Fiscal Rules and Unemployment: Online Appendix

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Abstract

This is the online appendix to the paper "Fiscal rules and unemployment". It presents details on the model, the data and the model estimation.

Online Appendix

A Model derivations

A.1 The intertemporal value of a job

The value of a match for the firm after the shock realization ε is known is

$$\tilde{J}_t(\varepsilon) = \Big(a_t mc_t - \varepsilon_t - w_t(\varepsilon_t)\Big)(1 - \tau_t^p) + E_t \Lambda_{t,t+1} J_{t+1}. \tag{1}$$

The worker-firm pair knows at this stage that they are not exogenously separated. The expected stochastic discount factor is $E_t \Lambda_{t,t+1} = \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \frac{d_{t+1}}{d_t}$ and $w_t(\varepsilon)$ denotes individual wages that depend on the idiosyncratic shock realization ε. The future value of a match for the firm is given by

$$\begin{aligned} E_t J_{t+1} =& E_t(1 - \phi_{t+1}) \int_{-\infty}^{v_{t+1}^f} \frac{\big(a_{t+1} mc_{t+1} - \varepsilon_{t+1} - w_{t+1}(\varepsilon_{t+1})\big) g(\varepsilon)}{1 - \phi_{t+1}^e} d\varepsilon_{t+1} (1 - \tau_{t+1}^p) \\ & - E_t \Big[(1 - \phi^x) \phi_{t+1}^e V_{t+1} + \phi^x V_{t+1} + (1 - \phi_{t+1}) \Lambda_{t+1,t+2} J_{t+2} \Big]. \end{aligned} \tag{2}$$

The first term captures the expected (after tax) profits of the match in period $t + 1$, i.e., aggregate revenue minus expected idiosyncratic costs and expected wages, given that no separation occurs. Note that the conditional expected revenue depends on the density of ε conditional on not endogenously separating. This conditional density can be expressed as $g(\varepsilon | \varepsilon_{t+1} < v_{t+1}^f) = \frac{g(\varepsilon)}{G(v_{t+1}^f)} = \frac{g(\varepsilon)}{1-\phi_{t+1}^e}$. Production is priced at marginal costs given that intermediate good producers sell on a perfectly competitive market. The second term represents the expected value of a vacancy in case of endogenous separation. The third term captures the value of a vacancy in case of exogenous separation. The last term represents the expected discounted future value of the continued match in case of no separation.

A.2 The value of working and unemployment

The value of a match for the worker with shock realization ε is

$$W_t(\varepsilon_t) = w_t(\varepsilon_t)(1-\tau_t^n) + E_t\Lambda_{t,t+1}\Big[\phi_{t+1}U_{t+1} + (1-\phi_{t+1})\int_{-\infty}^{v_{t+1}^f} \frac{W_{t+1}(\varepsilon_{t+1})}{1-\phi_{t+1}^e} g(\varepsilon)d\varepsilon_{t+1}\Big] \tag{3}$$

and the value of an unemployed worker is

$$U_t = b + E_t\Lambda_{t,t+1}\Big[\eta_{t+1}(1-\phi_{t+1})\int_{-\infty}^{v_{t+1}^f} \frac{W_{t+1}(\varepsilon_{t+1})}{1-\phi_{t+1}^e} g(\varepsilon)d\varepsilon_{t+1} + \big(1-\eta_{t+1}(1-\phi_{t+1})\big)U_{t+1}\Big]. \tag{4}$$

B Data description

Data construction and sources

If necessary, series are seasonally adjusted using Census-X12-ARIMA. NIPA refers to the official national accounts as reported by the *Bureau of Economic Analysis* of the US.

General variables

- Gross domestic product (GDP): Real per capita GDP (NIPA). The nominal gross series is scaled with the GDP deflator (NIPA) and the labor force (NIPA).
- Inflation (yoy): Log difference of the GDP deflator in t and $t-4$ (NIPA).
- Interest rates: Official federal funds rate. Series are averaged to quarterly frequency.

Labor market variables

- Official unemployment rate (Bureau of Labor Statistics, BLS).
- Job-finding and separation rates: I update the series of Shimer (2012) until 2011Q4. Labor market flows are deduced from data on employment, unemployment and short-term unemployment. The monthly US series is converted

to quarterly terms as follows: The probability to find a job/lose a job in at least one of the three months is $\eta_q = 1 - (1 - \eta_{m1}) \times (1 - \eta_{m2}) \times (1 - \eta_{m3})$, etc.

Fiscal variables

- Government spending: Government consumption expenditures and gross investment of federal, state, and local government (NIPA). Series are transformed to real per capita terms and are seasonally adjusted.

- Government debt: Real per capita debt. Market value of federal debt held by public from the Dallas Federal Reserve. The market value more accurately represents the debt burden than the par value and has been used in a number of recent studies (e.g., Drautzburg and Uhlig, 2015, Zubairy, 2014).

- Effective tax rates on labor, capital and consumption (see below). The profit tax in the model is represented by a general tax on capital income in the data. This approach is a short-cut given that the model has no capital. This short-cut allows me to use the standard and consistent computation of effective tax rates on income, consumption and capital that goes back to Mendoza et al. (1994). I checked the robustness of my results towards using a series for a profit tax in the estimation. I computed the effective profit tax from the US NIPA tables as proposed by Mertens and Montiel Olea (2013). The two series have a strong positive correlation of 0.88, although the profit tax has a lower mean (23.7 percent) compared to the capital tax (39.1 percent). The results on the fiscal multipliers are, however, robust towards using either the capital or the profit tax series for the estimation.

Constructing effective tax rates

In order to obtain aggregate effective tax rates for consumption, labor, and profit taxes, I follow Mendoza et al. (1994). The calculation uses data from the *OECD Revenue Statistics* and detailed national accounts that is partly only available at annual frequency. The data aggregates federal, state, and local government (see Fernández-Villaverde et al., 2015 for a discussion). I follow Forni et al. (2009) and interpolate annual series using quarterly indicators with Chow and Lin (1971) and

Santos Silva and Cardoso (2001). Table 1 summarizes the variables and data series used in constructing the tax rates (notation follows Mendoza et al., 1994).

Following Mendoza et al. (1994), the tax rates are computed as

1. Effective tax rate on consumption

$$\tau_c = \left[\frac{5110 + 5121}{C + G - GW - 5110 - 5121}\right] \times 100$$

2. Household's average tax rate on total income:

$$\tau_h = \left[\frac{1100}{OSPUE + PEI + W}\right] \times 100$$

3. Effective tax rate on labor income:

$$\tau_w = \left[\frac{\tau_h W + 2000 + 3000}{W + 2200}\right] \times 100$$

4. Effective tax rate on capital income:

$$\tau_p = \left[\frac{\tau_h(OSPUE + PEI) + 1200 + 4100 + 4400}{OS}\right] \times 100.$$

Quarterly revenue data is available as part of the official NIPA tables (see Jones, 2002). The only variables that are required for the Mendoza et al. (1994) calculations and that are not available at quarterly frequency are taxes on payroll and workforce, taxes on financial and capital transactions, general taxes on goods and services, and excise taxes. I follow the proposition of Forni et al. (2009) and interpolate to quarterly levels using wages, private and public consumption, or a linear trend in the case of taxes on financial and capital transactions. The series span from 1965Q1 to 2011Q4.

Figure 1 shows the tax rates (aggregated to annual levels) in comparison to the annual effective tax rates constructed by Mendoza et al. (1994) and Trabandt and Uhlig (2011). The series constructed here are very close to the most recent data of Trabandt and Uhlig (2011) and also fit the overall movement of the Mendoza et al.

