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The role of search frictions for output and inflation dynamics: a Bayesian assessment*

Martin Menner**

Abstract

A search-theoretic monetary DSGE model with capital and inventory investment is estimated, and its implications on output and inflation dynamics are contrasted with those of standard flexible price monetary models: a cash-in-advance and a portfolio adjustment cost model. Model estimation and comparison is conducted in a Bayesian way in order to account for possible model misspecification. The search model can track inflation and output data better. It dominates the other models in the ability to predict the autocorrelations of inflation, the contemporaneous correlation between output growth and inflation, and in the persistent (dis-)inflation process after a (technology) monetary shock. It generates a hump-shaped but delayed output response to a monetary shock that matches the data better than the other models.

Keywords: Inflation and Output Dynamics, Business Cycle, Search-Theory of Money, Bayesian Estimation, Model Comparison.

JEL Codes: C11, D83, E10, E31, E32

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1. Introduction

Starting from Kiyotaki and Wright (1991), (1993) search theory has developed into the main paradigm of the micro-foundation of money. Giving money an essential role - money augments the set of achievable allocations[1] - this approach has become a useful tool for monetary theory. However, little quantitative analysis has been undertaken so far with search models of money.[2]

This paper addresses quantitatively the implications of search frictions in the goods market for inflation and output dynamics in three different dimensions: Can a search-theoretic model track US output growth and inflation data better than other standard flexible price monetary models like the cash-in-advance (CIA) model or limited participation models? Can it create more realistic contemporary and lagged correlations between output growth and inflation? And: How well do dynamic responses to shocks to money growth and technology match its empirical counterparts? The aim is to assess whether search frictions in the goods market have the potential to improve substantially the models used as laboratories to study the effects of monetary policy.

Search-theoretic monetary business cycle models explore the consequences of search frictions in the goods market for aggregate variables in business cycle frequencies, but are not tailored to fit the data. Thus, any version of this model class is probably highly misspecified, i.e., we cannot believe that any of these models comes close to the true data generating process (DGP). The same is true for the standard CIA and limited participation models. Obviously, one could try to enrich the models with many additional features like habit formation, investment adjustment costs, etc. – so as to deal with less misspecified models. But the question arises what one can really learn from a comparison of highly complex models where many frictions interact with each other. Here we take another road: to keep the models simple I follow Schorfheide (2000) in applying a Bayesian methodology that allows comparing potentially misspecified models by use of a highly parameterized reference model that achieves a good fit to the data, namely a VAR.

[1] See Kocherlakota (1998) and Wallace (1998) on the issue of essentiality.

[2] In his lecture at the Canadian Economics Association Meetings (Hamilton 2005), published in Shi (2006), Shi gives an overview of the literature, highlighting the quantitative contributions of Shi (1998), Wang and Shi (2006), and Menner (2006), and urging for more quantitative analysis in the field of monetary search-theory.

The model chosen from the class of search-theoretic monetary models (STM) is based on the full fledged business cycle model of Menner (2006) that combines search frictions in the goods market[3] and capital formation.[4] There are several reasons for this choice. First, there are only few models of the search-theoretic literature capable of addressing macroeconomic issues. To study the effects of changes in money growth the early literature had to assume an upper bound in money holdings.[5] Shi (1998) was the first to develop a tractable search-theoretic Dynamic Stochastic General Equilibrium (DSGE) model where prices are determined endogenously and money holdings are not bounded. His model exhibits a persistent mechanism propagating monetary shocks that arises from the interaction of search-intensity and inventory investment but lacks the possibility of capital formation. Second, allowing for capital formation as in Menner (2006) potentially helps the model to propagate shocks as it does in standard business cycle models. Moreover, capital formation breaks the close link between employment and output present in a model with fixed capital.[6] Since we are interested in inflation and output dynamics it is better not to rely too heavily on outcomes of the labor market in determining output responses and hence to use a model with capital formation.

What about alternatives? Faig (2002) has developed a model where the production sector is neoclassical and capital is accumulated by using the firm's own product as investment. The commerce sector is separated from the production sector. His model differs in many other details from the present model and the analysis concentrates on welfare implications of money growth across different steady states. It is not clear from the outset whether it can generate such rich dynamics as the present model, since Faig studies only monetary policies that keep the nominal interest rate constant.

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[3] Although Menner (2006) assumes also search frictions in the labor market, I only consider model versions with flexible labor markets in order to compare the models on equal grounds.

[4] In the model in Menner (2006) capital adjustment costs were necessary to render stable equilibrium dynamics given the chosen calibration. A previous working paper version of the present work, Menner (2007), documents that the capital adjustment cost parameter cannot be estimated properly and that the estimation procedure is able to find parameters that imply stable dynamics also in the absence of capital adjustment costs. Hence, we do not consider them here.

[5] See Rupert et al. (2000) for an excellent overview of the literature on search-theoretic monetary models before the year 2000.

[6] Log-linearizing the production function $y = k_0^{ek} n_t^{1-ek}$ with k_0 fix, one sees immediately the proportionality between log-deviations of output $\underline{y}_t$ and employment $\underline{n}_t$: $\underline{y}_t = (1 - ek)\underline{n}_t$.

Recently, a different approach to avoid assuming bounded money holdings was proposed by Lagos and Wright (2005). Their model, where agents alternate in visiting decentralized and centralized goods markets has been used by many researchers, recently. Although some extensions of the Lagos-Wright model allow for capital formation, they assume that only matched sellers produce, so there are no inventories. Together with the fact that all changes in money holdings in the decentralized markets are undone in the following centralized market, this presumably implies weak inter-temporal links and a weak propagation of monetary shocks.[7] Comparing different types of search models is left for future research.

As stated above we will compare a *search-theoretic* monetary model with other standard *flexible price* models, not with *sticky price* and/or *sticky wage* models[8]. Costs of price adjustments on the firm level do not necessarily induce a considerable degree of price stickiness on the aggregate level. Golosov and Lucas (2007) estimate the real effects of menu costs on the firm level to be very small. So, menu-costs do not seem to be a very convincing micro-foundation of price-stickiness. The assumption of sticky prices is, thus, more-less ad-hoc. Therefore, one might want to step back and ask what aspects of a monetary economy lead to real effects of monetary surprises even when prices are flexible. Frictions in the goods market and in the asset market are candidates examined here.[9]

To summarize, I contrast a modification of the search model of Menner (2006) that features a Walrasian labor market instead of labor search with two standard flexible price models: a cash-in-advance (CIA) model and a limited participation model with portfolio-adjustment costs (PAC). The former has as the only friction the constraint on the representative household to have enough money on hand to pay for the purchased goods, while the latter assumes, in addition, frictions in the portfolio adjustment.[10]

[7] Arouba and Wright (2003) find a dichotomy between the real and monetary sector, while Aruoba, Waller and Wright (2007) propose different variations where the monetary trades in the decentralized goods market have some influence on capital formation.

[8] Models with nominal rigidities are now widely used for policy evaluation. Most prominent examples are Christiano, Eichenbaum and Evans (2005), and Smets and Wouters (2003).

[9] A different route is taken in a very recent preliminary and incomplete paper by Aruoba and Schorfheide (2007) who introduce price stickiness into the centralized market of a Lagos-Wright (2005) type model and estimate it in a Bayesian way. Their search theoretic micro-structure of the decentralized market, however, is rejected by the marginal data density criterion in favor of a money-in-the-utility specification.

[10] Since I use the same methodology and the same time series as Schorfheide (2000) - but with a longer sample up to 2008 - this research updates his model comparison of the CIA and PAC model and extends it to include search-theoretic monetary models.

Estimation of model parameters is undertaken by use of Monte Carlo Markov Chain methods that generate draws from the posterior parameter distributions. According to the marginal data density the search-theoretic model tracks the post-war time series of U.S. output growth and inflation better than the portfolio adjustment cost model and the standard CIA model - coming close to VAR's with 1 to 4 lags. Loss functions are used to compare the ability of the models to account for current, lagged and leading cross correlations of output growth and inflation, autocorrelations of inflation and impulse responses to monetary and technology shocks. In each case expectations are calculated using a mixture of VAR(1) to VAR(4) and the DSGE models, weighted by their posterior probabilities.

The expected loss, or risk, a researcher incurs when choosing the STM model is considerably lower for cross correlations at "lags" -1 and 0 than the ones he incurs when choosing one of the alternative models. However, when looking at other periods ahead and behind the STM model ranks least. Moreover, while the STM model improves slightly on the CIA model in replicating the dynamic responses of output to shocks to money growth, it is the PAC that minimizes the loss in this dimension. The propagation mechanism of the STM model is not strong enough to replicate fully the persistence present in output, and the magnitude of the response in the first quarters. However, the imposed frictions on portfolio adjustment turn out to be estimated too large and the response of the PAC model overshoots in the medium and long run. The STM model can predict well the persistent disinflation process after a technology shock and the autocorrelations up to lag 3 of inflation, which neither of the two other models can. Hence, search frictions in the goods market add a new propagation mechanism to the CIA model that behaves in some dimensions similar, but in other dimensions different to the mechanism created by frictions in the portfolio management of consumers.

The rest of the paper is organized as follows: Section 2 contains an outline of the three models, of the solution and detrending method and of how the policy functions are transformed into state space form. Section 3 lays out the empirical strategy of Bayesian estimation and model evaluation. The results of the estimation process and the model comparison are presented in section 4, and section 5 concludes.

