DEMS
Department of Economics, Management and Statistics

DEMS WORKING PAPER SERIES

The (Ir)Relevance of Rule-of-Thumb Consumers for U.S. Business Cycle Fluctuations

Alice Albonico, Qazi Haque
and Guido Ascari

No. 453/r - November 2020
Rev - October 2022

Department of Economics, Management and Statistics
University of Milano – Bicocca
Piazza Ateneo Nuovo 1 – 2016 Milan, Italy
http://dems.unimib.it/

The (Ir)Relevance of Rule-of-Thumb Consumers for U.S. Business Cycle Fluctuations*

Alice Albonico†
University of Milano - Bicocca
CefES

Guido Ascari‡
University of Pavia
De Nederlandsche Bank

Qazi Haque§
University of Adelaide
Centre for Applied Macroeconomic Analysis

June 27, 2022

Abstract

We estimate a medium-scale model with and without rule-of-thumb consumers over the pre-Volcker and the Great Moderation periods, allowing for indeterminacy. Passive monetary policy and sunspot fluctuations characterize the pre-Volcker period for both models. In both subsamples, the estimated fraction of rule-of-thumb consumers is low, such that the two models are empirically almost equivalent; they yield very similar impulse response functions, variance and historical decompositions. We conclude that rule-of-thumb consumers are irrelevant to explain aggregate U.S. business cycle fluctuations.

Keywords: rule-of-thumb consumers, indeterminacy, business cycle fluctuations
JEL classification: E32, E52, C11, C13

---

*We thank the Editor Pok-sang Lam and two anonymous referees for helpful feedback. We also thank Andrea Colciago, Chiara Punzo and the seminar participants at University of Milano - Bicocca for comments. Haque acknowledges generous support from the Australian Research Council, under the grant DP170100697.

†Address: Department of Economics, Management and Statistics, University of Milano - Bicocca, Piazza dell'Ateneo Nuovo 1, 20126 Milano, Italy. Phone: +390264483041. Email: alice.albonico@unimib.it

‡Address: Department of Economics and Management, University of Pavia, Via San Felice 5, 27100 Pavia, Italy. E-mail address: guido.ascari@unipv.it.

§Address: School of Economics and Public Policy, The University of Adelaide, 10 Pulteney Street, Adelaide SA 5005, Australia. Email: qazi.haque@adelaide.edu.au.

1 Introduction

Most empirical papers investigating U.S. business cycle fluctuations rely on Representative Agent New Keynesian (RANK, henceforth) models where monetary policy is active and the so-called Taylor Principle holds. This is the case of Smets and Wouters (2007), for example, which has become the benchmark for estimated models for the U.S. economy. However, some seminal papers in the literature ascribe the occurrence of the Great Inflation episode to “bad policy” of the Federal Reserve. Clarida et al. (2000) point toward self-fulfilling expectations due to indeterminacy arising from passive monetary policy as an explanation of the high inflation episode in the U.S. during the 1970s. Lubik and Schorfheide (2003, 2004) propose a method to quantitatively assess the importance of equilibrium indeterminacy and the propagation of fundamental and sunspot shocks. Following Lubik and Schorfheide’s (2004) methodology and allowing for non-trivial monetary and fiscal interactions, Bhattarai et al. (2016) find that passive monetary and passive fiscal policy regime prevailed in the pre-Volcker period, which resulted in equilibrium indeterminacy, while active monetary and passive fiscal policy prevailed post-Volcker. According to these views, the switch from passive to active monetary policy brought about a stable and determinate environment since the early 1980s. In a related study, Boivin and Giannoni (2006) find that this switch has also been instrumental in reducing observed output and inflation volatility.[1]

All these papers share two common features, they: (i) focus on small-scale models; (ii) rely on the standard Representative Agent models. This paper relaxes these two assumptions to investigate the role of (a particular sort of) heterogeneity in the transmission of shocks on U.S. business cycle and in the narrative about the U.S. monetary policy using an empirically relevant medium-scale DSGE model.

Regarding (i), there have been recent progress from a methodological point of view. Bianchi and Nicolò (2019) propose a new method for solving and estimating linear rational expectations models under indeterminacy that can handle more complex medium-scale models and can be implemented even when the boundaries of the determinacy region are unknown.[2] Building on this, Nicolò (2020) estimates the medium-scale model of Smets and Wouters (2007) for different

[1] Hirose, Kurozumi and Van Zandweghe (2020), using an estimated NK model with positive trend inflation, show that both systematic monetary policy as well as changes in the level of trend inflation resulted in a switch to determinacy after 1982.

[2] See Farmer et al. (2015) for an alternative methodology.

subsamples while allowing for indeterminacy.

Regarding (ii), a notable exception is Bilbiie and Straub (2013), where the authors estimate a small-scale Two-Agents New-Keynesian (TANK) model to study the Great Inflation and the Great Moderation periods in the U.S.. They put forward an alternative explanation of the Great Inflation episode arguing that the different monetary policy transmission mechanisms which characterized those periods could be related to a structural change in asset market participation. The main assumption is the presence of the so-called *Rule-of-Thumb* (ROT, henceforth) consumers. In line with the seminal papers by Galí et al. (2007) and Bilbiie (2008), ROT consumers are liquidity constrained households who cannot access financial and capital markets and thus cannot smooth consumption. Bilbiie and Straub (2013) build on Bilbiie's (2008) finding of an Inverted Aggregate Demand Logic (IADL) mechanism, which leads to an upward sloping AD curve for a high enough share of ROT. They find evidence of both a passive monetary policy and limited asset market participation during the pre-Volcker period, thereby implying determinacy in a IADL environment.[3] They further show that as the share of agents participating in asset markets had increased, the IS curve's slope flipped and policy became active which results in equilibrium determinacy for the Great Moderation period. The change in the sign of the IS curve's slope in the early 1980s is also documented by Bilbiie and Straub (2012) using single-equation reduced-form GMM estimation.

The ROT assumption enables to move from the standard Representative Agent (RANK) specification while keeping the model tractable from an analytical point of view (see Bilbiie, 2020). The presence of ROT consumers proved also to be beneficial for New Keynesian models from an empirical point of view in reproducing empirical dynamics in response to government spending shocks (Galí et al., 2007; Bilbiie et al., 2008), investment shocks (Furlanetto et al., 2013) and technology shocks (Furlanetto and Seneca, 2012). Kaplan et al. (2014), among others, show that liquidity constrained agents could be relevant empirically. Moreover, the ROT assumption has been introduced in estimated operational macroeconomic models. Nowadays, important institutions such as the Federal Reserve (Brayton et al., 2014) and the European Commission (Kollmann et al., 2016) are including this type of agents in their benchmark estimated models used for forecasting and for the analysis of macroeconomic issues. Coenen

[3] Haque et al. (2021) also find support for determinacy in the pre-Volcker period, albeit for different reasons. In the presence of substantial wage rigidity and well-identified commodity price-shocks, they show that the Federal Reserve responded aggressively to inflation but negligibly to the output gap in the pre-Volcker period.

at al. (2012), Forni et al. (2009) and Albonico et al. (2019), among others, estimate medium-scale DSGE models with ROT for the Euro area. For the U.S., the literature focuses more on standard Representative Agent models such as Smets and Wouters (2007).

In this paper, we investigate the relevance of ROT consumers in explaining U.S. business cycle fluctuations, revisiting the findings of Bilbiie and Straub (2013). We introduce the presence of ROT consumers in a medium-scale DSGE model with all the standard bells and whistles similar to Smets and Wouters (2007). We then estimate the model over two different subsamples (the pre-Volcker and the Great Moderation periods), while allowing and testing for (in)determinacy, and compare our results with the standard RANK specification. In this context, indeterminacy can arise due to different combinations of parameters. For instance, for low values of the degree of ROT, indeterminacy can arise due to passive monetary policy, dubbed the Standard Aggregate Demand Logic (SADL), as in Lubik and Schorfheide (2004). In contrast, for high enough values of the degree of ROT share, IADL might be in place as in Bilbiie (2008), resulting in either indeterminacy due to active monetary policy or determinacy if monetary policy is passive, as found by Bilbiie and Straub (2013). Our paper is also related to Nicolò (2020), who estimates the model of Smets and Wouters (2007) for different subsamples while allowing for indeterminacy and employing the methodology proposed by Bianchi and Nicolò (2019). He shows that monetary policy was passive in the Great Inflation period and active afterwards. Similar to Lubik and Schorfheide (2004), he finds that indeterminacy manifested primarily by altering the propagation of structural shocks, while sunspot shocks played only a limited role in explaining macroeconomic volatility.

We find that introducing ROT consumers in a medium-scale model is irrelevant to explain aggregate business cycle fluctuations in U.S. data. The reason is that the estimated fraction of ROT consumers is so low that it is not affecting the dynamics of the model compared to a standard representative agent model (RANK). First, the estimations of both a model with ROT and one without (RANK) point to an indeterminate equilibrium in the pre-Volcker period, due to passive monetary policy, and to a determinate equilibrium in the post-Volcker period with active monetary policy, as in Lubik and Schorfheide (2004) and Nicolò (2020). Second, in the pre-Volcker period the log-likelihoods of the two models are very close, while in the latter period the RANK model is preferred by the data. Third, in both subsamples, the RANK and ROT models yield almost the same impulse response functions, variance and historical decompositions, such that they share the same narrative of U.S. business cycle fluctuations. Therefore, the presence of ROT consumers is not substantive to explain these fluctuations. The estimation results of the empirically rich medium-scale New Keynesian model therefore contrast with the ones in Bilbiie and Straub (2013), who employ a small-scale model.

Our main finding, that including ROT in a RANK model does not change the interpretation of aggregate U.S. fluctuations, does not mean obviously that modelling ROT, or heterogeneous agents more generally, is not important to explain other dimensions of the economy. In recent years, a growing body of literature evolved from simple TANK models to the more complex Heterogeneous-Agents (HANK) models, following Kaplan et al. (2018). However, the ROT assumption is sufficiently simple to allow us to explore the indeterminacy vs. determinacy issue in the context of an empirically relevant medium-scale DSGE model, using the Bianchi and Nicolò (2019) methodology. This would not have been feasible with a full HANK model. Moreover, Debortoli and Galí (2017) compare the implications for business cycles fluctuations between a HANK model and a simpler TANK model with ROT consumers. Identifying the three sources of heterogeneity arising in the HANK framework[4], they show that the most important component of heterogeneity for output fluctuations is the consumption gap between the two types of consumers (constrained and unconstrained). Interestingly, they show that a simple TANK model, with a constant share of constrained households and no heterogeneity within either type, approximates the implications of a HANK model regarding output fluctuations reasonably well, thereby supporting the use of a TANK model in quantitative analysis of U.S. business cycle fluctuations. Notwithstanding, our empirical findings go a step further and suggest that, in fact, estimating a TANK model does not materially change the estimated shocks and frictions relative to a RANK model. As such, our results point toward the irrelevance of ROT consumers and imply that a medium-scale RANK model, like Smets and Wouters (2007), does not need to be enlarged by the presence of ROT to study the drivers of U.S. business cycle fluctuations. Along these lines, our results reinforce Bayer et al. (2020)'s findings, who show that adding data on inequality does not affect aggregate fluctuations in the U.S.[5] Finally,

[4]Namely, i) changes in the average consumption gap between constrained and unconstrained households, ii) variations in consumption dispersion within unconstrained households, and iii) changes in the share of constrained households.

[5]Nevertheless, Bayer et al. (2020) show that the estimated shocks from their HANK model have significantly contributed to the evolution of U.S. wealth and income inequality.

using survey data from the U.S. Survey of Consumer Finances, Kaplan et al. (2014) measure the fraction of the so-called *poor Hand-to-Mouth consumers*[6] being only 14% on average in the U.S. between 1989 and 2010, which is consistent with our findings.

The paper is organized as follows. Section 2 briefly presents the model. Section 3 explains the estimation strategy based on Bianchi and Nicolò (2019). Section 4 discusses the main results and Section 5 provides some robustness, while Section 6 concludes.

2 Model

We develop a Dynamic Stochastic General Equilibrium (DSGE) model following Smets and Wouters (2007) in particular. Smets and Wouters's (2007) model has become the workhorse model for the empirical analysis of the U.S. economy. It includes all the standard features and frictions of New-Keynesian models, while still remaining tractable. We depart from their model only in few aspects. First, we introduce the presence of Rule-of-Thumb (ROT) consumers, on the footsteps of Galí et al. (2007) and Bilbiie (2008). There is a fraction θ of households who do not have access to financial and capital markets and consume all their disposable labor income in each period. Second, we consider a separable utility function in consumption and hours, to stay close to Bilbiie and Straub (2012, 2013). Wage decisions are made by unions which optimally reset the nominal wage according to a Calvo (1983) scheme. The supply side is composed of final producers operating under perfect competition and intermediate monopolistically competitive firms. Prices are sticky following a Calvo (1983) mechanism. Intermediate goods are packed by final firms with a Kimball (1995) aggregator.

The model includes the usual frictions considered in New-Keynesian medium-scale models: external habits in consumption, variable capital utilization, investment adjustment costs, sticky wages and prices, indexation on past and trend inflation.

Given that the model is rather standard, we leave a more detailed description of the model equations in the Appendix.

[6]Poor Hand-to-Mouth consumers are similar to our ROT consumers.

2.1 Households

There is a continuum of households indexed by $i \in [0,1]$. A share $1-\theta$ of households are Ricardian ($i = o$), such that they can access financial markets, hold government bonds, accumulate physical capital, and rent capital services to firms. The remaining θ households are ROT consumers ($i = rt$), as specified above.

Households maximize the following utility function:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{1}{1-\sigma} \left(c_t^i - bc_{t-1}\right)^{1-\sigma} - \frac{\left(h_t^i\right)^{1+\phi_l}}{1+\phi_l} \right\}, \tag{1}$$

where individual and aggregate consumption (c_t^i, c_t) are adjusted by the deterministic growth trend g_z, h_t^i stands for individual hours worked, $0 < \beta < 1$ is the subjective discount factor, σ measures the inverse of the intertemporal elasticity of substitution and ϕ_l is the inverse of Frisch elasticity. The parameter $0 < b < 1$ measures the degree of external habits in consumption.

Ricardian households budget constraint is standard:

$$P_t C_t^o + P_t I_t^o + \frac{B_{t+1}^o}{\varepsilon_t^b} = R_{t-1} B_t^o + W_t h_t^o + P_t D_t^o + \left[R_t^k u_t^o - a\left(u_t^o\right) P_t\right] K_t^o - T_t^o, \tag{2}$$

where $a\left(u_t^o\right) = \gamma_{u1}\left(u_t^o - 1\right) + \frac{\gamma_{u2}}{2}\left(u_t^o - 1\right)^2$ defines the capital utilization cost function, in line with Christiano at al. (2005). Ricardian households allocate their resources between consumption C_t^o, investments I_t^o and government-issued bonds B_t^o. They receive income from labor services $W_t h_t^o$, from dividends D_t^o, from renting capital services $u_t^o K_t^o$ at the rate R_t^k and from holding government bonds. P_t is the aggregate price index, R_t is the gross nominal interest rate, K_t^o is the physical capital stock and u_t^o defines capital utilization. T_t^o are lump-sum taxes. ε_t^b is a risk premium shock that affects the intertemporal margin, creating a wedge between the interest rate controlled by the central bank and the return on assets held by the households.

The capital accumulation equation is:

$$K_{t+1}^o = (1-\delta) K_t^o + \varepsilon_t^i \left[1 - S\left(\frac{I_t^o}{I_{t-1}^o}\right)\right] I_t^o, \tag{3}$$

with the investment adjustment costs function defined as:

$$S\left(\frac{I_t^o}{I_{t-1}^o}\right) = \frac{\gamma_I}{2}\left(\frac{I_t^o}{I_{t-1}^o} - g_z\right)^2, \tag{4}$$

where δ is the capital depreciation rate and γ_I is a parameter measuring the degree of investment adjustment costs. ε_t^i is a shock to the marginal efficiency of investment (see Justiniano et al., 2010).

