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Dynamics of Monetary-Fiscal Interaction under Learning

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Dynamics of Monetary-Fiscal Interaction under Learning

Josef Hollmayr* and Christian Matthes**

February 13, 2014

VERY PRELIMINARY AND INCOMPLETE

Abstract

The interaction between monetary and fiscal policy and the associated uncertainty about this interaction have been put on center stage by the recent financial crisis and the associated recession. In our model agents learn about both fiscal and monetary policy rules via the Kalman filter. In particular, we study how an economy populated with agents acting as econometricians reacts to discrete changes in the actual policy rules.

JEL codes: E32, D83, E62

Keywords: DSGE, MONETARY-FISCAL POLICY INTERACTION, LEARNING

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1 Introduction

This paper asks what happens after changes in fiscal and monetary policy when private agents have to use past data to estimate the nature of the policy changes they face. We contribute to the vast literature on monetary and fiscal interaction. Pioneered by Sargent and Wallace (1982), Sims (1994), Leeper (1991) and Leeper and Davig (2011) under full information rational expectations, there have been some first steps approaching this topic under learning. One paper in this vein is Eusepi and Preston (2011). Both our setup of learning and the research question are different as we are more interested in tracing out the effects that different views about the economy and the nature of policy changes have on economic outcomes.

We set up a standard, relatively small New-Keynesian model with habits and nominal frictions. Households face a CES-utility function and optimize with respect to consumption and leisure. Firms are profit maximizing and set prices optimally according to the Calvo setup (compare Calvo (1983)). The Government sector is comprised of a monetary and a fiscal branch. The fiscal sector is allowed to run budget deficits over time and accumulate debt if labor taxes are not sufficient to pay for government spending and transfers. The monetary authority sets the interest rate according to a simple monetary rule (Taylor (1993)) with inflation as the only input. With this relatively standard model we simulate our model economy to tackle the research questions mentioned above.

2 Model

Our model is a typical version of the a medium scale new-keyensian model that incorporates nominal frictions, habits and a fiscal sector. The fiscal branch can accumulate debt if its income from the distortionary labor tax is not matching outlays of government spending and transfers. The only real friction are external habits of households. Capital is not included as an input factor in production. First-order conditions and the complete log-linearized model may be found in the Appendix. The calibration for all parameters is standard in the literature and is also delegated in the Appendix.

2.1 Households

Households maximize their expected utility ¹ where the instantaneous utility function of the representative household i takes the following form:

$$U_t = \frac{(C_t - hC_{t-1})^{1-\sigma}}{1-\sigma} - \frac{L_t^{1+\phi}}{1+\phi} \quad (1)$$

Consumption of household i is denoted by C_t which should not vary too much from the external habit of last period's overall consumption C_{t-1} and labor by L_t . Each period households can choose to either consume or save in the form of government bonds (B_t). Therefore the maximization runs over the infinite sum of discounted utility under the budget constraint:

$$C_t + B_t = W_t L_t (1 - \tau_t^L) + R_{t-1} B_{t-1} + Z_t \quad (2)$$

The household's income stems from working at the wage W_t and interest payments on their savings at the rate R_t . Z_t represents lump-sum transfers or taxes. τ_t^L denotes the distortionary labor tax rate that the government levies on labor.

2.2 Firms

The production function of firm j is linear in technology and labor:

$$Y_t(j) = A_t L_t(j) \quad (3)$$

where Y_t denotes the output produced with a certain level of technology A_t and labor $L_t(j)$. Technology follows an AR(1) process. The exogenous process for technology is an AR(1):

$$A_t = \rho_a A_{t-1} + \epsilon_t^A \quad (4)$$

The real marginal costs are in this case simply given by the real wage

$$MC_t(j) = \frac{W_t(j)}{A_t P_t(j)}.$$

¹This statement encompasses the coefficients in the fiscal as well as in the monetary policy rule, which they treat as fixed when making their decisions. We use an *anticipated utility* assumption, which is common in the literature on adaptive learning. A more thorough description follows in the section where the learning algorithm is described more in detail.

In terms of price setting we assume that retailers set their prices according to the Calvo (1983) mechanism, i.e. each period the fraction $(1 - \theta_i)$ of all firms are able to reset their prices optimally. Furthermore I allow that firms that cannot reoptimize their prices in period t index their prices to the current inflation rate. Profits of firm j (in nominal terms) are then equal to

$$\Pi_t(j) = (P_t(j) - MC_t(j)) \left(\frac{P_t(j)}{P_t} \right)^{-\epsilon_j} Y_t(j) \quad (5)$$

2.3 Government

The government budget constraint is given by:

$$B_t = \frac{B_{t-1}R_{t-1}}{1 + \pi_t} - W_t L_t \tau_t^L + G_t + Z_t \quad (6)$$

One of the fiscal policy instruments has to incorporate a response to the past value of debt. Otherwise fiscal policy would follow an active behavior, i.e. debt would not be stabilized and follow an explosive path. In other words the coefficient of any fiscal rule on lagged debt must be bigger than $\frac{1}{\beta} - 1$ so that debt is stationary. We choose the labor tax rule to behave accordingly. All other fiscal rules follow normal AR(1) processes with their respective white noise component. Government spending is given by:

$$\log(G_t) = G_c + \rho_g \log(G_{t-1}) + \epsilon_t^G \quad (7)$$

Z_t denotes transfers which behave as follows:

$$\log(Z_t) = Z_c + \rho_z \log(Z_{t-1}) + \epsilon_t^Z, \quad (8)$$

As mentioned above, the labor tax rate is modelled as a rule with the feedback coefficient $\rho_{L,b}$ which the agents do not know for sure and have to infer:

$$\log(\tau_t^L) = \tau_c^L + \rho_{L,b} \log(B_{t-1}) + \epsilon_t^L \quad (9)$$

The monetary policy is given by simple Taylor type rule, which is only reacting to inflation and not to production. A major difference is that the timing is different from usual models with the interest reaction to lagged inflation instead of contemporaneous

or even lead inflation. This is an assumption which is crucial for the learning algorithm but not entirely consistent with real world monetary policy implementation.

$$\log(R_t) = R_c + \rho_{R,\pi} \log(\pi_{t-1}) + \epsilon_t^R \quad (10)$$

The firms and households in our model know the form of the labor tax rule and the monetary policy rule as described above, but they do not know the coefficients, which they have to estimate. They also know that the government budget constraint has to hold in every period.

2.4 Market Clearing

Demand on the part of the government and households must fully absorb the output of the firm:

$$Y_t = C_t + G_t$$

The bond market in our model is simple and market clearing in this market implies that all bonds issued by the government are bought by the households in the economy.

3 Learning Mechanism

Our approach to modelling learning is borrowed from our earlier work Hollmayr and Matthes (2013), which in turn builds on Cogley *et al.* (2011).