(1994) data. Figure 2 shows the quarterly effective tax rates used in the estimation. The correlation with data constructed in line with Jones (2002) is 0.99, 0.98, and 0.96 for the labor tax, the consumption tax and the capital tax, respectively.

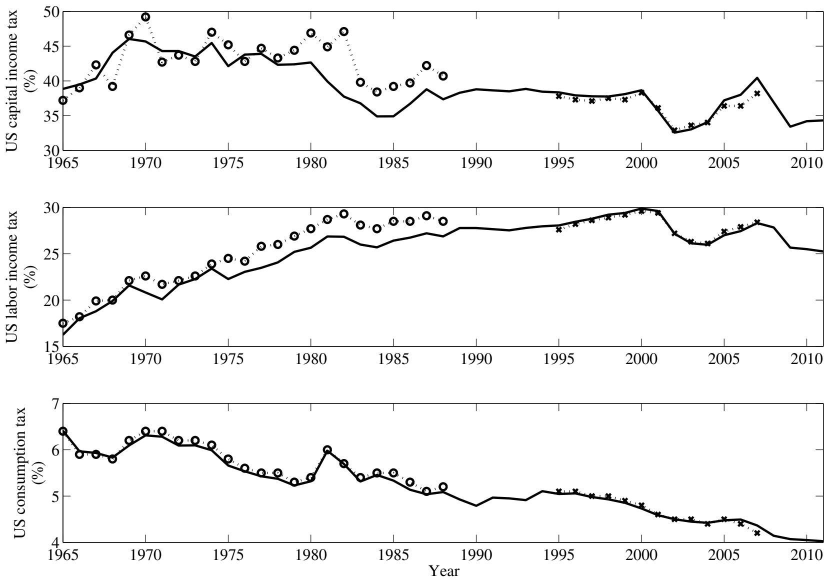

Figure 1: Annual effective tax rates. Comparison of data constructed here (solid lines), data of Mendoza et al., 1994 (lines marked by dots), and the data series computed by Trabandt and Uhlig, 2011 (lines marked by crosses).

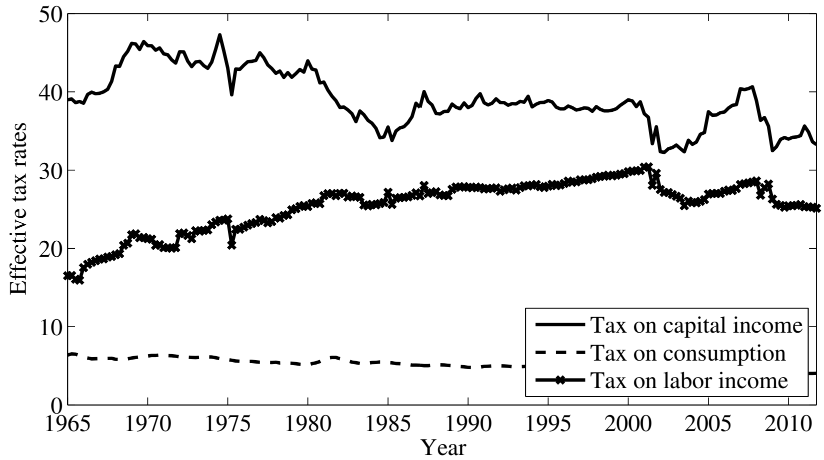

Figure 2: Quarterly effective tax rates in the US.

Variable	Description	Data source [quarterly indicator if interpolation is necessary]
Revenue statistics		
1100	Taxes on income, profits, and capital gains of individuals	NIPA (3.1: line 3+3.2: line 3)
1200	Taxes on income, profits, and capital gains of corporations	NIPA (3.1: line 5)
2000	Total social security contributions	NIPA (3.1: line 7)
2200	Employer's contribution to social security	NIPA (1.12: line 8)
3000	Taxes on payroll an workforce	OECD [wages]
4100	Recurrent taxes on immovable property	NIPA (3.3: line 8)
4400	Taxes on financial and capital transactions	OECD [linear trend]
5110	General taxes on goods and services	OECD [private and public consumption]
5121	Excise taxes	OECD [private and public consumption]
National accounts		
C	Private final consumption expenditure	NIPA (1.5: line 2)
G	Government final consumption expenditure	NIPA (1.5: line 22)
GW	Compensation of employees paid by producers of gvmt. services	NIPA (3.10.5: line 4)
OSPUE	Operating surplus of private unincorporated enterprises	NIPA (1.12: line 12 + 13 + 18)
PEI	Household's property and entrepreneurial income	NIPA (1.12: line 9)
W	Wages and salaries	NIPA (1.12: line 3)
OS	Total operating surplus of the economy	NIPA (1.10: line 9)

Table 1: Constructing quarterly effective tax rates. OECD refers to the *OECD Revenue Statistics*. NIPA refers to the official national accounts as reported by the *Bureau of Economic Analysis*.

C Estimation output, model fit and variance decomposition

C.1 Prior and posterior distributions and convergence

Figure 3, 4 and 5 show the prior (dashed grey) and posterior distributions (solid black) of all estimated parameters as obtained in the baseline model. Figure 6 illustrates CUSUM plots that visualize the convergence of the Markov chains. The figures plot the cumulative mean minus the overall mean (Bauwens et al., 2000). A detailed discussion of the estimation results can be found in the main text in Section 3.3. Further details on the exact numbers are summarized in Table 3 and 4 in the main text, the prior distributions are given in Table 2 in the main text.

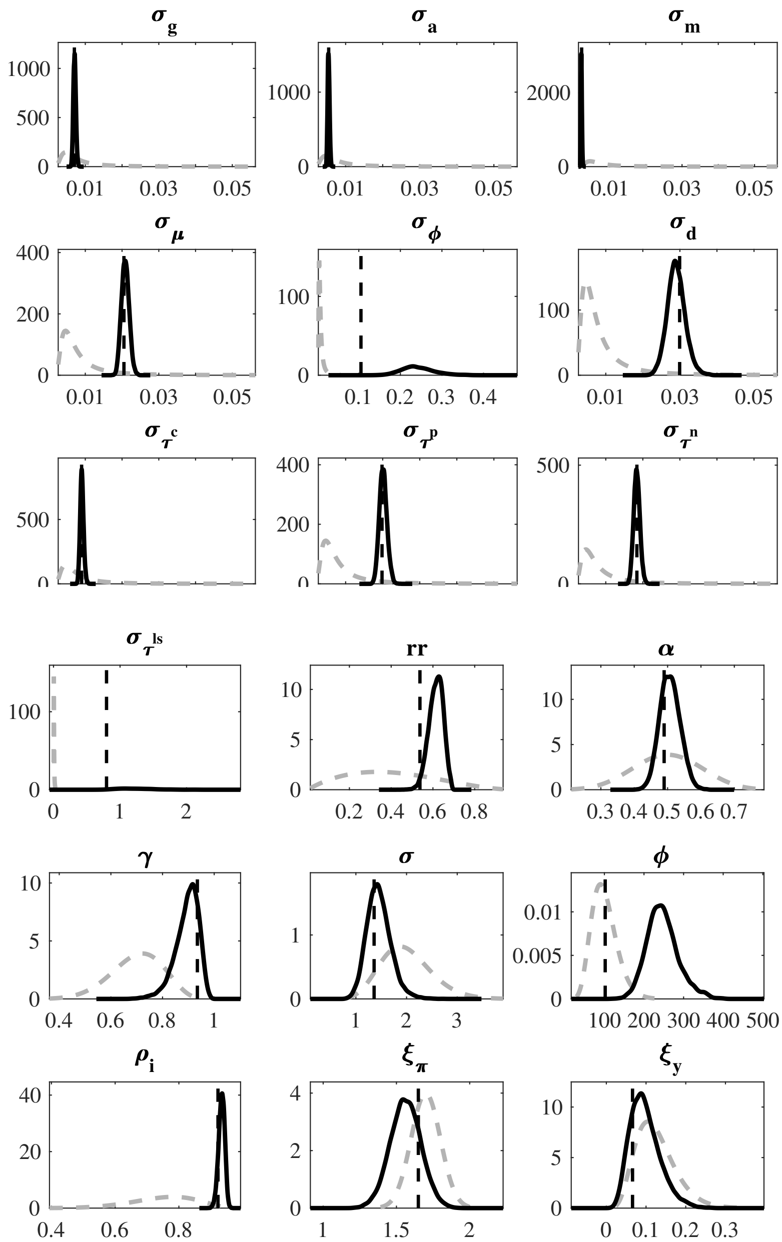

Figure 3: Prior (dashed grey) and posterior distributions (solid black) for baseline estimation. The vertical lines mark the posterior mode.

