_t \mathcal{E}_t^i\right) = \psi \neq 0, \ \forall \ t;$
2. $\mathbf{E}\left(z_t \mathcal{E}_t^s\right) = 0, \ \forall \ t$ and $s \neq i$.

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 $\mathbf{B}$.[8]

[7] 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.

[8] The implementation of the instrumental variable method is explained carefully in Appendix G. The choice of

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 one standard deviation innovation to each structural shock. The VAR includes $p = 4$ lags. The shaded areas are 95% confidence intervals computed using bootstrap with 10,000 replications.

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.[9]

instruments follows some of the best practice in the literature. In particular, instrumenting the TFP shock using the innovations to the Fernald (2014) utilization adjusted TFP measure follows recent work by Caldara and Kamps (2017); Fisher (2006) uses the innovations to the relative price of investment to measure the investment specific shock; finally, the narrative-based measure of defense expenditure shocks is advocated by Ramey (2011) and Ramey and Zubairy (2018).

[9] The result that the job finding rate falls on impact following a positive TFP shock is not new in the literature.

The effect of the exogenous expenditure shock on the labor market are also found to be 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 consider the job finding and separation shocks. The latter is identified by imposing a zero short-run restriction (assuming the orthogonal job separation shock has no effect on the job finding rate on impact).[10] Both shocks have a substantial impact on the unemployment inflow and outflow rates. Moreover, the job finding and separation rate appear to be strongly intertwined with, for example, shocks to the job separation rate lowering substantially the job finding rate. These dynamics are protracted, with the peak impact occurring roughly one year after the shock. The interplay between the inflows and outflows is, therefore, playing an important role to explain the labor market business cycle dynamics.[11]

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 it corresponds to the typical business cycle periodicity, and 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 (as described in, for example, An and Schorfheide, 2007).[12] The model is estimated on quarterly US data spanning 1948:q1 until 2018:q3,

Balleer (2012) also exploits a structural VAR model for the job finding and separation rates and, like us, includes a measure of productivity and the relative price of investment. Instead of using short-run exclusion restrictions, the author identifies the structural productivity shock based on long-run restrictions, and similarly to us finds that the job finding rate falls conditional on a neutral technology shock and increases conditional on an investment specific shock. Christiano et al. (2016) also report similar results.

[10] Of course, the job separation shocks is allowed to affect the job finding rate subsequently. Indeed, this effects appear to be important. For example Coles and Moghaddasi Kelishomi (2018) argue that layoff shocks cause subsequent falls in the job finding rate.

[11] If the structural VAR model is not invertible, the proxy VAR method yields identification of the IRF but does not identify the contribution of each shock to the macroeconomic volatility (see Plagborg-Møller and Wolf, 2018, for a discussion of this). In section 4 we obtain forecast error variance decompositions based on the estimated DSGE model.

[12] Details about the estimation method are provided in Appendix H.

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);
$\underline{\mathrm{G}}/\underline{\mathrm{Y}}$	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);

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.[13]

4.1 Parameter restrictions and steady state gross flows

Not all parameters of the model are to be estimated, and we follow the standard practice of calibrating some of the parameters to match selected secular features of the macroeconomic time series (as in, for example, Christiano et al., 2016). All the calibrated parameters and the targets determining their calibration are reported in Table 1. As they are less standard, we explain more carefully the calibration of the parameters that shape the gross labor market flows in steady state: $\left(\underline{f}, \underline{s}, \underline{\pi}_s, \underline{\pi}_u, \underline{\pi}_o\right)$. In particular, as explained in Section 2, for a given aggregate participation rate $\underline{\Pi}$, the participation rates chosen by the different groups of individuals not in employment (in turn, $\underline{\pi}_s$, $\underline{\pi}_u$, and $\underline{\pi}_o$) are not uniquely pinned down by the equilibrium conditions. Thus, their values in steady state can be set to target some specific steady state gross worker flows.

[13] Including measurement error in the observation equations for the job separation and finding rates is also 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). The estimation of a DSGE model with measurement error offers a good approach to deal with such measurement problems.

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

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 (based on calculations by Gomes, 2015), and using system (40) obtain $\underline{f} = \underline{\phi_{ue}} / \left(1-\underline{\phi_{uo}}\right) = 0.738$. Similarly, we set the average job separation rate, $\underline{s}$, to match the CPS gross flows, using the relationship $\underline{s} = \underline{\phi_{eu}} / \left(1-\underline{f}\right) + \underline{\phi_{eo}} = 0.190$, and $\underline{\pi}_s = 1 - \underline{\phi_{eo}}/\underline{s} = 0.547$. We set the value for $\underline{\pi}_u$ to match the transition probability from unemployment to non-participation, $\underline{\pi}_u = 1 - \underline{\phi_{uo}} = 0.624$. Finally, $\underline{\pi}_o = 0.255$, to match the steady state historical average participation rate of individuals aged 16 to 64 of 71.0% (our aggregate participation target, $\underline{\Pi}$).[14]

Table 2 compares the empirical gross flows to the steady state gross flows implied by the calibrated model. Despite its parsimony, the model is able to match the empirical transition rates remarkably well, roughly on a par with the richer incomplete markets model by Krusell et al. (2017).

[14] Although we do not use it as a target, the calibration yields and unemployment rate in steady state equal to

$$\underline{u} = \frac{\underline{s}\left(1-\underline{f}\right)}{\underline{f}\left(1-\underline{s}\right)+\underline{s}} = 6.32\%,$$

which is very close to the historical average unemployment rate in the US.

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

In columns 3 – 5 of Table 3 we report, in turn, the posterior mode, the posterior standard deviation, and the 80% credible set for each parameter, obtained by the Metropolis-Hastings algorithm. The marginal posterior densities for most parameters are at least an order of magnitude tighter compared to the corresponding prior distributions, indicating that all parameters are well identified. Interestingly, the persistence of the three serially correlated exogenous stochastic disturbances is found to be less than what is commonly found in the literature. Specifically, the TFP, IS and EE shocks AR(1) coefficients are estimated to be, in turn, 0.833, 0.810 and 0.737. In contrast, in the literature these coefficients are often estimated to be above 0.9. This finding suggests that the internal propagation in the model is stronger than in the canonical DSGE model. Of course, an important source of propagation in our model is the response of the job finding rate to each shock, implied by the structural MA process in equation (39).

Next, we turn to the estimates of the main structural parameters. We are particularly interested in the structural parameters in the intratemporal labor participation condition of the non-employed, that are directly relevant for the propagation of shocks through the labor market: κ_ξ and κ_w. The parameter κ_ξ controls the propagation of shocks through the job finding rate, while κ_w controls the degree of wage rigidity (the elasticity of the real wage to changes in average labor productivity).

Starting with κ_ξ, its posterior mode is estimated at $\kappa_\xi = 0.277$, and the parameter is well identified, judging from the tightness of the posterior distribution. To interpret this value, recall that κ_ξ

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	$[0.470$, $0.570]$
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.

manifests itself in the following log-linear equilibrium condition

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

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. Note that if κ_ξ is zero, participants in the labor market only forgo utility conditional on employment and $\kappa_\xi \hat{f}_t$ drops from equation (41). In that case, fluctuations in the opportunity cost cancel out with fluctuations in the effective wage, and our framework reduces to the standard RBC model with indivisible labor supply.