The agents in our model observe all relevant economic outcomes and use those observations to estimate the coefficients of the policy rules. They know all other aspects of the model. All private agents share the same beliefs and carry out inference by using the Kalman filter. If we denote by $\mathbf{\Omega}_t$ the vector of coefficients of all policy rules and by ξ_t the vector of the interest rate and the tax rate at time t then the observation equation for the state space system used by the Kalman filter is given by: We denote by $\mathbf{\Omega}_t$ the vector of policy rule coefficients that agents want to estimate. In order for agents to be able to use the Kalman Filter for inference, we need to build a state space system than encompasses our assumptions on the learning behavior of agents. The observation equation represents the policy rules, whereas the state equation represents the perceived dynamics in policy rule coefficients.

The vector of observations is given by ²

$$\xi_t = \begin{bmatrix} \log(R_t) - R_c \\ \log(\tau_t^L) - \tau_c^L \end{bmatrix} \quad (11)$$

$$\xi_t = \mathbf{X}_{t-1} \boldsymbol{\Omega}_t + \eta_t \quad (12)$$

where η_t collects the iid disturbances in the policy rules. \mathbf{X}_{t-1} collects the right-hand side variables in the policy rules. What is left to specify then is the perceived law of motion for $\boldsymbol{\Omega}_t$ - how do firms and households in the economy think policy rule coefficients change over time? We study two assumptions: agents either know when the policy rule changes and take into account that policy rule coefficients before and after the break date or they suspect that policy changes every period. The following law of motion for the coefficients encodes these assumptions, inspired by the literature on time-varying coefficient models in empirical macroeconomics (such as Cogley and Sargent (2005) or Primiceri (2005)) ³:

$$\boldsymbol{\Omega}_t = \boldsymbol{\Omega}_{t-1} + \mathbf{1}_t \nu_t \quad (13)$$

If we set the variance of ν_t to a conformable matrix of zeroes, then the private agents in our model believe that policy rule coefficients do not change and they estimate unknown constant coefficients. The indicator function $\mathbf{1}_t$ selects in what periods agents perceive there to be a change in policy. We will entertain two assumptions on this indicator function: one in which it is always 1, so agents always assume there is a change in parameters and one in which this indicator function is 0 unless the policy rule actually changes ⁴. Given beliefs for $\boldsymbol{\Omega}_t$, agents in our model will adhere to the anticipated utility theory of decision-making: they will act as if $\boldsymbol{\Omega}_t$ is going to be fixed at the currently estimated level forever onwards ⁵. This is a common assumption in

²For simplicity, we assume that the intercepts in the policy rules remain unchanged and are known to the private agents (Cogley *et al.* (2011) highlight that the differences between dynamics under learning and the full information case emerge mainly from different views held by agents on policy rule response coefficients, not intercepts).

³This assumption has been applied in the learning literature by Sargent *et al.* (2006), for example.

⁴If agents always perceive policy rule coefficients to change even though there is no policy change, their estimators will fluctuate around the true values. The magnitude of those fluctuations is determined by the signal to noise ratio inherent in the state space systems that we will endow agents with.

⁵We use the posterior mean coming out of the Kalman Filter as a point estimate which the agents in the model condition on when forming expectations. We follow most of the learning literature in imposing a projection facility that makes agents reject an estimate if that estimate implies that no stable PLM exists. In our benchmark case we also impose a projection facility by which agents reject an estimate if it implies that the perceived steady state changes by more than 50 percent from one period to the next. In contrast to Cogley *et al.* (2011) in our application the mapping from estimates

the literature on learning, see for example Milani (2007).

A change in beliefs about policy will also induce a change in the beliefs about the steady state of the economy. The beliefs (i.e. parameter estimates) and expectations that influence time t equations are dated $t-1$ because of our timing assumption: agents enter the current period (and make decisions in that period) with beliefs updated at the end of the previous period. This makes the solution method recursive, otherwise we would have to jointly solve for outcomes and beliefs every period. We could have alternatively let beliefs depend on time $t-1$ information, but let time t information be in the information set used to compute expectations as we did in our previous work. Both assumptions are commonly used in the learning literature (Evans and Honkapohja (2001)).

If we denote the vector of all variables (plus a constant intercept) in the model economy by \mathbb{Y}_t , then we can stack the log-linearized equilibrium conditions (approximated around the perceived steady state) and the estimated policy rules to get the log-linearized perceived law of motion in the economy:

$$\mathbf{A}(\boldsymbol{\Omega}_{t-1})\mathbb{Y}_t = \mathbf{B}(\boldsymbol{\Omega}_{t-1})\mathbf{E}_{t-1}^*\mathbb{Y}_{t+1} + \mathbf{C}(\boldsymbol{\Omega}_{t-1})\mathbb{Y}_{t-1} + \mathbf{D}\varepsilon_t^* \quad (14)$$

ε_t^* contains the actual shocks the innovations that agents observe as well as the perceived policy shocks (the residuals in the estimated policy rules). This system can be solved using a number of algorithms such as gensys (Sims (1994)). The resulting reduced form perceived law of motion is given by:

$$\mathbb{Y}_t = \mathbf{S}(\boldsymbol{\Omega}_{t-1})\mathbb{Y}_{t-1} + \mathbf{G}(\boldsymbol{\Omega}_{t-1})\varepsilon_t^* \quad (15)$$

$\mathbf{S}(\boldsymbol{\Omega}_{t-1})$ solves the following matrix quadratic equation⁶:

$$\mathbf{S}(\boldsymbol{\Omega}_{t-1}) = (\mathbf{A}(\boldsymbol{\Omega}_{t-1}) - \mathbf{B}(\boldsymbol{\Omega}_{t-1})\mathbf{S}(\boldsymbol{\Omega}_{t-1}))^{-1}\mathbf{C}(\boldsymbol{\Omega}_{t-1}) \quad (16)$$

and $\mathbf{G}(\boldsymbol{\Omega}_{t-1})$ is given by

$$\mathbf{G}(\boldsymbol{\Omega}_{t-1}) = (\mathbf{A}(\boldsymbol{\Omega}_{t-1}))^{-1}\mathbf{D} \quad (17)$$

It is convenient at this point to re-express the system using one-step ahead expectations (in order to use gensys, for example, we would have to do this anyway). An example on how to do this by extending the number of variables is given in Sims (1994).

to perceived steady states can be highly non-linear depending on parameter values.

⁶The perceived law of motion can be derived by assuming a VAR perceived law of motion of order 1 and then using the method of undetermined coefficients.