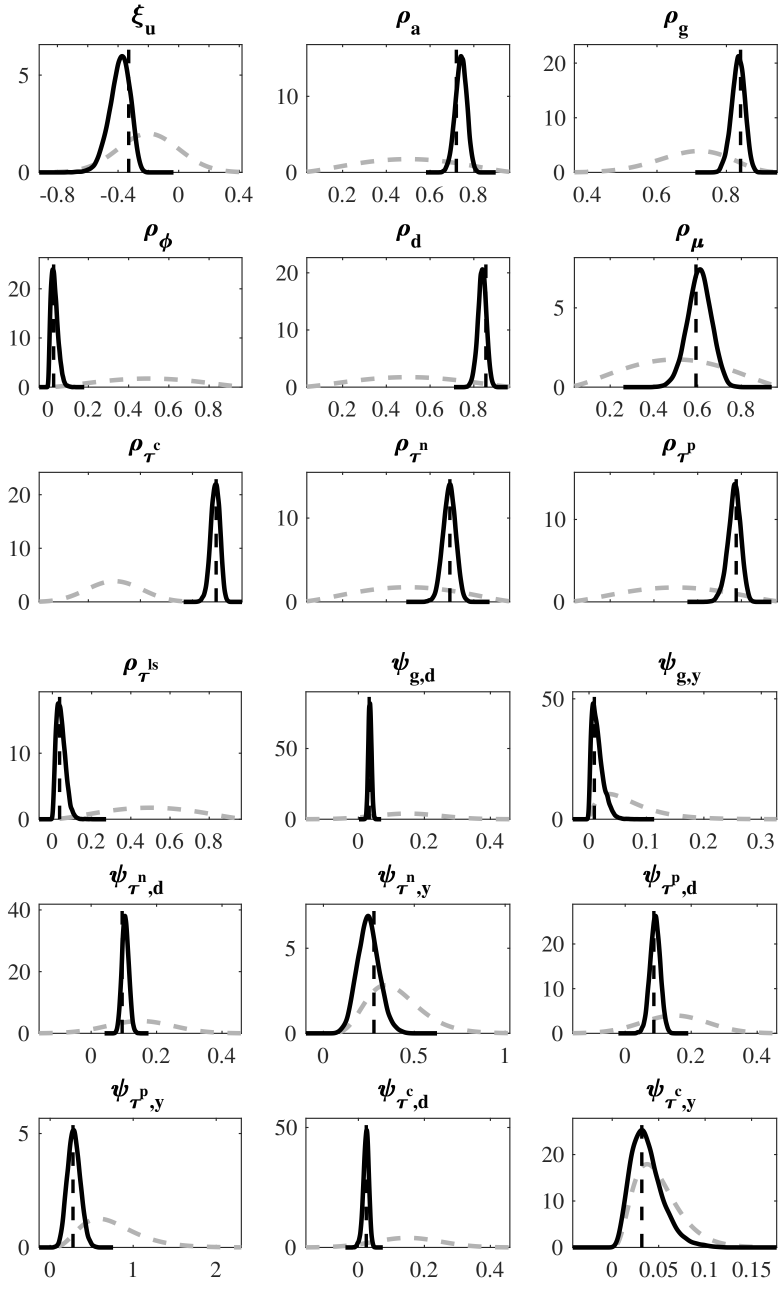

Figure 4: Prior (dashed grey) and posterior distributions (solid black) for baseline estimation (ctd.). The vertical lines mark the posterior mode.

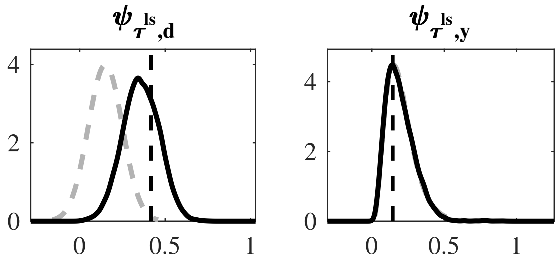

Figure 5: Prior (dashed grey) and posterior distributions (solid black) for baseline estimation (ctd.). The vertical lines mark the posterior mode.

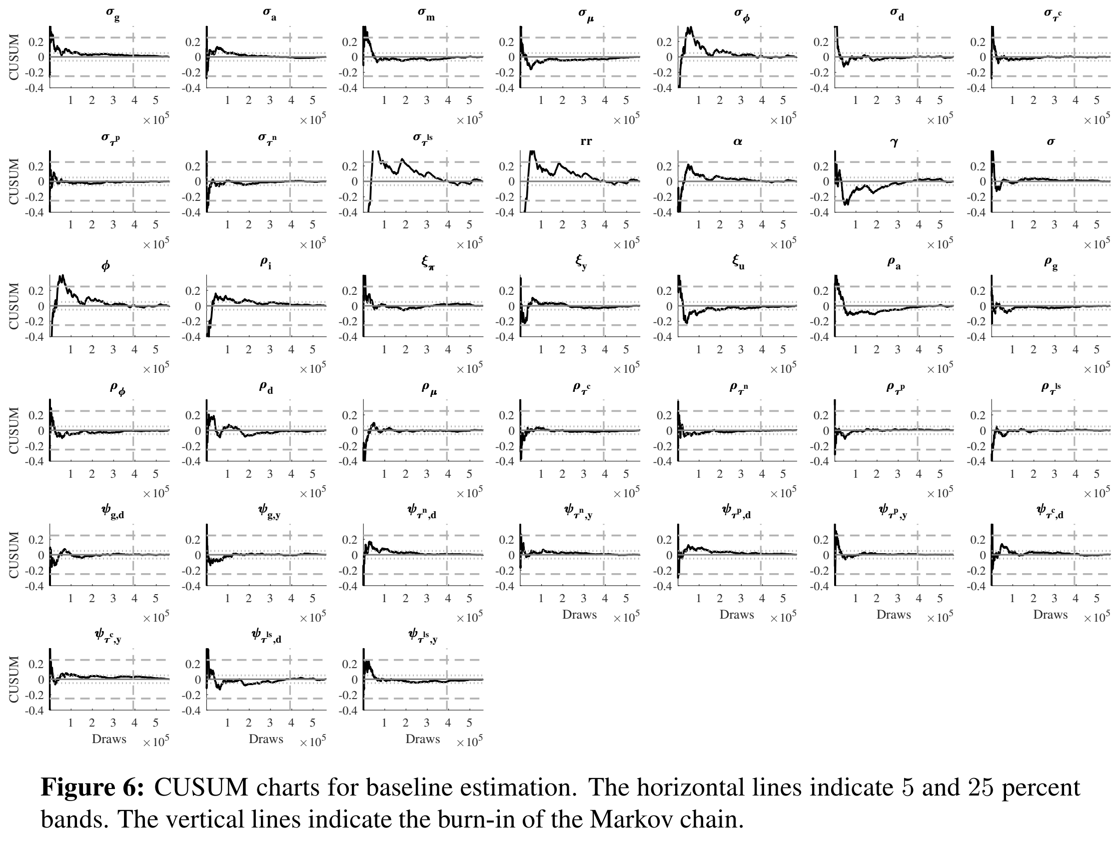

Figure 6: CUSUM charts for baseline estimation. The horizontal lines indicate 5 and 25 percent bands. The vertical lines indicate the burn-in of the Markov chain.