ROT households maximize (1) subject to the following budget constraint:

$$P_t C_t^{rt} = W_t h_t^{rt} - T_t^{rt}. \tag{5}$$

A generic aggregate variable is expressed as $X_t = \theta X_t^{rt} + (1-\theta) X_t^o$.

2.2 Labor market

Each household supplies the bundle of labor services $h_t^i = \left\{\int_0^1 [h_t^i(j)]^{\frac{1}{1+\lambda_t^w}} dj\right\}^{1+\lambda_t^w}$ that firms demand. For each labor type j, the wage setting decision is allocated to a specific labor union. At the given nominal wage W_t^j, households supply the amount of labor that firms demand. Following Colciago (2011), demand for labor type j is split uniformly across the households, so that households supply identical amount of labor services, $h_t = h_t^i$. λ_t^w represents an exogenous shock to the net wage markup.

2.2.1 Wage setting

Nominal wages are sticky à la Calvo (1983). In each period, union j can optimally reset the nominal wage with probability $(1-\xi_w)$. Those unions that cannot re-optimize the wage adjust the wage according to the scheme $W_t^j = g_z \pi_{t-1}^{\chi_w} \pi^{(1-\chi_w)} W_{t-1}^j$, where π is the steady state (or trend) inflation rate. Non-reset wages are partially indexed to past inflation and trend inflation, with $\chi_w \in [0,1]$ allowing for any degree of combination of indexation between the two components. The aggregate wage is thus:

$$W_t = \left[\xi_w \left(g_z \pi_{t-1}^{\chi_w} \pi^{1-\chi_w} W_{t-1}\right)^{\frac{1}{\lambda_t^w}} + (1-\xi_w)\left(\tilde{W}_t\right)^{\frac{1}{\lambda_t^w}}\right]^{\lambda_t^w}, \tag{6}$$

where $\tilde{W}_t$ is the optimal reset wage.

Following Colciago (2011), we assume that the representative union's objective function is a weighted average $(1-\theta,\,\theta)$ of the two household types' utility functions, subject to the labor demand $h_t = h_t^d \int_0^1 \left(\frac{W_t^j}{W_t}\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}} dj$, (2) and (5). The resulting first order condition is:

$$E_t \sum_{s=0}^{\infty} (\xi_w \beta)^s h_{t+s}^j \left\{ \tilde{W}_t^j \frac{g_z^s \pi_{t,t+s-1}^{\chi_w} \pi^{s(1-\chi_w)}}{P_{t+s} g_z^{t+s}} \left(1 - \frac{1+\lambda_t^w}{\lambda_t^w}\right) \left[\begin{array}{c} (1-\theta)\left(c_{t+s}^o - bc_{t+s-1}\right)^{-\sigma} \\ +\theta\left(c_{t+s}^{rt} - bc_{t+s-1}\right)^{-\sigma} \end{array} \right] \right. \tag{7}$$
$$\left. + \frac{1+\lambda_t^w}{\lambda_t^w} \left[(1-\theta)\left(c_{t+s}^o - bc_{t+s-1}\right)^{-\sigma} MRS_{t+s}^o + \theta\left(c_{t+s}^{rt} - bc_{t+s-1}\right)^{-\sigma} MRS_{t+s}^{rt} \right] \right\} = 0.$$

2.3 Production

2.3.1 Final good firms

The final good Y_t is produced under perfect competition. A continuum of intermediate inputs Y_t^z is combined as in Kimball (1995). The final good producers maximize profits:

$$\max_{Y_t, Y_t^z} P_t Y_t - \int_0^1 P_t^z Y_t^z dz \tag{8}$$

$$s.t. \int_0^1 G\left(\frac{Y_t^z}{Y_t}; \lambda_t^p\right) dz = 1,$$

with G strictly concave and increasing and $G(1) = 1$ and λ_t^p is the net price markup, which is assumed to be exogenous.

2.3.2 Intermediate good firms.

Intermediate firms z are monopolistically competitive and use as inputs capital and labor services, $u_t^z K_t^z$ and h_t^z, respectively. The production technology is a Cobb-Douglas function $Y_t^z = \varepsilon_t^a [u_t^z K_t^z]^\alpha [g_z^t h_t^z]^{1-\alpha} - g_z^t \Phi$, where Φ are fixed production costs. ε_t^a is a temporary total factor productivity shock. The term g_z is a deterministic growth trend.

2.3.3 Price setting

Intermediate goods prices are sticky à la Calvo (1983). A firm z can optimally reset its price with probability $\left(1-\xi_p\right)$. Firms that cannot re-optimize adjust the price according to the scheme $P_t^z = \pi_{t-1}^{\chi_p} \pi^{1-\chi_p} P_{t-1}^z$, where $\chi_p \in [0,1]$ allows for any degree of combination of indexation to past or trend inflation.

The aggregate price index is:

$$P_t = \left(1-\xi_p\right) \tilde{P}_t^z G'^{-1}\left(\frac{\tilde{P}_t^z \iota_t}{P_t}\right) + \xi_p \pi_{t-1}^{\chi_p} \pi^{1-\chi_p} P_{t-1} G'^{-1}\left(\frac{\pi_{t-1}^{\chi_p}\pi^{1-\chi_p} P_{t-1}\iota_t}{P_t}\right), \tag{9}$$

where $\iota_t = \int_0^1 G'\left(\frac{Y_t^z}{Y_t}\right)\frac{Y_t^z}{Y_t} dz$.

The representative firm chooses the optimal price $\tilde{P}_t^z$ that maximizes expected profits subject to the demand schedule. The resulting first order condition is:

$$E_t \sum_{s=0}^{\infty} \xi_p^s \frac{\Xi_{t,t+s}}{P_{t+s}} Y_{t+s}^z \left[\tilde{P}_t^z \pi_{t,t+s-1}^{\chi_p} \pi^{s(1-\chi_p)} + \left(\tilde{P}_t^z \pi_{t,t+s-1}^{\chi_p}\pi^{s(1-\chi_p)} - MC_{t+s}^z\right) \frac{1}{G'^{-1}\left(\omega_{t+s}\right)} \frac{G'\left(x_{t+s}\right)}{G''\left(x_{t+s}\right)}\right] = 0, \tag{10}$$

where $\omega_t = \frac{\tilde{P}_t^z}{P_t}\iota_t$ and $x_t = G'^{-1}\left(\omega_t\right)$.

2.4 Government

The government budget constraint is:

$$P_t G_t + R_{t-1} B_t = B_{t+1} + T_t. \tag{11}$$

We assume that it is balanced every period. Government spending evolves exogenously.

The monetary authority sets the nominal interest rate according to the same Taylor rule as in Smets and Wouters (2007):

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\phi_R} \left[\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y_t^{flex}}\right)^{\phi_y}\right]^{1-\phi_R} \left(\frac{Y_t/Y_{t-1}}{Y_t^{flex}/Y_{t-1}^{flex}}\right)^{\phi_{\Delta y}} \varepsilon_t^r, \tag{12}$$

where Y_t^{flex} is the level of output prevailing in a flexible prices and wages environment and ε_t^r is an exogenous interest rate shock.

3 Estimation strategy

3.1 Data

To estimate the model, we use Bayesian techniques and the measurement equations that relate the macroeconomic data to the endogenous variables of the model are defined as:

$$\begin{bmatrix} dlGDP_t \\ dlCONS_t \\ dlINV_t \\ dlWAG_t \\ lHOURS_t \\ dlP_t \\ FEDFUNDS_t \end{bmatrix} = \begin{bmatrix} \overline{\gamma} \\ \overline{\gamma} \\ \overline{\gamma} \\ \overline{\gamma} \\ \overline{h} \\ \overline{\pi} \\ \overline{R} \end{bmatrix} + \begin{bmatrix} \widehat{y}_t - \widehat{y}_{t-1} \\ \widehat{c}_t - \widehat{c}_{t-1} \\ \widehat{i}_t - \widehat{i}_{t-1} \\ \widehat{w}_t - \widehat{w}_{t-1} \\ \widehat{h}_t \\ \widehat{\pi}_t \\ \widehat{R}_t \end{bmatrix} \tag{13}$$

where dl denotes the percentage change measured as log difference, l denotes the log, and hatted variables denote log deviations from steady state. The observables are the seven quarterly U.S. macroeconomic time series used in Smets and Wouters (2007), and they match the number of fundamental shocks that affect the economy. The series considered are: the growth rate in real GDP, consumption, investment and wages, log of hours worked, inflation rate measured by the GDP deflator, and the federal funds rate. Similar to Smets and Wouters (2007), $\overline{\gamma}$ denotes a deterministic growth trend common to the real variables GDP, consumption, investment and wages ($\overline{\gamma} = 100\,(g_z - 1)$), $\overline{h}$ is the (log) steady-state hours worked (normalized to zero), $\overline{\pi}$ is the quarterly steady-state net inflation rate, and $\overline{R}$ is the quarterly steady-state net nominal interest rate.

We include seven fundamental shock processes in the estimation (the same as in Smets and Wouters, 2007): a technology shock, a risk premium shock, an investment shock, a monetary policy shock, a government spending shock, a price markup shock and a wage markup shock. All shocks have an autoregressive component of order 1. The first four shocks are AR(1) processes with i.i.d. Normally distributed innovations. The government spending shock is also correlated with the technology shock. The two markup shocks also have a MA(1) component.

3.2 Calibration and Priors

We calibrate a number of parameters. In particular, the discount factor β is fixed at 0.9975, corresponding to a 2.6% annual real interest rate at the prior mean. The steady-state depreciation rate δ is 0.025, corresponding to a 10% depreciation rate per year. The elasticity of the demand for goods is set at 6, which implies a 20% net price markup in steady state. We set the government spending-to-GDP ratio at 20%, in line with its sample average.

Table 1 reports the prior distributions for the structural parameters of the model and the exogenous processes that drive the dynamics of the economy, which are set in accordance with Smets and Wouters (2007). The only differences relate to the Taylor rule coefficient associated with the response of the monetary authority to changes in the inflation rate (ϕ_π) and the fraction of ROT consumers (θ) which is absent in the RANK model of Smets and Wouters (2007). For ϕ_π, Smets and Wouters (2007) specify a normal distribution truncated at 1, centered at 1.50 and with standard deviation 0.25 and impose determinacy. Instead, here, we want to deal with the possibility of indeterminacy. Figure 1 shows the determinacy/indeterminacy regions as ϕ_π and θ vary. For low values of the fraction of ROT agents, the model behaves like a standard NK model, so that it admits a unique stable rational expectations equilibrium when the Taylor principle is satisfied, i.e., $\phi_\pi > 1$. However, as it is well known from the literature, when θ is sufficiently high the result flips, so that the model needs a passive monetary policy, i.e., $\phi_\pi < 1$, for determinacy to arise. Bilbiie (2008) calls this possibility the inverted-aggregate-demand-logic (IADL). The threshold value for θ that makes the model enter the IADL region of the parameter space depends on the properties of the model and on parameter calibration. While Bilbiie (2008) shows that in standard three equation NK model with ROT agents this threshold value for θ can be relatively low, Colciago (2011) shows that nominal wage rigidity increases the threshold value substantially (see also Ascari et al., 2017).[7] In our medium-scale model, with parameters calibrated at their prior means, this threshold value in Figure 1 is around 0.6. Moreover, other possibilities arise in a medium-scale model, because some parameter combinations yield instability and some other a degree of indeterminacy greater than one. The next Section explains how we deal with the determinacy/indeterminacy issue

[7] Few papers analyse determinacy region in a medium-scale model with ROT. Motta and Tirelli (2012, 2014) highlight the role of the interaction between the fraction of ROT and the degree of habits in consumption. Neither paper includes capital and the related frictions. Albonico et al. (2019) show the results for the determinacy regions of a medium-scale model with respect to both the degree of habits and its specification.

in the estimation, following Bianchi and Nicolò (2019). Regarding priors, we consider a prior which assigns roughly equal probability of observing indeterminacy as well as a unique solution. In particular, for ϕ_π we set a flatter normal prior distribution centered at 1 and with standard deviation 0.35 following Nicolò (2020). The fraction of ROT θ is assumed to follow a Beta distribution with mean 0.3 and standard deviation 0.1, in line with Bilbiie and Straub (2013).

3.3 Methodology

Bianchi and Nicolò (2019) develop a new method to solve and estimate linear rational expectations (LRE) models that accommodates both determinacy and indeterminacy. Their characterization of indeterminate equilibria is equivalent to Lubik and Schorfheide (2003, 2004) and Farmer et al. (2015). We closely follow Bianchi and Nicolò (2019) and in the following briefly sketch their methodology while referring the readers to their paper for detailed exposition. The LRE model can be compactly written in the canonical form as:

$$\Gamma_0\left(\Theta\right) s_t = \Gamma_1\left(\Theta\right) s_{t-1} + \Psi\left(\Theta\right) \varepsilon_t + \Pi\left(\Theta\right) \eta_t, \tag{14}$$

where s_t is the vector of endogenous variables, Θ is the vector of model parameters, ε_t is the vector of fundamental shocks, and η_t are one-step ahead forecast errors for the expectational variables. Bianchi and Nicolò (2019) propose to augment the original model by appending an independent process, which could be either stable or unstable. First, for our medium-scale ROT model with priors set as above, the occurrence of indeterminacy of degree two (or higher) is *a-priori* very low and so in what follows we focus on one degree of indeterminacy. Second, the priors are such that there is roughly a 50-50 prior probability of determinacy and one degree of indeterminacy. Following Bianchi and Nicolò (2019), we append the following autoregressive process to the original LRE model:

$$\omega_t = \varphi^* \omega_{t-1} + \nu_t - \eta_{f,t},$$

where ν_t is the sunspot shock and $\eta_{f,t}$ can be any element of the forecast error vector η_t. As proven by Bianchi and Nicolò (2019), it is without loss of generality that we include the forecast error associated with the inflation rate $\eta_{\pi,t} = \pi_t - E_{t-1}\left(\pi_t\right)$ as $\eta_{f,t}$ in the augmented representation. The key insight consists of choosing this auxiliary process in a way to deliver the 'correct' solution. When the original model is determinate, the auxiliary process must be stationary so that the augmented representation also satisfies the Blanchard-Kahn condition. Accordingly, we set φ^* such that its absolute value is inside the unit circle. Then the autoregressive process for ω_t does not affect the solution for the endogenous variables s_t. On the other hand, under indeterminacy, the additional process should be explosive so that the Blanchard-Kahn condition is satisfied for the augmented system, though it is not for the original model. Hence, the absolute value of φ^* is set outside the unit circle. Under indeterminacy, we estimate the standard deviation of the sunspot shock, σ_ν, and so we specify a uniform distribution over the interval $[0, 1]$ following Nicolò (2020). In addition, the newly defined sunspot shock, ν_t, is potentially related to the structural shocks of the model. Nicolò (2020) finds that the correlation between this newly defined sunspot shock and the price markup shock is the only one statistically different from zero, implying that the price markup shock has a contemporaneous effect on inflation through this channel. Hence in what follows, we report estimation results corresponding to the correlations with the remaining shocks set to zero.[8] For the correlation between the sunspot shock and the price markup shock, we set a uniform prior distribution over the interval $[-1, 1]$ as in Nicolò (2020).

We use Bayesian techniques to estimate the model parameters and to test for (in)determinacy using posterior model probabilities. First, we find the mode of the posterior distribution by maximizing the log posterior function, which combines the prior information on the parameters with the likelihood of the data. In a second step, the Metropolis-Hastings algorithm is used to simulate the posterior distribution and to evaluate the marginal likelihood of the model.[9]

4 Results

We estimate both our baseline model and a model without ROT (where $\theta = 0$) for the pre-Volcker (55:Q4-79:Q2) and the Great Moderation (84:Q1-07:Q3) periods separately.[10] Table

[8] We also confirm that this is actually favoured by the data.