We call this extended vector of variables $\bar{\mathbf{Y}}_t$. The reduced form PLM is derived using steps similar to those outlined above, adjusting only the derivation of the response to the shocks.

$$\bar{\mathbf{A}}(\Omega_{t-1})\bar{\mathbf{Y}}_t = \bar{\mathbf{B}}(\Omega_{t-1})\mathbf{E}_t^*\bar{\mathbf{Y}}_{t+1} + \bar{\mathbf{C}}(\Omega_{t-1})\bar{\mathbf{Y}}_{t-1} + \bar{\mathbf{D}}\varepsilon_t^* \quad (18)$$

To derive the ALM, we replace the perceived policy rule coefficients in $\bar{\mathbf{C}}(\Omega_{t-1})$ with the actual policy rule coefficients and use the actual innovation vector ε_t :

$$\bar{\mathbf{A}}(\Omega_{t-1})\bar{\mathbf{Y}}_t = \bar{\mathbf{B}}(\Omega_{t-1})\mathbf{E}_t^*\bar{\mathbf{Y}}_{t+1} + \bar{\mathbf{C}}^{\text{actual}}(\Omega_{t-1})\bar{\mathbf{Y}}_{t-1} + \bar{\mathbf{D}}\varepsilon_t \quad (19)$$

To solve the model, we can plug the PLM into the ALM twice to get

$$\bar{\mathbf{A}}(\Omega_{t-1})\bar{\mathbf{Y}}_t = \bar{\mathbf{B}}(\Omega_{t-1})(\bar{\mathbf{S}}(\Omega_{t-1})^2\bar{\mathbf{Y}}_{t-1} + \bar{\mathbf{S}}(\Omega_{t-1})\bar{\mathbf{G}}(\Omega_{t-1})\varepsilon_t^*) + \bar{\mathbf{C}}^{\text{actual}}(\Omega_{t-1})\bar{\mathbf{Y}}_{t-1} + \bar{\mathbf{D}}\varepsilon_t \quad (20)$$

Note that there are two types of shocks appearing in the last equation: the true and the perceived shocks. We can solve for the dynamics of $\bar{\mathbf{Y}}_t$ by only inverting $\bar{\mathbf{A}}(\Omega_{t-1})$ as long as we can derive an expression for the perceived shocks that only depends on pre-determined and exogenous variables. Fortunately enough, this is true in our case.

$$\bar{\mathbf{D}}\varepsilon_t^* = \bar{\mathbf{D}}\varepsilon_t + (\bar{\mathbf{C}}^{\text{actual}}(\Omega_{t-1}) - \bar{\mathbf{C}}(\Omega_{t-1}))\bar{\mathbf{Y}}_{t-1}$$

Multiplying both sides of this equation by $\bar{\mathbf{A}}(\Omega_{t-1})^{-1}$, we get

$$\bar{\mathbf{G}}(\Omega_{t-1})\varepsilon_t^* = \bar{\mathbf{A}}(\Omega_{t-1})^{-1}(\bar{\mathbf{D}}\varepsilon_t + (\bar{\mathbf{C}}^{\text{actual}}(\Omega_{t-1}) - \bar{\mathbf{C}}(\Omega_{t-1}))\bar{\mathbf{Y}}_{t-1})$$

This derivation departs from the derivation used in Cogley *et al.* (2011) because we found our approach of solving for the equilibrium dynamics to be more numerically stable (once we have solved for the ALM, our approach only requires invertibility of $\bar{\mathbf{A}}(\Omega_{t-1})$).

4 Simulation Setup

As a first pass to analyze how agents in our economy react to changes in fiscal and monetary policy, we consider the A scenario in which monetary policy becomes passive and distortionary taxes react less to the level of debt. In particular, we consider a one time switch in the policy rule coefficients α_π and ρ_b from 1.5 and .2 to .8 and .03. The

calibration for all other parameters is given in the appendix. The calibration borrows parameter values from Hollmayr and Matthes (2013) and Leeper *et al.* (2010). Other parameter values used are standard in the literature.

We run 100 simulations of 200 periods with the policy switch happening in period 50.

⁷ We analyze different assumptions about the perceived amount of time variation in policy rule coefficients that private agents hold. We assume agents use a covariance matrix of the innovations in the perceived policy rule coefficients of the following form⁸:

$$\mathbf{E}(\nu_t \nu_t') = \begin{bmatrix} (scale * (1.5 - 0.8))^2 & 0 \\ 0 & (scale * (0.2 - 0.03))^2 \end{bmatrix} \quad (21)$$

For the case in which $\mathbf{1}_t = 1 \forall t$ we consider the following values for *scale*: .01, .05 and .1, while for the case in which the indicator matrix is only non-zero during the actual policy change, we use the values 1/3, 1/2 and 1. We use smaller values for the first case to avoid large swings in beliefs during times when there is no policy change.

5 Results

The following plots give the results for our benchmark cases. We plot beliefs, standard deviations, average outcomes and average perceived steady states. We see that the estimates in all our cases converge quite quickly. This seems re-assuring, but looking at average outcomes and perceived steady states, we see that the outcomes under learning are very different from those under full information rational expectations⁹. This holds true for all our specifications. A natural first prospective culprit for these outcomes would be the projection facility on changes in perceived steady states of debt that we impose. The change in steady states under FI is quite large after all. Thus we re-do the analysis dropping this projection facility. This leads to substantially increased volatility while at the same time not leading to convergence of perceived steady states to their

⁷We choose to not put the policy switch at the beginning of the simulations to minimize the effect of the choice of the initial covariance matrix for the Kalman Filter.

⁸We have used covariance matrices of this form in our previous work and found them handy to interpret the perceived amount of time variation.

⁹Agents could *not* figure out that their beliefs have not converged to the FI solution by trying to estimate the steady state of the variables in the model. The economy fluctuates around the perceived steady state.