C.2 Model fit and properties

Figure 7 provides a visual representation of the auto- and cross-covariances of the model and the data. The fit is satisfactory given that the baseline model does not embed typical features to increase model fit such as habit persistence, real wage rigidities, capital adjustment costs or further frictions, e.g., financial frictions. The one-step ahead Kalman forecast of the estimated model in Figure 8 matches the data series including the flow rates. The one-period ahead forecast of inflation is too volatile in the model compared to the data as inflation is purely foreward looking in this model. Given that this paper does not focus on monetary policy and inflation, I do not allow for indexation to last period's inflation as introduced in estimated medium scale DSGE models (e.g., Smets and Wouters, 2007).

Table 2 illustrates the conditional and unconditional cross-correlations in the data and in artificial data simulated from the estimated model. In line with the discussion above, the estimated model perturbed by all structural shocks replicates the data correlations. The conditional correlations highlight the role of supply versus demand side disturbances. In the data, the correlation of GDP and interest rates is negative, but close to zero (-0.02). Productivity shocks generate a strong negative correlation of GDP and interest rates (-0.94). Preference shocks induce a positive correlation (0.32). Fiscal policy shocks also imply a positive correlation of GDP and interest rates. However, fiscal shocks are restricted by the data on the observable fiscal instruments. For this reason, a combination of productivity and preference shocks is a necessary model feature to explain aggregate data dynamics.

Preference shocks (and demand shocks in general) generate a strong correlation (close to one) of GDP and labor market flow rates. Given productivity stays constant, demand side disturbances necessarily amplify towards the labor market as production can then only rise if employment increases. Consequently, there is no Shimer (2005) puzzle in light of demand side disturbances. In contrast, in response to a positive productivity shock, production rises at least partly due to productivity gains. As a result, the corresponding correlation of GDP and labor market flows is far below one. In fact, in the estimated model, employment falls after a positive productivity shock. The sign of the employment response depends on the exact parameterization of the model, in particular, on monetary policy and the shock persistence. Intuitively, employment rises

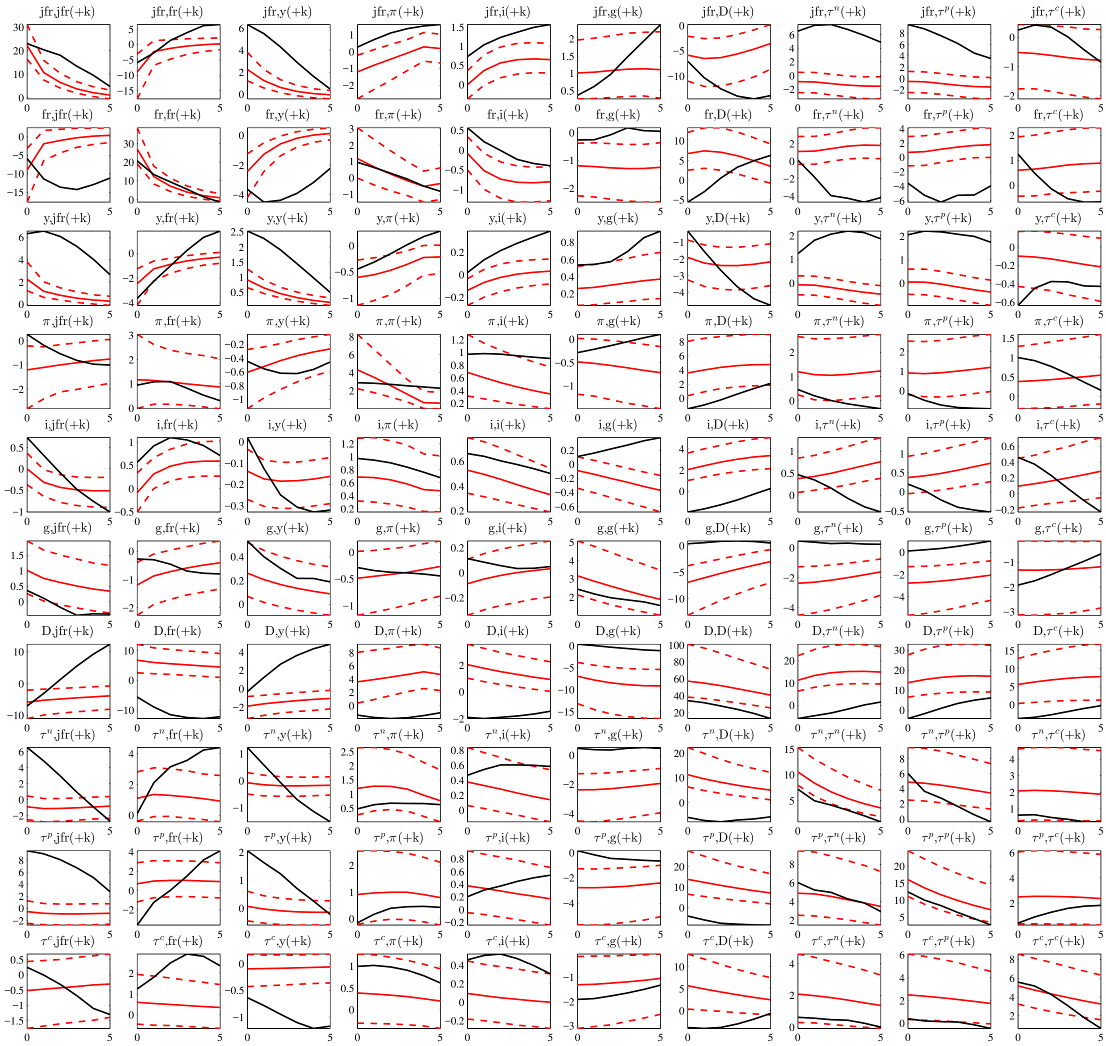

Figure 7: Auto- and cross-covariances at t and $t+k$ of US data (black solid line) and estimated model (red lines, dashed lines represent 5th and 95th percentiles, solid lines represent the posterior median). Model covariances are computed from simulated data as follows: I took 500 draws from the posterior distribution and simulated 100 samples for each draw of the same size as the observed data series after a burn-in of $1,000$ periods. The diagonal elements show auto-covariances, off-diagonal elements show cross-covariances.