2. The Models

In the following I will present the three models to be compared. Since the reader is probably less familiar with the search-theoretic monetary model than with the portfolio adjustment cost model and the cash-in-advance model, I will explain the former in more detail and restrict myself to a short exposition of the others.

2.1 The Search-Theoretic Monetary (STM) Model

2.1.1 The Economy and its Matching Process

In the model of Menner (2006) there are two search frictions: costly search for consumption and investment goods, as well as costly labor search. In the following, however, I will consider only Walrasian labor markets.

The economy is populated by a continuum of households with measure one, denoted by H. A continuum of goods with measure one, also denoted by H, can be produced with labor and fixed capital as inputs to production. Each good is storable only by its producer. Purchased investment goods can be installed as capital by incurring an installation cost, i.e. there exists a (quadratic) capital adjustment cost. Each household $h \in H$ produces good h and wants to consume a subset of goods different from its own product, and only goods from this subset can be used as capital for the production of good h. This induces a need for exchange before consumption / investment is possible. In the absence of a centralized market with a Walrasian auctioneer households have to search for trading partners with the desired goods. Generally, there will be no double-coincidence of wants. The literature following Kiyotaki and Wright (1991), (1993) established that in random search models under certain parameterizations fiat money gets valuable and is the only medium of exchange. To establish this in the present model would require a more detailed consideration of the exchange patterns. Instead, here it is simply assumed that fiat money is required in each transaction.

Because of random matching in the goods markets money holdings, inventories of unsold goods and capital stocks would not be equally distributed among households/firms. To avoid the need of tracking the distributions of these individual state variables, it is assumed that the decision unit - the household-firm - consists itself of a continuum of different agents. The members of the household share the purchased consumption-investment goods and regard the household's utility as the common objective. The household decides how much to consume and how much to invest.

All the firms of a household are assigned the same amount of investment goods. Hence, all start the next period with the same capital stock. They also equally share workers and inventories. Finally, resource sharing of firms within a household allows the payment of wages regardless of whether the firms had a suitable match in the goods market. Under these assumptions the random matching process does not create idiosyncratic risk.

The household consists of five groups: one group enjoys leisure, the other four groups are active in markets: Entrepreneurs (set A_p with measure a_p), unemployed (A_n, measure u) workers (A_{nt}, measure: $a_p n_t$), and buyers (A_b, measure a_b). The values of a_p, u and a_b are assumed to be constant, while the number of workers $a_p n_t$ may vary over time. An entrepreneur consists of two agents: a producer and a seller. A producer in household h hires workers from other households to produce good h, which is sold by the seller. A buyer searches with search intensity s_t to buy the household's desired good. The sellers' search intensity is normalized to 1. In the following a hat on a variable indicates that the household takes this variable and all its future values as given when making the decisions at t.

The number of goods market matches is given by the matching function:

$$g(\hat{s}) \equiv z_1 (a_b \hat{s})^\alpha (a_p)^{1-\alpha} = z\, a_b \hat{s}^\alpha, \quad z \equiv z_1 \left(\frac{a_b}{a_p}\right)^{\alpha-1}. \tag{1}$$

Let $B = a_b/a_p$ be the buyers/sellers ratio. The matching rate per unit of search intensity is $g_b(\hat{s}) \equiv z\hat{s}^{\alpha-1}$, so that buyers find a desirable seller at rate sg_b, and sellers meet a buyer at rate $g_s(\hat{s}) \equiv zB\hat{s}^\alpha$. Thus, the measure of the set of buyers with suitable matches, A_{b*}, is $sg_b a_b$ and that of sellers with suitable matches, A_{p*}, is $g_s a_p$.

Each buyer j having found a seller $-j$ with his desired good exchanges $\hat{m}_t(j)$ units of money for $\hat{q}_t(-j)$ units of good $-j$, implying a price in this match of $\hat{P}_t(j) = \hat{m}_t(j)/\hat{q}_t(-j)$ and an average price of goods of $\hat{P}_t$.

Each producer j hires $n_t^d(j)$ workers in a Walrasian labor market who can work immediately. In a different version of the model discussed below, workers can start working only in the next period, so employment is a predetermined variable. Each of the $a_p n_t$ workers of the HH supplies in-elastically one unit of labor in the current period and receives a wage W_t in units of money.

2.1.2 The Household's Decisions

At the beginning of period t each household receives a lump sum monetary transfer τ_t from the central bank. The household distributes its money holdings M_t evenly among the buyers. Then the four active groups go to their respective markets and do not meet until the end of the period. At the end of the period the members of the household arrive at home carrying their trade receipts and residual balances and profits, respectively. They consume together the fraction of the bought goods that was dedicated for consumption and share the rest among the firms to increase each firm's capital stock. Also, goods inventories and employees are shared among the household's firms. Finally, the money not spent by buyers, the wages earned and profits are added to the money balance of the household for next period's shopping.

Households decide at the beginning of each period about their consumption c_t, their total investment x_t and next period's total capital stock K_{t+1}, as well as on next period's money holdings M_{t+1}. The household treats the member of a group all the like, assigning the same stocks of capital and money and the same decision rules for each. Thus, each buyer receives $m_t = M_t/a_b$ units of money and each firm holds a capital stock $k_{t+1} = K_{t+1}/a_p$. Households choose the buyers' search intensity s_t, the desired inventory level in period $t+1$, i_{t+1}, as well as current employment n_t. In the version with predetermined employment they choose future employment n_{t+1}. The depreciation rates of inventories δ_i and capital δ_k are assumed to be constant. The individual firm's production function has the form

$$f^i(n,k) = k_t^{e_k} (\Psi_t n_t)^{1-e_k} \quad \text{, where } e_k < 1.$$

For convenience denote the individual firm's production function in terms of aggregate capital K as

$$f(n,K) \equiv f^i\left(n, {K_t}/{a_p}\right) = F_0 K_t^{e_k} (\Psi_t n_t)^{1-e_k} \text{, with } F_0 = a_p^{-e_k}.$$

In their decision households take the sequence of the terms of trade $\{\hat{q}_t, \hat{m}_t\}_{t\geq 0}$ and the wages as given, as well as $\{M_0, K_0, i_0\}$. Since both buyers and sellers have a positive surplus from trade, it is optimal for households to choose M_{t+1}, K_{t+1} and i_{t+1} such that in period $t+1$ every buyer carries the required amount of money $\hat{m}_{t+1}$ and that every seller has $\hat{q}_{t+1}$ units of good h to be sold. The assumptions $M_0 \geq a_b \hat{m}_0$ and $i_0 + f_0 \geq \hat{q}_0$ ensure that buyers and sellers carry the necessary amounts of money and goods also in period 0.

Regarding preferences it is assumed that the utility of consuming is logarithmic, the disutility of working one unit of time is denoted by φ and the disutility of a buyer's search intensity is $\Phi(s) = \varphi(\varphi_0\, s)^{1+1/\varepsilon_\Phi}$.

Households choose the sequence $\{c_t,\ x_t,\ s_t,\ n_t\ ,n_t^d,\ M_{t+1},\ K_{t+1},\ i_{t+1}\}_{t\geq 0}$ to maximize their expected lifetime utility:

$$\max E_0\left\{\sum_{t=0}^{\infty}\beta^t\left[\ln c_t\right]-\left|A_{n_t}\right|\varphi-\left|A_b\right|\Phi(s_t)\right\} \qquad (PH-STM)$$

$$\text{s.t.:}\qquad c_t+x_t\leq\left|A_{b_t*}\right|\hat{q}_t \qquad (2)$$

$$\hat{m}_{t+1}\leq\tfrac{M_{t+1}}{a_b} \qquad on\ A_{b\,t+1^*} \qquad (3)$$

$$\hat{q}_{t+1}\leq i_{t+1}+f\left(n_{t+1}^d,K_{t+1}\right) \qquad on\ A_{p\,t+1^*} \qquad (4)$$

$$M_{t+1}\leq M_t+\tau_t-\left|A_{b_t*}\right|\hat{m}_t+\left|A_{n_t}\right|\hat{P}_t\hat{W}_t+\left|A_{p_t*}\right|\hat{m}_t-\left|A_p\right|\hat{P}_t\hat{W}_t n_t^d \qquad (5)$$

$$K_{t+1}\leq(1-\delta_k)K_t+x_t \qquad (6)$$

$$\left|A_p\right|i_{t+1}\leq(1-\delta_i)\left\{\left|A_p\right|\left(i_t+f\left(n_t^d,K_t\right)\right)-\left|A_{p_t*}\right|\hat{q}_t\right\} \qquad (7)$$

The first constraint states that a household's consumption and investment has to be bought by buyers that successfully meet a trading partner. The next condition represents the constraint for each suitably matched buyer in $t+1$ to have the required money $\hat{m}_{t+1}$ on hand, while the fourth is a trading restriction for suitably matched sellers: each should have a sufficient stock of inventory and newly produced goods to satisfy a costumer's demand $\hat{q}_{t+1}$ in $t+1$. The law of motion of money balances states that money holdings at the beginning of period $t+1$ are no bigger than previous money holdings augmented by the monetary injection minus the money spent plus wages earned and cash receipts from firms. Then there's the usual capital accumulation equation. Finally, inventories in period $t+1$ consist of the fraction of the excess supply of goods in period t that has not depreciated.

2.1.3 Solution of the model

Optimality conditions can be derived which together with the laws of motion for money balances, capital and inventories (5) - (7) determine the solution to this decision problem, once the terms of trade are specified and the equilibrium conditions are imposed. The terms of trade are determined by Nash bargaining.[11] The equilibrium definition and the equations describing equilibrium are documented in Appendix A.1.