Equation (41) uncovers two channels through which the participation margin is affected. The first channel is through returns to market work and it is based on the cyclical behavior of the effective wage rate, $\hat{w}_t + \hat{f}_t$, the right-hand side of (41). The second channel is through the opportunity cost of employment and it is based on the behavior of the cyclical component of the opportunity cost, $(1 - \kappa_\xi)\hat{f}_t$, the left-hand side of (41). In turn, it follows that the net effective wage rate, taking into account fluctuation in the opportunity cost, reduces to $\hat{w}_t + \kappa_\xi \hat{f}_t$. Fluctuations in the participation margin are controlled by the behavior of the net wage rate. In light of the previous discussion, equation (41) reduces to

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

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.

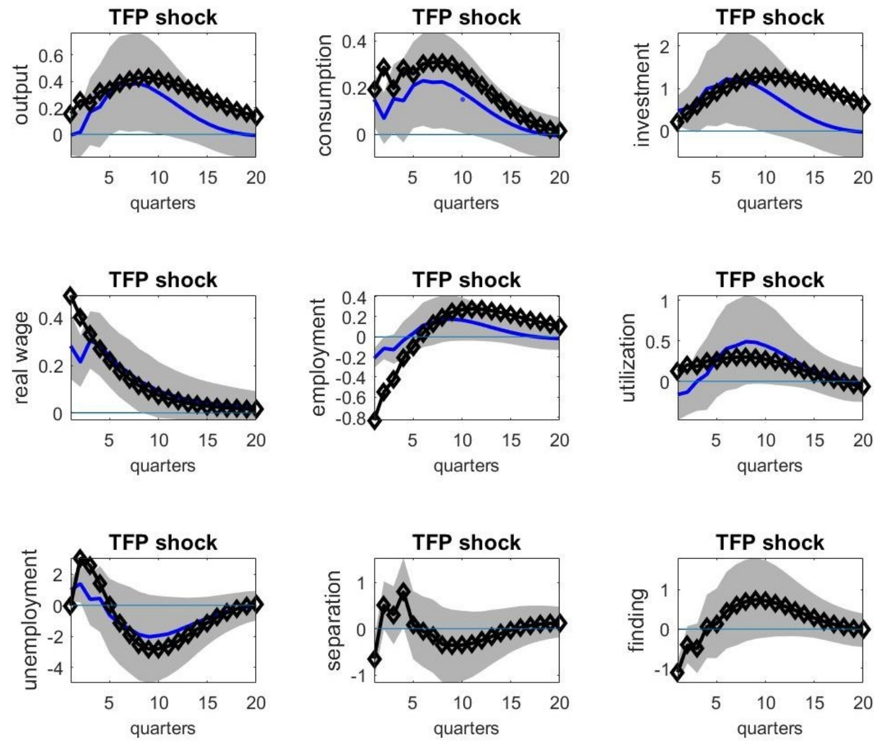
The parameter κ_w controls the elasticity of the real wage rate to changes in average labor productivity. The posterior mode of this elasticity is $\kappa_w = 0.502$. Thus, the real wage is estimated to respond quite strongly to changes in productivity. This result echoes well with the findings by Pissarides (2009) and Haefke et al. (2013), based on micro level data, that the real wage of new hires is volatile. Indeed, κ_w is identified from (42), the labor supply condition relevant for the the non-employed individuals and, hence, potential newly hired workers. Therefore, the finding that κ_w is equal to 0.502 is in line with the micro evidence that the wage of the newly hired is volatile.

Finally, the estimated posterior mode for the habits persistence parameter, $\chi = 0.015$, is negligibly small, which is in sharp contrast with other available estimates in the literature. The elasticity of the cost of changing investment posterior mode is estimated $\kappa_x = 8.497$, slightly lower than other available estimates. Importantly, both parameters are well identified (as the marginal posterior for both χ and κ_x is tightly distributed and located away from the prior). Finally, the inverse elasticity of capital utilization to changes in the return to capital has posterior mode $\kappa_\iota = 0.806$, similar to what is found elsewhere in the literature. Overall, these results suggest that the model's internal propagation relies less on habits and adjustment costs. Instead, the persistency and protractedness in the adjustment to shocks is accounted for by the adjustment in the job finding rate. We illustrate this result clearly in what follows.

4.4 Business cycle dynamics

Our main purpose is to arrive at a model which is successful at matching gross worker flows. But before focusing on the labor market dynamics, we consider how the estimated DSGE model accounts for the business cycle phenomena broadly. To do this, we begin by looking at the model's estimated

Figure 3: 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.

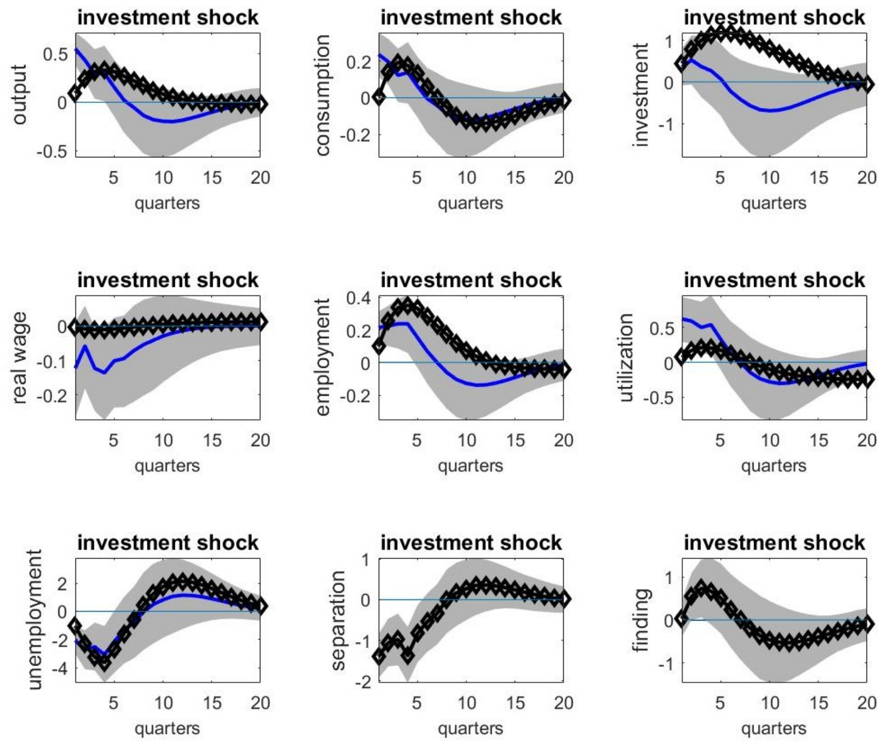
impulse response functions (IRF), and comparing those to the IRF obtained using the structural FAVAR in Section 3. Next, we look at the contribution of each structural shock to explain the business cycle volatility in terms of conditional forecast error variance decompositions.