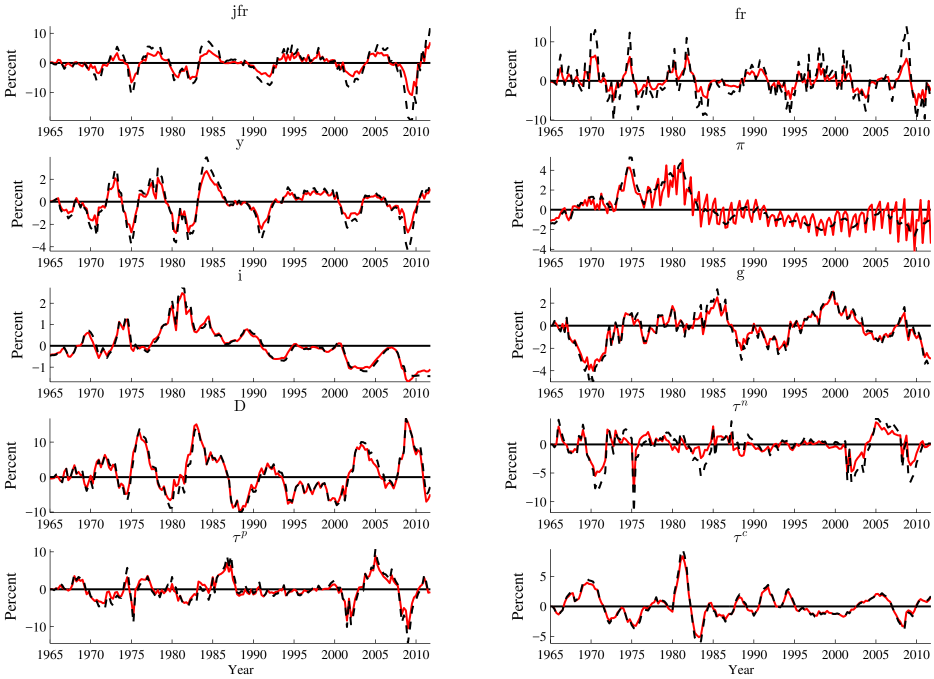

Figure 8: Comparison of US data (black dashed line) versus one-period ahead forecasts of observables of the estimated model (red solid lines). The plot shows deviations from steady state/trend. The one-period ahead forecast is obtained by Kalman filtering the state space representation of the estimated model at the posterior mean.

only if households' consumption demands rise by more than the output increase from productivity gains. Monopolistic competitors only increase production if profits rise. The response of profits depends on the demand elasticity as monopolistic competitors face a downward sloping demand curve. This result is well in line with the prediction of standard New Keynesian models and the SVAR result by Galí (1999) on hours worked. Similarly, Balleer (2012) documents that job-finding rates show a negative, while separation rates show a positive response to productivity shocks in a similar SVAR.

	GDP, job-finding rate	GDP, separation rate	GDP, interest rate	GDP, inflation
Data	0.83	-0.51	-0.02	-0.18
All shocks	0.52	-0.52	-0.20	-0.30
	[0.30; 0.69]	[-0.68; -0.28]	[-0.44; 0.07]	[-0.49; -0.09]
Productivity shocks	-0.47	0.47	-0.94	-0.89
	[-0.54; -0.38]	[0.38; 0.54]	[-0.96; -0.92]	[-0.94; -0.82]
Preference shocks	0.98	-0.98	0.32	0.15
	[0.97; 0.98]	[-0.98; -0.97]	[0.26; 0.39]	[-0.01; 0.42]
Monetary policy shocks	0.98	-0.98	-0.98	-0.15
	[0.97; 0.99]	[-0.99; -0.97]	[-0.99; -0.97]	[-0.50; 0.38]
Government spending shocks	0.98	-0.98	0.13	-0.04
	[0.97; 0.99]	[-0.99; -0.97]	[0.00; 0.23]	[-0.15; 0.08]

Table 2: Conditional and unconditional correlations in the model and in US data. Data correlations are obtained from one-sided HP filtered data (1965Q1 to 2011Q4). Model correlations are obtained from simulated data for the observable variables (deviations from trend). I report the median and the 5 and 95 percentiles. Simulations are based on 500 draws from the posterior distribution and 100 simulated data samples each. Simulated data is of the same size as the US data (after discarding the first $1,000$ simulated periods). In order to compute conditional correlations, the model is simulated based on one structural shock only.

C.3 Variance decomposition

The search and matching literature disagrees about the sources of labor market fluctuations. Given that search and matching models stand in the tradition of RBC models, the literature has focused on productivity shocks. Recently, fueled by the discussion on the Shimer (2005) puzzle and the incorporation of search and matching frictions in New Keynesian models, demand shocks have been put forward.

Table 3 illustrates the conditional forecast error variance decomposition of the estimated model. Productivity shocks explain only 15 percent of the dynamics of the job-finding and the separation rate; approximately 20 percent of unemployment dynamics. Instead, demand shocks to preferences and monetary policy explain a large share. Preference shocks drive approximately 45 percent of US flow rates and 60 percent of the dynamics of the unemployment rate. This finding fits to the notion of Hall (1997). Nevertheless, productivity shocks explain more than 40 percent of output fluctuations in the long run. Approximately 30 percent of the variation in US flow rates is triggered by matching shocks. However, matching shocks do not explain movements in unemployment. The reason is that a temporarily higher matching efficiency increases the job-finding rate, but, everything else equal, the effect is offset as firms separate more workers due to endogenous separations. Monetary policy explains approximately 10 percent of labor market flow and 15 percent of unemployment fluctuations.

Figure 9 shows a historical variance decomposition of GDP and unemployment. In general, these figures confirm the earlier results obtained from the overall variance decomposition. Interestingly, preference shocks are an important driving force of GDP and in particular unemployment in the Great Recession. This finding is in line with Hall (2017) who argues that there is a connection between discounting and unemployment. The preference shock indeed stands in as a shock representing disturbances from financial markets in a model without explicit financial markets. Note that monetary policy shocks destabilize for example in the Great Recession. The reason for this finding is the following: The Taylor rule of monetary policy responds strongly to deviations from GDP and unemployment from steady state. For this reason, in the Great Recession, interest rates are decreased strongly via the Taylor rule until the zero lower bound binds. This binding constraint is captured in this (linear) model via positive monetary policy shocks.