[11] See Menner (2006) for details.

2.2 The Portfolio Adjustment Cost (PAC) Model

The first flexible price monetary model I consider is a cash-in-advance model with portfolio adjustment costs (PAC).[12] The model economy is populated by a representative household, a firm and a financial intermediary. The household starts period t with an amount of money M_t and has to decide how much money to deposit as savings deposits D_t at the bank and how much to hold as cash $Q_t = M_t - D_t$ before shocks are known. This timing convention is called "limited participation" assumption, since the participation of the household in the asset market is limited to the time span before shocks are realized. After the realization of shocks no portfolio changes are allowed for the current period. In other words, the household decides about his future portfolio (Q_t, D_t) after the realization of the shocks in time t, not about its current portfolio. Cash does not pay interest but is needed to buy consumption goods, while deposits earn an interest rate r_t^d.

The representative firm does not hold money at the beginning of the period. In order to pay its wage bill it borrows money from the banks. The bank receives a monetary injection τ_t from the central bank and lends it together with the deposits to the firm at an interest rate r_t^f. Since the household cannot change its deposits after a surprise change in the monetary injection, the additional funds have to be absorbed by the firm. But the firm will borrow a higher amount of funds only at a lower interest rate.

Therefore, a monetary injection leads to a 'liquidity effect' because of the '*limited participation*' of the household in the asset market. To render this liquidity effect more persistent Christiano and Eichenbaum (1992) assume in addition to limited participation that portfolio management is time consuming and therefore reduces utility by foregone leisure to the amount of:

$$\tilde{p}_t = \alpha_1 \left[\exp\left(\alpha_2 \left[\frac{Q_t}{Q_{t-1}} - m^* \right] \right) + \exp\left(-\alpha_2 \left[\frac{Q_t}{Q_{t-1}} - m^* \right] \right) - 2 \right] \qquad (8)$$

The household consists of a worker and a shopper. The worker supplies N_t^s hours of labor and receives wage payments of $W_t N_t^s$ by the firm in the form of cash before consumption goods are purchased. The buyer then goes to the goods market where his purchases are prone to a cash-in-advance constraint, which means that all consumption purchases must be paid for with cash at hand:

$$P_t C_t \le Q_t + W_t N_t^s \qquad (9)$$

[12] This model is laid out in Christiano (1991), and Christiano and Eichenbaum (1992). Nason and Cogley (1994) discuss in detail the optimality condition of the model, detrending and log-linearization.

At the end of the period the household gets back its saving deposits together with interest and receives the firm's and the bank's net cash inflow as dividends F_t and B_t, respectively, all of that forming together with the unspent money the next period's money stock M_{t+1}.

So, in the beginning of period t after shocks are known the household chooses C_t, N_t^s, M_{t+1} and Q_{t+1} to maximize its discounted expected lifetime utility:

$$\max_{C_t, N_t^S, M_{t+1}, Q_{t+1}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left[(1-\phi) \ln C_t + \phi \ln (1 - N_t^s - \widetilde{p}_t) \right] \right\} \qquad (PH - PAC)$$

s. t. $$P_t C_t \le Q_t + W_t N_t^s \qquad (9)$$

$$Q_t \le M_t \qquad (10)$$

$$M_{t+1} \le (Q_t + W_t N_t^s - P_t C_t) + (1 + r_t^d)(M_t - Q_t) + F_t + B_t \qquad (11)$$

The firm accumulates capital and hires labour services from the household and pays the wage bill out of the money borrowed from the bank. Then it produces under a Cobb-Douglas technology $F(N_t, K_t) = K_t^{e_k} (\Psi_t N_t)^{1-e_k}$ and uses its sales receipts to repay the loan plus interest and to pay the resulting profits as dividends to the household. Since the firm is owned by the household which values a unit of nominal dividends in terms of the consumption it buys next period its objective is to maximize the expected lifetime dividends discounted by date $t+1$ marginal utility of consumption. Hence the firm chooses next period's capital stock K_{t+1}, labour demand N_t^d, loans L_t and dividends F_t to solve the problem:

$$\max_{L_t, N_t^d, F_t, K_{t+1}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^{t+1} \frac{F_t}{C_{t+1} P_{t+1}} \right\} \qquad (PF - PAC)$$

s.t. $$F_t \le P_t \left\| K_t^{e_k} (\Psi_t N_t)^{1-e_k} - x_t \right\| - W_t N_t^d - r_t^f L_t \qquad (12)$$

$$K_{t+1} \le (1 - \delta_k) K_t + x_t \qquad (13)$$

$$W_t N_t^d \le L_t \qquad (14)$$

The bank is also owned by the household and solves:

$$\max_{B_t, L_t, D_t} E_0 \left\{ \sum_{t=0}^{\infty} \beta^{t+1} \frac{B_t}{C_{t+1} P_{t+1}} \right\} \qquad (PB - PAC)$$

$$\text{s.t.} \quad B_t \leq r_t^f L_t - r_t^d D_t + \tau_t \qquad (15)$$

$$L_t \leq D_t + \tau_t \qquad (16)$$

Markets clear when $N_t^d = N_t^s$, $P_t C_t = M_t + \tau_t$, and $Y_t = C_t + K_{t+1} - (1 - \delta_k) K_t$. In equilibrium also $r_t^f = r_t^d$ must hold.

2.3 The Cash-in-Advance (CIA) Model

For the purpose of model comparison it is convenient to use a version of the CIA model that can be generated from the PAC model by changing just two assumptions. First, there are no costs to adjust ones portfolio, i.e. $\tilde{p}_t = 0$. Second, there is no limited participation in asset markets because agents get to know the realization of the money growth shock before they make their decision on deposits. This leads to the modified maximization problem of the household:

$$\max_{C_t, N_t^s, M_{t+1}, D_t} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left[(1 - \phi) \ln C_t + \phi \ln (1 - N_t^s) \right] \right\} \qquad (PH - CIA)$$

subject to the same constraints as above. Additional funds from the Central Bank do not alter the interest rate since the household can adjust its saving deposits in the light of the observed monetary shock to neutralize the effect of the injection on loanable funds. Note that since $\tilde{p}_t = 0$, the parameters α_1 and α_2 get obsolete.

2.4 Specification of Shocks and Detrending

We consider two exogenous shocks. The monetary injection takes place at the beginning of the period such that money growth follows an AR(1) process:

$$\ln \gamma_t = (1 - \rho_M) \ln \gamma + \rho_M \ln \gamma_{t-1} + \varepsilon_{M\,t} \qquad \text{where } \gamma_t = M_{t+1} / M_t \qquad (17)$$

The production technology is prone to a technology shock. Recall, that the production function was assumed to be $f(n_t, K_t) = F_0 K_t^{e_k} (\Psi_t n_t)^{1-e_k}$ in the search-theoretic model and to be $f(N_t, K_t) = K_t^{e_k} (\Psi_t N_t)^{1-e_k}$ in the PAC model. In both cases labour augmenting technological progress is assumed to follow a random-walk with drift:

$$\ln \Psi_t = \zeta + \ln \Psi_{t-1} + \varepsilon_{\Psi t} \tag{18}$$

The vector of innovations $\varepsilon_t = [\varepsilon_{M t}, \varepsilon_{\Psi t}]'$ is assumed to be i.i.d. $\sim N(0, \Sigma_\varepsilon)$, with $\Sigma_\varepsilon = diag(\sigma_M^2, \sigma_\Psi^2)$.

To get a stationary economy it is necessary to detrend all real variables by dividing by Ψ_t. Nominal variables are handled as follows. In the CIA and the PAC model, the price level has to be divided by Ψ_t / M_t and other nominal variables *(D_t, L_t, W_t)* have to be divided by M_t. In the search model all the multipliers are detrended by multiplying with Ψ_t. For the two former models the literature has shown that a steady state equilibrium exists in the detrended variables. For the search model we do not provide a formal proof of existence. However, we find a steady state by construction in almost the entire parameter space.

2.5 State-Space Representation

Collecting the observable variables of interest, namely output growth and inflation, in a vector y_t the linear policy functions characterizing the solution of the log-linearized model can be represented in state-space form by:

$$\begin{aligned} y_t &= \Theta_0 + \Theta_1 \nu_t + \Theta_2 \varepsilon_t \\ \nu_t &= \Xi_1 \nu_{t-1} + \Xi_2 \varepsilon_t , \end{aligned} \tag{19}$$

where ν_t is a vector of percentage deviations of the state variables of the model from their steady states. The second equation describes the evolution of the state vector, while the first equation, the so called “observation equation” links the data to the model solution characterized by the states and the current shocks.

As is well known, the system matrices Θ_i and Ξ_i are nonlinear functions of the structural DSGE parameters θ, and the DSGE models generate a joint probability distribution for the data $Y_T = [y_1, \ldots, y_T]'$. Assuming normality of the shocks, the state-space representation allows the use of the Kalman-Filter to evaluate the likelihood of the different parameter draws for each model.

3. Empirical Strategy

3.1 Dealing with Model Misspecification

When comparing the empirical fit of estimated DSGE models one has to be aware of the potential misspecification of the models. Although their theoretical structure intends to capture various features of reality like capital formation and frictions, they are highly stylized and probably not very close to the true data generating process (DGP) of our real world data. One way to deal with the problem of misspecification is the Loss-function based Bayesian approach of Schorfheide (2000): Using a highly-parameterized reference model that fits the data considerably well, e.g. a VAR, a combined DGP is constructed by averaging the considered models and the reference model. Deviations of model characteristics (e.g. second moments or impulse response functions) from the ones implied by the constructed DGP are then quantified via different loss functions.