[9] All estimations are done using Dynare (https://www.dynare.org/wp-repo/dynarewp001.pdf). The posterior distributions are based on 500,000 draws, with the first 100,000 draws being discarded as burn-in draws. The average acceptance rate is around 25-30%.

[10] We exclude the years of the Volcker disinflation and the end of the second subsample is marked by the onset of the Great Recession.

2 shows the log-data densities of the four possibilities (determinacy vs. indeterminacy, ROT vs. RANK) for both subsamples. Comparing the log-likelihoods, both models (ROT and RANK) point definitely toward indeterminacy in the first subsample and determinacy in the second subsample. The probability of indeterminacy and determinacy in the two subsamples, respectively, are calculated as in Lubik and Schorfheide (2004) and are equal to one in both cases.

Then, let us focus on the first subsample under indeterminacy. The ROT model is marginally preferred to the RANK model. The Bayes factor comparing the two alternative models is 1.7, which according to the classification in Kass and Raftery (1995) is "not worth more than a bare mention" as evidence against the RANK model.[11] Indeed, the two models are very close, so that our estimates deliver two main results.

First, consistent with most of the results in the literature (e.g., Lubik and Schorfheide, 2004, or more recently Nicolò, 2020), the RANK model in the first sub-sample yields indeterminacy, because of a passive monetary policy rule (the estimated posterior mean for ϕ_π is 0.798, see Table 1). However, contrary to the evidence in Bilbiie and Straub (2013), this is also the case for the ROT model. The estimated posterior mean for the fraction of ROT, θ, is low, equal to 0.219, far below the threshold value for the IADL region in our model (recall the discussion in Section 3.2 and Figure 1). Figure 2 shows that data are informative for the posterior distribution for θ. Bilbiie and Straub (2013) found that the data preferred determinacy when estimating a small-scale ROT model for the pre-Volcker period, as a result of passive monetary policy and a high fraction of ROT (their posterior mean for θ is 0.5), that is, the model is in the IADL region of the parameter space. According to our medium-scale model, instead, the ROT model delivers indeterminacy, exactly for the same reason as the RANK model: a passive monetary policy (the estimated posterior mean for ϕ_π is 0.796, see Table 1). The estimated ROT fraction is too low to put the model in the IADL region.

Second, the estimated ROT fraction is actually so low that the two models are extremely similar, delivering almost identical estimated posterior means of all the parameters, variance and historical decompositions, and impulse response functions to shocks. Table 1 shows the posterior means for all the parameters; there are barely any differences across the two models

[11] We report the Bayes Factor as suggested in Kass and Raftery (1995), calculated as 2(log-data density H1 - log-data density H0), where the null hypothesis (H0) is always the less preferred model (while the alternative hypothesis, H1, is the preferred one). Hence, we weight evidence against the null hypothesis.

and the estimates are consistent with the standard value in the RANK-DSGE literature. Table 3 presents the variance decompositions for the pre-Volcker period. For both models, output and consumption volatility is mainly determined by the technology and the risk-premium shocks (the later being relatively more important for consumption). Government spending shock is also important for output fluctuations. In both models, inflation volatility is mainly driven by the wage markup, the technology and the price markup shocks, but also by the sunspot shock. So inflation dynamics was driven by self-fulfilling expectations both for the RANK and the ROT model. This is confirmed by the historical decomposition of inflation and the output gap, shown in Figures 3 - 6. The narrative about the main drivers of U.S. business cycle fluctuations that comes out from the estimated DSGE model is the same in both models, and corroborate the results in Nicolò (2020). In the Great Inflation period of the '70s, the dynamics of the output gap is mainly driven by risk-premium shocks, which generate 'stagflation' dynamics under indeterminacy. A positive risk-premium shock has a contractionary effect on the economy, but because of passive monetary policy agents form self-fulfilling inflationary expectations (see the impulse responses in Figure A.4 in the Appendix). In the same period, high inflation is caused by technology shocks, demand shocks and the sunspot shock. Passive monetary policy alters the dynamics of inflation in response to shocks, particularly to technology, risk premium and monetary policy shocks. The presence of ROT consumers does not alter this interpretation of U.S. business cycle fluctuations during this subsample, because their fraction is too low. The impulse response functions to the different shocks almost overlap for the two models (indicated as ROT-IND and RANK-IND in the Figures) with two expected exceptions: the responses of aggregate consumption to the government spending shock and to the investment shock.[12] Figure 7 shows that the positive reaction of output to a government spending shock induces higher consumption of the ROT consumers that only partially compensate the decrease in consumption of optimizing consumers, who adhere to standard Ricardian equivalence dynamics. As a result, aggregate consumption decreases much less in the ROT-IND model than in the RANK-IND one. Similarly, Figure 8 shows that in response to the investment shock, the increase in income pushes up the consumption of ROT consumers, while optimizing consumers decrease their consumption to finance the increase in investment. As a result, aggregate consumption decreases slightly on

[12] Hence, in the main text we just include the impulse response functions to these two shocks, while the others are confined to the Appendix.

impact, but then it increases faster in the ROT-IND model with respect to the RANK-IND one. However, these differences are quantitatively negligible regarding the narrative of U.S. business cycle fluctuations according to the two models. The historical decomposition figures demonstrate that these two shocks are not quantitatively important drivers of consumption fluctuations. The variance decompositions in Table 3 are also unaffected.[13]

To sum up, the estimations of the two empirically rich models in the pre-Volcker subsample yield two main results that contrast with the ones in Bilbiie and Straub (2013), who estimate a small-scale model. First, a model with ROT consumers delivers indeterminacy due to passive monetary policy, just like a standard RANK model. Second, the estimate of the fraction of ROT consumers is so low that the RANK and the ROT models deliver almost exactly the same dynamics and interpretation of aggregate U.S. business cycle fluctuations.

Therefore, the presence of ROT consumers is not substantive to explain these fluctuations. Indeed, the difference in the log-data densities between the RANK-IND and the ROT-IND models are negligible. The next Section presents further robustness checks on the two main results of our paper.

The results for the second subsample are less surprising and in line with the existing literature. Both the RANK and the ROT model point towards determinacy and active monetary policy (see Table 2). The posterior mean for θ, as seen in Table 4, is very low (0.1), such that the two models are even more similar. Again, the estimated posterior means of all the other parameters of the model (see Table 4), the variance (see Table 5) and historical decompositions, and the impulse response functions are very similar across the two specifications, and they are in accordance with the results in Nicolò (2020). The Bayes factor (equal to 11) favours the RANK model 'very strongly', according to Kass and Raftery's (2015) classification. In accordance with the literature (Stock and Watson, 2003; Primiceri, 2005; Sims and Zha, 2006; Justiniano and Primiceri, 2008), the standard deviations of the fundamental shocks are substantially lower in this Great Moderation subsample, pointing to a change in both the shock volatilities and the conduct of monetary policy as the explanation for the conquest of American inflation.

[13] If anything, somewhat surprising, the fraction of the (forecast error) variance of consumption explained by these two shocks is higher in the RANK-IND model than in the ROT-IND one. While substantially so in percentage terms, the numbers are still miniscule.

5 Robustness

Our results point to the irrelevance of ROT consumers for aggregate business cycle fluctuations in the U.S. – i.e., the dynamics of the model with and without ROT consumers are very similar such that both models provide a similar interpretation of U.S. business cycles. In what follows, we first check if our results survive if we calibrate the share of ROT consumers, θ, to a higher value as found in some works in the literature. Then, we check whether our results hinge on the assumption of sticky wages that could dampen the role of ROT consumers as potential amplifier of shocks. Next, for similar reason, we look at a more realistic specification of the fiscal side of the model, relaxing the assumption of a balance budget. Finally, we check the robustness of the indeterminacy result in the pre-Volcker sample.

5.1 Alternative calibration for θ

In our estimates, the estimated fraction of ROT consumers turns out to be quite low: 22% and 11% for the two sub-samples respectively. Bilbiie and Straub (2013) estimate a small-scale TANK model and find the fraction of ROT consumers to be higher: 50% in their pre-Volcker sample and 20% in their post-1984 sample. In fact, the estimated ROT fraction for the pre-Volcker period in Bilbiie and Straub (2013) turns out to be high enough for the economy to be in the so-called inverse aggregate demand logic (IADL) region whereby a passive monetary policy implies determinacy. In contrast, our results show that estimating a similar TANK model with richer dynamic and stochastic structure implies a smaller role for ROT consumers in both sub-samples. One interpretation could be that missing propagation mechanisms and structural shocks are misinterpreted as high degree of ROT consumers in estimated small-scale models.

Nevertheless, direct estimates of the marginal propensity to consume (MPC) from Jappelli and Pistaferri (2020) and Fagereng, Holm and Natvik (2021) find the MPC to be around 0.4 at an annual level. Hence, to check the robustness of our results, we calibrate the fraction of ROT consumers to 0.4 for both sub-samples and re-estimate the model. Table 6 shows the log-data densities and estimated posterior model probabilities. For ease of comparison, in Table 6 we report our baseline results too. First, we find that the pre-Volcker period continues to be characterized by indeterminacy due to passive monetary policy. However, and in contrast to our baseline results, the post-84 period is now also characterized by indeterminacy and passive monetary policy as the posterior puts more than 80% weight in the indeterminacy region. Nonetheless, our baseline estimations, whereby we estimate the fraction of ROT consumer, fit significantly better in both sub-samples, suggesting that a low fraction of ROT consumers is preferred by the data through the lens of the full-system Bayesian estimation.

5.2 The cyclicality of inequality and the degree of wage stickiness

Bilbiie (2020) characterizes the conditions for the presence of ROT consumers to lead to an amplification or a dampening of monetary and fiscal policy shocks. Bilbiie (2020) shows that the key object is the constrained agent's (i.e. ROT consumer's) income elasticity to aggregate income. When this elasticity is larger (smaller) than one, the model dynamics amplifies (dampens) the effects of monetary and fiscal policies relative to RANK models. Bilbiie (2020) labels this finding as the 'cyclical inequality' channel: when the constrained agent's income over-reacts (under-reacts) to aggregate income, inequality between unconstrained and constrained is countercyclical (procyclical), and the model delivers amplification (dampening) relative to a RANK model. Bilbiie (2020) suggests that the cyclical behavior of inequality between the two types of agents, however, could depend on the degree of wage stickiness. According to Bilbiie (2020), the 'cyclical inequality' channel relies crucially on flexible wages, as a TANK model with sticky wages, along the lines of Colciago (2011) and Ascari et al. (2016, 2017), would imply smaller monetary and fiscal multipliers. This Section investigates to what extent the assumption of sticky wages in our model affects the cyclicality of inequality, and in so doing it affects the magnitude and features of business cycles. We simulate the estimated ROT model for the two sub-samples for different degrees of wage stickiness - keeping the other parameters at their posterior mean - and compute the following statistics: (i) cyclicality of Ricardian consumer's income, $\rho(\widehat{y}_t^o, \widehat{y}_t)$; (ii) cyclicality of ROT consumer's income, $\rho(\widehat{y}_t^{rt}, \widehat{y}_t)$; (iii) cyclicality of inequality, $\rho(ineq_t, \widehat{y}_t)$, where inequality is the defined as the difference between the log-deviations of Ricardian and ROT income, i.e. $ineq_t = \widehat{y}_t^o - \widehat{y}_t^{rt}$; and (iv) volatility of output fluctuations measured as the standard deviation of aggregate income, $std(\widehat{y}_t)$.

Table 7 shows the results. Both the incomes of the Ricardian and of the ROT consumers are strongly procyclical with the former more procyclical than the latter. An increase in wage stickiness increases the procylicality of both constrained and unconstrained agents' income.

However, note that what matters for amplification/dampening according to Bilbiie (2020) is not the cyclicality of different agents' income, but rather the cyclicality of inequality, which relies on the income elasticity of constrained and unconstrained agents to changes in aggregate income. Table 7 shows that inequality is countercyclical in both sub-samples when wages are relatively more flexible. As wage stickiness increases, inequality turns and becomes more and more procyclical.

Does this imply that business cycles in our model become dampened as wage stickiness increases? To see this, we look at the volatility of aggregate output. Our results suggest a non-monotonic relationship between the degree of wage stickiness and the volatility of output. When stickiness is very low, an initial increase in wage stickiness dampens output fluctuations. In contrast, when stickiness is moderate, further increase in wage stickiness amplifies output fluctuations. These results imply that it is possible in principle to have amplification in our medium-scale model - in the sense of higher output volatility - even when wages becomes stickier and inequality becomes more procyclical. One might find this counterintuitive given Bilbiie's (2020) results. However, note that Bilbiie's (2020) findings regarding amplification/dampening pertains to the real effects of demand-type shocks, i.e., the monetary and fiscal policy multipliers. On the other hand, our model features a combination of both demand and supply shocks, as is common in estimated medium-scale models.[14]

5.3 Fiscal policy rules

In this section, we relax the assumption that the government budget is balanced in every period and introduce a richer fiscal structure. In our two-agents environment this may be potentially relevant. In fact, it is well known from the literature that ROT consumers break the Ricardian equivalence. Thus, for example, while in a representative agent model government lump-sum transfers/taxes have no effects, they do have effects, however, when a fraction of agents are non-Ricardian.[15] This may be important for our estimates, as ROT and Ricardian agents have different reactions to changes in fiscal variables and, in line with Bilbiie (2020)'s arguments, this could also alter the cyclicality of inequality.[16]

[14] A detailed analysis of how the cyclical inequality channel affects amplification/dampening for supply shocks is beyond the scope of this paper and we leave it for future research.

[15] See, for example, Giambattista and Pennings (2017).

[16] We thank an anonymous referee for pointing this out.

We introduce fiscal feedback rules for distortionary taxes on consumption, labor income and capital together with a rule for lump-sum transfer/taxes, closely following Leeper, Traum and Walker (2017) and Zubairy (2014), and then re-estimate the model. In the linear version of the model, all fiscal instruments respond to government debt.[17] We find that our baseline results remain essentially unchanged. The estimated fraction of ROT along with the estimates for the other structural and shock parameters are very similar with respect to our baseline estimates, thereby also delivering similar results in terms of log data densities (see Table 8), impulse responses functions, and historical and variance decompositions. In addition, our conclusions regarding the cyclicality of inequality remain unchanged in the model with taxes.

5.4 Pre-Volcker sample

Our main result concerns the irrelevance of ROT consumers for aggregate business cycle fluctuations in U.S. data. Given previous results in the literature, this is surprising for the pre-Volcker sample in particular. In this Section, we check the robustness of this result for the pre-Volcker sample with respect to changes to: (i) the prior for the fraction of ROT consumers, θ; (ii) the specification of the Taylor rule; (iii) the subsample splits.

5.4.1 Prior for θ

Our baseline prior for θ is in line with Bilbiie and Straub (2013). To give a fair chance to higher values of θ, we re-estimate the model for the pre-Volcker period with a uniform prior (0,1) for θ. In this case, results are sensitive to the initial values, i.e. they depend on the region of the parameter space the estimations are launched in (as shown in Table A.1 in the Appendix).[18] Starting from a parameter configuration from the usual determinacy region (standard aggregate demand logic, SADL, in Bilbiie's (2008) terminology), we find the same results as above, and the data strongly favour an indeterminate model. However, when we initialize the estimation algorithm in the IADL region, we do find results consistent with Bilbiie and Straub (2013). That is, we find determinacy due to a passive monetary policy (posterior mean of $\phi_\pi = 0.50$)

[17] We calibrate the steady state of distortionary taxes and the feedback parameters on debt, following Leeper, Traum and Walker (2017) and Zubairy (2014). The coefficient on consumption taxes is set to 0.02, in line with the other taxes. For more details, see the Appendix.