4.4.1 Impulse Response Functions

In Figures 3 to 7, 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.[15]

[15] 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

Figure 4: IRF to investment specific shock: model and SVAR



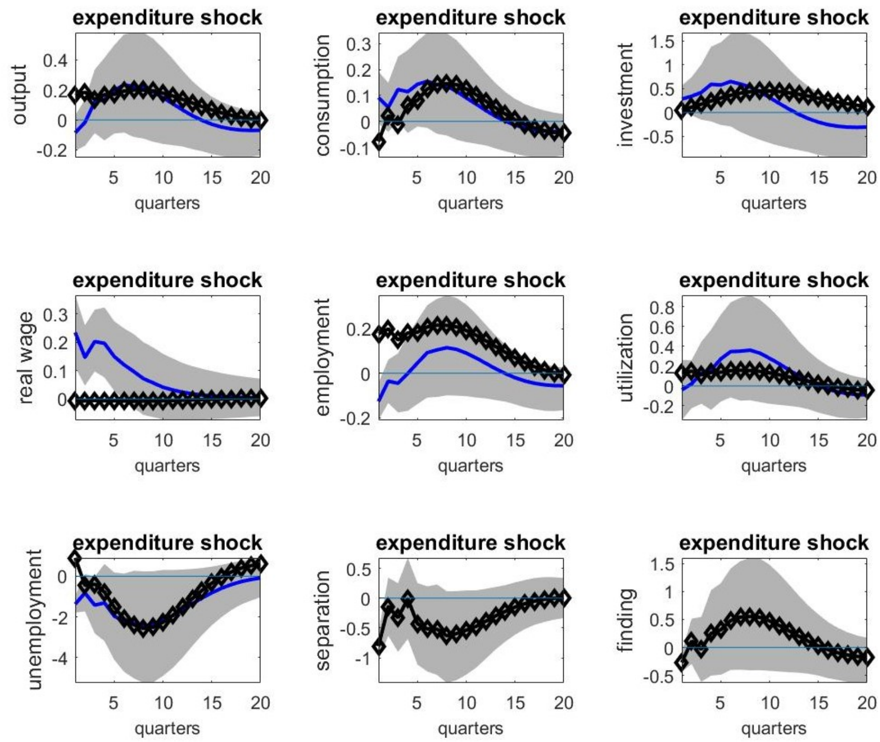
Note: See notes to Figure 3.

Starting from Figure 3, we look at the adjustment following a TFP shock. Noticeably, the model matches well the conditional dynamics of all variables, although the response of employment to the TFP shock is too strong on impact. Consistent with the FAVAR model, the response of investment to the TFP shock is protracted and humped shaped. The estimated model is also successful at matching quite well the response of consumption and output to the TFP shock. Specifically, the response of consumption is strong and persistent, as higher TFP and capital utilization raise output, despite the fall in employment. The response of employment is driven by the job finding rate which falls sharply following a positive TFP shock and, thus, lowers the return to participation.

Turning to the investment specific (IS) shock in Figure 4, ϵ^v, we find the model matches the conditional business cycle dynamics very well. At almost all horizons the model responses are within their 95% confidence interval FAVAR counterparts. Noticeably, both consumption and employment increase on impact. Underpinning these dynamics is an increase in the job finding rate conditional on

dynamics of unemployment inflows and outflows.

Figure 5: IRF to expenditure shock: model and SVAR



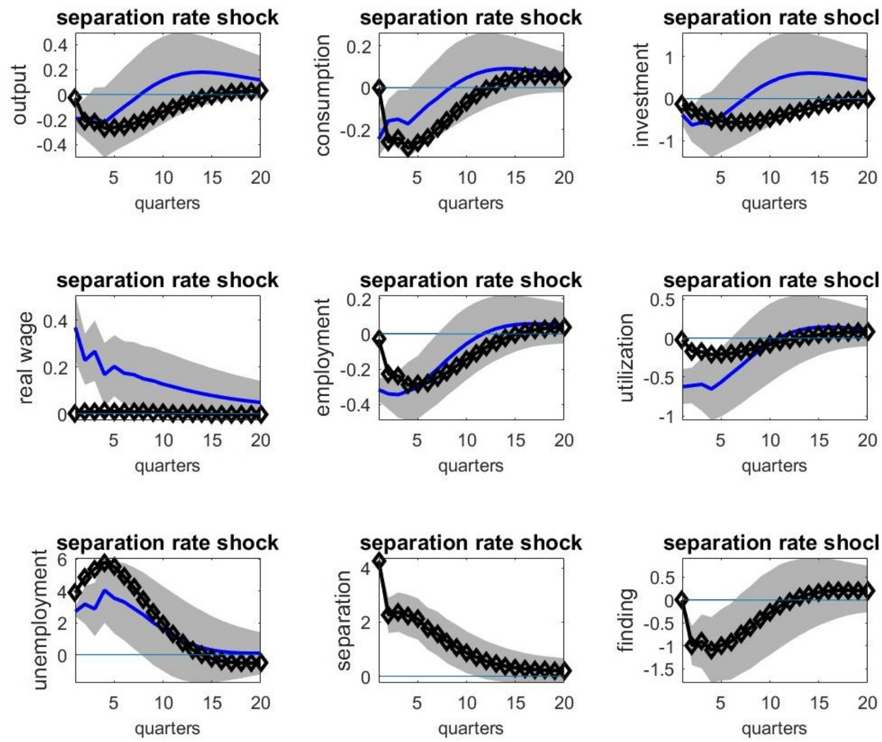
Note: See notes to Figure 3.

a positive IS shock. For a given mass of participants, the higher job finding rate raises employment and, thus, lowers the real wage (the reduction in the real wage is attenuated by an increase in capital utilization, as the capital-output ratio falls). However, the effective real wage rises as the finding rate increases and, thus, consumption must increase. Hence, the effective wage channel allows the model to match the positive conditional correlation between consumption and investment following an investment specific shock.

Next, Figure 5 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, which is consistent with empirical findings elsewhere in the literature (Monacelli et al., 2010).

Finally, in Figures 6 and 7 we consider the structural shocks to the labor market frictions. Figure 6 shows the conditional response to job separation shock. The first important observation is that,

Figure 6: IRF to job separation shock: model and SVAR

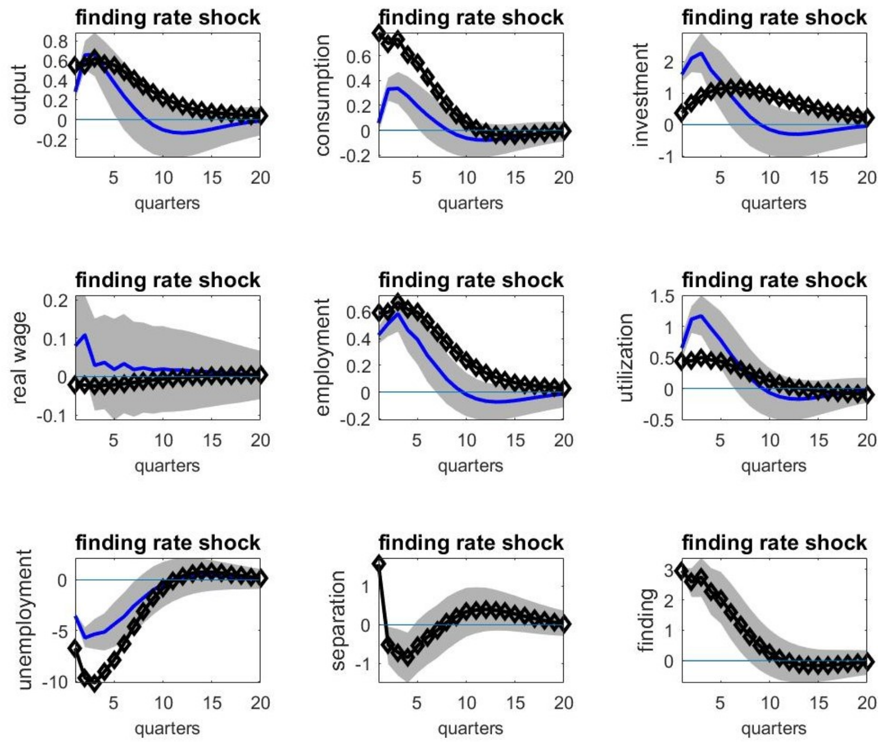


Note: See notes to Figure 3.