3.2 Evaluation Procedure

Traditional Bayesian Model Comparison is based on the calculation of posterior odds ratios. Following the arguments and the notation of Schorfheide (2000), and assigning prior probabilities to the models M_i under consideration, the posterior model probability of model M_i can be calculated by

$$\pi_i = p(M_i / Y) = \frac{\pi_{i0}\, p(Y / M_i)}{\sum_{i=0}^{n} \pi_{i0}\, p(Y / M_i)}, \tag{20}$$

where $p(Y/M_i)$ is the marginal data density

$$p(Y / M_i) = \int p(Y / \theta_{(i)}, M_i)\, p(\theta_{(i)} / M_i)\, d\theta_{(i)} \; . \tag{21}$$

The latter is the integral over the parameter space of the posterior, i.e. the likelihood $p(Y / \theta_{(i)}, M_i)$ times the prior $p(\theta_{(i)} / M_i)$, where $\theta_{(i)}$ is the vector of parameters of model i. Because of the following expression

$$\ln p(Y_T / M_i) = \sum_{t=1}^{T} \ln p(y_t / Y_{T-1}, M_i), \tag{22}$$

the log of the marginal data density can be interpreted as predictive score, i.e. as the one-step-ahead forecasting performance of model M_i.

The posterior odds ratio is then the ratio of two posterior model probabilities. Schorfheide stresses, that these odds do not change by the introduction of a reference model since its effect on the denominator in (20) cancels out when calculating the odds ratio. The model with the higher odds could be chosen as the model that better fits the data in the above mentioned sense.
This corresponds to use a (0,1) loss function, that assigns a loss of 0 to the model with higher odds and 1 to the others. When dealing with potentially misspecified models this is probably not a good criterion, since it does not give the researcher a measure of how much he looses in choosing one misspecified model over another.

The proposal of Schorfheide (2000) is to use different loss functions to quantify the deviations of some characteristics, ξ, like a vector of moments or of impulse responses of the model, with the ones obtained from the assumed combined DGP. His methodology is characterized by 3 steps.

<u>Step 1</u>

Generate posterior distributions $p\left(\theta_{(i)} / Y, M_i\right)$ for all the model parameters $\theta_{(i)}$ by simulating Monte-Carlo-Markov-Chains, then calculate marginal data densities by Laplace-Approximation or Harmonic Mean estimators, and calculate the posterior model probabilities as in (20).

<u>Step 2</u>

As the population characteristic ξ is a function of the model parameters $\theta_{(i)}$ one can generate a posterior distribution of ξ conditional on model M_i by drawing from the posterior distribution of $\theta_{(i)}$. The posteriors $p\left(\xi / Y, M_i\right)$ of the models are then combined to the overall posterior of ξ by the mixture

$$p(\xi / Y) = \sum_{i=0}^{n} \pi_i p\left(\xi / Y, M_i\right), \qquad (23)$$

where the weights are determined by the posterior model probabilities.

<u>Step 3</u>

Choose appropriate loss functions that penalize deviations of DSGE model predictions $\hat{\xi}$ from population characteristics ξ (i.e., characteristics generated by the overall posterior distribution). Then, the optimal predictor of ξ - based only on model M_i – is

$$\hat{\xi}_i = \arg\min_{\tilde{\xi}} \int L\left(\xi, \tilde{\xi}\right) p(\xi / Y) d\xi \, . \qquad (24)$$

The three DSGE models are then judged according to the expected loss (risk) of the predictor $\hat{\xi}_i$ under the overall posterior $p(\xi / Y_T)$:

$$R(\hat{\xi}_i / Y) = \int L(\xi, \hat{\xi}_i) p(\xi / Y) d\xi. \tag{25}$$

"The posterior risk $R(\hat{\xi}_i / Y_T)$ provides an absolute measure of how well model M_i predicts the population characteristic. Risk differences across DSGE models yield a relative measure of model adequacy that allows model comparison. For instance, one can select the DSGE model M_i that minimizes $R(\hat{\xi}_i / Y_T)$. (Schorfheide (2000), p. 652)"

3.3 Specification of the Priors

Most priors for common parameters are taken from Schorfheide (2000), for the rest of common parameters a wider prior distributions is assumed, s.t. the prior means used there and the calibrated values in Menner (2006) are equally likely. Model-specific parameters of the STM model are centered around calibrated values.[13] Table 1 provides a summary of the assumed prior distributions:

3.4 Data

Data on output, prices and population from 1950:1 to 2008:1 are taken from the FRED database at the FRB of St. Louis. The output series is quarterly real GDP in chained year 2000 $'s (A191RX1) divided by the NIPA population series (B230RC0), the implicit GDP deflator in year 2000 $'s (A191RD3) is used as price index. To get quarterly growth rates, the resulting series are log-differenced.

4. Results

4.1 Parameter estimates

Since the posteriors of the DSGE models do not belong to a well-known class of distributions, it is impossible to draw from the posterior directly. Instead one can only evaluate numerically the product of prior and likelihood. Hence a random walk Metropolis-Hastings algorithm is used to generate draws from the posterior distributions. Technical details on how to generate draws and statistics from the VAR and DSGE posteriors are thoroughly explained in the appendix of Schorfheide (2000). In what follows, I only state where I differed from his approach.

[13] Posterior reweighting does not indicate strong dependence of results on the prior. A Matlab reweighting program and posterior files to perform sensitivity analysis on prior specifications can be obtained on request.

To ensure convergence of the Metropolis-Hastings algorithm I generated 1 million draws from the posterior and discarded the first 500.000.[14] To avoid serial correlation I only used every hundredth draw. All results are based on these 5000 draws from the posterior parameter distribution. In the algorithm candidate draws are drawn from a proposal (jumping) distribution. For the CIA and PAC models I use the same jumping distribution as in Schorfheide (2000), i.e. a Gaussian with mean at the current draw and variance of 0.2 times the inverse Hessian at the posterior mode. In the case of the STM model I choose a uniform distribution as jumping distribution. Since jumps are then bounded, it happens to be easier to achieve convergence of the Metropolis- Hastings algorithm where there are many parameters to estimate. The spread of the jump distribution was chosen parameter by parameter to achieve an average acceptance rate of about 25-30%, which has found to be a good choice for models with many parameters.

Recursive mean plots and potential scale reduction factors (see Gelman et al. (1995)) have been used to assess convergence. The potential scale reduction factors were less than 1.005 for all models indicating that the number of draws is large enough to achieve convergence of the transition kernel of the Markov chain and that we arrived at the invariant posterior distribution of the parameters. To assess robustness of the estimation results with respect to the choice of the prior I conducted a “posterior reweighting” as suggested by Geweke (1999). Reducing the variance of the prior distributions by 10% does not change the posterior means significantly.[15] Posterior means and standard errors are calculated from the output of the Metropolis-Hastings algorithm and shown in Table 2.

Note, that Table 2 presents the results of two different versions of the search-theoretic monetary model: STM1 stands for the model with standard Walrasian labor market. Alternatively, model STM2 makes the assumption that labor is predetermined since workers hired in a period start to work in the following period. Negative adjustment by firing is not profitable when firing costs at least as high as the marginal product are assumed. Then it pays out to produce in excess and pile up inventories. This second model variant is considered since in a model with search-frictions in the labor market, labor would be predetermined, too. As shown in Menner (2007) the labor market variables in such a search model cannot be estimated properly from the inflation and output data used in Schorfheide (2000). But a version with parameters fixed at values implying very flexible labor markets did a good job in matching the data. Here, we try to figure out, if the assumption of predetermined labor is essential for these kinds of results.

[14] CIA and PAC models are estimated using F. Schorfheide's GAUSS code, while for the search-model I programmed the code in MATLAB making use of H. Uhlig's (1997) "Toolkit for analyzing nonlinear dynamic stochastic models easily" to solve for the policy functions in the Kalman filter step.

[15] See footnote 13.

Consider first the estimation of the common model parameters. All of them are estimated quite precisely. For the CIA and PAC model we might expect differences to the results in Schorfheide (2000), as the prior distribution for the parameter β and δ has been widened. Indeed, the discount factor is reduced, implying an annualized real interest rate of 5% and 10% respectively. The capital depreciation rate δ, however, does not change significantly; neither does the capital share ε_K. The STM models' estimates are much lower for the real interest rate and higher for δ, while the money growth rate and hence inflation is estimated lower. The capital share is lower, especially in the STM1 model, and the autocorrelation of money shocks is smaller in the STM2 model. The biggest difference is in the trend of technology growth which is estimated 50% and 100% higher in the search models. For the PAC model, the data assigns a high portfolio adjustment cost parameter. Going from STM1 to STM2 leaves the other search-model specific parameters apart from the scale in the matching function z almost untouched.

4.2 Model Comparison

4.2.1 Posterior Model Probabilities

The first row of Table 3 shows the assumed prior model probabilities. Because of our ignorance about the best lag length for the VAR, a mixture of lags 1 to 4 is used. So, each model is assigned a prior probability of ¼. The two versions of the search-theoretic model are analyzed alternatively. STM1 stands for the model with standard Walrasian labor market, in STM2 labor is predetermined.