[18] This signals a problem of the estimation algorithm in allowing the crossing of the determinacy boundaries. Bianchi and Nicolò (2019) thoroughly discuss this problem.

and a high value of ROT consumers (posterior mean of $\theta = 0.65$) and, hence, the parameter estimates put the model in the IADL region. The log-data density, however, notably drops to (-702.59), while it is equal to (-609.66) for the indeterminate model estimated when the algorithm is initialized in the SADL region. The Bayes factor comparing these two log-data densities is as large as 185.9 signalling a very strong evidence against the determinate model with a high value of θ.

5.4.2 Forward-looking Taylor rule

We run a robustness check assuming a forward-looking Taylor rule where the interest rate reacts to expected inflation as opposed to contemporaneous inflation as in our baseline model. Bilbiie (2008) shows that the 'inverted Taylor principle' holds in the IADL case in his small-scale NK model for a smaller fraction of ROT consumers with a forward-looking Taylor rule compared to a contemporaneous Taylor rule. In addition, Bilbiie and Straub (2013) use a forward-looking Taylor rule whereby the monetary authority responds to expected inflation. First, we find that the determinacy-indeterminacy boundary with a forward-looking rule in our medium-scale model is the same as in Figure 1. Second, Table A.2 in the Appendix shows that the estimation results are very similar to our baseline results with contemporaneous inflation in the Taylor rule.[19]

5.4.3 Subsamples

Table 9 displays the results of different experiments with four different subsamples for the Great Inflation years. The first two correspond to the two subsamples in Nicolò (2020), who argues that it is important to split the original sample in pre and post 1970, because the '70s are characterized by slower productivity growth, resulting in a distinct balanced growth path. Not surprisingly, our results are in line with Nicolò (2020) and the data favours the indeterminate model in both subsamples. Moreover, comparing the log-data densities, we show that there is 'positive' evidence against the ROT model compared to the RANK one. Hence, considering this split of our original pre-Volcker sample would reinforce our argument of rejecting the usefulness of a model with ROT consumers to fit the U.S. business cycle.

[19] This is also true for most parameter estimates. For this exercise, we used a Uniform (0,1) prior for θ, while all the other priors are same as before.

The third subsample (60:Q1-79:Q2) is the sample used by Lubik and Schorfheide (2004) and also by Bilbiie and Straub (2013). In this case, we find results similar to our baseline, so that the data favours the indeterminate model with basically no difference in terms of fit between the ROT and the RANK models. Hence, the fact that our results differ from the ones in Bilbiie and Straub (2013) is not due to us employing a different sample for the pre-Volcker period.

Finally, we experiment also with 66:Q1-79:Q2 which is the sample used in their seminal paper by Smets and Wouters (2007). To our surprise, here the results differ and it is worth spending few words on this result, because it might have been overlooked by the literature. Our results are consistent with Smets and Wouters (2007) because the data favour a determinate model for this particular subsample. Determinacy follows from the estimate of an active monetary policy and a small fraction of ROT consumers. In Kass and Raftery's (1995) terminology, there is positive evidence against indeterminacy. This is true for both the ROT and the RANK models, again signalling that the two models are empirically indistinguishable, despite the log-data density being marginally larger for the ROT model. Hence, whether or not the estimation finds indeterminacy in the pre-Volcker sample seems to be sensitive to the choice of the dates. We conjecture that the reason why the 66:Q1-79:Q2 sample yields determinacy is because of the increase in the real interest rate in the last years of '60s that pushes the estimation towards an active monetary policy.[20] The determinacy result seems to be confined to this particular sample period, so this could be just a minor point. However, given that papers in the literature might choose this sample period to compare their results with Smets and Wouters (2007), we think its important to point out that choosing this particular sample has an impact on the long standing debate about bad vs. good monetary policy in the pre-Volcker period.

6 Conclusion

We estimate a medium-scale model with ROT consumers over two different subsamples (the pre-Volcker and the Great Moderation periods), while allowing and testing for (in)determinacy, and compare our results with the standard RANK specification. Our main finding is that

[20] Real interest rates were mostly rising in the late 1960s, which suggests Fed's strong responsiveness to inflation during that time. Indeed, Coibion and Gorodnichenko (2011) find a strong response to inflation and an associated high probability of determinacy in the late 1960s. This suggests that the increase in the real rate in the mid-to-late 1960s more than compensates for the loose policy during the 70s such that overall we find the posterior mass lying mostly in the determinacy region in the 1966Q1-1979Q2 sub-sample.

including ROT in a RANK model is irrelevant to explain U.S. aggregate business cycle fluctuations. The reason being that the ROT model preferred by the data has a very low fraction of ROT consumers, that only marginally affects the dynamics of the model relative to a RANK specification. The two models are empirically equivalent. In both subsamples, the RANK and ROT models yield almost the same impulse response functions, variance and historical decompositions, such that they share the same narrative of U.S. business cycle fluctuations

In line with Lubik and Schorfheide (2004) and Nicolò (2020), we find that passive monetary policy and self-fulfilling fluctuations characterize the pre-Volcker period for both the ROT and the RANK model. This contrasts with previous findings in the literature by Bilbiie and Straub (2013), who employ a small-scale model. In the pre-Volcker period the log-likelihoods of the ROT and the RANK models are very close, while in the second period the RANK model is preferred by the data.

Our main finding, that including ROT in a RANK model does not change the interpretation of aggregate U.S. business cycle fluctuations, does not mean that modelling ROT, or heterogeneous agents more generally, is not important to explain other dimensions of the data. However, in line with some others in the HANK literature (e.g., Bayer et al., 2020), it suggests that adding heterogeneity may not be substantive to explain aggregate fluctuations, at least for U.S. data.

References

[1] Albonico, A., Paccagnini, A., P. Tirelli, 2019, Limited Asset Market Participation and the Euro Area Crisis: an Empirical DSGE Model. *Economic Inquiry*, 57, 1302-1323.

[2] Ascari, G., A. Colciago, L. Rossi, 2016, Limited asset market participation, sticky wages and monetary policy, *Economic Inquiry*, 55, 878-897.

[3] Ascari, G., A. Colciago, L. Rossi, 2017, Determinacy analysis in high order dynamic systems: The case of nominal rigidities and limited asset market participation, *Economics Letters*, 159, 82-87.

[4] Bayer, C., B. Born, R. Luetticke, 2020, Shocks, Frictions, and Inequality in US Business Cycles, CEPR Discussion Paper 14364.

[5] Bhattarai, S., J. W. Lee, and W. Y. Park, 2016. Policy Regimes, Policy Shifts, and U.S. Business Cycles. *Review of Economics and Statistics*, MIT Press, 98(5), 968-983.

[6] Bianchi, F. and G. Nicolò, 2019. A Generalized Approach to Indeterminacy in Linear Rational Expectations Models, Finance and Economics Discussion Series 2019-033, Board of Governors of the Federal Reserve System (U.S.).

[7] Bilbiie, F.O., 2008. Limited asset market participation, monetary policy and (inverted) aggregate demand logic. *Journal of Economic Theory* 140, 162–196.

[8] Bilbiie, F.O., 2020. The New Keynesian cross. *Journal of Monetary Economics* 114, 90-108.

[9] Bilbiie, F.O., A. Meier, G.J. Müller, 2008. What Accounts for the Changes in US Fiscal Policy Transmission?, *Journal of Money, Credit and Banking,* 40(7), 1439-1470.

[10] Bilbiie, F.O. and R. Straub, 2012. Changes in the output Euler equation and asset markets participation, *Journal of Economic Dynamics and Control*, Elsevier, 36(11), 1659-1672.

[11] Bilbiie, F.O. and R. Straub, 2013. Asset Market Participation, Monetary Policy Rules, and the Great Inflation, *The Review of Economics and Statistics*, MIT Press, 95(2), 377-392.

[12] Boivin, J. and M. P. Giannoni, 2006. Has Monetary Policy Become More Effective? *The Review of Economics and Statistics*, MIT Press, 88(3), 445-462.

[13] Brayton, F., T. Laubach, D. Reifschneider, 2014. The FRB/US Model: A Tool for Macroeconomic Policy Analysis, FEDS Notes. Washington: Board of Governors of the Federal Reserve System, April 03, 2014. https://doi.org/10.17016/2380-7172.0012

[14] Calvo, G.A., 1983. Staggered prices in a utility-maximizing framework, *Journal of Monetary Economics*, Elsevier, 12(3), 383-398.

[15] Christiano, L.J., M. Eichenbaum, C.L. Evans, 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy, *Journal of Political Economy*, University of Chicago Press, 113(1), 1-45.

[16] Clarida, R., J. Galí, M. Gertler, 2000. Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory, *Quarterly Journal of Economics,* 115(1), 147-180.

[17] Coenen, G., R. Straub, M. Trabandt, 2012. Fiscal Policy and the Great Recession in the Euro Area, *American Economic Review*, Papers & Proceedings, American Economic Association, 102(3), 71-76.

[18] Colciago, A., 2011. Rule-of-thumb consumers meet sticky wages. *Journal of Money, Credit and Banking* 43, 325–353.

[19] Colciago, A., A. Samarina, J. de Haan, 2019. Central Bank Policies And Income And Wealth Inequality: A Survey, *Journal of Economic Surveys*, Wiley Blackwell, 33(4), 1199-1231.

[20] Debortoli, D. and J. Galí, 2017. Monetary policy with heterogeneous agents: Insights from TANK models, Economics Working Papers 1686, Department of Economics and Business, Universitat Pompeu Fabra, revised Jun 2018.

[21] Fagereng, A., M.B. Holm, G.J. Natvik, 2021. MPC Heterogeneity and Household Balance Sheets. *American Economic Journal: Macroeconomics*, 13 (4), 1-54.

[22] Farmer, R.E.A., V. Khramov, G. Nicolò, 2015. Solving and estimating indeterminate DSGE models, *Journal of Economic Dynamics and Control*, Elsevier, 54(C), 17-36.

[23] Forni, L., L. Monteforte, L. Sessa, 2009. The General Equilibrium Effects of Fiscal Policy: Estimates for the Euro Area, *Journal of Public Economics*, 93(3–4), 559–85.

[24] Galí, J., D. López-Salido, J. Vallés, 2007. Understanding the effects of government spending on consumption, *Journal of the European Economic Association* 5 (1), 227–270.

[25] Giambattista, E., S. Pennings, 2017. When is the Government Transfer Multiplier Large? *European Economic Review*, 100, 525-543.

[26] Haque, Q., N. Groshenny, M. Weder, 2021. Do we really know that US monetary policy was destabilizing in the 1970s?, *European Economic Review*, 131, 103615.

[27] Hirose, Y., T. Kurozumi, W. Van Zandweghe, 2020. Monetary Policy and Macroeconomic Stability Revisited, *Review of Economic Dynamics,* 37, 255-274.

[28] Jappelli, T., and L. Pistaferri, 2020. Reported MPC and Unobserved Heterogeneity. *American Economic Journal: Economic Policy*, 12 (4), 275-97.

[29] Justiniano, A., and G.E. Primiceri, 2008. The Time-Varying Volatility of Macroeconomic Fluctuations. *American Economic Review*, 98 (3), 604-41.

[30] Justiniano, A., G. Primiceri, A. Tambalotti, 2010. Investment shocks and business cycles, *Journal of Monetary Economics*, Elsevier, 57(2), 132-145, March.

[31] Kaplan, G., B. Moll, G.L. Violante, 2018. Monetary Policy According to HANK, *American Economic Review*, 108 (3): 697-743.

[32] Kaplan, G., G.L. Violante, J. Weidner, 2014. The Wealthy Hand-to-Mouth, *Brookings Papers on Economic Activity*, Economic Studies Program, The Brookings Institution, 45(1), 77-153.

[33] Kass, R. E. and A. E. Raftery. 1995. Bayes Factors, *Journal of the American Statistical Association* 90 (430): 773–95

[34] Kimball, M.S., 1995. The Quantitative Analytics of the Basic Neomonetarist Model, *Journal of Money, Credit and Banking*, Blackwell Publishing, 27(4), 1241-77.

[35] Kollmann, R., B. Pataracchia, R. Raciborski, M. Ratto, W. Roeger, L. Vogel, 2016. The post-crisis slump in the Euro Area and the US: Evidence from an estimated three-region DSGE model, *European Economic Review*, Elsevier, 88(C), 21-41.

[36] Leeper, E. M., N. Traum, T. B. Walker, 2017. Clearing Up the Fiscal Multiplier Morass, *American Economic Review*, 107, 2409-54.

[37] Lubik, T.A. and F. Schorfheide, 2003. Computing sunspot equilibria in linear rational expectations models, *Journal of Economic Dynamics and Control*, Elsevier, 28(2), 273-285.

[38] Lubik, T.A. and F. Schorfheide, 2004. Testing for Indeterminacy: An Application to U.S. Monetary Policy, *American Economic Review*, American Economic Association, 94(1), 190-217.

[39] Motta, G. and P. Tirelli, 2012, Optimal Simple Monetary and Fiscal Rules under Limited Asset Market Participation. *Journal of Money, Credit and Banking*, 44(7), 1351–74.

[40] Motta, G. and P. Tirelli, 2014. Limited Asset Market Participation, *Income Inequality and Macroeconomic Volatility*, Working Papers 65170975, Lancaster University Management School, Economics Department.

[41] Nicolò, G., 2020. Monetary Policy, Self-Fulfilling Expectations and the U.S. Business Cycle, Finance and Economics Discussion Series 2020-035, Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2020.035.

[42] Primiceri, G. E., 2005. Time Varying Structural Vector Autoregressions and Monetary Policy, *Review of Economic Studies*, Oxford University Press, 72(3), 821-852.

[43] Sims, C. A., and T. Zha, 2006. Were There Regime Switches in U.S. Monetary Policy?, *American Economic Review*, American Economic Association, 96(1), 54-81, March.

[44] Slacalek, J., O. Tristani, G.L. Violante, 2020. Household balance sheet channels of monetary policy: A back of the envelope calculation for the euro area, *Journal of Economic Dynamics and Control*, Elsevier, 115(C).

[45] Smets, F., R. Wouters , 2007. Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach, *American Economic Review*, American Economic Association, 97(3), pp. 586-606.

[46] Stock, J. H., and M.W. Watson. 2003. Forecasting Output and Inflation: The Role of Asset Prices, *Journal of Economic Literature*, 41 (3), 788-829.

[47] Zubairy, S., 2014. On Fiscal Multipliers: Estimates from a Medium-Scale DSGE Model, *International Economic Review*, 55, 169-195.