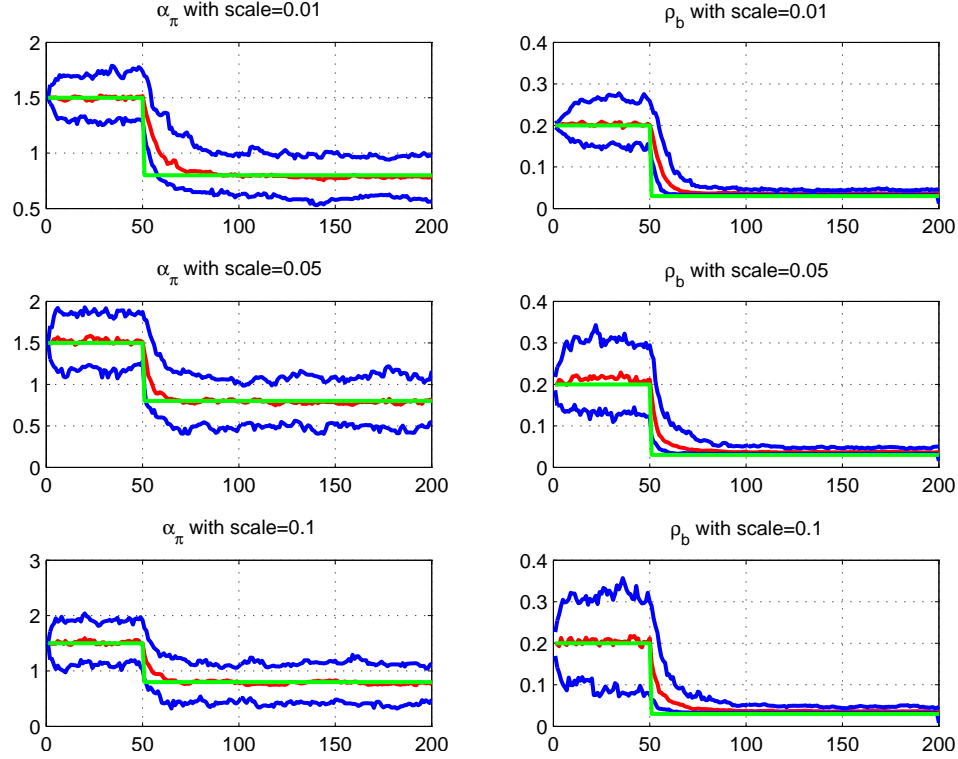


Figure 1: Beliefs, covariance of perceived innovations to parameters is always non-zero

FI counterparts¹⁰. To further analyze the source of this lack of convergence we analyze a scenario in which the monetary policy rule does not change and the agents know the monetary policy rule coefficients. This scenario confirms that it is indeed uncertainty about ρ_b that drives our results. In fact what drives our results is that the mapping from ρ_b to the steady state of debt is highly non-linear and differences in ρ_b that seem insignificant can lead to substantial differences in steady states across economies. Our results can be interpreted as a cautionary tale: when setting up a learning model, one should be careful of possible non-linearities in the mapping from estimates to the ALM and ultimately to the PLM. Only if we really believe that those non-linearities (in our case coming through steady state calculations) are indeed reasonable should we believe those results. Otherwise researchers might want to consider other learning mechanisms that do not feature these strong non-linearities. If we instead think those non-linearities are a feature that we want in our models then small differences estimates can lead to large differences in outcomes.

¹⁰To economize on space, we only carry out the simulation in that case for one value of the *scale* parameter.