Marginal data densities can only be calculated analytically for the VAR's. Row 3 shows therefore the Laplace-Approximation that uses the Hessian at the posterior mode to calculate a penalty on the value of the posterior at the mode. The VARs with 1 and 3 lags share more than 90% of the total posterior probability, the VAR(2) has about 9% of posterior probability. The VAR(4) and the DSGE models contribute very little to the overall DGP. Thus, in the following sections we take as reference model a mixture of VAR(1), VAR(2) and VAR(3) weighted by their marginal densities and ignore the contribution of the VAR(4) and the DSGE models.

Once we have calculated posterior probabilities we can compare the odds of different models although they cannot grasp well the data because of misspecification. Computing standard posterior odds with respect to the CIA model one sees that the latter outperforms the PAC model by a factor 732000.[16]

[16] Notwithstanding, the PAC model performs slightly better than in the analysis of Schorfheide (2000), which is in line with the robustness analysis he reports. Remember, that in calculating posterior odds the VAR reference model does not interfere, since its contribution to the denominator of (20) cancels.

Although their odds are still far from the odds of the VAR, the search models outperform greatly the other two DSGE models: their predictive score comes a big step closer to the one of the VAR's in the case of search model 1, and still improves on the CIA model by a factor 8.2E+9 in case of model STM2.

How does it come that the search models do better? The broad answer is that they capture better the dynamics of the data. The competitor models seem to impose too strong restrictions on the model dynamics. The fact that the search models are more highly parameterized cannot explain their better performance per se. First, in the VAR case the VAR(4) has the highest number of parameters and performs worst, and the VAR(1) does equally well than the VAR(3) – so more parameters do not lead automatically to better fit. Second, the penalty in the calculation of the Laplace Approximation is generally higher the more parameters are estimated, so that an over-parameterization is penalized. As we will see below, the search models outperform the other two DSGE models in replicating dynamic correlations and autocorrelations of output growth and inflation, and hence track the dynamics of the time series better. The reason behind this is that the search-frictions in the goods market lead to a propagation mechanism that works through search-inventory feedbacks - as already highlighted by Shi(1998) and Menner(2006). As we will see below, with respect to inflation and output dynamics this will do better in many relevant aspects than the propagation only through capital as in the CIA model or additionally through asset market frictions as in the PAC model.

4.2.2 Co-movement and Autocorrelation

Let's turn to the loss function analysis of second moments. Consider first the cross-correlation of GDP growth and the inflation rate. Table 4 presents the results for these correlations up to 2 leads and 2 lags. The first two rows show the upper and lower bound of the 90% intervals of highest posterior density of the overall posterior of the constructed DGP. Mode predictions of the CIA and PAC models of the contemporaneous correlation fall outside this interval, which is reflected in a very high L_p risk, whereas the STM models predict the contemporaneous correlation of output growth and inflation very well. The predetermined labor STM does also better for 1 lag, followed by CIA and PAC, but fails to hit the 90% interval for 2 lags. In the latter the ranking of the models is CIA, PAC, STM2 and STM1. For the leads the ranking between CIA and PAC is reversed.

The evidence favours the two STM models more clearly if we consider all correlations together. Table 5 documents the statistic $C\chi 2$ that is used to calculate the $L\chi 2$ risk, together with the latter and the L_p risk of choosing one of the models according to the behaviour of the joint dynamic correlations between output and inflation. In all the cases the ranking is STM2, STM2, PAC, CIA although each of the risks is very high.

The search-theoretic model is even more successful if we look at autocorrelations of inflation up to 4 lags in Table 6. While the mode predictions of the PAC and CIA models lie outside the 90% interval for the first two or three lags, respectively, the ones of the search models lie all inside. This is reflected in L_p risks of roughly 1 for the CIA and PAC model and considerably lower L_p risks for the search models. Only at lag 4 the PAC model shows a lower L_p risk than the search models.

Looking at the joint fit of the autocorrelations in Table 7, we see that the PAC does slightly better at matching all the autocorrelations together than the CIA model, but the two search models show considerably lower $L\chi 2$ and L_q risks.

Summarizing, search-frictions in the goods market can improve the fit of contemporaneous and lagged correlations of output and inflation, and the autocorrelations of inflation with regard to standard flexible price monetary models with Walrasian goods markets.

4.2.3 Impulse Response Functions

This subsection compares impulse responses to a transitory and a permanent shock. In the VAR, they are identified via a standard long-run identification scheme as in Blanchard and Quah (1989). In the models, they correspond to a shock to money growth and technology.[17] Figure 1 plots the results. Dotted lines correspond to the 90% intervals of the impulse responses stemming from the assumed DGP, the solid line is the corresponding mean response. The dash-dotted line represents the responses of the CIA model, the dashed line the ones of the PAC model and the dotted line with "+" shows impulse responses of the corresponding search model.

A monetary shock does not induce strong *output responses* in the CIA model, and they go in the wrong direction. Assuming limited participation in asset markets and portfolio adjustment costs, as the PAC model does, is sufficient to get a hump shape output response. However, the response overshoots after some 8-10 quarters and leaves the error bands at quarter 13.

The estimation procedure chooses apparently a too high portfolio adjustment cost parameter to get a suf-ficiently persistent propagation mechanism to fit the data, but not enough to get a good fit of the marginal data density and too much to fit the impulse responses. To get a hump shape output response search-frictions in the goods market also do the job, although not on impact. Predetermined labor can prevent a strong negative impact and delivers a more pronounced hump. The output responses of both variants of the search model show a delayed hump but remain then close to the mean response of the DGP. *Inflation* shows considerable persistence in the data after a transitory shock. While the CIA and the PAC model overpredict the impact response of inflation lacking some persistence afterwards, the search models track considerably well the inflation response over the whole horizon.

Turning to effects of a permanent shock in Figure 2, we see a large 90% interval for the output responses. The response of the STM1 model lying outside the upper bound for various periods and then entering the 90% interval again, while the PAC and CIA models under-predict the mean response and leave the error bands sooner or later, but still doing better than the standard search model STM1. Assuming predetermined labor in STM2, however, makes the search model's response nearly coincide with the mean response of the DGP, although overshooting slightly at the end of the 40 quarter horizon.

To quantify the ability of the models to predict dynamic responses let's turn again to the loss function analysis. Table 8 presents the L_q risk and the $L\chi 2$ risk for the four different impulse responses. Part a) of the table considers jointly the responses from 1 to 12 quarters after the shock, while part b) considers jointly the responses from quarter 1 up to 32 after the shock.[18] The L_q and the $L\chi 2$ statistics confirm the visual impression from figures 1 and 2. Consider first the medium horizon up to 12 quarters in Table 8.a. Looking at the first column we see that the STM2 model improves slightly on the CIA model but is poorer than the PAC model in predicting the impulse response of output to a monetary shock when using the L_q criterion.

[17] Following Schorfheide (2000) magnitudes of structural shocks are normalized by their long-run effects rather than by use of the estimated parameters σ_M and σ_A, that correspond to an estimation resulting in insignificant posterior probability. Thus, I consider a transitory (monetary) shock that increases the price level by 1% and a permanent (technology) shock that increases output by 1%.

Things are different considering the $L\chi2$ -risk. The STM2 does much worse, and in contrast to the result in Schorfheide (2000) the CIA model performs better than the PAC. This result seems to be sensitive to the precision of the calculation of the inverted Hessian at the mode. With respect to responses of inflation to a monetary shock the two criteria give both the ordering STM2 better than STM1, and PAC better than CIA, but the L_q criterion ranks STM1 least, letting the standard monetary models the places 2 and 3 in the ranking: the PAC model dominates the CIA model, which outperforms the search model. Output effects of technology shocks follow the same pattern, only CIA dominates PAC under L_q loss. A striking feature of column 4 is the large losses the latter models incur when looking at the ability to predict inflation responses to a technology shock. Here, the STM model clearly outperforms its competitors.

Considering the longer horizon of 8 years as documented in part b) of Table 8 the ranking changes in favour of the search-theoretic models after a monetary shock. According to the L_q loss the output response is tracked best by STM2, and both search models outperform the other models with respect to the inflation response. Regarding technology shocks the ranking of output responses is the same under L_q loss, while now the PAC model improves and shares with the STM2 model the least $L\chi2$ risk. The losses of the inflation responses after a technology shock are now closer for the two search models, and the STM2 model does better under the $L\chi2$ loss. But otherwise the ranking is the same as in the case of a 12 quarters' horizon.

5. Conclusion

Search models of money put more structure to the goods market as models with a Cash-in-Advance constraint by assuming bilateral trade and costly search for trading partners in the goods market. Bayesian model comparison can provide a quantitative assessment of the role of these goods market frictions: Both, the standard search model (STM1) and the one with predetermined labor (STM2), outperform their two competitor models by their predictive score measured by the marginal data density. Moreover, the STM2 model improves on the standard Cash-in-Advance model in nearly all of the considered dimensions.

[18] The weighting matrix W in the calculation of the Lq risk is the k x k identity matrix scaled by the factor 1/k, where k is the number of quarters considered.

Search in the goods market adds a propagation mechanism that results in hump shaped output responses to a monetary shock that delivers a smooth reaction of output on a technology shock and generates a persistent disinflation after a technology shock. Contemporaneous and lagged correlations of inflation and output growth can be predicted considerably better, although not for longer lags and for leads. Finally, the search model predicts very well the autocorrelations of inflation, while the CIA model can not. Thus, search frictions do make a difference.