Tables and Figures

Table 1. Parameter estimates for the sample 55-79

		Priors			ROT ind			RANK ind		
		shape	mean	st. dev.	post. mean	90% HPD interval		post. mean	90% HPD interval	
TR response to inflation	ϕ_π	norm	1	0.35	0.796	0.618	0.984	0.798	0.620	0.985
TR response to output	ϕ_y	norm	0.12	0.05	0.152	0.086	0.219	0.142	0.073	0.206
TR response to output growth	ϕ_{gy}	norm	0.12	0.05	0.184	0.136	0.230	0.179	0.129	0.227
TR interest rate smoothing	ϕ_R	beta	0.75	0.1	0.840	0.767	0.917	0.833	0.756	0.912
inverse Frisch elasticity	ϕ_l	gamm	2	0.75	1.393	0.610	2.145	1.410	0.623	2.207
habits	b	beta	0.7	0.1	0.487	0.373	0.601	0.537	0.427	0.646
investment adjustment costs	γ_I	gamm	4	1.5	4.563	2.496	6.476	4.896	3.023	6.868
Calvo price stickiness	ξ_p	beta	0.5	0.1	0.724	0.641	0.811	0.725	0.646	0.809
Calvo wage stickiness	ξ_w	beta	0.5	0.1	0.874	0.825	0.927	0.856	0.796	0.918
price indexation	χ_p	beta	0.5	0.15	0.275	0.095	0.445	0.269	0.094	0.443
wage indexation	χ_w	beta	0.5	0.15	0.373	0.178	0.552	0.374	0.185	0.565
capital utilization elasticity	σ_u	beta	0.5	0.15	0.397	0.205	0.584	0.455	0.265	0.647
ROT fraction	θ	beta	0.3	0.1	0.219	0.131	0.309	-	-	-
intertemporal elasticity	σ	norm	1.5	0.37	1.309	0.996	1.645	1.358	1.036	1.690
capital share	α	norm	0.3	0.05	0.192	0.159	0.224	0.191	0.157	0.223
ss growth	g_z	norm	0.4	0.1	0.292	0.192	0.394	0.283	0.189	0.378
ss hours	$\bar{h}$	norm	0	2	-0.429	-2.331	1.412	-0.555	-2.439	1.270
ss inflation	$\bar{\pi}$	gamm	0.62	0.1	0.616	0.455	0.779	0.614	0.449	0.770
Shocks persistences										
risk premium	ρ_b	beta	0.5	0.2	0.755	0.617	0.901	0.743	0.610	0.884
investment	ρ_i	beta	0.5	0.2	0.629	0.488	0.769	0.680	0.545	0.824
monetary	ρ_r	beta	0.5	0.2	0.335	0.177	0.489	0.338	0.182	0.492
price markup	ρ_p	beta	0.5	0.2	0.350	0.039	0.675	0.364	0.048	0.692
wage markup	ρ_w	beta	0.5	0.2	0.837	0.677	0.985	0.829	0.641	0.989
government spending	ρ_g	beta	0.5	0.2	0.913	0.869	0.960	0.908	0.862	0.954
technology	ρ_a	beta	0.5	0.2	0.984	0.975	0.993	0.982	0.971	0.993
Shocks other parameters										
MA component price markup	ρ^p_{ma}	beta	0.5	0.2	0.560	0.305	0.844	0.525	0.272	0.777
MA componentwage markup	ρ^w_{ma}	beta	0.5	0.2	0.655	0.440	0.885	0.624	0.375	0.860
gov spending-tech correlation	ρ_{gy}	norm	0.5	0.25	0.590	0.473	0.706	0.602	0.484	0.716
Shocks standard deviations										
risk premium	σ_b	invg	0.1	2	0.222	0.141	0.295	0.222	0.141	0.295
investment	σ_i	invg	0.1	2	0.441	0.324	0.548	0.441	0.324	0.548
monetary	σ_r	invg	0.1	2	0.177	0.153	0.201	0.177	0.153	0.201
price markup	σ_p	invg	0.1	2	0.372	0.308	0.434	0.372	0.308	0.434
wage markup	σ_w	invg	0.1	2	0.226	0.183	0.269	0.226	0.183	0.269
government spending	σ_g	invg	0.1	2	0.480	0.422	0.538	0.480	0.422	0.538
technology	σ_a	invg	0.1	2	0.711	0.622	0.799	0.711	0.622	0.799
sunspot	σ_ν	unif	0.5	0.289	0.195	0.122	0.265	0.195	0.122	0.265
Shocks correlations										
corr sunspot, price markup	$\rho_{\nu p}$	unif	0	0.577	0.821	0.648	1.000	0.821	0.648	1.000

Table 2. Determinacy versus Indeterminacy

Sample	Model	Log-data density		Probability		KR ratio
		Determinacy	Indeterminacy	Determinacy	Indeterminacy	
1955Q4-1979Q2	ROT	−624.85	−609.07	0	1	31.6
	RANK	−619.20	−609.94	0	1	18.5
KR ratio		11.3	1.7			
1984Q1-2007Q3	ROT	−403.26	−408.82	1	0	11.1
	RANK	−397.69	−403.17	1	0	11.0
KR ratio		11.1	11.3			

Notes: The prior probability of determinacy is 0.51. ROT and RANK stand for *Rule of Thumb* and *Representative Agent New Keynesian*, respectively. Log marginal data densities are approximated by Geweke's (1999) harmonic mean estimator. The posterior probabilities are calculated based on the output of the Metropolis algorithm. KR stands for Kass and Raftery.

Table 3. Variance Decompositions (ROT-IND vs. RANK-IND), 1955Q4-1979Q2

	$\triangle c$	$\triangle y$	π	$\triangle w$	$\triangle i$	R	$\triangle c^{rt}$	$\triangle c^{o}$
$ROT-IND$								
ε^a	23.61	37.37	14.06	21.26	7.23	12.79	12.89	27.01
ε^b	45.23	19.00	6.76	2.36	7.27	7.78	22.44	38.25
ε^i	0.80	9.25	1.61	0.78	67.54	1.88	9.81	4.45
ε^r	12.60	6.25	7.17	1.35	3.56	11.24	8.14	9.64
ε^p	9.63	4.25	7.94	20.02	0.91	5.14	15.26	4.84
ε^w	1.99	2.57	43.45	53.44	9.27	44.42	10.87	6.60
ε^g	0.10	18.32	1.07	0.15	2.45	1.01	16.88	4.39
ε^v	6.04	2.99	17.93	0.64	1.79	15.74	3.69	4.81
$RANK-IND$								
ε^a	27.46	43.48	15.77	22.19	9.14	13.65	–	–
ε^b	44.91	19.78	8.41	3.36	8.64	9.46	–	–
ε^i	1.74	7.54	0.89	0.45	68.53	0.95	–	–
ε^r	9.73	5.34	7.19	1.45	3.90	12.92	–	–
ε^p	5.71	3.25	12.72	20.87	1.52	8.74	–	–
ε^w	5.19	3.15	38.95	51.13	6.18	40.30	–	–
ε^g	1.50	15.49	0.53	0.04	0.67	0.47	–	–
ε^v	3.76	1.98	15.55	0.52	1.41	13.52	–	–

Table 4. Parameter estimates for the sample 84-07

		ROT det			RANK det		
		post. mean	90% HPD interval		post. mean	90% HPD interval	
TR response to inflation	ϕ_π	2.280	1.920	2.645	2.248	1.882	2.611
TR response to output	ϕ_y	0.059	0.013	0.097	0.058	0.010	0.095
TR response to output growth	ϕ_{gy}	0.167	0.117	0.219	0.169	0.119	0.219
TR interest rate smoothing	ϕ_R	0.807	0.761	0.855	0.811	0.765	0.857
inverse Frisch elasticity	ϕ_l	1.890	1.042	2.752	2.064	1.159	2.948
habits	b	0.421	0.309	0.527	0.439	0.331	0.539
investment adjustment costs	γ_I	5.614	3.197	7.971	5.983	3.497	8.405
Calvo price stickiness	ξ_p	0.801	0.733	0.874	0.803	0.737	0.871
Calvo wage stickiness	ξ_w	0.696	0.602	0.790	0.668	0.566	0.769
price indexation	χ_p	0.471	0.257	0.682	0.473	0.254	0.684
wage indexation	χ_w	0.523	0.282	0.760	0.513	0.271	0.761
capital utilization elasticity	σ_u	0.712	0.564	0.875	0.697	0.534	0.856
ROT fraction	θ	0.105	0.052	0.157	-	-	-
intertemporal elasticity	σ	1.377	0.993	1.769	1.361	0.973	1.755
capital share	α	0.177	0.140	0.215	0.179	0.143	0.216
ss growth	g_z	0.460	0.421	0.501	0.458	0.418	0.497
ss hours	$\bar{h}$	-0.538	-2.619	1.558	-0.588	-2.516	1.425
ss inflation	$\bar{\pi}$	0.655	0.524	0.785	0.660	0.530	0.788
Shocks persistences							
risk premium	ρ_b	0.769	0.635	0.909	0.825	0.731	0.919
investment	ρ_i	0.683	0.558	0.814	0.698	0.567	0.827
monetary	ρ_r	0.361	0.206	0.517	0.354	0.201	0.511
price markup	ρ_p	0.883	0.799	0.970	0.882	0.795	0.977
wage markup	ρ_w	0.983	0.970	0.996	0.975	0.957	0.994
government spending	ρ_g	0.967	0.948	0.987	0.967	0.946	0.989
technology	ρ_a	0.944	0.911	0.978	0.935	0.897	0.972
Shocks other parameters							
MA component price markup	ρ^p_{ma}	0.629	0.450	0.815	0.644	0.468	0.823
MA componentwage markup	ρ^w_{ma}	0.600	0.397	0.809	0.509	0.300	0.717
gov spending-tech correlation	ρ_{gy}	0.470	0.318	0.624	0.471	0.320	0.619
Shocks standard deviations							
risk premium	σ_b	0.125	0.078	0.169	0.106	0.071	0.139
investment	σ_i	0.336	0.258	0.411	0.314	0.240	0.385
monetary	σ_r	0.121	0.104	0.138	0.120	0.103	0.137
price markup	σ_p	0.122	0.086	0.157	0.119	0.084	0.153
wage markup	σ_w	0.375	0.285	0.465	0.402	0.287	0.513
government spending	σ_g	0.379	0.334	0.425	0.380	0.334	0.427
technology	σ_a	0.406	0.356	0.455	0.406	0.356	0.454

Table 5. Variance Decompositions (ROT-DET vs. RANK-DET), 1984Q1-2007Q3

	$\triangle c$	$\triangle y$	π	$\triangle w$	$\triangle i$	R	$\triangle c^{rt}$	$\triangle c^{o}$
$ROT-DET$								
ε^a	4.25	18.18	2.40	1.88	4.61	5.04	5.14	5.97
ε^b	41.01	19.83	12.23	12.49	2.68	32.21	22.49	32.59
ε^i	1.18	9.88	6.18	2.30	76.35	16.36	6.85	3.63
ε^r	17.06	8.81	10.03	6.83	1.53	5.74	11.16	12.95
ε^p	10.65	10.14	24.90	28.56	6.35	5.64	28.20	4.17
ε^w	21.37	11.72	43.16	47.55	7.52	31.64	17.77	30.98
ε^g	4.49	21.44	1.10	0.39	0.96	3.37	8.40	9.70
$RANK-DET$								
ε^a	6.43	20.84	2.26	1.88	4.13	4.61	–	–
ε^b	36.34	18.76	18.44	15.40	3.28	44.89	–	–
ε^i	2.69	9.18	4.59	1.75	73.98	11.39	–	–
ε^r	15.54	8.40	9.39	7.65	1.69	6.52	–	–
ε^p	7.46	9.51	27.64	25.86	9.05	7.17	–	–
ε^w	24.66	12.53	36.91	47.13	7.41	23.25	–	–
ε^g	6.87	20.78	0.76	0.33	0.47	2.17	–	–

Table 6. Determinacy versus Indeterminacy - Alternative calibration for $\theta; \theta = 0.4$.

		Log-data density		Probability		KR ratio
Sample	Model	Determinacy	Indeterminacy	Determinacy	Indeterminacy	
1955Q4-1979Q2	ROT $_{(Baseline)}$	-624.85	-609.07	0	1	31.6
	ROT $_{(\theta=0.40)}$	-623.52	-613.16	0	1	20.7
KR ratio		2.7	8.2			
1984Q1-2007Q3	ROT $_{(Baseline)}$	-403.26	-408.82	1	0	11.1
	ROT $_{(\theta=0.40)}$	-421.51	-420.02	0.18	0.82	3.0
KR ratio		36.5	22.4			

Table 7. Simulation results on cyclicality of inequality
and volatility of output

	$\xi_w = 0.87$	$\xi_w = 0.70$	$\xi_w = 0.50$	$\xi_w = 0.30$	$\xi_w = 0$
1955Q4-1979Q2					
$\rho(\widehat{y}_t^o, \widehat{y}_t)$	0.987	0.980	0.970	0.957	0.902
$\rho(\widehat{y}_t^{rt}, \widehat{y}_t)$	0.958	0.944	0.910	0.872	0.814
$\rho(ineq_t, \widehat{y}_t)$	0.489	0.175	0.012	-0.104	-0.332
$std(\widehat{y}_t)$	6.20	5.32	5.21	5.23	5.54
1984Q1-2007Q3					
$\rho(\widehat{y}_t^o, \widehat{y}_t)$	0.999	0.994	0.980	0.973	0.963
$\rho(\widehat{y}_t^{rt}, \widehat{y}_t)$	0.990	0.830	0.798	0.802	0.792
$\rho(ineq_t, \widehat{y}_t)$	0.892	0.073	-0.386	-0.481	-0.517
$std(\widehat{y}_t)$	26.24	4.41	2.54	2.37	2.39

Table 8. Determinacy versus Indeterminacy - Model with taxes

Sample	Model	Log-data density		Probability		KR ratio
		Determinacy	Indeterminacy	Determinacy	Indeterminacy	
1955Q4-1979Q2	ROT	−619.10	−609.77	0	1	18.7
	RANK	−618.78	−609.62	0	1	18.3
KR ratio		0.6	0.3			
1984Q1-2007Q3	ROT	−402.47	−407.23	1	0	9.5
	RANK	−397.69	−403.28	1	0	11.2
KR ratio		9.6	7.9			

Notes: The prior probability of determinacy is 0.50.

Table 9. Determinacy versus Indeterminacy - Sub-sample estimation

Sample	Model	Log-data density		Probability		KR ratio
		Determinacy	Indeterminacy	Determinacy	Indeterminacy	
1955Q4-1969Q4	ROT	−369.15	−354.86	0	1	28.6
	RANK	−366.81	−352.16	0	1	29.3
KR ratio		4.7	5.4			
1970Q1-1979Q2	ROT	−289.04	−287.42	0.17	0.83	3.2
	RANK	−287.38	−285.13	0.10	0.90	4.5
KR ratio		3.3	4.6			
1960Q1-1979Q2	ROT	−507.91	−503.89	0.02	0.98	8.0
	RANK	−519.03	−505.23	0	1	27.6
KR ratio		22.2	2.7			
1966Q1-1979Q2	ROT	−368.85	−371.30	0.92	0.08	4.9
	RANK	−370.24	−371.87	0.84	0.16	3.3
KR ratio		2.8	1.1			

Notes: The prior probability of determinacy is 0.51. ROT and RANK stand for *Rule of Thumb* and *Representative Agent New Keynesian*, respectively. Log marginal data densities are approximated by Geweke's (1999) harmonic mean estimator. The posterior probabilities are calculated based on the output of the Metropolis algorithm. KR stands for Kass and Raftery.

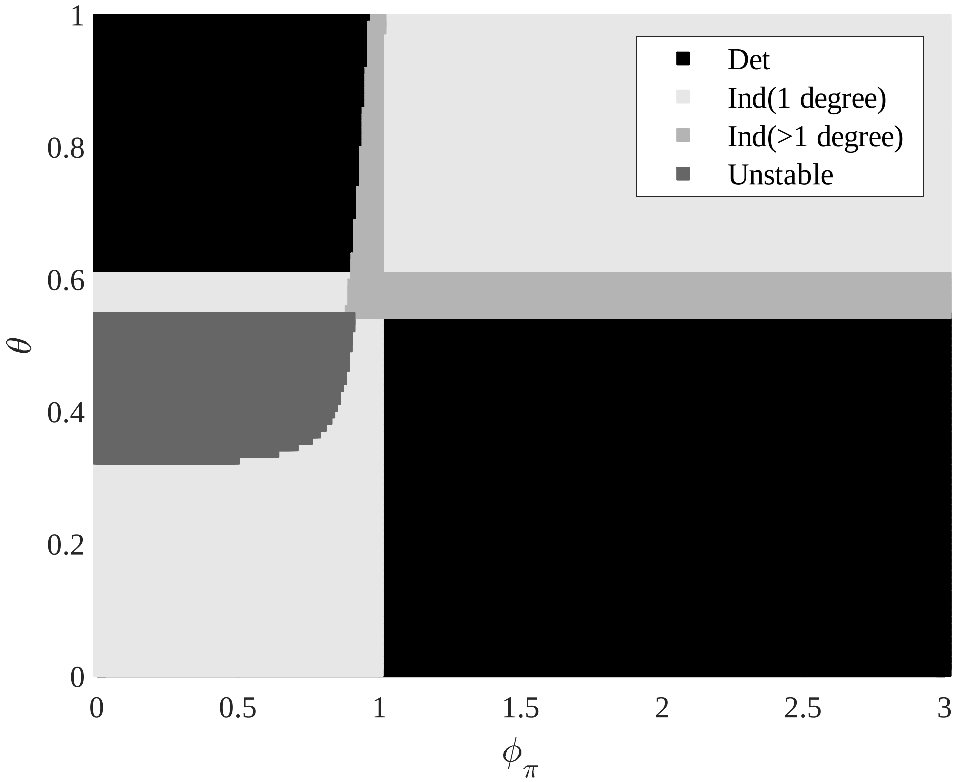

Figure 1: Determinacy region for ϕ_π against θ; the remaining structural parameters of the model are set at the prior mean .