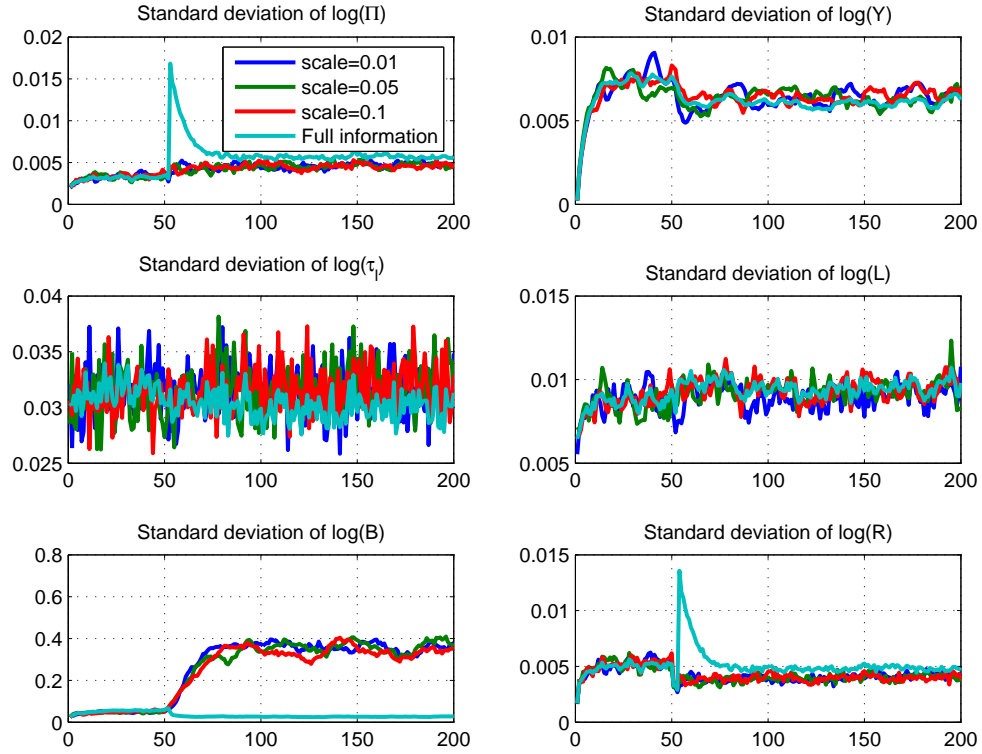


Figure 2: covariance of perceived innovations to parameters is always non-zero

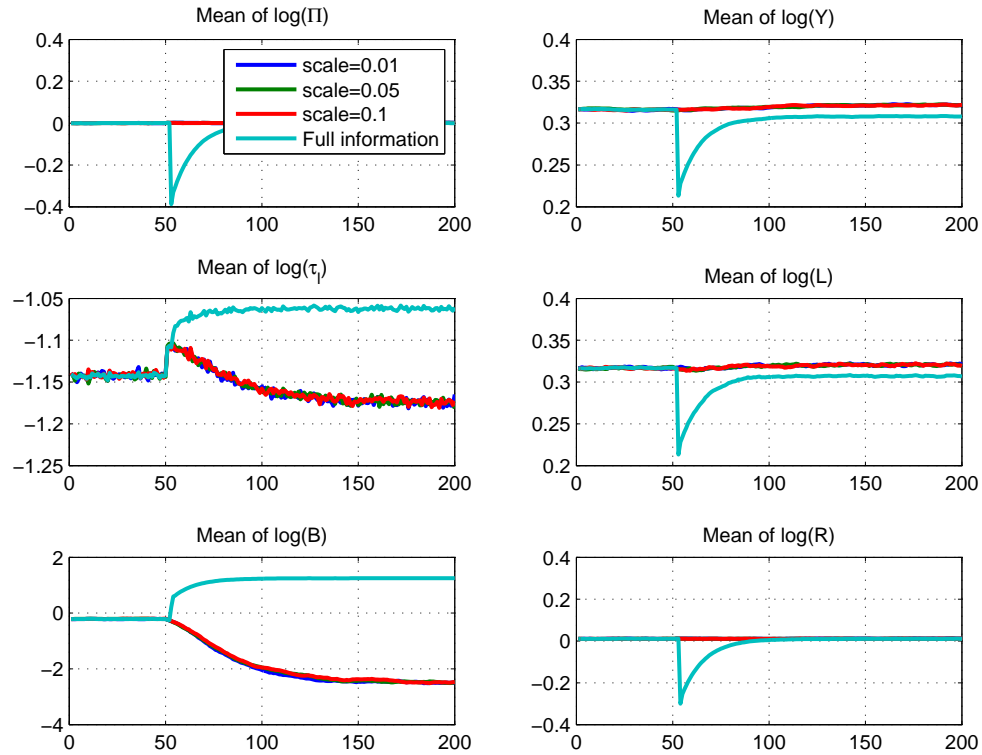


Figure 3: covariance of perceived innovations to parameters is always non-zero

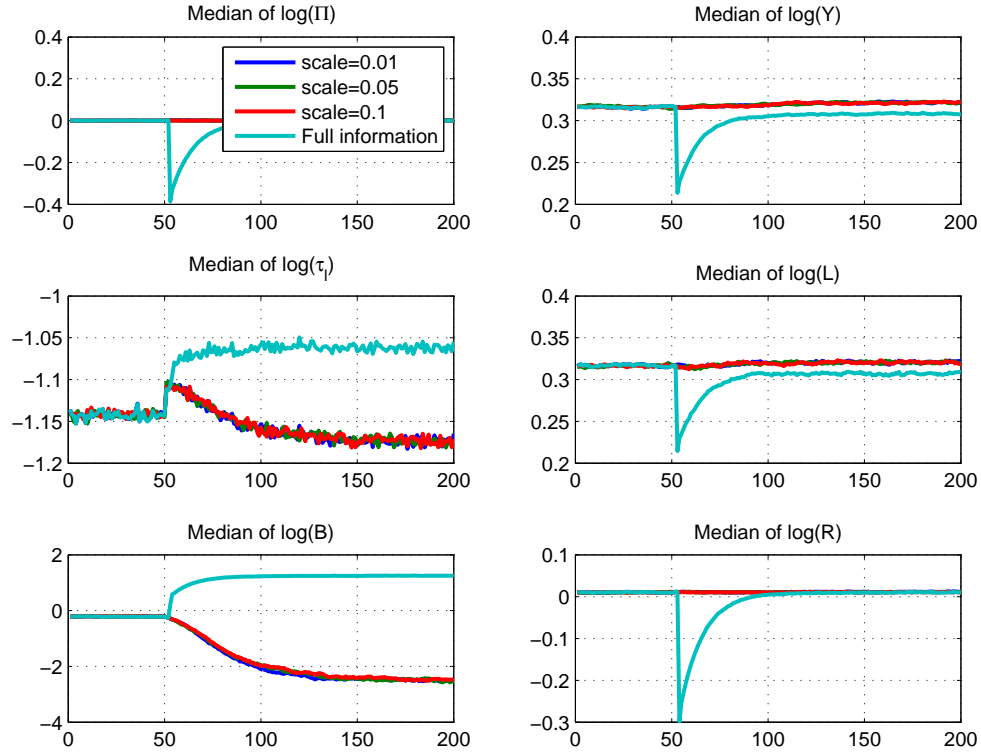


Figure 4: covariance of perceived innovations to parameters is always non-zero

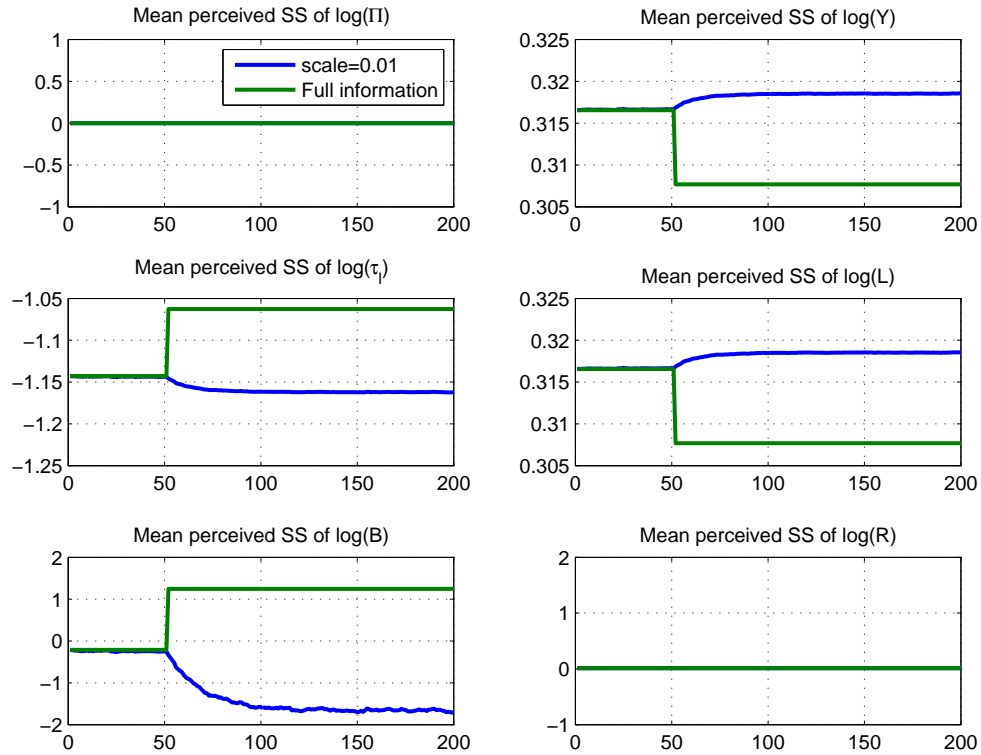


Figure 5: covariance of perceived innovations to parameters is always non-zero