given the block-recursive structure of the system of equilibrium conditions described in Section 2, the job separation shocks, ϵ^s, are only transmitted to consumption, investment and employment, through their impact on the job finding rate. In particular, we can see from the bottom two panels of Figure 6 that a positive job separation shock persistently lowers the job finding rate, although the effect on impact is restricted to be zero. The reduction in the job finding rate leads to a protracted reduction in consumption, investment and output, which matches very well the estimated IRF based on the FAVAR model. The model also matches the conditional dynamics of employment and unemployment rate following the job separation shock, even if it slightly overestimates the magnitude of the response of the unemployment rate.

Lastly, following a shock to the job finding rate the model matches very well the response of all the macroeconomic aggregates, even if it overestimates the magnitude of 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 4 and 7),

Figure 7: IRF to job finding shock: model and SVAR



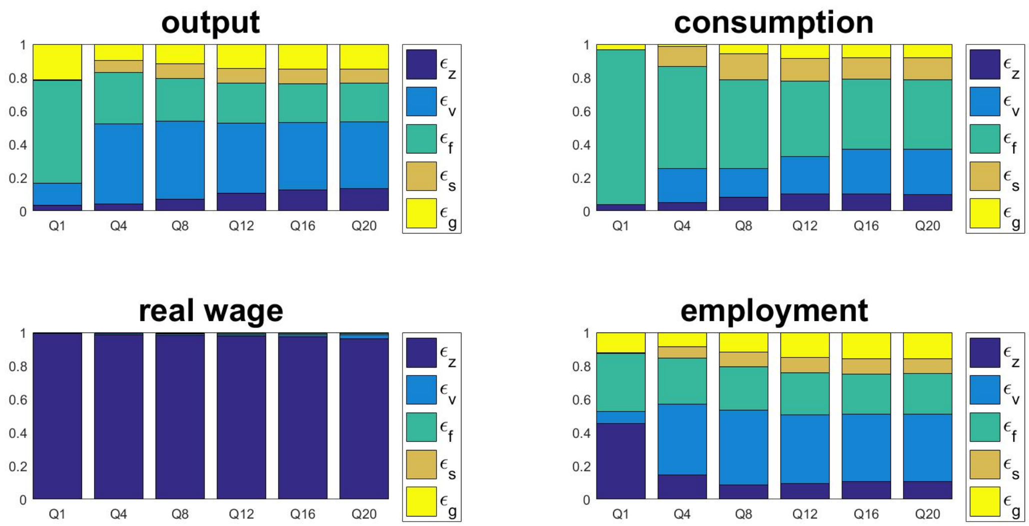
Note: See notes to Figure 3.

suggesting an analogous propagation mechanism.

4.4.2 Variance decompositions

Next we consider the contribution of each shock to business cycle volatility. In Figure 8 we report the contribution of each shock to the forecast error variance (FEV) decomposition obtained at different horizons (in turn, 1, 4, 8, 12, 16 and 20 quarters), for output, consumption, real wages and employment. Turning first to output and consumption, the shocks that play the predominant role are, over very short horizons, the job finding rate shock, and at medium to long-run horizons both the job finding rate shock and the investment specific (IS) shock. This result highlights the importance of the internal propagation mechanism through which fluctuations of $\hat{f}_t$ affect the dynamics of output and consumption. Moreover, given that the volatility of the real wage is driven entirely by the TFP shock, the contribution of the IS shock to consumption over longer horizons is transmitted solely through its impact on the job finding rate. Finally, turning to employment, the

Figure 8: forecast error variance decomposition of main aggregates



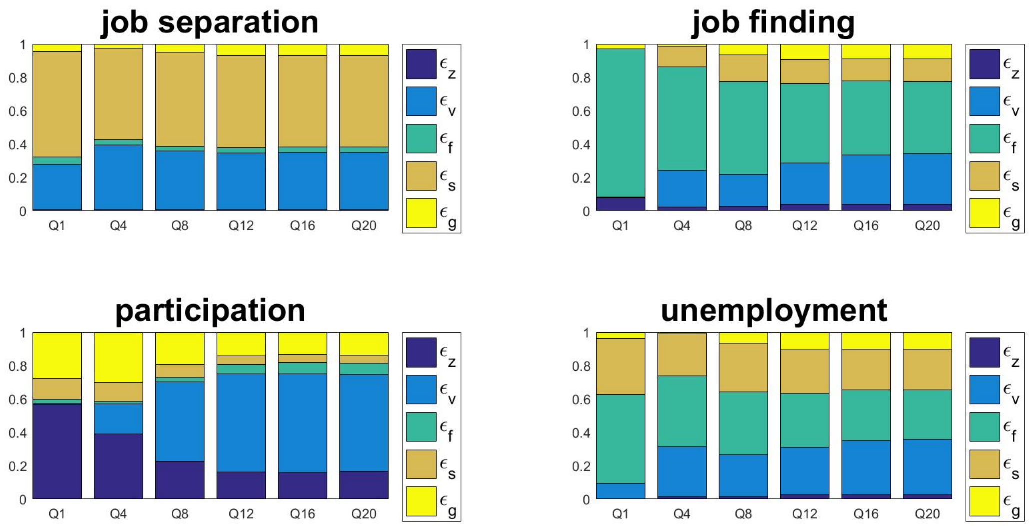
TFP shock explains almost 50% of its volatility over very short horizons, indicating that wage rate fluctuations account for the bulk of employment volatility in the short run. However, over longer horizons, the contribution of the TFP shock to the volatility of employment is less than 20%, and the bulk of the volatility is explained by the job finding rate shock and the IS shock.

Figure 9 shows the FEV decomposition for the unemployment inflows and outflows, the labor force participation and the unemployment rate. Starting with the job separation rate (the upper-left panel in Figure 9), we see that the investment specific shock explains around 40% of its volatility at all horizons, indicating the importance of these shocks for job layoffs. Equally important to explain the volatility of the job separation rate is the exogenous separation shock, while the TFP and exogenous expenditure shock appear unimportant.

Turning to the FEV decomposition for the job finding rate, the TFP shock explains only a very small share of its overall volatility. The exogenous expenditure shock also plays a moderate role. Exogenous shocks to labor market frictions and, to a lesser extent, investment specific shocks explain most of the fluctuations in the job finding rate. As an upshot, the unemployment volatility over medium and long-run horizons is largely explained by these shocks.

These findings echo the Shimer puzzle (Shimer, 2005). Specifically, technology shocks which directly affect average labor productivity and job creation are not sufficient to explain the empirical volatility

Figure 9: forecast error variance decomposition of inflows and outflows



of the main labor market aggregates. The estimated model must assign a large role to exogenous shocks to the finding rate and other structural disturbances which affect the job finding rate. Two important shocks which affect the job finding rate are the investment specific shock and the job separation shock. In assigning an important role to the latter shock to explain unemployment volatility, our results also accord well with Fujita and Ramey (2009), although the job destruction and job creation appear intertwined, and job separation shock transmits largely through its effect on the job finding rate.