The additional frictions imposed on the portfolio choice of the consumers in the PAC model also act as a mechanism to propagate monetary shocks persistently - at least with respect to output. Its response to a monetary shock is more pronounced and more persistent than the response of output in the STM2 model but overshoots the empirical counterpart. The PAC model is not as good as the STM2 model at predicting the persistent disinflation process after a technology shock and the persistent inflation after a monetary shock. The predictions of the output response to technology shocks are considerably worse than those of the STM2 model. The PAC model shares with the CIA model the failure to predict the autocorrelations of inflation and the contemporaneous correlations of inflation and output growth. So, with respect to the question whether the frictions in the goods market or the frictions in the asset market provide a better model to predict characteristics of the data, this analysis gives more evidence for the former. Given that the search models gives a micro-foundation of money and on the other hand portfolio adjustment cost are assumed ad-hoc on an ad-hoc model of money, these quantitative results reiterate the appeal of the former and the hope that future extensions of search models allow the applied economist to address the sort of policy questions the ad hoc models were built to answer in the first place.

Appendix A.1. Equilibrium and Optimality Conditions

A.1.1 Search Model STM$_1$ (Standard Walrasian Labor Market)

After substituting (2) into the objective function, necessary conditions for an optimum are the FOCs (with respect to $M_{t+1}, i_{t+1}, K_{t+1}, x_t, s_t, n_t$ and n_t^d):

$$\omega_{Mt} = \beta E_t \{\omega_{Mt+1} + g_b(\hat{s}_{t+1}) s_{t+1} \Lambda_{t+1}\} \tag{26}$$

$$\omega_{it} = \beta E_t \{g_s(\hat{s}_{t+1})\omega_{qt+1} + (1-\delta_i)\omega_{it+1}\} \tag{27}$$

$$\omega_{Kt} = E_t \{\beta(1-\delta_K)\omega_{Kt+1} + a_p \omega_{it} f_K(n_{t+1}, K_{t+1})\} \tag{28}$$

$$U'(c_t) = \omega_{Kt} \tag{29}$$

$$\Phi'(s_t) = g_b(\hat{s}_t)[U'(c_t)\hat{q}_t - \omega_{Mt}\hat{m}_t] \tag{30}$$

$$\varphi = P_t W_t \tag{31}$$

$$\beta P_t W_t = E_t \{\omega_{it-1} f_n(n_t, K_t)\} \tag{32}$$

with the slackness conditions associated with (3) and (4):

$$\Lambda_{t+1}\left[\tfrac{M_{t+1}}{a_b} - \hat{m}_{t+1}\right] = 0 \qquad \forall j \in A_{b\,t+1^*} \tag{33}$$

$$\omega_{qt+1}\left[i_{t+1} + f(n_{t+1}^d, K_{t+1}) - \hat{q}_{t+1}\right] = 0 \qquad \forall j \in A_{p\,t+1^*} \tag{34}$$

and the transversality equation:

$$\lim \beta^{-t} E_t \{\omega_{Kt+1} K_t\} = 0 \tag{35}$$

Symmetric Nash-bargaining in the goods market implies

$$\omega_{qt} = \omega_t - (1-\delta_i)\omega_{it} \tag{36}$$

$$\bar{\lambda}_t = U'(\bar{c}_t) - \bar{\omega}_t \tag{37}$$

with $\omega_t \equiv P_t \omega_{Mt}$ and $\lambda_t \equiv P_t \Lambda_t$, and the bars indicating the variables of the matched HH.

Definition: A *symmetric search equilibrium* is defined as a sequence of house-holds′ choices $\{\Gamma_{ht}\}_{t\geq 0}$, $\Gamma_{ht} \equiv \{c_t, x_t, s_t, n_t, n_t^d, M_{t+1}, K_{t+1}, i_{t+1}\}_h$, expected quantities in a trade $\{\hat{X}_t\}_{t\geq 0}$, $\hat{X}_t \equiv (\hat{q}_t, \hat{m}_t)$, realized "terms of trade" $\{X_t\}_{t\geq 0}$, $X_t \equiv (q_t, m_t)$, the wage rate W_t and expected average search-intensity $\hat{s}_t$, such that

(i) these variables are identical across households and relevant individuals;

(ii) given $\{\hat{X}_t\}_{t\geq 0}$, W_t, and $\{M_0, K_0, i_0\}$, $\{\Gamma_{ht}\}_{t\geq 0}$ solves (PH-STM) with $s_t = \hat{s}_t$;

(iii) X_t is a solution to the Nash bargaining process;

(iv) $\hat{X}_t = X_t, \ \forall t \geq 0.$

Considering only symmetric equilibria, hats and bars can be suppressed. Attention will be restricted to the case where $\lambda > 0$ and $\omega > 0$ which is the case around the steady state. It is now possible to reduce the system of equations defining this equilibrium. See Menner (2006) for details.

Using the convention to date predetermined variables as of date t-1, this leads to a system of static equations:

$$q_t = i_{t-1} + f(n_t, K_{t-1}) \tag{38}$$

$$x_t = a_p B z s_t^{\alpha} q_t - c_t \tag{39}$$

$$U'(c_t) = \omega_{Kt} \tag{40}$$

$$\Phi'(s_t) s_t^{1-\alpha} = z q_t \left[U'(c_t) - \omega_t\right] \tag{41}$$

$$\beta\varphi = \omega_{it-1} f_n(n_t, K_{t-1}) \tag{42}$$

that jointly determines $\{q_t, c_t, x_t, s_t, n_t\}$ as functions of the states $\{i_{t-1}, K_{t-1}\}$ and the co-states $\{\omega_t, \omega_{it}, \omega_{Kt}\}$.

Substituting (38)-(42) into (6)-(7) and (26)-(28) one gets the dynamic system:

$$i_t = (1-\delta_i)\left(i_{t-1} + f(n_t, K_{t-1})\right) - B z s_t^{\alpha} q_t \tag{43}$$

$$K_t = (1-\delta_k) K_{t-1} + a_p B z s_t^{\alpha} q_t - c_t \tag{44}$$

$$\omega_t = \beta E_t \left\{ \frac{q_{t+1}}{\gamma_t q_t} \left(\omega_{t+1} + z s_{t+1}^{\alpha} U'(c_{t+1}) - \omega_{t+1}\right) \right\} \tag{45}$$

$$\omega_{it} = \beta E_t \left\{ (1-\delta_i)\omega_{it+1} + B z s_{t+1}^{\alpha} \left(\omega_{t+1} - (1-\delta_i)\omega_{it+1}\right) \right\} \tag{46}$$

$$\omega_{Kt} = E_t \left\{ \beta (1-\delta_K) \omega_{Kt+1} + a_p \omega_{it} f_K(n_{t+1}, K_t) \right\} \tag{47}$$

where (43) - (44) are the laws of motion of the state variables $\{i_{t-1}, K_{t-1}\}$ and the others are expectational equations for the jump variables $\{\omega_t, \omega_{it}, \omega_{Kt}\}$

A.1.2 Search Model STM_2 (Labor Market with Predetermined Labor):

In the model comparison we also consider a version of the search model with predetermined labor. Think of a Walrasian labor market where you can hire and fire without costs but the workers start to work only after one period. Then employment is a predetermined variable denoted by n_{t-1} at date t, and we replace (42) by

$$\beta\varphi = E_t\{\omega_{it} f_n(n_t, K_t)\} \tag{48}$$

Appendix A.2. Loss functions

Loss functions

1. Quadratic loss function (L_q)

$$L_q(\xi, \hat{\xi}) = (\xi - \hat{\xi}) W (\xi - \hat{\xi}), \tag{49}$$

where W is a positive definite m × m weight matrix. As shown in Schorfheide (2000), the posterior risk then depends only on the weighted distance between $\hat{\xi}$ and the expectation of ξ with respect to the overall posterior, $E[\xi/Y]$, but not on higher moments of the posterior distribution.[15]

***2.* L_p loss function**

$$L_p(\xi, \hat{\xi}) = I\{p(\xi/Y) > p(\hat{\xi}/Y)\}, \tag{50}$$

where $I\{\}$ denotes the indicator function that is equal to one if its argument is true, and zero otherwise. This loss function penalizes point predictions that lie in regions of low posterior probability. If the posterior is uni-modal, the expected L_p loss tells us how far the model prediction lies in the tails of the posterior distribution, similar as are indicating usual p-values.

3. L_{x^2} loss function

$$L_{\chi^2}(\xi, \hat{\xi}) = I\{C_{\chi^2}(\xi/Y) < C_{\chi^2}(\hat{\xi}/Y)\}, \tag{51}$$

where

$$C_{\chi^2}(\xi/Y) = (\xi - E[\xi/Y])' V_\xi^{-1} (\xi - E[\xi/Y]), \tag{52}$$

and V_ξ is the posterior covariance of ξ under p(ξ/Y).

L_{x^2} and L_p-loss are identical, if the posterior distribution of ξ is Gaussian. In general, under the L_p-loss models are compared based on the height of the posterior density at $\hat{\xi}$, while under L_{x^2} the comparison is based on the weighted distance between $\hat{\xi}_i$ and the posterior mean $E[\xi/\mathrm{Y}]$.

Optimal predictors:

The optimal predictor for L_q is the posterior mean of ξ under model M_i, whereas for the other two loss functions $\hat{\xi}_i$ depends on the shape of the posterior distribution. Since the predictor ought to be calculated only by information contained in p(ξ/Y; M_i), the latter replaces p(ξ/Y) in (28), and it follows that the optimal predictor $\hat{\xi}_i$ for the L_p-loss is the posterior mode of p(ξ/Y; M_i) and for the L_{x^2}-loss it is the posterior mean $E[\xi/\mathrm{Y}]$.