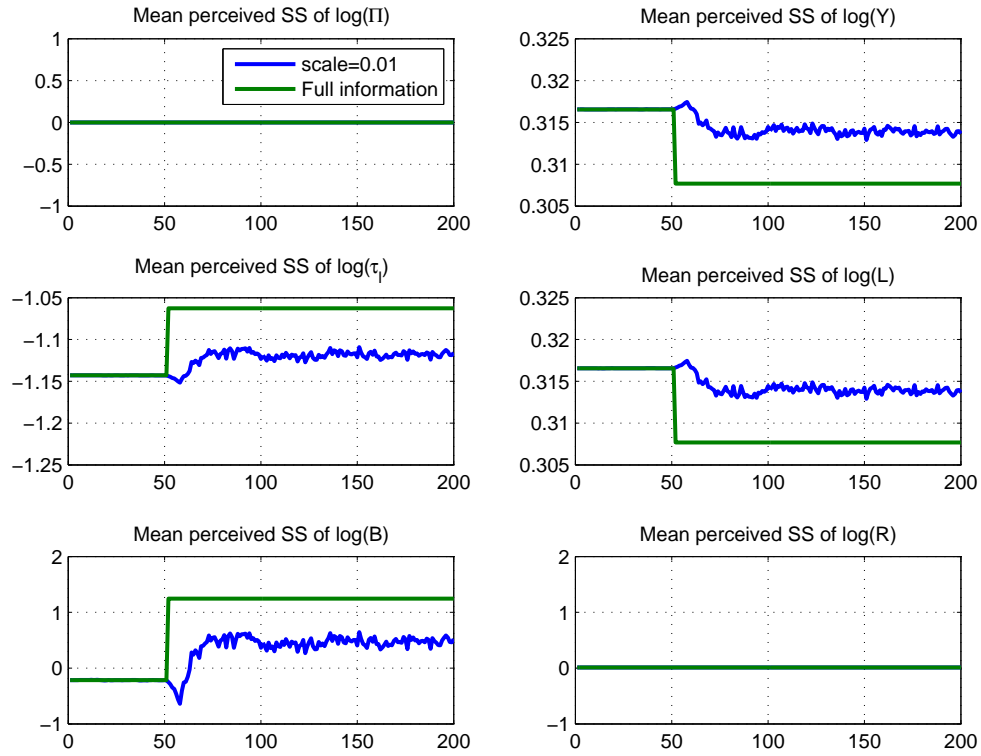


Figure 6: Perceived steady states, no projection facility on perceived steady states, covariance of perceived innovations to parameters is always non-zero

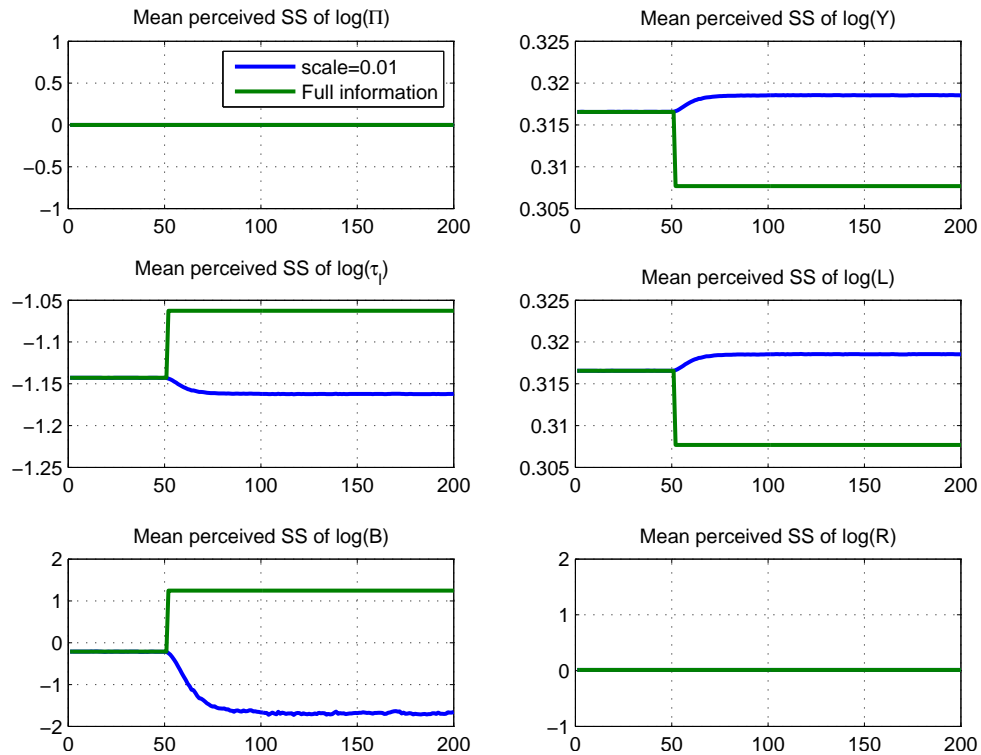


Figure 7: Perceived steady states, learning about ρ_b only, covariance of perceived innovations to parameters is always non-zero

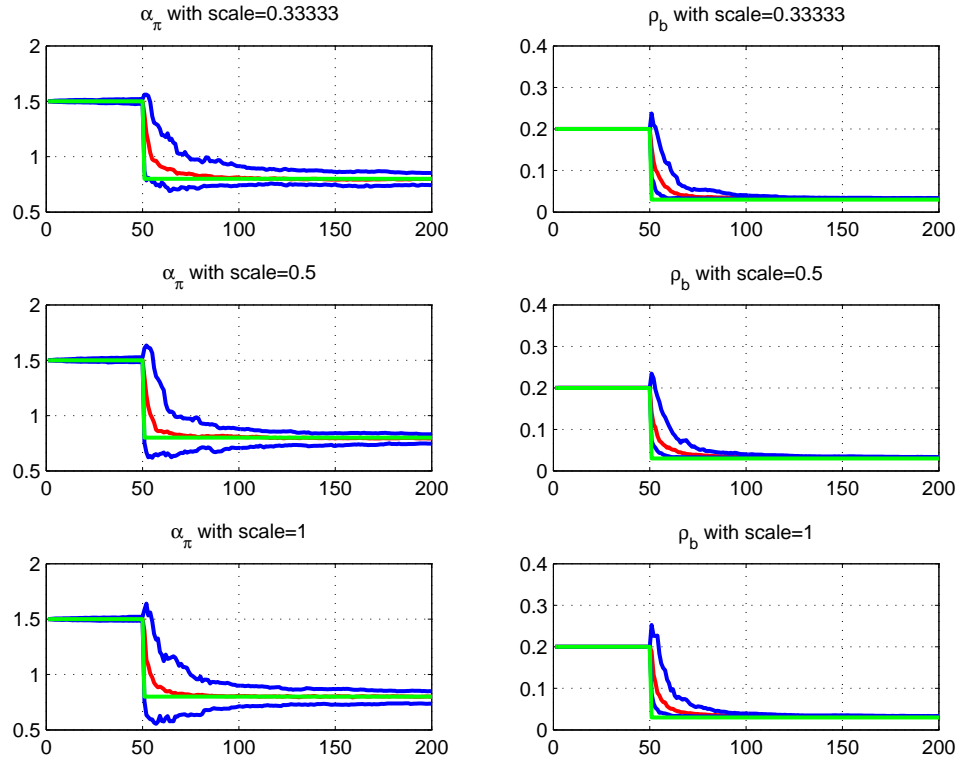


Figure 8: Beliefs, covariance of perceived innovations to parameters is zero except when policy changes