Turning to labor force participation, we find a dissonance between the shocks which matter to explain unemployment volatility and those that matter for participation. In particular, over short horizons, the TFP shock explains almost 60% of participation volatility, and only over longer horizons the contribution of the investment specific shock increase. Instead, the contribution of the job finding rate shock is less important, even at longer horizons, which suggest that persistent shocks to the finding rate are not as important to explain labor force participation.[16]

[16]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

5 Labor market business cycles

This section presents the quantitative implications of our estimated model for the flows of workers across labor market states over the business cycle. We begin with a discussion of the cyclical behavior of labor market stock variables (employment, unemployment, and labor force participation), and then turn our attention to gross worker flows. Finally, we conclude with a discussion of the role assigned to measurement error in the inflows and outflows of unemployment, through the lenses of the estimated DSGE model.

5.1 Employment, unemployment and participation

We first look at the model's ability to match the cyclical movements of the 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. In particular, 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 imply 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.[17]

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

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.

[17] Other prominent examples include Veracierto (2008), Shimer (2013), Krusell et al. (2020) baseline models, which obtain correlations between participation and output exceeding 90% and participation rates substantially more volatile than employment, so that the unemployment rate is either acyclical or, even, mildly procyclical. The latter study is able to generate less procyclical movements in the participation rate (correlation of 78%) and countercyclical unemployment, only if both TFP and labor market frictions shocks are included, echoing some of our findings.

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 [−0.924 ; −0.912]	0.834	0.632 [0.620 ; 0.643]	0.615	0.701 [0.688 ; 0.711]
investment	−0.618	−0.346 [−0.357 ; −0.336]	0.835	0.898 [0.895 ; 0.900]	3.025	3.907 [3.840 ; 3.976]
real wage	−0.178	0.163 [0.147 ; 0.178]	0.384	−0.013 [−0.054 ; 0.026]	0.700	0.208 [0.193 ; 0.223]
employment	−0.718	−0.676 [−0.685 ; −0.666]	0.746	0.925 [0.916 ; 0.934]	0.649	1.086 [1.074 ; 1.098]
participation	−0.194	0.002 [−0.012 ; 0.017]	0.410	0.642 [0.628 ; 0.655]	0.305	0.801 [0.787 ; 0.815]
separation rate	0.672	0.729 [0.723 ; 0.734]	−0.389	−0.503 [−0.511 ; −0.495]	2.418	3.605 [3.564 ; 3.646]
finding rate	−0.802	−0.956 [−0.957 ; −0.956]	0.772	0.629 [0.620 ; 0.638]	2.615	2.562 [2.531 ; 2.594]
unemployment	1	1	−0.736	−0.667 [−0.676 ; −0.658]	7.137	10.911 [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.

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.[18]

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

[18]An equilibrium real wage which is nearly acyclical is consistent with the empirical evidence on US business cycles. For instance, Stock et al. (1999) find no correlation between the cyclical components of the hourly real wage and GDP in US time series.

of the second order moments of the main macroeconomic aggregates, such as output, consumption, investment and employment.

5.2 Cyclical properties of gross flows

We have emphasized the acyclical nature of the participation rate. But this result does not imply that variations along the participation margin, controlled by the behavior of the flows UO and OU, are not an important determinant of the unemployment variation. In fact, Elsby et al. (2015) show that a flow-based decomposition of the unemployment rate attributes one-third of its variation to the participation margin. Thus, in this Section we investigate the model's ability to match the the gross worker flows in our sample, from 1976:q1 until 2011:q2, which corresponds to the period over which the quarterly empirical gross flows are available.[19]

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

$$\phi_{eo,t} = s_t \left(1 - \pi_{s,t}\right) \tag{43}$$

$$\phi_{uo,t} = \left(1 - \pi_{u,t}\right), \tag{44}$$

$$\phi_{oo,t} = \left(1 - \pi_{o,t}\right). \tag{45}$$

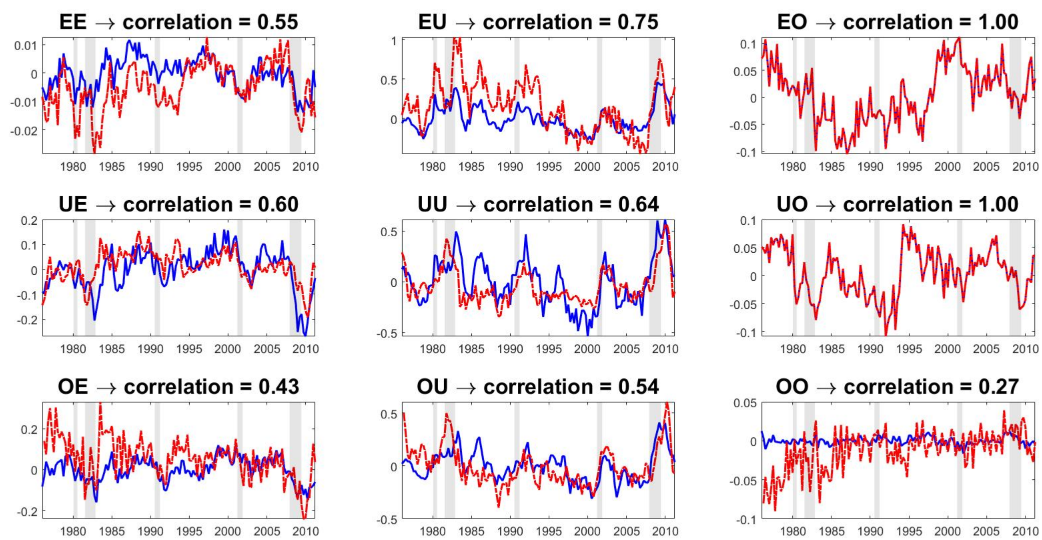
Since $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$ are not pinned down uniquely in equilibrium (recall the discussion in Section 2), it follows that we can pick values for any two elements in $\{\pi_{u,t}, \pi_{o,t}, \pi_{s,t}\}$ to exactly match two of the above gross flows. Given these, the equilibrium value 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 remaining labor market transitions that can readily 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. To test the model's fit we 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.

In Figure 10 we show all transition probabilities, while Table 5 reports their standard deviations and the correlations with the unemployment rate. The correlation between the model's generated gross flows and their counterpart is high for all flows, and the relative volatilities and correlation

[19] Quarterly gross flows are obtained from Gomes (2015).

Figure 10: Baseline scenario: gross worker flows



Note: data [blue line] and in-sample model fit [dashed red line]

with unemployment are also similar. In particular, the model matches well the flows EU and UE, with correlation coefficients at 75% and 60% respectively, and similar second order moments. This is significant because it has been documented by Elsby et al. (2015) that the flows EU and UE account for two-thirds of the unemployment variation. At any rate, the model matches very well the upwards and downwards spikes of all the flows, particularly during the 2008 Great Recession. We elaborate on this point separately in the next Section, where we show how we manage to overcome difficulties with the measurement of f_t over the 2008 – 2009 period.

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

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	0.039	−0.713	−0.787
EU	0.643	1.527	0.785	0.784
EO	0.205	0.245	0.027	−0.248
UE	0.323	0.290	−0.844	−0.475
UU	0.923	0.832	0.781	0.743
UO	0.169	0.202	−0.432	−0.499
OE	0.227	0.470	−0.689	−0.319
OU	0.573	0.854	0.706	0.710
OO	0.020	0.121	−0.068	−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).