[15] In this paper I use an identity matrix as weight matrix, although one could give more or less importance to some of the characteristics in the vector ξ, to mimic, e.g., the different importance RBC researchers give to certain second moments in their informal comparison of simulated and actual data.

Appendix A.3. TABLES

Prior Distributions:

Table 1	Name	Range	Density	Mean	SE
All Models:	e_K	[0, 1]	Beta	0.3560	(0.0200)
	β	[0, 1]	Beta	0.9930	(0.0030)
	ζ	R	Gaussian	0.0085	(0.0030)
	γ	R	Gaussian	0.0100	(0.0025)
	ρ_M	[0, 1]	Beta	0.6000	(0.2230)
	δ	[0, 1]	Beta	0.0165	(0.0080)
	σ_A	R^+	InvGamma*	0.712 %*	(2.000*)
	σ_M	R^+	InvGamma*	0.600 %*	(2.000*)
CIA / PAC:	ϕ	[0, 1]	Beta	0.6500	(0.0500)
Only PAC:	κ	R^+	Gamma	50.000	(20.000)
Only STM:	α	[0, 1]	Beta	0.5000	(0.1000)
	B	[0, 1]	Beta	0.5263	(0.0500)
	δ_i	[0, 1]	Beta	0.0072	(0.0010)
	e_Φ	R^+	Gamma	0.5000	(0.2500)
	z	[0, 1]	Uniform	0.5000	(0.2887)
	a_p	0.0069	fix	0.0069	(0.0000)
	φ_0	1	fix	1.0000	(0.0000)

* InvGamma stands for the Inverse Gamma (ν, s) distribution and the documented values in the columns "Mean" and "SE" correspond to its parameters s and ν, respectively. For $\nu = 2$ the SE is infinite.

Notes: CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM2 is the search- theoretic monetary model with predetermined labor in an otherwise Walrasian labor market. The parameter φ of the STM's is determined from steady state conditions since n^* is normalized to 100. Note also, that $e_K = 1 - e_N$, and $\delta = \delta_k - \zeta$. Finally a_p is fixed as in the calibrated model to match employment, and φ_0 is normalized to 1.

Posterior Parameter Distributions:

Table 2	CIA Model		PAC Model		STM $_1$ Model		STM $_2$ Model	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
e_K	0.4257	(0.0216)	0.4317	(0.0218)	0.3433	(0.0193)	0.3879	(0.0171)
β	0.9871	(0.0032)	0.9724	(0.0055)	0.9983	(0.0007)	0.9989	(0.0018)
ζ	0.0041	(0.0009)	0.0044	(0.0010)	0.0065	(0.0007)	0.0080	(0.0013)
γ	1.0129	(0.0013)	1.0127	(0.0015)	1.0056	(0.0027)	1.0024	(0.0018)
ρ_M	0.8646	(0.0284)	0.8591	(0.0334)	0.8206	(0.0159)	0.8060	(0.0217)
δ	0.0022	(0.0012)	0.0036	(0.0019)	0.0234	(0.0082)	0.0463	(0.0103)
σ_A	0.0127	(0.0008)	0.0155	(0.0010)	0.0092	(0.0007)	0.0162	(0.0009)
σ_M	0.0028	(0.0002)	0.0034	(0.0002)	0.0035	(0.0002)	0.0034	(0.0002)
ϕ	0.6904	(0.0470)	0.6852	(0.0496)	-	-	-	-
κ	-	-	71.942	(25.818)	-	-	-	-
α	-	-	-	-	0.4522	(0.0964)	0.4987	(0.0949)
B	-	-	-	-	0.4876	(0.0510)	0.5089	(0.0516)
δ_i	-	-	-	-	0.0066	(0.0009)	0.0066	(0.0010)
e_Φ	-	-	-	-	0.2820	(0.1413)	0.3085	(0.1441)
z	-	-	-	-	0.0140	(0.0062)	0.0064	(0.0035)
ap	-	-	-	-	0.0069	(0.0000)	0.0069	(0.0000)
φ_0	-	-	-	-	1	(0.0000)	1	(0.0000)

Notes: Posterior means and standard errors. CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM_1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM_2 is the search- theoretic monetary model with predetermined labor in an otherwise Walrasian labor market.

Model Comparison:

Table 3	CIA	PAC	STM 1	STM2
Prior Prob. $\pi_{i,0}$	1/4	1/4	(1/4)	(1/4)
Marginal Data Density ln $p(Y/M_i)$	N/A	N/A	N/A	N/A
Laplace Approximation	1502.11	1492.59	1549.97	1524.94
Posterior. Probability π_i	2.46E-025	1.8E-029	1.5E-4	2.0E-015
Posterior Odds π_i/π_1	1	7.32E-05	6.08E+020	8.20E+09

Table 3 continued	VAR(1)	VAR(2)	VAR(3)	VAR(4)
Prior Prob. $\pi_{i,0}$	1/16	1/16	1/16	1/16
Marginal Data Density ln $p(Y/M_i)$	1559.44	1557.73	1559.31	1553.75
Laplace Approximation	N/A	N/A	N/A	N/A
Posterior. Probability π_i	0.4848	0.0877	0.4257	0.0016
Posterior Odds π_i/π_1	1.97E+24	3.56E+23	1.73E+24	6.66E+21

Notes: The marginal data density ln $p(Y_T/M_i)$ is exact for the VARs. For the DSGE models it is approximated by the Laplace Approximation. CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM2 is the search-theoretic monetary model with predetermined labor in an otherwise Walrasian labor market.

Correlation ($\triangle$GDP $_t$, Inflation $_{t+h}$)

Table 4	Model	h=-2	h=-1	h = 0	h = 1	h = 2
90% Interval (U)		0.0524	0.0709	-0.0407	0.1534	0.1925
90% Interval (L)		-0.2465	-0.2156	-0.2440	-0.1375	-0.0899
Mode Prediction	CIA	0.0009	0.0018	-0.5612	-0.0286	0.0278
	PAC	0.0132	0.0276	-0.4525	0.0137	0.0051
	STM 1	0.1000	0.1302	-0.0791	-0.0707	-0.0622
	STM 2	0.0696	-0.0049	-0.0439	-0.0596	-0.0629
L_p-risk	CIA	0.6706	0.4266	0.9992	0.0864	0.2202
	PAC	0.7482	0.6228	0.9959	0.0000	0.0740
	STM 1	0.9772	0.9585	0.0000	0.2499	0.3832
	STM 2	0.9507	0.3666	0.2666	0.2141	0.3870

Notes: Dynamic correlations of output growth and inflation at leads and lags: mode predictions and L_p risk. CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM2 is the search-theoretic monetary model with predetermined labor in an otherwise Walrasian labor market.

Table 5	Joint correlations			
	CIA	PAC	STM 1	STM 2
C_{χ^2}	254.6148	177.2644	24.2330	13.3853
L_{χ^2} - risk	1.000	1.000	0.9970	0.9649
L_q - risk	0.2312	0.1405	0.1005	0.0541

Notes: Joint dynamic correlations of output growth and inflation at leads and lags: Statistic C_{χ^2}, L_{χ^2} risk and L_q risk. CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM2 is the search-theoretic monetary model with predetermined labor in an otherwise Walrasian labor market.

Autocorrelation of Inflation: Corr (Inflation $_t$, Inflation $_{t-h}$)

Table 6	Model	h = 1	h = 2	h = 3	h = 4
90% Interval (U)		0.8468	0.7652	0.7049	0.6310
90% Interval (L)		0.6781	0.4905	0.3424	0.2329
Mode Prediction	CIA	0.4540	0.3931	0.3390	0.2944
	PAC	0.4972	0.4308	0.3745	0.3267
	STM $_1$	0.8202	0.6705	0.5486	0.4493
	STM $_2$	0.8173	0.6663	0.5457	0.4493
L_p-risk	CIA	0.9999	0.9899	0.7776	0.4363
	PAC	0.9999	0.9720	0.6178	0.2336
	STM $_1$	0.7762	0.3569	0.3106	0.3469
	STM $_2$	0.7518	0.3130	0.3070	0.3470

Notes: Autocorrelations of inflation up to 4 lags. Mode predictions and L_p risk. CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM2 is the search-theoretic monetary model with predetermined labor in an otherwise Walrasian labor market.

Table 7	Joint correlations			
	CIA	PAC	STM 1	STM 2
C_{x^2}	106.3872	76.1335	2.4274	1.9537
L_{x^2} - risk	1.0000	0.9998	0.4838	0.3959
L_q - risk	0.1943	0.1216	0.0070	0.0063

Notes: Joint autocorrelations of and inflation up to 4 lags: Statistic C_{x^2}, L_{x^2} risk and L_q risk. CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM2 is the search-theoretic monetary model with predetermined labor in an otherwise Walrasian labor market.