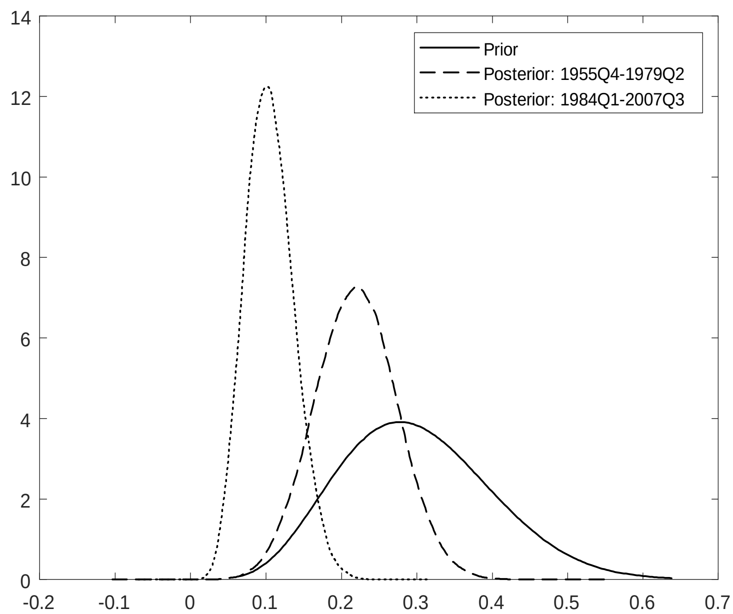

Figure 2: Prior-posterior plot for θ

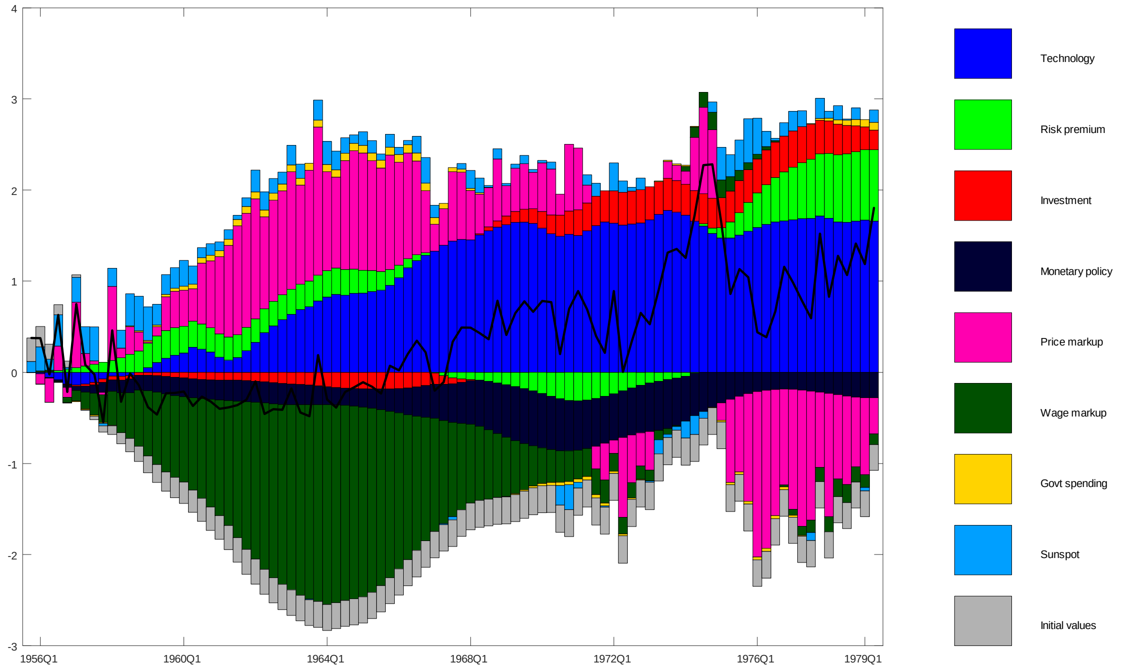

Figure 3: Historical Decomposition of Inflation from the ROT model under INDETERMINACY (Sample: 1955Q4-1979Q2).

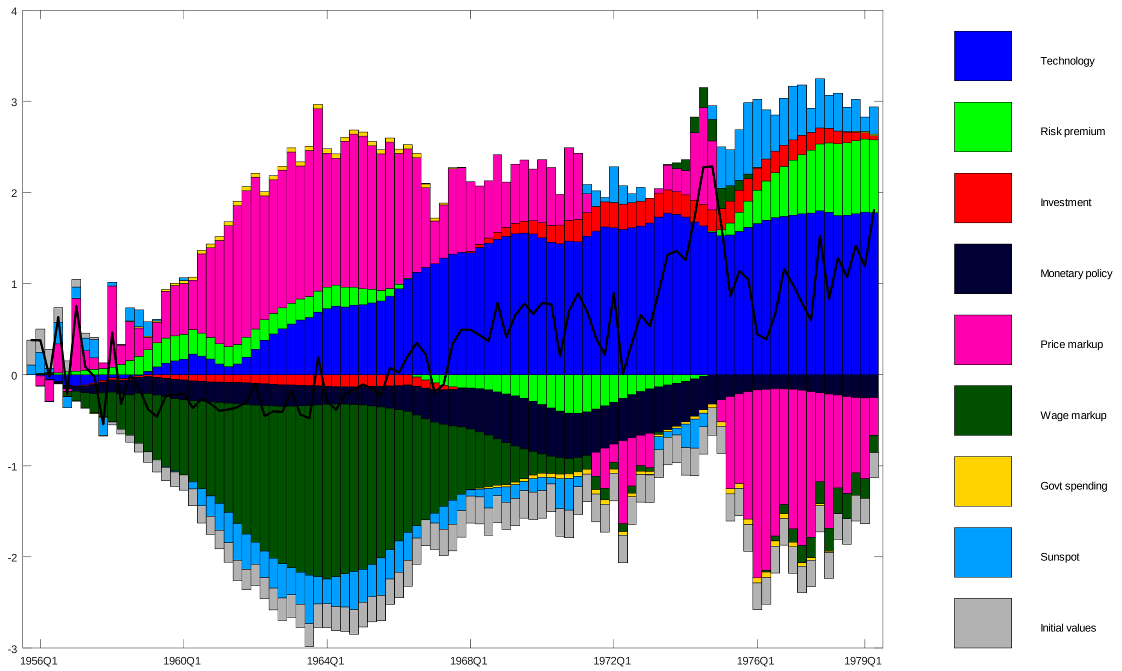

Figure 4: Historical Decomposition of Inflation from the RANK model under INDETERMINACY (Sample: 1955Q4-1979Q2).

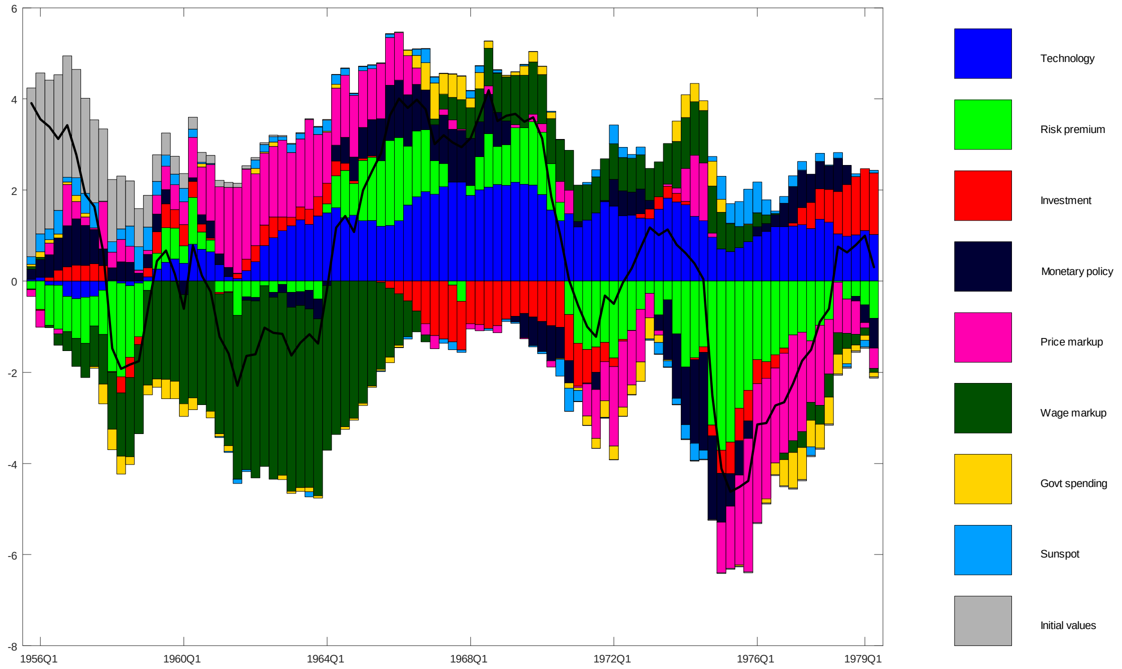

Figure 5: Historical Decomposition of the Output Gap from the ROT model under INDETERMINACY (Sample: 1955Q4-1979Q2).

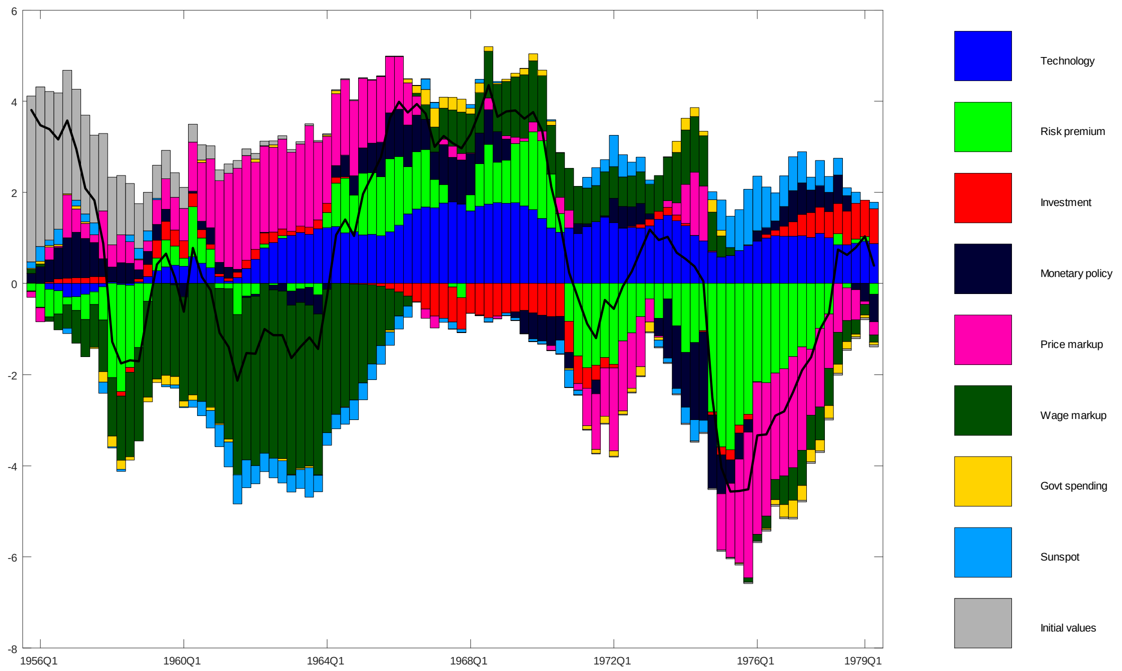

Figure 6: Historical Decomposition of the Output Gap from the RANK model under INDETERMINACY (Sample: 1955Q4-1979Q2).

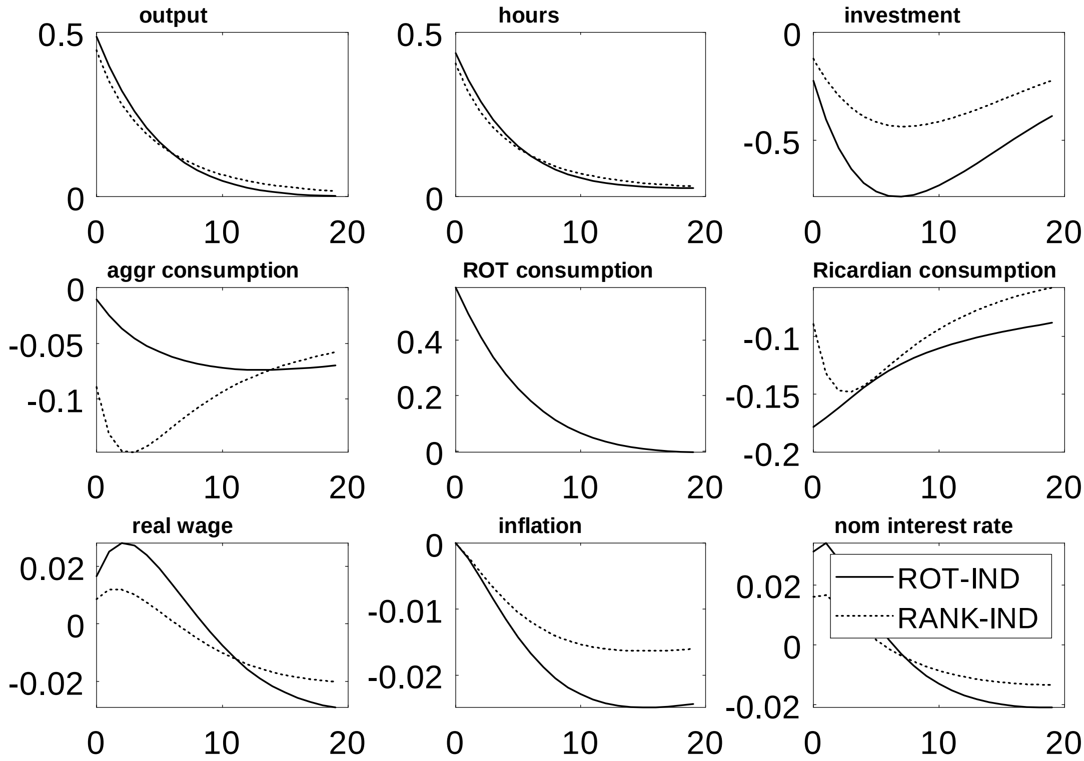

Figure 7: Impulse responses to a one standard deviation government spending shock (Sample: 1955Q4-1979Q2)