Horizon	Productivity shock		Monetary shock		Spending shock		Mark-up shock		Preference shock		Matching shock		Transfer shock		Tax shocks	
	Mean	90% interval	Mean	90% interval	Mean	90% interval	Mean	90% interval	Mean	90% interval	Mean	90% interval	Mean	90% interval	Mean	90% interval
Variance decomposition of job creation																
1	0.15	[0.11; 0.18]	0.10	[0.07; 0.12]	0.01	[0.00; 0.01]	0.02	[0.01; 0.04]	0.43	[0.37; 0.50]	0.29	[0.23; 0.36]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
5	0.12	[0.09; 0.15]	0.10	[0.08; 0.12]	0.01	[0.00; 0.01]	0.02	[0.01; 0.04]	0.38	[0.32; 0.45]	0.37	[0.28; 0.45]	0.00	[0.00; 0.00]	0.00	[0.00; 0.00]
20	0.12	[0.09; 0.16]	0.10	[0.08; 0.13]	0.01	[0.00; 0.01]	0.02	[0.01; 0.04]	0.38	[0.32; 0.46]	0.36	[0.27; 0.45]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
Variance decomposition of job destruction																
1	0.16	[0.12; 0.19]	0.10	[0.08; 0.12]	0.01	[0.00; 0.01]	0.02	[0.01; 0.04]	0.47	[0.38; 0.53]	0.24	[0.20; 0.29]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
5	0.13	[0.10; 0.16]	0.11	[0.09; 0.13]	0.01	[0.00; 0.01]	0.03	[0.01; 0.04]	0.43	[0.36; 0.49]	0.29	[0.24; 0.34]	0.00	[0.00; 0.00]	0.00	[0.00; 0.00]
20	0.14	[0.11; 0.17]	0.11	[0.09; 0.13]	0.01	[0.01; 0.01]	0.03	[0.01; 0.04]	0.43	[0.36; 0.49]	0.28	[0.23; 0.33]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
Variance decomposition of unemployment																
1	0.21	[0.15; 0.27]	0.14	[0.11; 0.16]	0.01	[0.01; 0.01]	0.03	[0.01; 0.05]	0.61	[0.54; 0.68]	0.00	[0.00; 0.00]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
5	0.18	[0.13; 0.23]	0.16	[0.14; 0.19]	0.01	[0.01; 0.01]	0.04	[0.02; 0.06]	0.60	[0.54; 0.66]	0.00	[0.00; 0.00]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
20	0.19	[0.13; 0.23]	0.16	[0.14; 0.19]	0.01	[0.01; 0.01]	0.04	[0.02; 0.06]	0.60	[0.53; 0.66]	0.00	[0.00; 0.00]	0.01	[0.00; 0.01]	0.00	[0.00; 0.00]
Variance decomposition of GDP																
1	0.18	[0.14; 0.23]	0.14	[0.11; 0.16]	0.01	[0.01; 0.01]	0.03	[0.01; 0.05]	0.63	[0.56; 0.69]	0.00	[0.00; 0.00]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
5	0.36	[0.29; 0.44]	0.13	[0.11; 0.15]	0.01	[0.00; 0.01]	0.03	[0.01; 0.05]	0.47	[0.39; 0.53]	0.00	[0.00; 0.00]	0.00	[0.00; 0.00]	0.00	[0.00; 0.00]
20	0.40	[0.33; 0.50]	0.12	[0.10; 0.14]	0.01	[0.00; 0.01]	0.03	[0.01; 0.04]	0.43	[0.36; 0.51]	0.00	[0.00; 0.00]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
Variance decomposition of inflation																
1	0.02	[0.01; 0.03]	0.00	[0.00; 0.00]	0.00	[0.00; 0.00]	0.97	[0.96; 0.98]	0.01	[0.01; 0.01]	0.00	[0.00; 0.00]	0.00	[0.00; 0.00]	0.00	[0.00; 0.00]
5	0.09	[0.05; 0.12]	0.00	[0.00; 0.01]	0.01	[0.00; 0.01]	0.85	[0.81; 0.89]	0.03	[0.02; 0.04]	0.00	[0.00; 0.00]	0.02	[0.01; 0.02]	0.00	[0.00; 0.00]
20	0.13	[0.07; 0.19]	0.02	[0.01; 0.03]	0.02	[0.01; 0.03]	0.71	[0.61; 0.80]	0.08	[0.04; 0.12]	0.00	[0.00; 0.00]	0.03	[0.02; 0.04]	0.01	[0.01; 0.01]
Variance decomposition of interest rates																
1	0.11	[0.09; 0.13]	0.51	[0.41; 0.61]	0.01	[0.00; 0.01]	0.07	[0.03; 0.11]	0.30	[0.20; 0.40]	0.00	[0.00; 0.00]	0.00	[0.00; 0.01]	0.00	[0.00; 0.00]
5	0.18	[0.14; 0.22]	0.19	[0.13; 0.25]	0.01	[0.01; 0.02]	0.02	[0.01; 0.03]	0.59	[0.50; 0.69]	0.00	[0.00; 0.00]	0.01	[0.00; 0.01]	0.00	[0.00; 0.00]
20	0.17	[0.11; 0.22]	0.11	[0.08; 0.15]	0.02	[0.01; 0.02]	0.01	[0.00; 0.02]	0.68	[0.60; 0.77]	0.00	[0.00; 0.00]	0.01	[0.00; 0.01]	0.00	[0.00; 0.00]

Table 3: Posterior forecast error variance decomposition. The forecast horizon is measured in quarters.

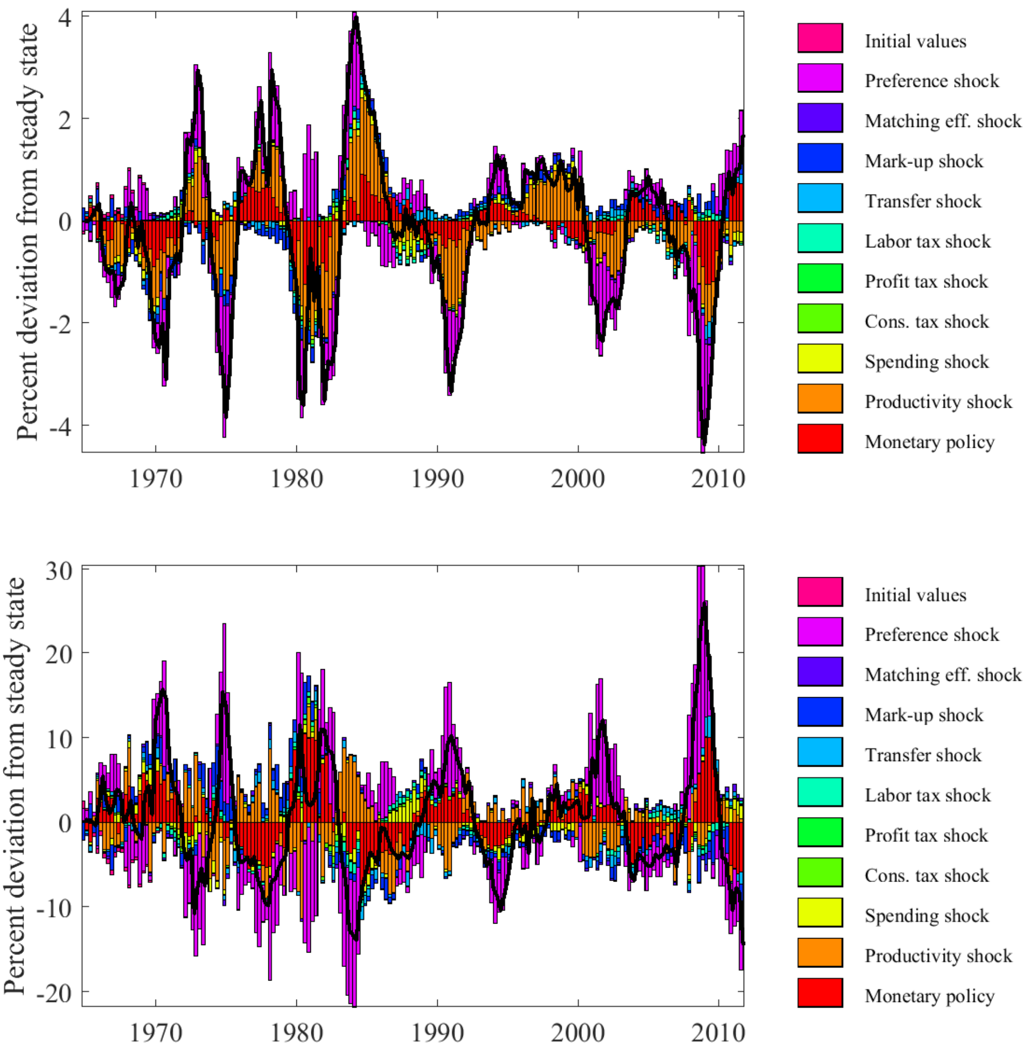

Figure 9: Historical variance decomposition of GDP (upper panel) and unemployment (lower panel).

In general, these findings on the driving forces of labor market flow rates are consistent with evidence based on SVARs (Ravn and Simonelli, 2007, Braun et al., 2009, Balleer, 2012). Using estimated DSGE models, Gertler et al. (2008), Krause et al. (2008), Sala et al. (2012), and Furlanetto and Groshenny (2016) also find evidence for variation in labor market variables due to non-productivity shocks. Nevertheless, these studies do not analyze labor market flow rates.

D Estimation output for model with complementarity in preferences

Figure 10, 11 and 12 show the prior (dashed grey) and posterior distributions (solid black) of all estimated parameters as obtained in the model that allows for a complementarity in household preferences. The model is discussed in Section 4.2 of the main text. Figure 13 illustrates CUSUM plots that visualize the convergence of the Markov chains.