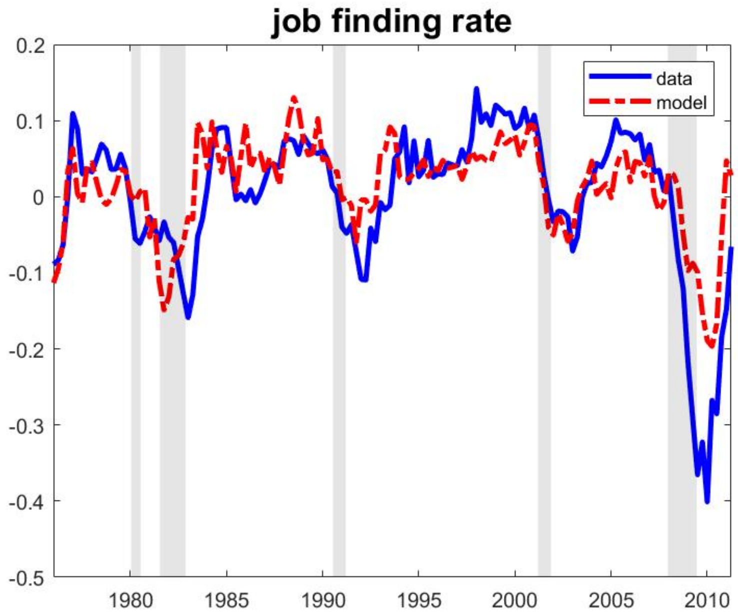
by the correlation between unemployment and the EU transition rate, which is 0.784 in the model (matching the data almost exactly). Subsequently these newly unemployed workers are more likely to exit the labor force, thus applying dynamic negative forces on labor force participation.

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.

5.3 Measurement error

The measurement of unemployment outflows is based on monthly transitions of individual workers across labor market state. At any rate, this measurement is prone to substantial measurement error and other biases due to several factors, including classification error in workers' labor force statuses, time aggregation problems, and sample rotation and attrition issues (Shimer, 2012). An advantage of our approach to combine the structural MA representation (identified with external instruments)

Figure 11: Ins and Outs (data [blue line] and in-sample model fit [dashed red line])



and the DSGE model, is that it becomes possible to include measurement error in the observation equations. Thus, the likelihood Kalman filter allows the estimation of smoothed series for the job finding, cleaned from measurement error.

Figure 11 plots the measured job finding rate (data) and its smoothed version obtained from the likelihood Kalman filter (model). Its most striking feature is the large estimated measurement error during the 2008 Great Recession. As it is, difficulties with the measurement of f_t over the 2008 – 2009 period have been well documented by Elsby et al. (2011). Over this period the job finding rate is found to be dramatically biased downward due to classification error. Specifically, individuals moving from out of the labor force into unemployment, who miss-report their unemployment duration (claiming to have been long-term unemployed), thus contributing to a spurious reduction in the job finding rate. Elsby et al. (2011) argue that this phenomenon was more pronounced during the Great Recession because many inactive workers returned to the labor force, consistent with the countercyclicality of the OU gross flow.

It is evident that the empirical measure of the job finding rate features a big drop during the 2008 – 2009 period, while the model generated smoothed series corrects for this spurious reduction. The ability of the model to account successfully for the pattern of the gross flows during the 2008 recession reflects in part the milder deterioration attributed to the job finding rate during this period.

Finally, the fact that the measurement problem is most pronounced in the 2008 – 2009 period is also reassuring, as it suggests that over the majority of the sample the exit from unemployment in measured coherently.

6 Conclusion

We develop a general equilibrium business cycle model with frictional labor markets and endogenous labor force participation. The model is agnostic about the determinants of unemployment inflows and outflows, allowing us to augment the DSGE model with a structural MA representation for the job finding and separation rate identified using external instruments applied to a factor augmented VAR model. Thus the DSGE model is entirely consistent with the conditional dynamics of the job finding and separation rates implied by the structural FAVAR, and yields equilibrium transitions rates across employment, unemployment, and non-participation that capture well the cyclical properties of labor market gross flows.

Although we allow for real wage rigidities, the elasticity of the real wage to fluctuations in the average product of labor is estimated to be large (consistent with existing micro level evidence). Furthermore, even if we allow for strong intertemporal substitution effects in labor supply, the participation rate is found to be only mildly procyclical, also consistent with the empirical evidence. This result emerges because shocks to the job finding rate and investment specific shocks are the predominant source of business cycle fluctuations. For a given labor force participation, these shocks raise the probability of finding employment and cause a reduction in the average product of labor. These offsetting forces induce mild shifts in the return to labor force participation, and explain the weak cyclical movements in participation despite intertemporal substitution being strong.

The model features individuals with heterogeneous employment histories whose transition across employment, unemployment and non-participation are shaped by both chance and individual choices. Thus, we look carefully at the equilibrium gross worker flows generated by the model. Despite the nearly acyclical labor force participation, the transition rates from participation to unemployment and employment are highly cyclical. 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 have established how it is possible to obtain an estimated DSGE model which is consistent with the recent empirical findings about labor market flows over the business cycle (Elsby et al., 2015, 2019). On the whole, our approach to modeling labor market business cycles is effective and versatile. We propose an agnostic approach to modeling the unemployment inflows and outflows (the labor market engine room), based on external instruments. The same method can readily be extended to account for other type of shocks, such as monetary policy and financial shocks. We believe this can yield fruitful results both in terms of accounting successfully for the business cycle dynamics in the labor market, but also uncovering the impact of policy interventions on labor market outcomes.

Appendix

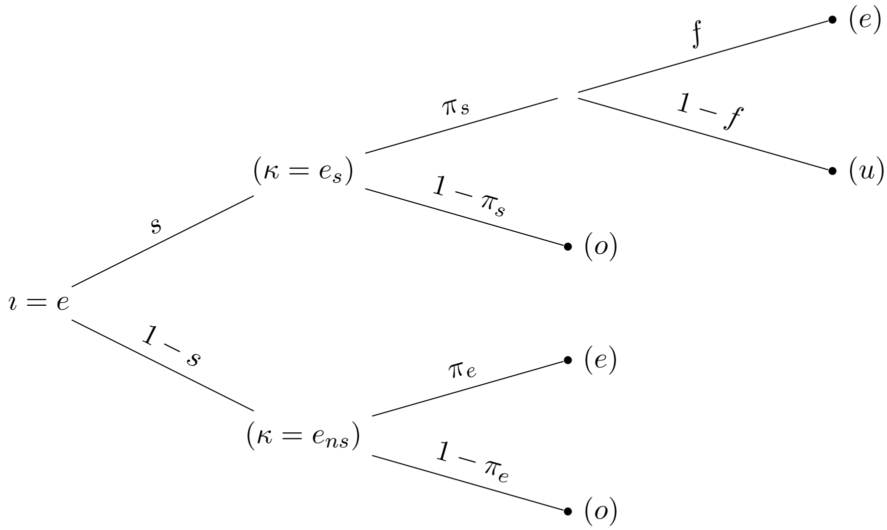
A Musical chairs and lotteries

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.[20] In Kokonas and Monteiro (2019) 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).

