A Bayesian Look at New Open Economy Macroeconomics

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This Draft: March 22, 2005

Please note: computational results reported in this paper are still preliminary. In particular, the number of draws from the MCMC algorithms has to be increased to raise the precision of the estimates.

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1 Introduction

We develop and estimate a two-country model that can be used for studying the conduct of monetary policy in the U.S. and the rest of the world. The theoretical model is rich enough to capture salient facts in international macroeconomics, yet parsimonious to be accessible to economic intuition. The model takes inspiration from the contribution by Clarida, Gali, and Gertler (2001) who develop a two-country model of the world economy. Under their symmetry assumptions, the monetary policy problem in open economies reduces to that in a closed economy, to wit inflation and output stabilization. We choose to model monetary policy in form of Taylor-type rules that are adapted to open economy issues as in Lubik and Schorfheide (2003). The main theoretical contribution is the extension of the small open economy framework in Monacelli (2005) to a large open economy setting. We introduce endogenous deviations from purchasing power parity (PPP) via price-setting importers that lead to imperfect passthrough.

The main feature of model is that the real side, that is, preferences and technologies, is fully symmetric, while the nominal side allows for asymmetries. Specifically, we let nominal rigidities in domestic and import sectors differ across countries, and distinguish between monetary policy rules at home and abroad. An attractive feature of the symmetry assumption is that in the absence of trade in goods and financial assets the model cleanly reduces to the standard New Keynesian DSGE model that has been widely used to study monetary policy in closed economies.

The model is driven by a variety of country-specific shocks and a world-wide technology shock that we model as a common trend to capture non-stationarity in the data. Each country is affected by a supply-side disturbance in the form of productivity shocks, by a demand-side, government purchases shock, and a monetary policy shock. On top of these structural shocks that have clear economic interpretation we also introduce essentially non-structural disturbances that are designed to measure deviations from purchasing power parity and uncovered interest parity. This is done in order to improve fit, but also to isolate the model's contribution in explaining exchange rate dynamics endogenously. Specifically, we use this model to study the propagation of shocks across countries and to make advances in identifying the determinants of exchange rate fluctuations. We apply the model to the economies of the U.S. and the Euro Area. The two economies are roughly of equal size and are each characterized by a unified monetary policy, which would not be the case for country-aggregate like the G-10.

In our approach we are aware of the tension inherent in structural empirical modelling: small, stylized models (e.g. Lubik and Schorfheide, 2003) can lead to misspecification, large-scale models (e.g. Smets and Wouters, 2003, Adolfsen, Laseen, Linde, and Villani, 2004) may introduce identification problems. We decided to use a fairly small-scale model but are conscious of potential misspecifications. Our focus here is not on a comparison to vector autoregressive (VAR) systems as in Schorfheide (2000) or Del Negro, Schorfheide, Smets, and Wouters (2004), but rather on an exploration of the model estimates themselves, and what we can learn from a structural modelling approach.

We use the Bayesian estimation methods developed in Schorfheide (2000) and subsequently widely used in the analysis of closed economy models, and increasingly in open economy issues. The advantage of this approach is that it is a system-based estimation method that allows the researcher to incorporate additional information on parameters through the use of priors. However, this carries the potential disadvantage that the parameter estimates may be contaminated by model misspecification. We consequently provide some discussion how Bayesian inference deals with the nexus of model misspecification and the identification problem. This component of our paper is intended as an accessible introduction to Bayesian estimation of DSGE models that aids communication between researchers, practitioners and policymakers. Hence, we carefully document the sensitivity of posterior estimates to changes in the specification of the model. Our special interest is on parameter estimates, the effects of monetary policy, and the determinants of exchange rate movements. We contrast how the estimates change when we move from a closed economy framework to the open economy; how tight versus diffuse priors affect the results; how the model behavior differs over long and short samples.

Our empirical results reveal that there are significant differences between closed and open economy modelling even when a large economy like the U.S. is fairly closed in trade terms. The most striking aspect is that while exchange rate targeting does not play a role in both policy rule, inflation and output coefficients change significantly when moving from a closed to an open economy model. The conclusions are reasonably robust to changes in the prior. Estimating the model over sub-samples reveals, however, that there may have been changes in the way monetary policy has been conducted in the late 1980s. A main finding in our model is that exchange rate movements between the U.S. and the Euro Area can be explained to 20% by endogenous factors. The rest is due to a non-structural PPP-shock that is designed to capture the deviations of the model from the data. We find that the main driving force behind the nominal exchange rate are movements in the real exchange rate due to Euro Area technology and government purchases shocks. Monetary shocks do not matter.