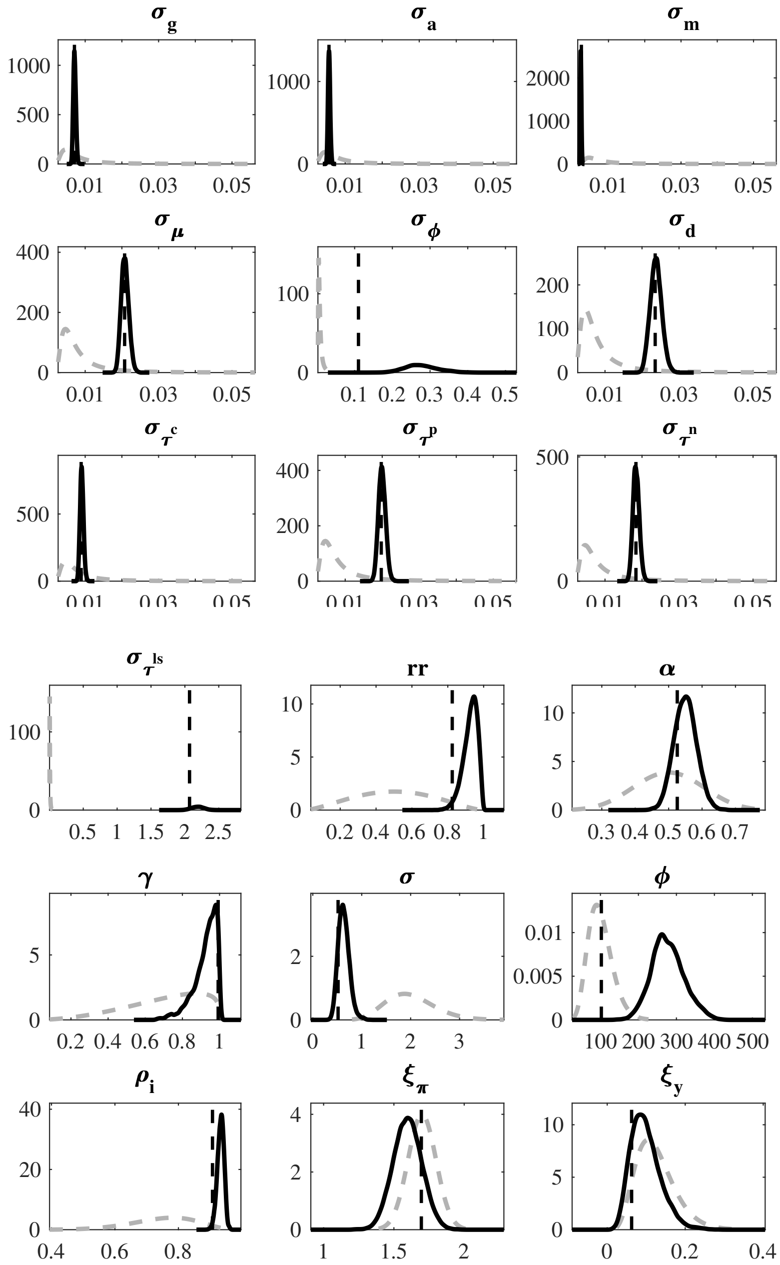

Figure 10: Prior (dashed grey) and posterior distributions (solid black) for model estimation with complementarity in preferences. The vertical lines mark the posterior mode.

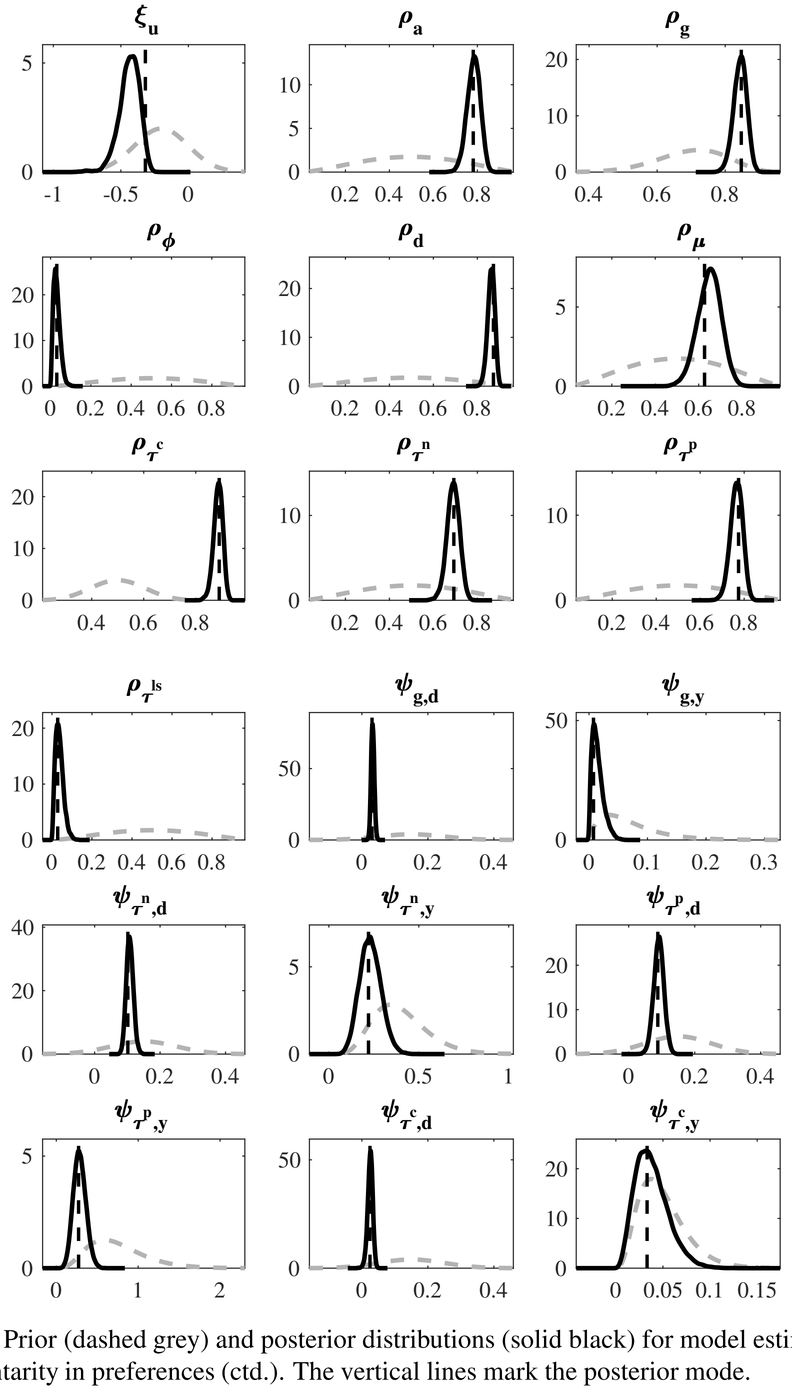

Figure 11: Prior (dashed grey) and posterior distributions (solid black) for model estimation with complementarity in preferences (ctd.). The vertical lines mark the posterior mode.

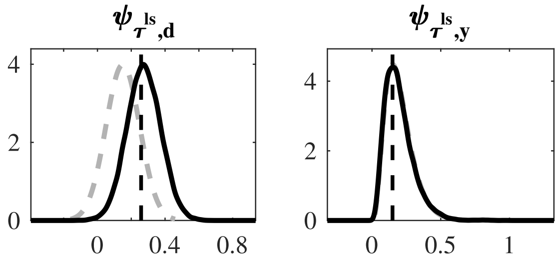

Figure 12: Prior (dashed grey) and posterior distributions (solid black) for model estimation with complementarity in preferences (ctd.). The vertical lines mark the posterior mode.