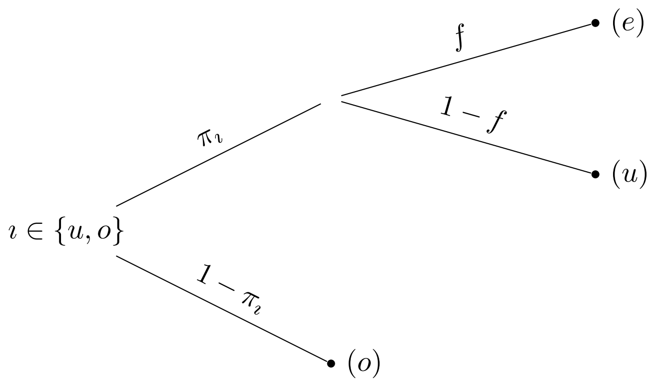
The economy is populated by a continuum of individuals of unit measure. There is a distinction between job and worker flows in the model. Individuals are distributed across three states or "islands": the employment "island"; the unemployment "island"; and the leisure "island". The mass of individuals 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 12a and 12b 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

[20] 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.



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



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

Figure 12: Sequence of events conditional on musical chairs' randomisation

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 "$\prime$" denote future values.

The Bellman equation characterising the problem solved by each individual is

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

with

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

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

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

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

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 resulting 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, $v\left(1-\underline{h}\right)$, where $\underline{h}$ is the amount of time devoted to employment. The opportunity cost of participation for each individual type is

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

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

$$c_{\tilde{\imath},\jmath} + k'_{\tilde{\imath},\jmath} + \sum_{\tilde{\imath}} \sum_{\jmath} q_{\tilde{\imath},\jmath} y_{\tilde{\imath},\jmath} = Rk + w \mathbb{1}_{\jmath} + y_{\tilde{\imath},\jmath}, \tag{A.2}$$

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

$$c_{\tilde{\imath},\jmath} = c, \tag{A.3}$$

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

$$c_{\tilde{\imath},\jmath}^{-1} = \beta \mathbf{V}_{k'}(K', k'_{\tilde{\imath},\jmath}); \tag{A.4}$$

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

$$k'_{\tilde{\imath},\jmath} = k', \tag{A.5}$$

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

The individual's consolidated decision reduces to

$$\begin{gathered}
\mathbf{V}(k) = \max_{c,k',\pi} \Big\{ \ln(c) - \Omega N_{-1}(1-s)\pi_e - \Psi\left(N_{-1}s\pi_s + U_{-1}\pi_u + O_{-1}\pi_o\right) + \beta \mathbf{V}(k') \Big\}, \\
s.t. \\
c + k' = Rk + w\Big[N_{-1}(1-s)\pi_e + \left(N_{-1}s\pi_s + U_{-1}\pi_u + O_{-1}\pi_o\right) f\Big], \\
\pi \in [0,1].
\end{gathered} \tag{A.6}$$

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 Interpreting the augmented DSGE

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). As we explain next, this system should be interpreted as the reduced form representation of equilibrium outcomes, in a labor market characterised with search frictions and endogenous job destruction.

In particular, suppose each period the stand-in firm receives exogenously the opportunity to post ν_t job vacancies, at zero marginal cost. Following the canonical Mortensen and Pissarides (1994) search and matching framework, the job finding rate is determined by a constant returns to scale (CRS) matching function

$$f_t = \frac{\mathbf{M}\left(H_t, \nu_t\right)}{H_t} = \mathbf{M}\left(1, \Theta_t\right), \tag{B.1}$$

where H_t is the mass of job seekers defined in (16), ν_t is the mass of vacancies, and $\Theta_t = \nu_t / H_t$ is the labor market tightness. Since the vacancies ν_t are a pure exogenous endowment, non-produced and non-storable, it is possible to justify f_t as the reduced form representation of an equilibrium outcome in the labor market, given an appropriately adapted process for the endowment of vacancies, ν_t.

C 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

$$\mathbf{S}_t = P_t \underline{h} - w_t. \tag{C.1}$$

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

$$\mathbf{J}_t = \mathbf{S}_t + \beta \mathbf{E}_t \left[\frac{\mu_{t+1}}{\mu_t} \left(1 - s_{t+1}\right) \mathbf{J}_{t+1} \right]. \tag{C.2}$$

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.[21] In effect, we separate the fragility of the employer-employee relationship from that of the job. Under this assumption, the equilibrium wage depends on the flow match surplus, rather than the present discounted value of match surpluses.[22]As a consequence, the capital value $\mathbf{J}$, being the present discounted value of flow surpluses, is determined unambiguously in

[21] The bargaining outcome depends, of course, on assumptions about what happens "out of equilibrium". Specifying that the job match is still in place at date $t+1$ if no agreement is reached at date t, constitutes an assumption about "out of equilibrium" play. Effectively, if no agreement is reached at date t, then the job becomes dormant, with the value of a dormant job being equal to the present discounted value of an active job.

[22] See Den Haan and Kaltenbrunner (2009) and Chahrour et al. (2020) for a similar assumption.

equilibrium. (Without modelling the vacancy creation process, the value of a job is not determined by vacancy costs (free entry), so we need to impose alternative restrictions.)

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

$$w_{1,t} = \max\left\{-\frac{v(1-\underline{h})}{\mu_t}, w_{2,t} + A_t\mathcal{B}\right\}, \tag{C.3}$$

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

$$\mathbf{S}_{2,t} = \zeta P_t\underline{h} - w_{2,t}. \tag{C.4}$$

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

$$w_{2,t} = \zeta P_t\underline{h}. \tag{C.5}$$

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

$$w_{1,t} = \max\left\{-\frac{v(1-\underline{h})}{\mu_t}, \zeta P_t\underline{h} + A_t\mathcal{B}\right\}, \tag{C.6}$$

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

$$\mathbf{S}_t = (1-\zeta)\, P_t \underline{h} - A_t \mathcal{B}. \tag{C.7}$$

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

$$\mathbf{J}_t = (1-\zeta)\, P_t \underline{h} - A_t \mathcal{B} + \mathbf{E}_t \left[\beta \frac{\mu_{t+1}}{\mu_t} \left(1 - s_{t+1}\right) \mathbf{J}_{t+1} \right]. \tag{C.8}$$

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

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

$$(\underline{C}/\underline{K}) = (\underline{Y}/\underline{K}) - (\underline{X}/\underline{K}) - (\underline{E}/\underline{K})\,, \tag{D.2}$$

$$\underline{V} = 1, \tag{D.3}$$

$$(\underline{X}/\underline{K}) = \mathcal{G} - (1-\delta)\,, \tag{D.4}$$

$$(\underline{L}/\underline{N}) = \underline{h}, \tag{D.5}$$

$$(\underline{K}/\underline{N}) = (1/\underline{h})\,(\underline{K}/\underline{Y})^{1/(1-\alpha)}\,, \tag{D.6}$$

$$\underline{N} = (1-\underline{u})\,\underline{\Pi}, \tag{D.7}$$

$$\underline{H} = \left(\underline{s}/\underline{f}\right) \underline{N}, \tag{D.8}$$

$$\underline{O} = 1 - \underline{\Pi}, \tag{D.9}$$

$$\underline{U} = \underline{u}\,\underline{\Pi}, \tag{D.10}$$

$$\underline{u} = \frac{\underline{s}(1-\underline{f})}{\underline{f}(1-\underline{s}) + \underline{s}} \tag{D.11}$$