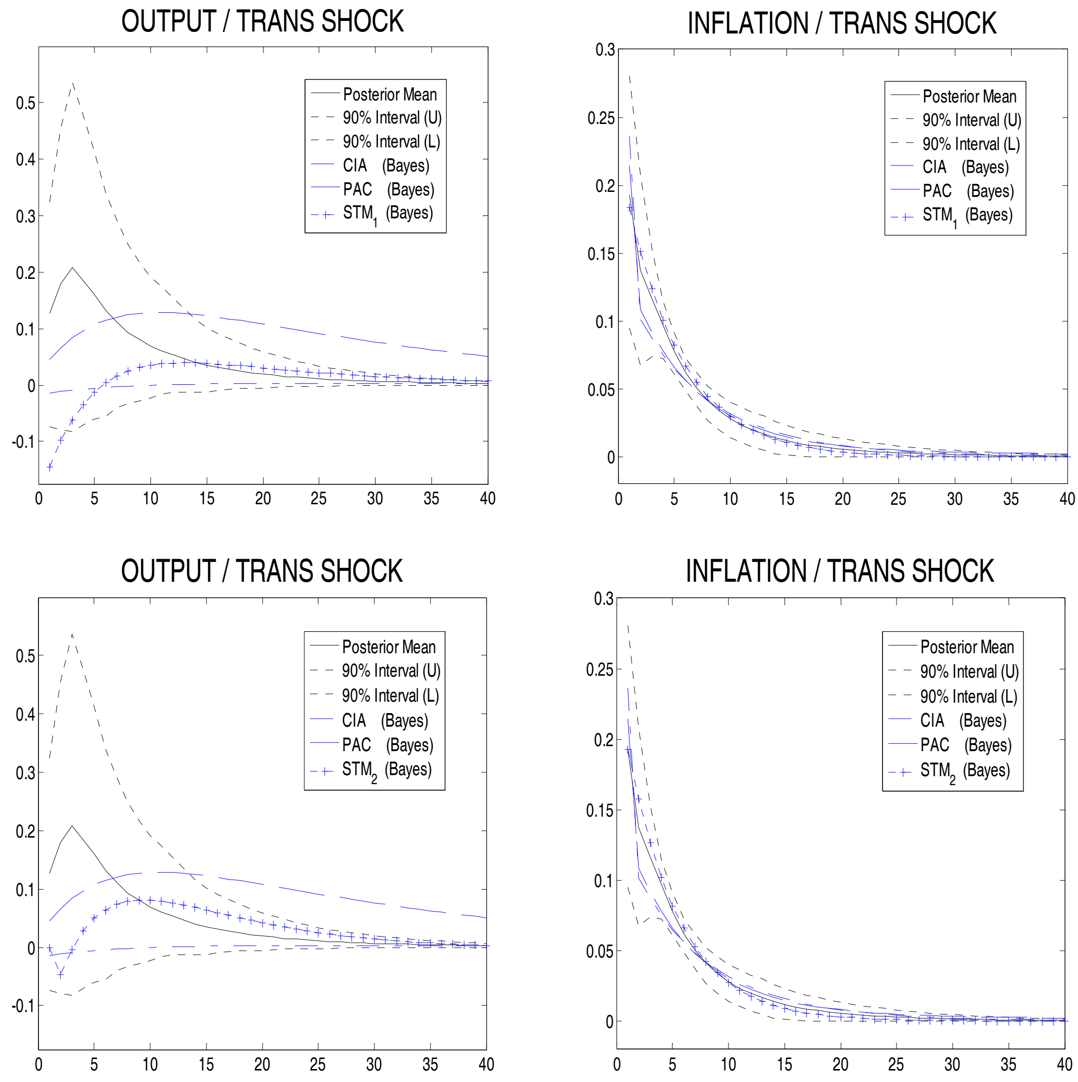
Impulse Responses

Table 8	Model	$dY/d\varepsilon_M$	$d\pi/d\varepsilon_M$	$dY/d\varepsilon_A$	$d\pi/d\varepsilon_A$
a) 12 periods					
L_q-risk	CIA	0.2266	0.0048	0.0877	0.0710
	PAC	0.0628	0.0025	0.4175	0.0438
	STM_1	0.3604	0.0083	0.5694	0.0004
	STM_2	0.1561	0.0006	0.0061	0.0108
$L\varkappa^2$-risk	CIA	0.2440	0.8998	0.9686	0.9938
	PAC	0.7284	0.8116	0.9302	0.9870
	STM_1	0.7758	0.6554	0.9882	0.2898
	STM_2	0.9120	0.2038	0.8908	0.7304
b) 32 periods					
L_q-risk	CIA	0.2346	0.0049	0.1214	0.0720
	PAC	0.1953	0.0026	0.6043	0.0461
	STM_1	0.3377	0.0005	0.6670	0.0104
	STM_2	0.1607	0.0008	0.0186	0.0128
$L\varkappa^2$-risk	CIA	0.2446	0.8326	0.9368	0.9796
	PAC	0.8834	0.8222	0.8970	0.9678
	STM_1	0.7378	0.3278	0.9714	0.7878
	STM_2	0.8676	0.2592	0.8972	0.7706

Notes: Joint analysis of impulse responses (2 different horizons). Table 8a: jointly considered are periods 1 to 12. Table 8b: jointly considered are periods 1 to 32. Column 1-4 are respectively: Output and Inflation response to (temporary) Monetary shock, Output and Inflation response to (permanent) Technology shock. Documented are L_p risk and $L\varkappa^2$-risk. CIA is the cash-in-advance model. PAC is the portfolio-adjustment-cost model. STM_1 is the search-theoretic monetary model with standard Walrasian labor market. Model STM_2 is the search-theoretic monetary model with predetermined labor in an otherwise Walrasian labor market.

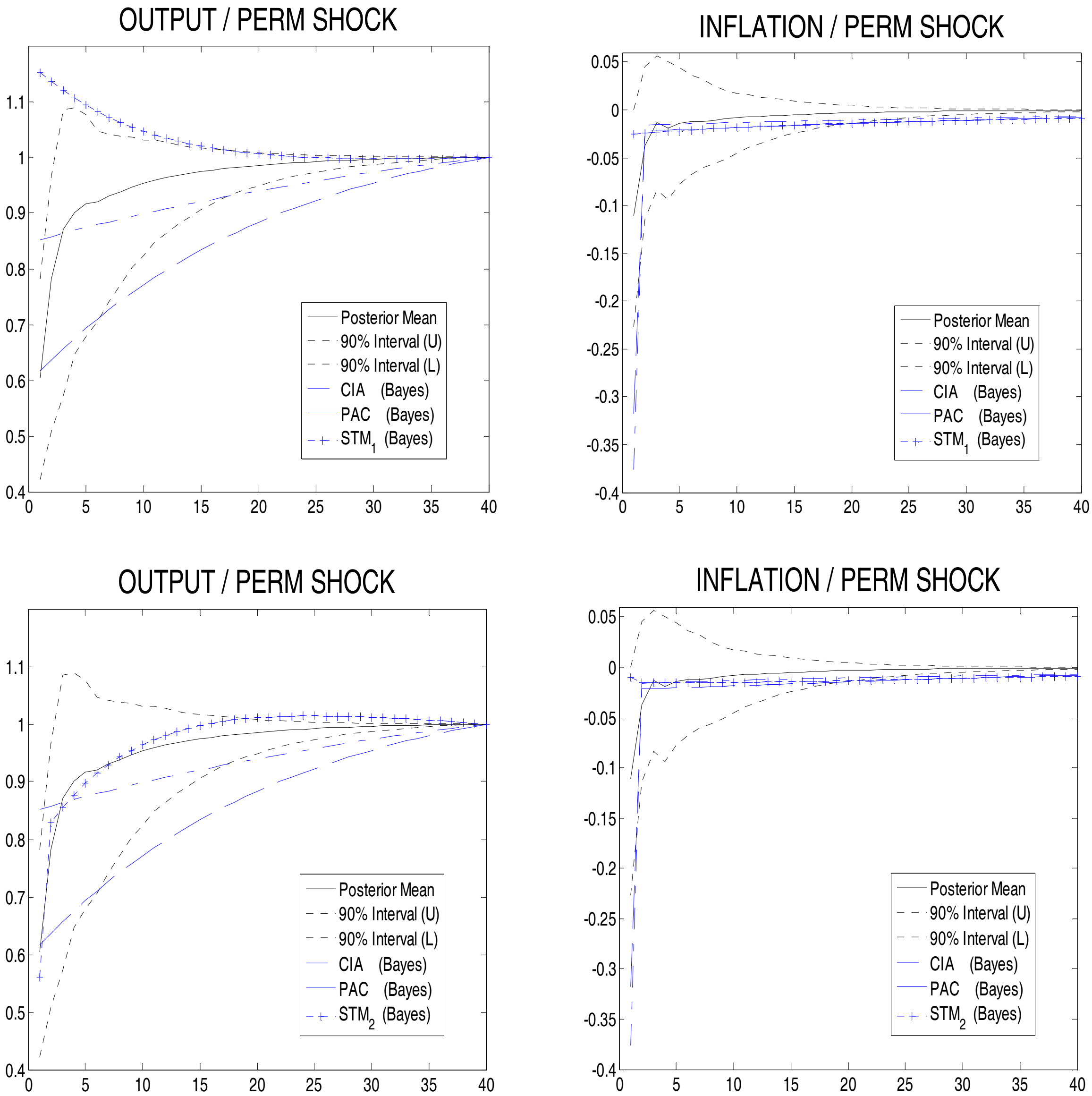
Appendix A.4. FIGURES

Figure 1:



Notes: Impulse Responses to a transitory monetary shock. In black are the posterior mean and the 90% probability bands of the posterior distribution of the constructed data generating process, dash dotted and dashed blue lines represent responses at posterior means of the CIA and PAC model parameters. The first row adds the mean response of model STM1 and the second of STM2, both marked with “+”.

Figure 2:



Notes: Impulse Responses to a permanent technology shock. In black are the posterior mean and the 90% probability bands of the posterior distribution of the constructed data generating process, dash dotted and dashed blue lines represent responses at posterior means of the CIA and PAC model parameters. The first row adds the mean response of model STM1 and the second of STM2, both marked with “+”.

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