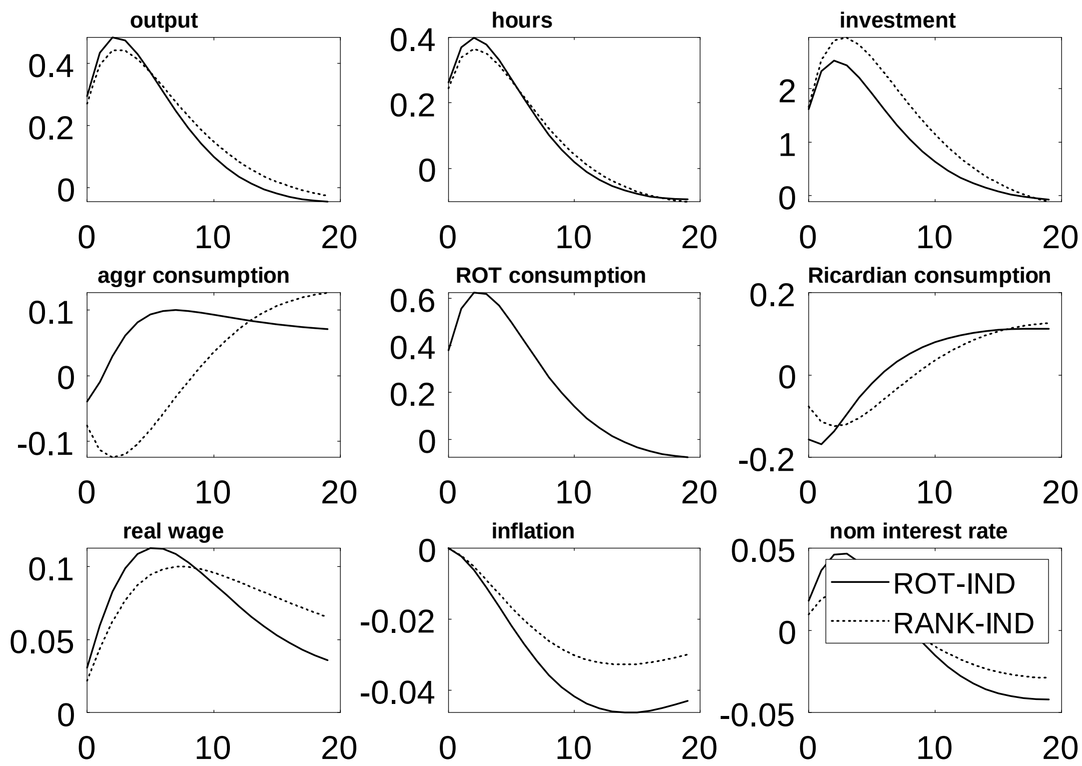

Figure 8: Impulse responses to a one standard deviation investment shock (Sample: 1955Q4-1979Q2)

A Appendix

A.1 System of non-linear equations

After deriving the first conditions of the model, we adjust variables to guarantes that the model has a balanced growth. Lower case letters stand for detrended variables, for example, $y_t = \frac{Y_t}{g_z^t}$, $w_t = \frac{W_t}{P_t g_z^t}$, $r_t^k = \frac{R_t^k}{P_t}$, $\lambda_t^o = \Lambda_t^o g_z^t$. Given that the model is then log-linearized, we omit price and wage dispersion variables. We add exogenous shock processes for the following variables: ε_t^a, ε_t^b, ε_t^i, ε_t^r, λ_t^p, λ_t^w, g_t. ROT lump-sum taxes are also modeled as exogenous shocks, which we are not estimating, thus they remain constant at their steady state. Given that the government budget constraint is balanced every period, we can omit this equation.

$$\left(c_t^o - bc_{t-1}\right)^{-\sigma} = \lambda_t^o \tag{15}$$

$$R_t = E_t\left[\frac{\pi_{t+1}}{\lambda_{t+1}^o}\right]\frac{g_z}{\beta}\frac{\lambda_t^o}{\varepsilon_t^b} \tag{16}$$

$$\begin{aligned} 1 \;&=\; Q_t^o \varepsilon_t^i \left\{1 - \gamma_I\left(g_z\frac{i_t}{i_{t-1}} - g_z\right) g_z\frac{i_t}{i_{t-1}} - \frac{\gamma_I}{2}\left(g_z\frac{i_t}{i_{t-1}} - g_z\right)^2\right\} \\ &\quad + g_z E_t\left\{\frac{\lambda_{t+1}^o}{\lambda_t^o} Q_{t+1}^o \varepsilon_{t+1}^i \beta\gamma_I\left(g_z\frac{i_{t+1}}{i_t} - g_z\right)\left(\frac{i_{t+1}}{i_t}\right)^2\right\} \end{aligned} \tag{17}$$

$$\frac{\beta}{g_z}E_t\left\{\frac{\lambda_{t+1}^o}{\lambda_t^o}\left\{\left[r_{t+1}^k u_{t+1} - a\left(u_{t+1}\right)\right] + Q_{t+1}^o\left(1-\delta\right)\right\}\right\} = Q_t^o \tag{18}$$

$$r_t^k = \gamma_{u1} + \gamma_{u2}\left(u_t - 1\right) \tag{19}$$

$$k_{t+1} = \left(1-\delta\right)\frac{k_t}{g_z} + \varepsilon_t^i\left[1 - \frac{\gamma_I}{2}\left(g_z\frac{i_t}{i_{t-1}} - g_z\right)^2\right] i_t \tag{20}$$

$$c_t^{rt} = w_t^{rt} h_t - t_t^{rt} \tag{21}$$

$$y_t = c_t + g_t + i_t + \frac{a\left(u_t\right)k_t}{g_z} \tag{22}$$

$$c_t = \theta c_t^{rt} + \left(1-\theta\right)c_t^o \tag{23}$$

$$\begin{aligned} 0 \;&=\; E_t\sum_{s=0}^{\infty}\left(\xi_w\beta\right)^s\left(\tilde{w}_t^j\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}}\left(\frac{\pi_{t,t+s-1}^{\chi_w}\bar{\pi}_{t,t+s}^{1-\chi_w}}{w_{t+s}\pi_{t,t+s}}\right)^{-\frac{1+\lambda_t^w}{\lambda_t^w}} h_{t+s}^d \cdot \\ &\quad \cdot\left\{\begin{array}{l} \tilde{w}_t^j\frac{\pi_{t,t+s-1}^{\chi_w}\bar{\pi}_{t,t+s}^{1-\chi_w}}{\pi_{t,t+s}}\left(1 - \frac{1+\lambda_t^w}{\lambda_t^w}\right)\left[\left(1-\theta\right)\left(c_{t+s}^o - bc_{t+s-1}\right)^{-\sigma} + \theta\left(c_{t+s}^{rt} - bc_{t+s-1}\right)^{-\sigma}\right] \\ + \frac{1+\lambda_t^w}{\lambda_t^w}\left[\left(1-\theta\right)\left(c_{t+s}^o - bc_{t+s-1}\right)^{-\sigma} MRS_{t+s}^o + \theta\left(c_{t+s}^{rt} - bc_{t+s-1}\right)^{-\sigma} MRS_{t+s}^{rt}\right] \end{array}\right\} \end{aligned} \tag{24}$$

$$w_t = \left[\xi_w \left(\frac{\pi_{t-1}^{\chi_w} \bar{\pi}_t^{1-\chi_w}}{\pi_t} w_{t-1} \right)^{\frac{1}{\lambda_t^w}} + (1 - \xi_w) (\tilde{w}_t)^{\frac{1}{\lambda_t^w}} \right]^{\lambda_t^w} \tag{25}$$

$$\frac{u_t k_t}{h_t g_z} = \frac{\alpha}{(1-\alpha)} \frac{w_t}{r_t^k} \tag{26}$$

$$mc_t = \alpha^{-\alpha} (1-\alpha)^{-(1-\alpha)} (\varepsilon_t^a)^{-1} \left(r_t^k\right)^{\alpha} w_t^{1-\alpha} \tag{27}$$

$$y_t = \varepsilon_t^a \left(u_t \frac{k_t}{g_z} \right)^{\alpha} \left(h_t^d\right)^{1-\alpha} - \Phi \tag{28}$$

$$E_t \sum_{s=0}^{\infty} (\xi_p \beta)^s \varepsilon_t^b \frac{\lambda_{t+s}^o}{\lambda_t^o} y_{t+s}^z \left[\tilde{p}_t^z \frac{\pi_{t,t+s-1}^{\chi_p} \bar{\pi}_{t,t+s}^{1-\chi_p}}{\pi_{t,t+s}} \left(1 + \frac{1}{G'^{-1}(\omega_{t+s})} \frac{G'(x_{t+s})}{G''(x_{t+s})} \right) - mc_{t+s} \frac{1}{G'^{-1}(\omega_{t+s})} \frac{G'(x_{t+s})}{G''(x_{t+s})} \right] = 0 \tag{29}$$

$$\begin{aligned} 1 \;\; = \;\; & (1-\xi_p) \tilde{p}_t^z G'^{-1} \left(\tilde{p}_t^z \int_0^1 G'\left(\frac{y_t^z}{y_t} \right) \frac{y_t^z}{y_t} dz \right) \\ & + \xi_p \pi_{t-1}^{\chi_p} \bar{\pi}_t^{1-\chi_p} \pi_t^{-1} G'^{-1} \left(\pi_{t-1}^{\chi_p} \bar{\pi}_t^{1-\chi_p} \pi_t^{-1} \int_0^1 G'\left(\frac{y_t^z}{y_t} \right) \frac{y_t^z}{y_t} dz \right) \end{aligned} \tag{30}$$

$$h_t = h_t^d \tag{31}$$

A.2 System of log-linearized equations

The above equations are log-linearized. We set the consumption ratio between the two groups (c^{rt}/c^o) in steady state at 1. Hatted variables are in log-deviation from their steady state. Fiscal variables are expressed in deviation from steady state output, so that for example, $\tilde{g}_t = \frac{g_t - g}{y}$. We define $\varpi = \frac{\theta}{1-\theta} \left(\frac{\frac{c^{rt}}{c} - b}{\frac{c^o}{c} - b} \right)^{-\sigma}$ and $A = \frac{1}{\lambda^p \alpha^p + 1}$, where α^p is elasticity of substitution between goods. It is implicit that the system below is completed with flexible prices and wages equilibrium conditions which are not reported here.

$$-\sigma \frac{1}{1 - b\frac{c}{c^o}} \hat{c}_t^o + \sigma \frac{b}{\frac{c^o}{c} - b} \hat{c}_{t-1} = \hat{\lambda}_t^o \tag{32}$$

$$\hat{R}_t = -\hat{\varepsilon}_t^b + E_t \hat{\pi}_{t+1} + \hat{\lambda}_t^o - E_t \hat{\lambda}_{t+1}^o \tag{33}$$

$$\hat{\imath}_t = \frac{1}{\gamma_I g_z^2 (1+\beta)} \left(\hat{Q}_t^o + \hat{\varepsilon}_t^i \right) + \frac{1}{1+\beta} \hat{\imath}_{t-1} + \frac{\beta}{1+\beta} E_t \hat{\imath}_{t+1} \tag{34}$$

$$E_t \hat{\lambda}_{t+1}^o - \hat{\lambda}_t^o + \frac{\beta}{g_z} r^k E_t \hat{r}_{t+1}^k + \frac{\beta}{g_z} (1-\delta) E_t \hat{Q}_{t+1}^o = \hat{Q}_t^o \tag{35}$$

$$\hat{r}_t^k = \frac{\gamma_{u2}}{r^k} \hat{u}_t \tag{36}$$

$$\hat{k}_{t+1} = \frac{(1-\delta)}{g_z} \hat{k}_t + \frac{i}{k} \hat{\imath}_t + \frac{i}{k} \hat{\varepsilon}_t^i \tag{37}$$

$$\frac{c^{rt}}{c}\frac{c}{y}\hat{c}_t^{rt} = \frac{wh}{c}\frac{c}{y}\left(\hat{w}_t^{rt} + \hat{h}_t\right) - \tilde{t}_t^{rt} \tag{38}$$

$$0 = \frac{c}{y}\hat{c}_t + \tilde{g}_t + \frac{i}{y}\hat{\imath}_t - \hat{y}_t + \frac{\gamma_{u1}k}{yg_z}\hat{u}_t \tag{39}$$

$$\hat{c}_t = \theta\frac{c^{rt}}{c}\hat{c}_t^{rt} + (1-\theta)\frac{c^o}{c}\hat{c}_t^o \tag{40}$$

$$\left(1+\beta\chi_p\right)\hat{\pi}_t = \chi_p\hat{\pi}_{t-1} + \beta E_t\hat{\pi}_{t+1} + A\frac{\left(1-\beta\xi_p\right)\left(1-\xi_p\right)}{\xi_p}\left(\widehat{mc}_t + \hat{\lambda}_t^p\right) \tag{41}$$

$$\hat{w}_t = -\frac{(1-\xi_w)(1-\xi_w\beta)}{(1+\beta)\xi_w}\left\{\hat{w}_t - \frac{1}{1+\varpi}\left(\widehat{MRS}_t^o + \varpi\widehat{MRS}_t^{rt}\right) - \frac{\lambda^w}{1+\lambda^w}\hat{\lambda}_t^w\right\} \tag{42}$$
$$+\frac{\beta}{1+\beta}E_t\hat{w}_{t+1} + \frac{1}{1+\beta}\hat{w}_{t-1} + \frac{\chi_w}{1+\beta}\hat{\pi}_{t-1} - \frac{(1+\beta\chi_w)}{1+\beta}\hat{\pi}_t + \frac{\beta}{1+\beta}E_t\hat{\pi}_{t+1}$$

$$\widehat{MRS}_t^o = \frac{\sigma}{1-b\frac{c}{c^o}}\hat{c}_t^o - \frac{b\sigma}{\frac{c^o}{c}-b}\hat{c}_{t-1} + \phi_l\hat{h}_t + \hat{\varepsilon}_t^l \tag{43}$$

$$\widehat{MRS}_t^{rt} = \frac{\sigma}{1-b\frac{c}{c^{rt}}}\hat{c}_t^{rt} - \frac{b\sigma}{\frac{c^{rt}}{c}-b}\hat{c}_{t-1} + \phi_l\hat{h}_t + \hat{\varepsilon}_t^l \tag{44}$$

$$\hat{u}_t + \hat{k}_t - \hat{h}_t - \hat{g}_{z,t} = \hat{w}_t - \hat{r}_t^k \tag{45}$$

$$\widehat{mc}_t = -\hat{\varepsilon}_t^a + \alpha\hat{r}_t^k + (1-\alpha)\hat{w}_t \tag{46}$$

$$\hat{y}_t = \frac{y+\Phi}{y}\left[\hat{\varepsilon}_t^a + \alpha\left(\hat{k}_t + \hat{u}_t\right) + (1-\alpha)\hat{h}_t\right] \tag{47}$$

$$\hat{R}_t = \phi_R\hat{R}_{t-1} + (1-\phi_R)\left(\phi_\pi\hat{\pi}_t + \phi_y\left(\hat{y}_t - \hat{y}_t^{flex}\right)\right) + \phi_{\Delta y}\left(\hat{y}_t - \hat{y}_{t-1} - \left(\hat{y}_t^{flex} - \hat{y}_{t-1}^{flex}\right)\right) + \hat{\varepsilon}_t^r \tag{48}$$