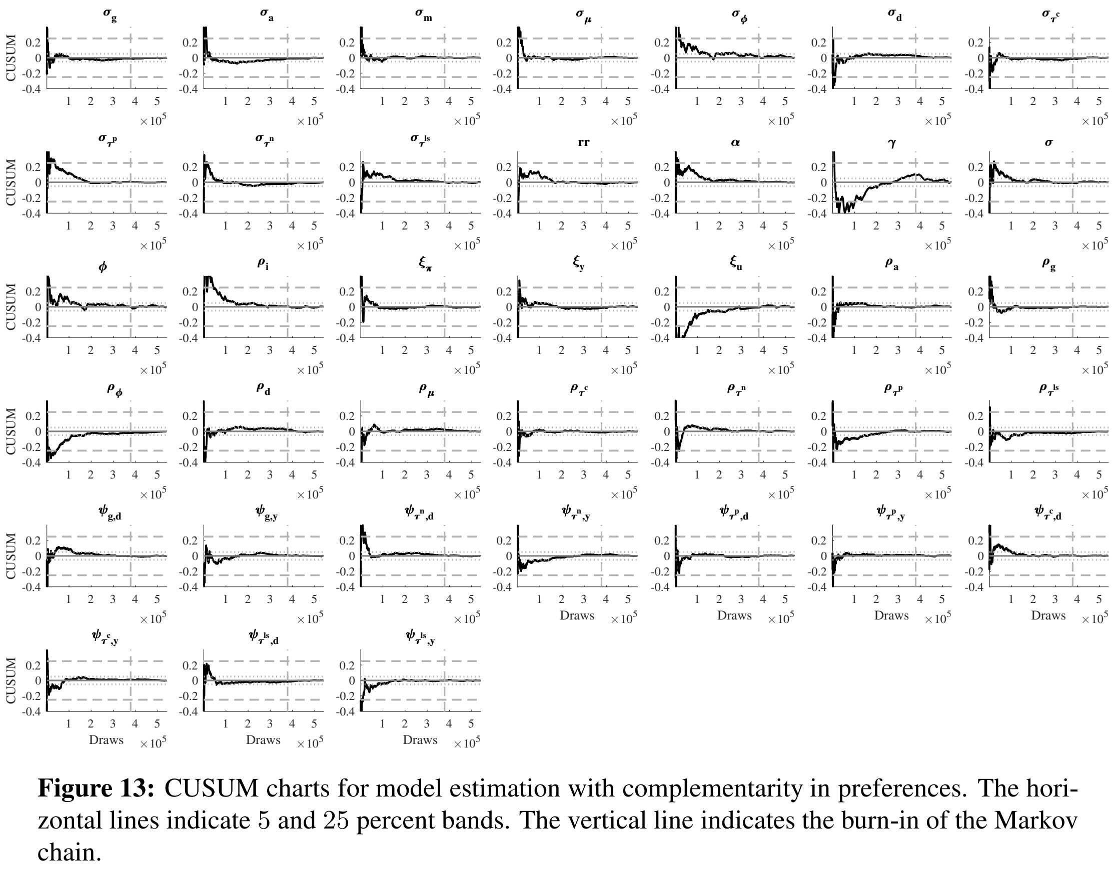

Figure 13: CUSUM charts for model estimation with complementarity in preferences. The horizontal lines indicate 5 and 25 percent bands. The vertical line indicates the burn-in of the Markov chain.

References

BALLEER, A. (2012): "New Evidence, Old Puzzles: Technology Shocks and Labor Market Dynamics," *Quantitative Economics*, 3, 363–392.

BAUWENS, L., M. LUBRANO, AND J.-F. RICHARD (2000): *Bayesian Inference in Dynamic Econometric Models*, Oxford: Oxford University Press.

BRAUN, H., R. DE BOCK, AND R. DICECIO (2009): "Supply Shocks, Demand Shocks, and Labor Market Fluctuations," *Federal Reserve Bank of St. Louis Review*, May, 155–178.

CHOW, G. C. AND A.-L. LIN (1971): "Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by Related Series," *The Review of Economics and Statistics*, 53, 372–75.

DRAUTZBURG, T. AND H. UHLIG (2015): "Fiscal Stimulus and Distortionary Taxation," *Review of Economic Dynamics*, 18, 894–920.

FERNÁNDEZ-VILLAVERDE, J., P. GUERRÓN-QUINTANA, K. KUESTER, AND J. RUBIO-RAMÍREZ (2015): "Fiscal Volatility Shocks and Economic Activity," *American Economic Review*, 105, 3352–3384.

FORNI, L., L. MONTEFORTE, AND L. SESSA (2009): "The General Equilibrium Effects of Fiscal Policy: Estimates for the Euro Area," *Journal of Public Economics*, 93, 559–585.

FURLANETTO, F. AND N. GROSHENNY (2016): "Mismatch Shocks and Unemployment during the Great Recession," *Journal of Applied Econometrics*, 31, 1197–1214.

GALÍ, J. (1999): "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *American Economic Review*, 89, 249–271.

GERTLER, M., L. SALA, AND A. TRIGARI (2008): "An Estimated Monetary DSGE Model with Unemployment and Staggered Nominal Wage Bargaining," *Journal of Money, Credit and Banking*, 40, 1713–1764.

HALL, R. E. (1997): "Macroeconomic Fluctuations and the Allocation of Time," *Journal of Labor Economics*, 15, 223–50.

——— (2017): "High Discounts and High Unemployment," *American Economic Review*, 107, 305–30.

JONES, J. B. (2002): "Has Fiscal Policy Helped Stabilize the Postwar U.S. Economy?" *Journal of Monetary Economics*, 49, 709–746.

KRAUSE, M. U., D. LOPEZ-SALIDO, AND T. A. LUBIK (2008): "Inflation Dynamics with Search Frictions: A Structural Econometric Analysis," *Journal of Monetary Economics*, 55, 892–916.

MENDOZA, E. G., A. RAZIN, AND L. L. TESAR (1994): "Effective Tax Rates in Macroeconomics: Cross-Country Estimates of Tax Rates on Factor Incomes and Consumption," *Journal of Monetary Economics*, 34, 297–323.

MERTENS, K. AND J. L. MONTIEL OLEA (2013): "Marginal Tax Rates and Income: New Time Series Evidence," *NBER Working Paper*, 19171.

RAVN, M. O. AND S. SIMONELLI (2007): "Labor Market Dynamics and the Business Cycle: Structural Evidence for the United States," *The Scandinavian Journal of Economics*, 109, 743–777.

SALA, L., U. SÖDERSTRÖM, AND A. TRIGARI (2012): "Structural and Cyclical Forces in the Labor Market during the Great Recession: Cross-Country Evidence," *NBER International Seminar on Macroeconomics*, 9, 345–404.

SANTOS SILVA, J. M. C. AND F. N. CARDOSO (2001): "The Chow-Lin Method Using Dynamic Models," *Economic Modelling*, 18, 269–280.

SHIMER, R. (2005): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 95, 25–49.

——— (2012): "Reassessing the Ins and Outs of Unemployment," *Review of Economic Dynamics*, 15, 127–148.

SMETS, F. AND R. WOUTERS (2007): "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, 97, 586–606.

TRABANDT, M. AND H. UHLIG (2011): "The Laffer Curve Revisited," *Journal of Monetary Economics*, 58, 305–327.

ZUBAIRY, S. (2014): "On Fiscal Multipliers: Estimates from a Medium Scale DSGE Model," *International Economic Review*, 55, 169–195.