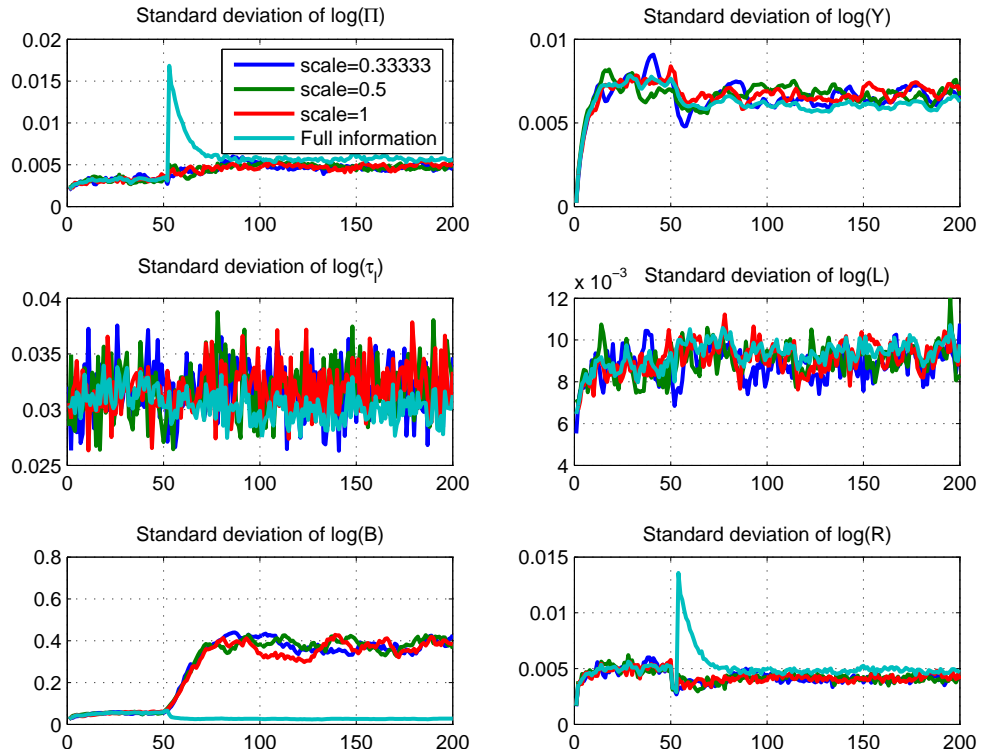


Figure 9: covariance of perceived innovations to parameters is zero except when policy changes

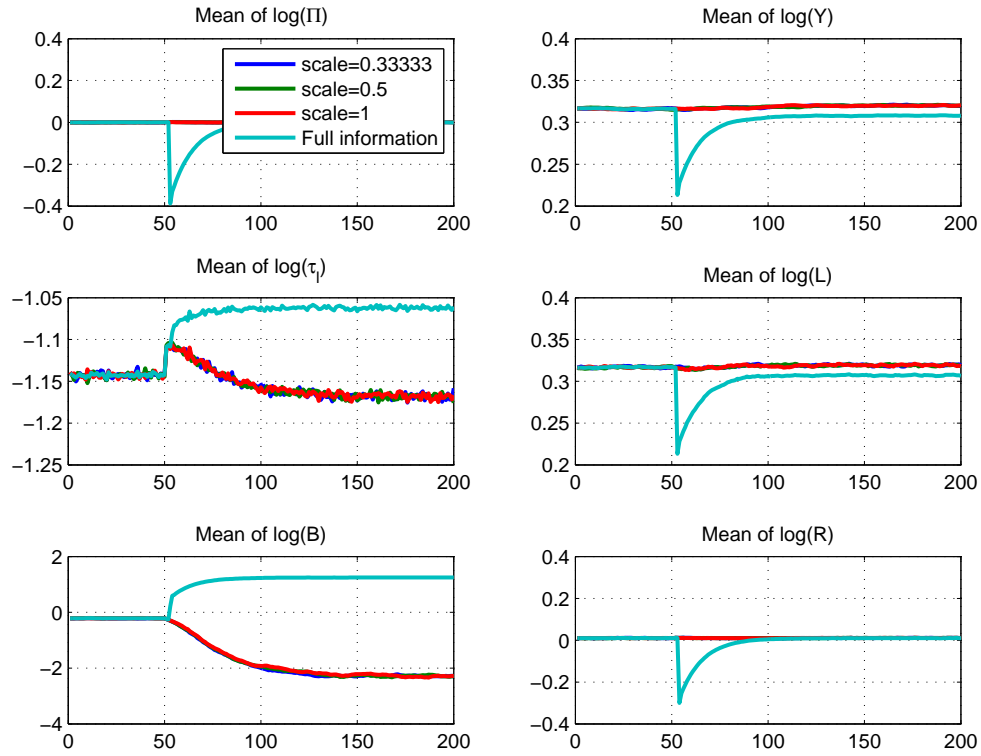


Figure 10: covariance of perceived innovations to parameters is zero except when policy changes

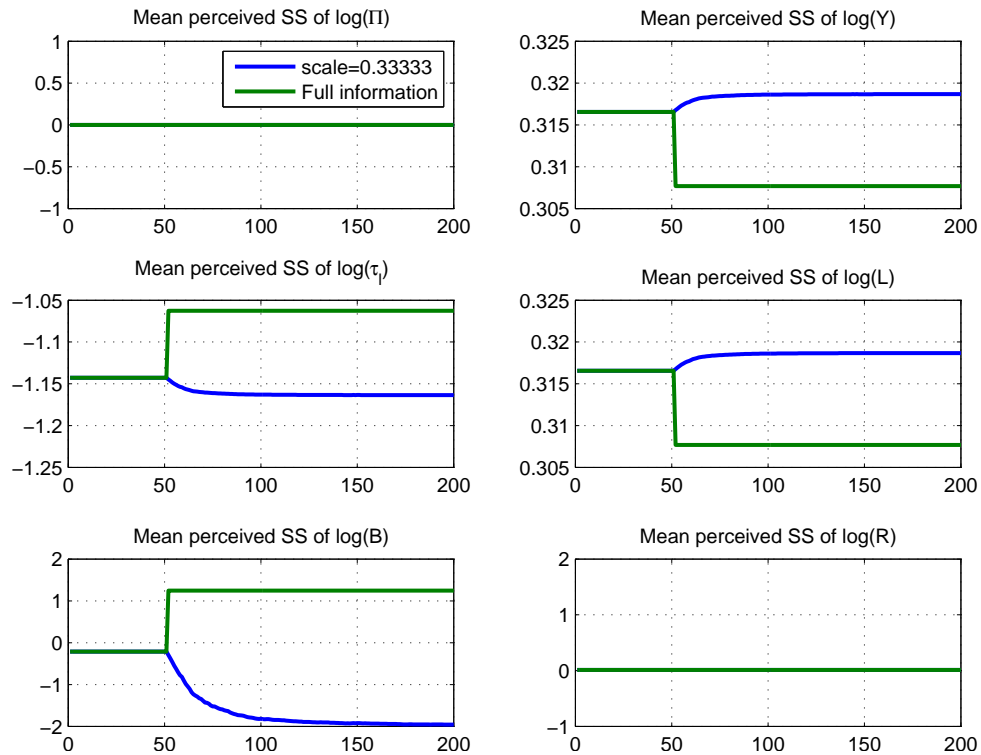


Figure 11: covariance of perceived innovations to parameters is zero except when policy changes