A.3 Model with taxes

We introduce distortionary taxes on consumption, labor income and capital, and lump-sum transfers/taxes for both consumers. This alters the problem of households and following are the modified equations for the model with taxes:

$$-\sigma \frac{1}{1-b\frac{c}{c^o}} \hat{c}_t^o + \sigma \frac{b}{\frac{c^o}{c}-b} \hat{c}_{t-1} - \frac{\tau^c}{1+\tau^c} \hat{\tau}_t^c = \hat{\lambda}_t^o \tag{49}$$

$$E_t \hat{\lambda}_{t+1}^o - \hat{\lambda}_t^o + \frac{\beta}{g_z}\left(1-\tau^k\right) r^k E_t \hat{r}_{t+1}^k + \frac{\beta}{g_z}\left(\delta - r^k\right) \tau^k E_t \hat{\tau}_{t+1}^k + \frac{\beta}{g_z}(1-\delta) E_t \hat{Q}_{t+1}^o = \hat{Q}_t^o \tag{50}$$

$$\begin{aligned} &(1+\tau^c) \frac{c^{rt}}{c} \hat{c}_t^{rt} + \frac{c^{rt}}{c} \tau^c \hat{\tau}_t^c + \frac{wh}{c} \tau^l \hat{\tau}_t^l \\ = \;& \left(1-\tau^l\right) \frac{wh}{c}\left(\hat{w}_t + \hat{h}_t\right) + \frac{y}{c} \widetilde{tr}_t \end{aligned} \tag{51}$$

$$\begin{aligned} \hat{w}_t \;=\; & -\frac{(1-\xi_w)(1-\xi_w \beta)}{(1+\beta)\xi_w} \left\{ \begin{array}{c} \hat{w}_t - \frac{1}{1+\varpi}\left(\widehat{MRS}_t^o + \varpi \widehat{MRS}_t^{rt}\right) \\ -\frac{\tau^c}{1+\tau^c} \hat{\tau}_t^c - \frac{\tau^l}{1-\tau^l} \hat{\tau}_t^l - \frac{\lambda^w}{1+\lambda^w} \hat{\lambda}_t^w \end{array} \right\} \\ & + \frac{\beta}{1+\beta} E_t \hat{w}_{t+1} + \frac{1}{1+\beta} \hat{w}_{t-1} + \frac{\chi_w}{1+\beta} \hat{\pi}_{t-1} - \frac{(1+\beta\chi_w)}{1+\beta} \hat{\pi}_t + \frac{\beta}{1+\beta} E_t \hat{\pi}_{t+1} \end{aligned} \tag{52}$$

Moreover, we need to consider the government budget constraint:

$$\begin{aligned} & \tilde{g}_t + \frac{R}{\pi g_z}\left[\tilde{b}_t + \frac{b}{y}\left(\hat{R}_{t-1} - \hat{g}_{z,t} - \hat{\pi}_t\right)\right] + \widetilde{tr}_t \\ = \;& \tilde{b}_{t+1} + \frac{c}{y} \tau^c \left(\hat{\tau}_t^c + \hat{c}_t\right) + \frac{wh}{c}\frac{c}{y}\left[\tau^l \hat{\tau}_t^l + \tau^l\left(\hat{w}_t + \hat{h}_t\right)\right] \\ & + \frac{k\tau^k}{y g_z}\left[r^k \hat{r}_t^k + \left(r^k - \gamma_{u1}\right)\hat{u}_t + \left(r^k - \delta\right)\left(\hat{\tau}_t^k + \hat{k}_t - \hat{g}_{z,t}\right)\right] \end{aligned} \tag{53}$$

Finally, the fiscal rules are the following:

$$\widetilde{tr}_t = -\phi_b^{tr} \tilde{b}_t$$

$$\hat{\tau}_t^c = \phi_b^{\tau c} \tilde{b}_t$$

$$\hat{\tau}_t^l = \phi_b^{\tau l} \tilde{b}_t$$

$$\hat{\tau}_t^k = \phi_b^{\tau k} \tilde{b}_t$$

where $\widetilde{tr}_t = \frac{tr_t - tr}{y}$, $\tilde{b}_t = \frac{b_t - b}{y}$, $\hat{\tau}_t^{c,l,k} = \frac{\tau_t^{c,l,k} - \tau^{c,l,k}}{\tau^{c,l,k}}$. We assumed also that transfers are symmetric to both type of individuals.

We calibrate the fiscal parameters as follows. The steady state tax rates are based on Leeper, Traum and Walker (2017), thus $\tau^c = 0.023$, $\tau^l = 0.186$, $\tau^k = 0.218$. The response of transfers to debt is based on their estimates and thus set at 0.03. The feedback parameters of taxes are borrowed from Zubairy (2014), who estimates $\phi_b^{\tau l} = 0.02$ and $\phi_b^{\tau k} = 0.017$. We set $\phi_b^{\tau c}$ similarly to 0.02.

A.4 Robustness

Table A.1. Determinacy versus Indeterminacy - Alternative Prior for θ (1955Q4-1979Q2)

		Log-data density		Probability		KR ratio
Region	Prior for θ	Determinacy	Indeterminacy	Determinacy	Indeterminacy	
SADL	Uniform(0,1)	−619.62	−609.66	0	1	19.9
IADL	Uniform(0,1)	−702.59	−705.28	0.94	0.06	5.4
KR ratio		165.9	95.6			

Notes: The prior probability of determinacy is 0.52. SADL and IADL stand for *standard aggregate demand logic* and *inverse aggregate demand logic*, respectively. Log marginal data densities are approximated by Geweke's (1999) harmonic mean estimator. The posterior probabilities are calculated based on the output of the Metropolis algorithm. KR stands for Kass and Raftery.

Table A.2. Determinacy versus Indeterminacy - Taylor Rule with expected inflation (1955Q4-1979Q2)

		Log-data density		Probability	
Region	Prior for θ	Determinacy	Indeterminacy	Determinacy	Indeterminacy
SADL	Uniform(0,1)	−620.59	−609.06	0	1
IADL	Uniform(0,1)	−703.32	−703.60	0.57	0.43
RANK	–	−625.21	−609.49	0	1

Notes: The prior probability of determinacy is 0.52. SADL and IADL stand for *standard aggregate demand logic* and *inverse aggregate demand logic*, respectively. Log marginal data densities are approximated by Geweke's (1999) harmonic mean estimator. The posterior probabilities are calculated based on the output of the Metropolis algorithm. KR stands for Kass and Raftery.

A.5 Impulse response functions

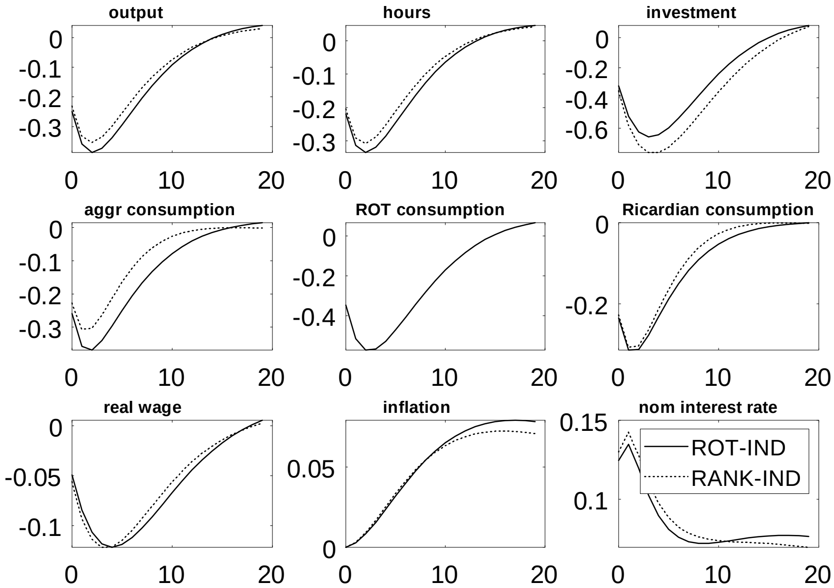

Figure A.1: Impulse responses to a one standard deviation monetary policy shock (Sample: 1955Q4-1979Q2)

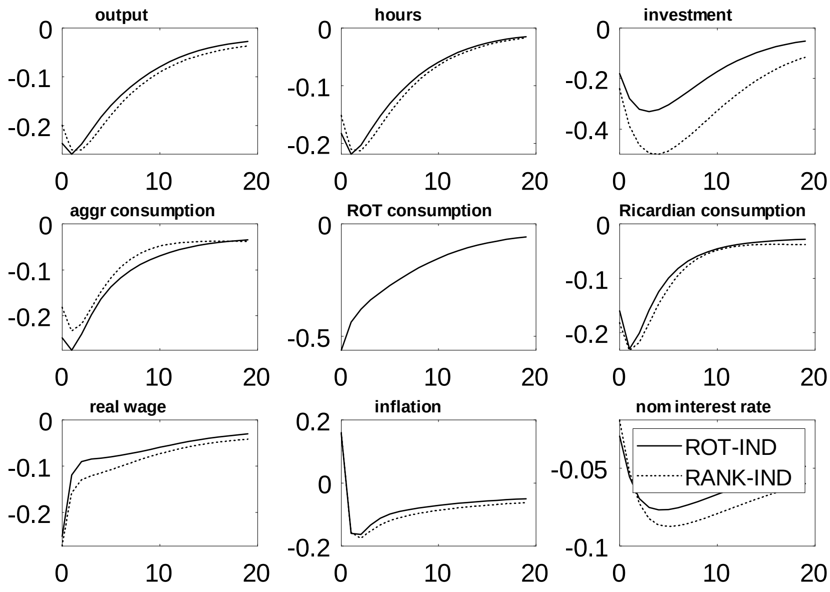

Figure A.2: Impulse responses to a one standard deviation price markup shock (Sample: 1955Q4-1979Q2)

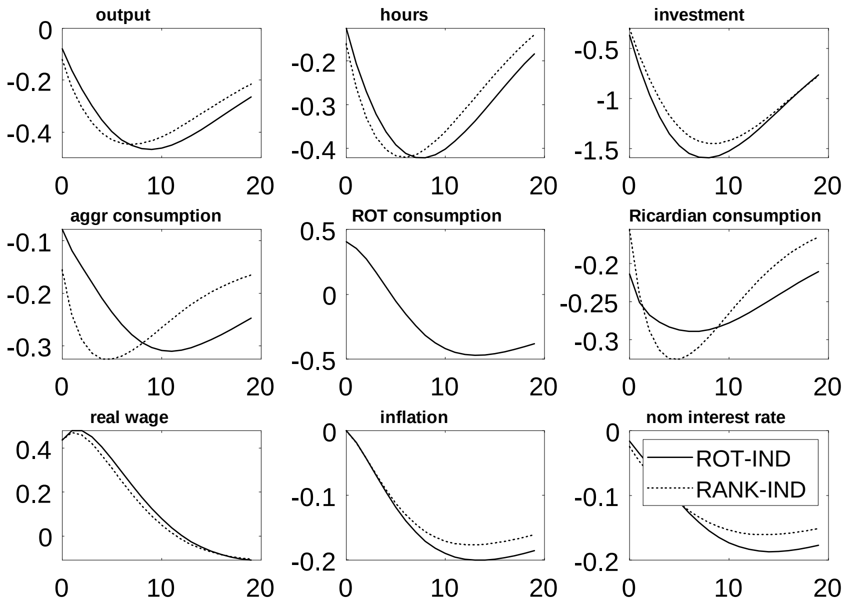

Figure A.3: Impulse responses to a one standard deviation wage markup shock (Sample: 1955Q4-1979Q2)

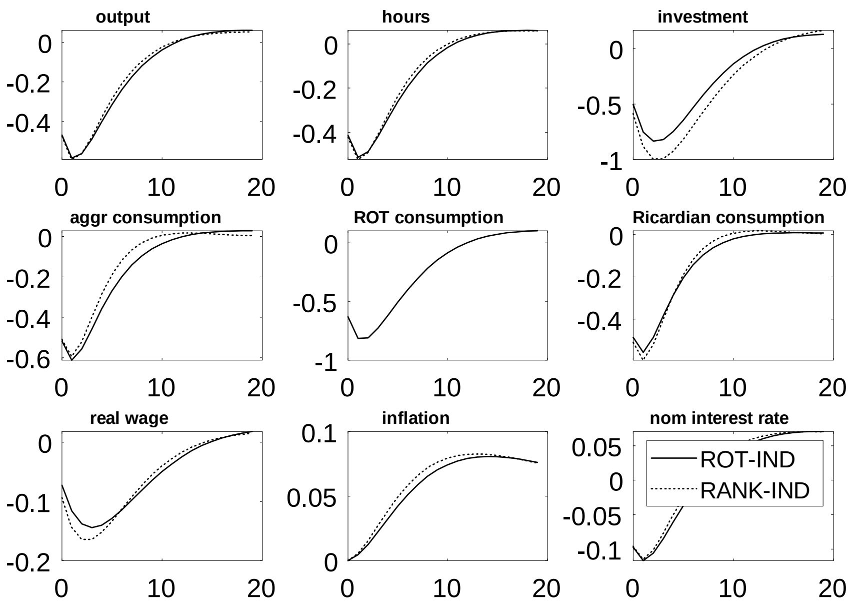

Figure A.4: Impulse responses to a one standard deviation risk premium shock (Sample: 1955Q4-1979Q2)

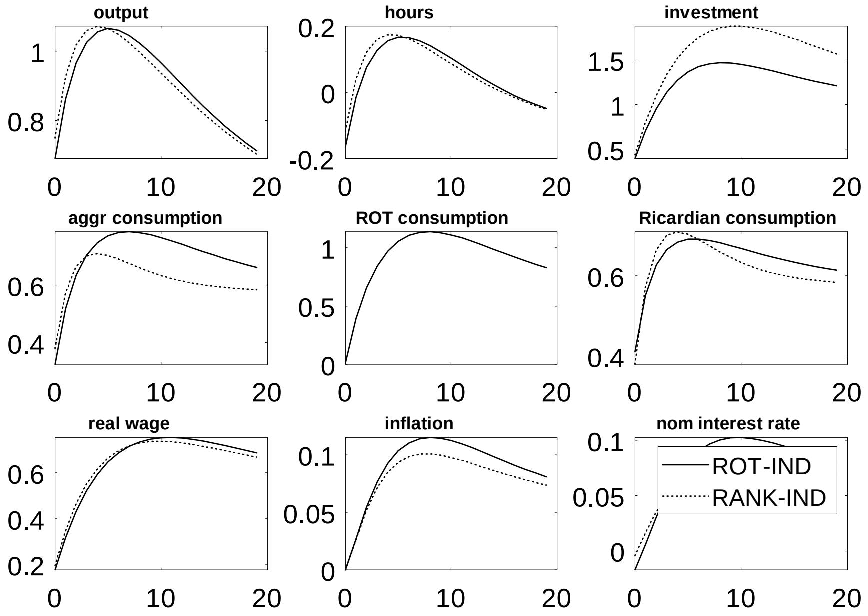

Figure A.5: Impulse responses to a one standard deviation technology shock (Sample: 1955Q4-1979Q2)

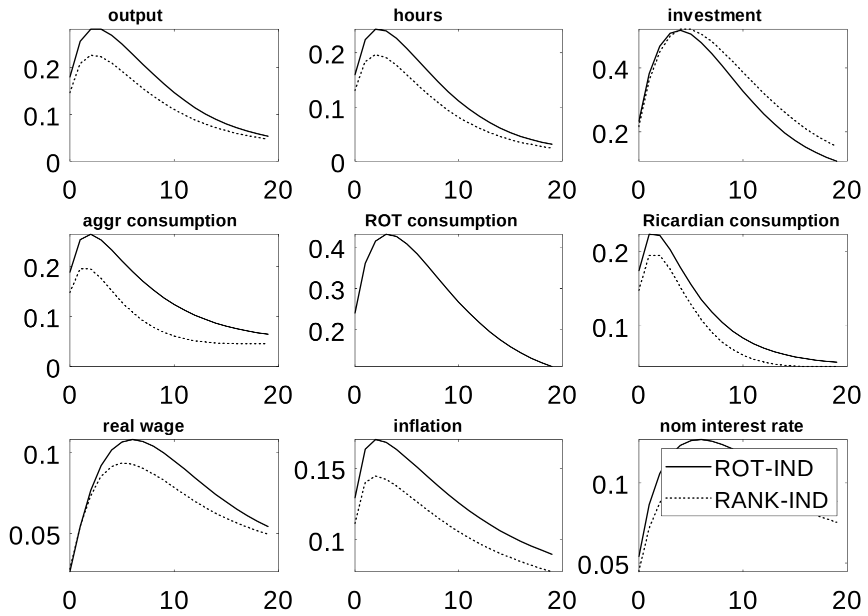

Figure A.6: Impulse responses to a one standard deviation sunspot shock (Sample: 1955Q4-1979Q2)