The structure of the paper is as follows. We begin by discussing the progress made so far in developing usable empirical models based on the New Open Economy Macroeconomics (NOEM). We focus our discussion on structural estimation methods and in particular on a Bayesian approach. Section 3 contains the theoretical model. Section 4 introduces and discusses the Bayesian estimation approach with a specific focus on misspecification and identification issues. Section 5 describes construction of the two-country data set. We also explain the derivation of a prior based on an extensive pre-sample analysis. The estimation results can be found in Section 6. We first present results from the benchmark specification. We then discuss in turn the effects of different priors, of different sample periods, of various shock specifications and the differences between closed and open economy estimation. The dynamics of the model, and in particular the transmission of shocks across countries are studied next making use of impulse response analysis. We conclude this section by identifying the sources of exchange rate fluctuations via variance decompositions and Kalman-filtering. The final section concludes and offers directions for promising future research.

2 In Search of an Empirical NOEM Model

The development of theoretical models in the NOEM mold has changed the nature of debate in international finance. While these models have proven to be quite successful at both a conceptual level and in terms of quantitative theory, progress has been slower in developing an empirically viable NOEM model. In recent years, however, the literature has made large strides towards that goal with the development and widespread use of Bayesian estimation techniques for dynamic stochastic general equilibrium (DSGE) models. In a seminal contribution, Leeper and Sims (1994) demonstrated that large-scale DSGE models can be estimated using full-information methods. Structural empirical modelling thereby became a viable alternative to non-structural and partial information methods. Schorfheide (2000) pushed the research agenda further by developing useful Bayesian techniques to estimate and evaluate DSGE models in the presence of model misspecification.[1] Using these methods, Smets and Wouters (2003) estimated a fully-specified, optimization-based model of the

[1] Other important early contributions to this literature are Fernandez-Villaverde and Rubio-Ramirez (2003) and Rabanal, Pau and Rubio-Ramirez, Juan F. (2002).

Euro Area that successfully matched the time series facts. This work has stimulated a host of research in closed economy models. The open economy literature has not been far behind in utilizing Bayesian techniques. In what follows we discuss the progress that has been made in search of an empirical NOEM model.

The first empirical NOEM papers were in the context of small open economies. From a modelling point of view, they could be regarded as an extension of the closed economy New Keynesian framework as detailed in, for instance, Clarida, Gali, and Gertler (1999). This interpretation is supported by the contribution of Gali and Monacelli (2005) who develop a small open economy NOEM that mimics the reduced-form structure of the New Keynesian paradigm model. This similarity facilitated the use of already established Bayesian techniques in a closed economy context.

A first example of this kind is Lubik and Schorfheide (2003) who estimate a simplified version of the Gali and Monacelli (2005) model to assess whether central banks respond to exchange rate movements. The NOEM framework in this paper simply serves as a data-generating process to provide identification restrictions for the estimation of the monetary policy rule. The need for instruments arises because of the joint endogeneity of the variables in the monetary policy rule. Earlier work on monetary policy in the open economy by Clarida, Gali, and Gertler (1998) has used GMM-estimation with a large and varied set of instruments in order to deal with endogeneity. While potentially robust to misspecification, this approach suffers from weak identification problems that can often lead to implausible estimates. Full-information based method, on the other hand, use the optimal set of instruments embedded in the model's cross-equation restrictions. Lubik and Schorfheide (2003) find that among the central banks of Australia, New Zealand, the United Kingdom, and Canada, only the latter one consistently responds to exchange rate movements. This conclusion is robust to changes in the sample period, to the type of inflation targeting (forward vs. current-looking) and to the type of international relative price variable targeted. The authors arrive at this conclusion by performing Bayesian posterior odds tests that utilize the entire information contained in the model and the data.[2]

Bergin (2004) is the closest precursor to our paper in terms of scope and purpose. Bergin develops a two-country model that combines features of international real business cycle models with the NOEM. Specifically, he allows for capital accumulation and investment dynamics to provide richer internal dynamics. Additionally, he assumes that firms can

[2] Subsequent empirical studies of SOE models include Adolfson *et al.* (2004), Del Negro (2003), and Justitiano and Preston (2004).

engage in local currency pricing which allows for deviations from the law of one price, and that international asset markets are incomplete. Since the linearized version of the model would imply non-stationary due to foreign asset accumulation, he introduces portfolio adjustment costs which render the dynamics stationary. Bergin applies the model to the U.S. and the G-6 countries and uses data on output, interest rates, inflation, exchange rates, and the current account. He imposes complete symmetry on the model and estimates it on output, inflation and interest rate *differentials*. He finds that the model has a similar fit as a VAR, and that it produces exchange rate forecasts that are slightly better than a random walk model.