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

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

$$-\hat{\mu}_t = \kappa_w\,(\hat{y}_t - \hat{n}_t) + \kappa_\xi \hat{f}_t, \tag{E.2}$$

$$(\mathcal{G}/\beta)\left[\hat{\mathcal{Q}}_t - \mathbf{E}_t\left(\hat{\mu}_{t+1} - \hat{\mu}_t\right)\right] = \alpha\left(\underline{Y}/\underline{K}\right)\mathbf{E}_t\left(\hat{y}_{t+1} - \hat{k}_{t+1} - \hat{\iota}_{t+1}\right) + (1-\underline{\delta})\mathbf{E}_t\left(\hat{\mathcal{Q}}_{t+1}\right), \quad \text{(E.3)}$$

$$\hat{\iota}_t = \kappa_\iota\left(\hat{y}_t - \hat{k}_t\right), \quad \text{(E.4)}$$

$$\mathcal{G}^2\kappa_x\left(\hat{x}_t - \hat{x}_{t-1}\right) = \hat{\mathcal{Q}}_t + \hat{v}_t + \mathcal{G}^2\beta\kappa_x\mathbf{E}_t\left(\hat{x}_{t+1} - \hat{x}_t\right), \quad \text{(E.5)}$$

$$\hat{y}_t = \alpha\left(\hat{\iota}_t + \hat{k}_t\right) + (1-\alpha)\,\hat{n}_t + z_t, \quad \text{(E.6)}$$

$$\left(\underline{C}/\underline{K}\right)\hat{c}_t + \left(\underline{X}/\underline{K}\right)\hat{x}_t + \left(\underline{E}/\underline{K}\right)\hat{e}_t = \left(\underline{Y}/\underline{K}\right)\hat{y}_t, \quad \text{(E.7)}$$

$$\mathcal{G}\hat{k}_{t+1} = \left(\underline{X}/\underline{K}\right)\left(\hat{x}_t + v_t\right) + (1-\underline{\delta})\,\hat{k}_t - \alpha\left(\underline{Y}/\underline{K}\right)\hat{\iota}_t, \quad \text{(E.8)}$$

$$\underline{u}\hat{u}_t = (1-\underline{u})\left(\hat{\pi}_t - \hat{n}_t\right), \quad \text{(E.9)}$$

$$\hat{n}_t = (1-\underline{s})\,\hat{n}_{t-1} + \underline{s}\left(\hat{h}_t + \hat{f}_t - \hat{s}_t\right). \quad \text{(E.10)}$$

Above, we use the definitions

$$\kappa_\xi \equiv \xi/\underline{\Psi}_{uo} \in (0,1), \quad \text{(E.11)}$$

$$\kappa_x \equiv \mathcal{S}'' > 0, \quad \text{(E.12)}$$

$$\kappa_w \equiv \left(1 - \mathcal{B}/\underline{w}\right) \in (0,1), \quad \text{(E.13)}$$

$$\kappa_\iota \equiv \delta'/\left(\delta' + \underline{\iota}\delta''\right) \in (0,1). \quad \text{(E.14)}$$

As explained in the main text, the system of equilibrium conditions is underdetermined. The models 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.

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 five 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.

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

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

where U_{τ} is total unemployment in month $\tau = 1, \ldots 3$ (within quarter t), and $U_{\tau}^{< \text{5 weeks}}$ 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

$$U_{\tau+1} = \Pi_\tau \left(\frac{\tilde{s}_\tau}{\tilde{s}_\tau + \tilde{f}_\tau}\right) + \Pi_\tau \left[U_\tau - \left(\frac{\tilde{s}_\tau}{\tilde{s}_\tau + \tilde{f}_\tau}\right)\right] e^{-\left(\tilde{s}_\tau + \tilde{f}_\tau\right)}, \tag{F.2}$$

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:

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

$$f_t = \sum_{\tau=1}^{3} \frac{1 - \exp\left(-3\tilde{f}_\tau\right)}{3}. \tag{F.4}$$

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

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

where η_t denotes the reduced form errors.[23] 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, $\mathbf{E}\left(\eta_t \eta_t'\right) = \mathbf{B}\mathbf{B}'$, 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

$$\begin{aligned} \left(\mathbf{B}\mathbf{B}'\right)^{-1} &= \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1}, \\ \psi \mathbf{B}^{\bullet\prime} \left(\mathbf{B}\mathbf{B}'\right)^{-1} \mathbf{B}^\bullet \psi &= \mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right), \\ \psi \mathbf{i}'\mathbf{i} \psi &= \mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right), \\ \psi &= \operatorname{sign}(\psi) \sqrt{\mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right)}. \end{aligned} \tag{G.2}$$

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

$$\mathbf{B}^\bullet = \operatorname{sign}(\psi)\, \mathbf{E}\left(\eta_t z_t\right) \left\{ \sqrt{\mathbf{E}\left(z_t \eta_t'\right) \left[\mathbf{E}\left(\eta_t \eta_t'\right)\right]^{-1} \mathbf{E}\left(\eta_t z_t\right)} \right\}^{-1}, \tag{G.3}$$

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),

[23] In Section 3, $\hat{s}_t$ and $\hat{f}_t$ are observable time-series and $\hat{m}_t$ is a vector of latent factors, so that (G.1) constitutes a FAVAR model. However, the identification of the IRF using instrumental variables applies more generally to any structural VAR model.

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

$$100 \times \begin{bmatrix} \log(\text{GDP})_t - \mathbf{P}_{t-h}\left(\log(\text{GDP})_t \mid \log(\text{CONS})_{t-h-i}\right) \\ \log(\text{CONS})_t - \mathbf{P}_{t-h}\left(\log(\text{CONS})_t \mid \log(\text{CONS})_{t-h-i}\right) \\ \log(\text{INV})_t - \mathbf{P}_{t-h}\left(\log(\text{INV})_t \mid \log(\text{INV})_{t-h-i}\right) \\ \log(\text{EMP})_t - \mathbf{P}_{t-h}\left(\log(\text{EMP})_t \mid \log(\text{EMP})_{t-h-i}\right) \\ \log(\text{UNP})_t - \mathbf{P}_{t-h}\left(\log(\text{UNP})_t \mid \log(\text{UNP})_{t-h-i}\right) \\ \log(\text{S})_t - \mathbf{P}_{t-h}\left(\log(\text{S})_t \mid \log(\text{S})_{t-h-i}\right) \\ \log(\text{F})_t - \mathbf{P}_{t-h}\left(\log(\text{F})_t \mid \log(\text{F})_{t-h-i}\right) \end{bmatrix} = 100 \times \begin{bmatrix} \hat{y}_t \\ \hat{c}_t \\ \hat{x}_t \\ \hat{n}_t \\ \hat{u}_t \\ \hat{s}_t \\ \hat{f}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ me_t^s \\ me_t^f \end{bmatrix}, \quad \text{(H.1)}$$

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.[24] 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

[24] The large sample approximation to the likelihood function is a Laplace approximation (Chernozhukov and Hong, 2003), obtained using Markov Chain Monte Carlo methods (MCMC). See the technical appendix in Christiano et al. (2011) for a description of the method.

Metropolis-Hasting chains, with 10,000 draws per chain, and keeping the last 50% of the draws. The acceptance rate achieved for each chain is around 30%.

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