6 Conclusion

to be written

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Appendix

Model Description, FOCs and Log-linearized Equation

A First-Order Conditions

Households:

$$\begin{aligned} (C_t - hC_{t-1})^{-\sigma} &= \beta R_t E_{t-1} \frac{(C_{t+1} - hC_t)^{-\sigma}}{1 + \pi_{t+1}} \\ L_t^{1+\phi} &= (C_t - hC_{t-1})^{-\sigma} (1 - \tau_t^L) W_t \end{aligned}$$

Firms:

$$\begin{aligned} W_t &= \frac{Y_t MC_t}{L_t} \\ \tilde{P}_t &= \frac{\psi}{\psi - 1} \frac{\left[\lambda_t MC_t Y_t + \beta \theta E_{t-1} \lambda_{t+l} MC_{t+1} Y_{t+l} \left(\frac{\pi}{\pi_{t+1}} \right)^{-\psi} \right]}{\left[\lambda_t Y_t + \beta \theta E_{t-1} \lambda_{t+l} MC_{t+1} Y_{t+l} \left(\frac{\pi}{\pi_{t+1}} \right)^{1-\psi} \right]} \\ P_t^{1-\psi} &= \theta (\pi P_{t-1})^{1-\psi} + (1 - \theta) \tilde{P}_t^{1-\psi} \end{aligned}$$

B Log-Linearized Model

Households:

$$\begin{aligned} (1 + \phi) \log(L_t) &= \text{Const}_L + \log(Y_t) + \log(MC_t) - \left(\frac{\tau_{ss}^L}{1 - \tau_{ss}^L} \right) \log(\tau_t^L) - \frac{\sigma}{1 - h} \log(C_t) + \frac{\sigma h}{1 - h} \log(C_{t-1}) \\ - \frac{\sigma(1 + h)}{1 - h} \log(C_t) &+ \frac{\sigma h}{1 - h} \log(C_{t-1}) = \text{Const}_C - \frac{\sigma}{1 - h} E_{t-1} \log(C_{t+1}) + \log(R_t) - \log E_{t-1}(\log(\pi_{t+1})) \end{aligned}$$

Firms:

$$\begin{aligned}
\log(Y_t) &= \text{Const}_{Agg} + \frac{C_{ss}}{Y_{ss}} \log(C_t) + \frac{G_{ss}}{Y_{ss}} \log(G_t) \\
\log(Y_t) &= \text{Const}^Y + \log(A_t) + \log(L_t) \\
\log(\pi_t) &= \text{Const}_\pi + \beta E_{t-1} \log(\pi_{t+1}) + \frac{(1-\theta\beta)(1-\theta)}{\theta} \log(MC_t)
\end{aligned}$$

Policy Rules and Shocks:

$$\begin{aligned}
\log(B_t) &+ \tau_{ss}^L \frac{Y_{ss} MC_{ss}}{B_{ss}} (\log(\tau_t^K) + \log(Y_t) + \log(MC_t)) \\
&= \text{Const}_B + \frac{1}{\beta} \log(R_{t-1}) + \frac{1}{\beta} \log(B_{t-1}) - \frac{1}{\beta} \log(\pi_t) + \frac{G_{ss}}{B_{ss}} \log(G_t) + \frac{Z_{ss}}{B_{ss}} \log(Z_t) \\
\log(G_t) &= \text{Const}_G + \rho_G \log(G_{t-1}) + \epsilon_t^G \\
\log(Z_t) &= \text{Const}_Z + \rho_Z \log(Z_{t-1}) + \epsilon_t^Z \\
\log(\tau_t^L) &= \text{Const}_{\tau^L} + \zeta \log(B_{t-1}) + \epsilon_t^L \\
\log(R_t) &= \text{Const}_R + \alpha \pi_{t-1} + \epsilon_t^R \\
\log(A_t) &= \text{Const}_A + \rho_A \log(A_{t-1}) + \epsilon_t^A
\end{aligned}$$

with the constants given by:

Constant	Expression
Const_G	$\log(G_{ss})(1 - \rho_G)$
Const_Z	$\log(Z_{ss})(1 - \rho_Z)$
Const_{τ^L}	$\log(\tau_{ss}^L) - \zeta \log(B_{ss})$
Const_R	$\log(R_{ss}) - \alpha \log(\pi_{ss})$
Const_B	$\log(B_{ss})(1 - \frac{1}{\beta}) + \tau_{ss}^L \frac{Y_{ss} MC_{ss}}{B_{ss}} (\log(\tau_{ss}^L) + \log(Y_{ss}) + \log(MC_{ss})) - \frac{1}{\beta} \log(R_{ss}) + \frac{1}{\beta} \log(\pi_{ss}) - \frac{G_{ss}}{B_{ss}} \log(G_{ss}) - \frac{Z_{ss}}{B_{ss}} \log(Z_{ss})$
Const_L	$(1 + \phi) \log(L_{ss}) - \log(Y_{ss}) + -\log(MC_{ss}) + \frac{\tau_{ss}^L}{1 + \tau_{ss}^L} \log(\tau_{ss}^L)$
Const_C	$-\log(R_{ss}) + \log(\pi_{ss}) + \left(\frac{\sigma h}{1-h} - \frac{\sigma(1-h)}{1-h} + \frac{\sigma}{1-h} \right) \log(C_{ss})$
Const_Y	$\log(Y_{ss}) - \log(A_{ss}) - \log(L_{ss})$
Const_A	$\log(A_{ss})(1 - \rho_A)$
Const_{Agg}	$\log(Y_{ss}) - \frac{C_{ss}}{Y_{ss}} \log(C_{ss}) - \frac{G_{ss}}{Y_{ss}} \log(G_{ss})$
Const_π	$(1 - \beta) \log(\pi_{ss}) - \frac{(1-\theta\beta)(1-\theta)}{\theta} \log(MC_{ss})$

C Parameters

Calibrated Parameters of simple model

Description	Parameter	Value
impatience	β	0.99
CES utility Consumption	σ	2
CES utility labor	ϕ	2
habits	h	0.5
Calvo Parameter	θ	0.75
Market Power elasticity	ψ	6
AR parameter Transfer rule	ρ_Z	0.9
AR parameter gov. Spending	ρ_G	0.9
AR parameter technology	ρ_a	0.9
Std.deviation technology	σ_a	0.0062
Std.deviation gov. spending	σ_g	0
Std.deviation transfers	σ_z	0
Std.deviation labor tax	σ_l	0.03
Std.deviation interest rate	σ_r	.0016

Table 1: Calibrated Parameters of the model