3 A Two-Country Model Usable for Empirical Analysis

We develop a model of a world economy with two large economic entities, the U.S. ('Home') and the rest of the world ('Foreign'), in the mold of the New Open Economy Macroeconomics.[3] We allow for endogenous deviations from purchasing power parity in the short run, but not in the long-run. Specifically, the same good can have different prices depending on where it is sold even after adjusting for exchange rate movements. Producers set prices monopolistically for the domestic as well as the world market in their own currency. Imported goods, however, are subject to price discrimination as monopolistic importers charge a mark-up to consumers at the border. We assume symmetric preferences and technologies, but allow for differences in price-setting, policies and disturbances affecting each economy. Under the assumption of complete international asset markets the model has a manageable reduced-form, but can allow for potentially rich exchange rate behavior. In terms of notation, we denote goods produced and activities associated with them in the Home (Foreign) country by 'H', while the location of economic activities is indexed by a '*' for the Foreign country, and no index for the Home country. For instance, c_H (c_F^*) is the consumption of the home- (foreign-) produced good in the Home (Foreign) country.

[3] Our framework extends Monacelli (2005) to a large open economy setting. This form of endogenous passthrough has also been studied by Justitiano and Preston (2004) and Lubik (2005).

3.1 Domestic Households

The domestic economy is populated by a continuum of households whose preferences are described by an intertemporal utility function[4]:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(\mathcal{C}_t / A_{W,t})^{1-\tau}}{1-\tau} - N_t \right], \tag{1}$$

where $\mathcal{C}_t = C_t - h\gamma C_{t-1}$ is effective consumption under habit formation and N_t is labor input. We assume that habits are internalized by the household. $0 \leq h \leq 1$ is the habit parameter, γ is the steady state growth rate of $A_{W,t}$, $\tau > 0$ is the coefficient of relative risk aversion. $0 < \beta < 1$ is the discount factor. $A_{W,t}$ is a non-stationary world-wide technology shock, where we define $z_t = A_{W,t}/A_{W,t-1}$.

C_t is an aggregate consumption index:

$$C_t = \left[(1-\alpha)^{\frac{1}{\eta}} C_{H,t}^{\frac{\eta-1}{\eta}} + \alpha^{\frac{1}{\eta}} C_{F,t}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{2}$$

where $0 \leq \alpha < 1$ is the import share and $\eta > 0$ is the intratemporal substitution elasticity between home and foreign consumption goods. Households allocate aggregate expenditure based on the demand functions:

$$C_{H,t} = (1-\alpha) \left(\frac{P_{H,t}}{P_t} \right)^{-\eta} C_t \text{ and } C_{F,t} = \alpha \left(\frac{P_{F,t}}{P_t} \right)^{-\eta} C_t, \tag{3}$$

where $P_{H,t}$, $P_{F,t}$ are domestic and foreign goods price indices, and

$$P_t = \left[(1-\alpha) P_{H,t}^{1-\eta} + \alpha P_{F,t}^{1-\eta} \right]^{\frac{1}{1-\eta}},$$

and is the consumption-based price index, the CPI.[5]

In the aggregate, households face the budget constraint:

$$P_{H,t} C_{H,t} + P_{F,t} C_{F,t} + E_t Q_{t,t+1} D_{t+1} \leq W_t N_t + D_t, \tag{4}$$

where W_t is the nominal wage for labor services provided to firms. $Q_{t,t+1}$ is the stochastic discount factor used for evaluating consumption streams, and D_t represents generic payments from a portfolio of assets. Under the assumption of complete asset markets, both

[4] We ignore household-specific indices for notational convenience.

[5] Each domestic- and foreign-produced goods aggregate is composed of differentiated individual products with demand functions:

$$C_{H,t}(i) = \left(\frac{P_{H,t}(i)}{P_{H,t}} \right)^{-\omega} C_{H,t} \text{ and } C_{F,t}(i) = \left(\frac{P_{F,t}(i)}{P_{F,t}} \right)^{-\omega} C_{F,t}$$

and associated price indexes. We abstract from this level of disaggregation since it is immaterial to our aggregate model specification.

domestically and internationally, this portfolio comprises a complete set of state-contingent claims.

Households maximize the intertemporal utility function subject to a sequence of budget constraints for all t. The labor-leisure choice is governed by the intratemporal optimality condition $\lambda_t^{-1} = W_t/P_t$, where λ_t is the marginal utility of income. Intertemporal consumption choice is given by:

$$A_{W,t}\lambda_t P_t = \mathcal{C}_t^{-\tau} - h\gamma\beta E_t[\frac{A_{W,t}}{A_{W,t+1}}\mathcal{C}_{t+1}^{-\tau}], \tag{5}$$

while optimal portfolio choice implies:

$$Q_{t,t+1} = \beta\frac{\lambda_{t+1}}{\lambda_t}\frac{P_t}{P_{t+1}}. \tag{6}$$

This can be used to construct the return on nominal government bonds, i.e. the nominal interest rate:

$$R_t^{-1} = \beta E_t\frac{\lambda_{t+1}}{\lambda_t}\frac{P_t}{P_{t+1}}, \tag{7}$$

which we take to be the monetary authority's instrument.

3.2 Domestic Producers

Domestic differentiated goods are produced by a continuum of monopolistically competitive producers which are subject to Calvo-type price setting. That is, each period a fraction $1-\theta_H$ of domestic firms set prices optimally, while θ_H firms remain at the previously chosen price. Each firm maximizes $j \in [0,1]$ discounted intertemporal profits subject to a downward-sloping demand curve. Demand for a firm's product derives both from domestic sources $C_{H,t}$ and government expenditure $G_{H,t}$, as well as from abroad $C_{H,t}^{*}$.[6] Each firm has access to a linear production technology that uses labor as its only input:

$$Y_{H,t} = A_{W,t}A_{H,t}N_t\left(j\right), \tag{8}$$

where $A_{H,t}$ is a stationary and country-specific technology shock.

Every firm thus derives its optimal price $P_{H,t}\left(j\right)$ by maximizing:

$$E_t\sum_{T=t}^{\infty}\theta_H^{T-t}Q_{t,T}Y_{H,t}\left(j\right)\left[P_{H,t}\left(j\right) - P_{H,t}MC_{H,t}\right], \tag{9}$$

[6] We assume for simplicity that firms world-wide do not engage in local currency pricing. An extension of the model in this regard would be a promising research direction.

where $MC_{H,t} = W_t / P_{H,t}$, subject to the demand function:

$$Y_{H,t}(j) = \left(\frac{P_{H,t}(j)}{P_{H,t}} \right)^{-\omega} \left(C_{H,t} + G_{H,t} + C^*_{H,t} \right). \tag{10}$$

Firms evaluate revenue streams by the households' stochastic discount factor $Q_{t,T}$. θ_H^{T-t} is the probability that the specific firm will not be allowed to adjust its price between periods t and T. The solution to the domestic firm's optimization problem then implies that prices are set as a (time-varying) mark-up over marginal cost. This results in the familiar Phillips-curve relationship between domestic inflation and marginal cost after aggregation over individual firms and imposing ex-post homogeneity.

3.3 Domestic Importers

Following Monacelli (2005) we assume that endogenous deviations from PPP in the short run arise due to the existence of monopolistically competitive importers. Domestic consumers are required to purchase foreign-produced goods form importers that exert market power. Importers purchase foreign goods at world-market prices $P^*_{F,t}$ (which are set by their respective producers in their own currency), so that the law of one price holds at the border. Importers sell these goods to domestic consumers and charge a mark-up over their cost, which creates a wedge between domestic and import prices of foreign goods when measured in the same currency. We can define define the law of one price (l.o.p.) gap as:

$$\psi_{F,t} = \frac{e_t P^*_{F,t}}{P_{F,t}}. \tag{11}$$

If PPP holds, then $\psi_{F,t} \equiv 1$. Therefore, passthrough from exchange rate changes to the domestic currency prices of imports is imperfect as importers adjust their pricing behavior to extract optimal revenue from consumers.

Similarly to domestic producers, importers operate under Calvo-style price-setting, with $1 - \theta_F$ importers setting prices optimally each period. Importers maximize the discounted stream of expected profits:

$$E_t \sum_{T=t}^{\infty} \theta_F^{T-t} Q_{t,T} C_{F,t}(j) \left[P_{F,t}(j) - e_t P^*_{F,t} \right], \tag{12}$$

subject to the demand function:

$$C_{F,t}(j) = \left(\frac{P_{F,t}(j)}{P_{F,t}} \right)^{-\omega} C_{F,t}. \tag{13}$$

where we assume that domestic government purchases cannot fall on foreign-produced goods. Note also that the marginal cost of acquiring foreign goods is the l.o.p. gap. Consequently, importers set domestic currency prices of foreign goods as a (time-varying) mark-up over $\psi_{F,t}$. These endogenous deviations from PPP then result in a Phillips-curve relationship between import-price inflation and the l.o.p. gap

3.4 The Foreign Economy

We assume that home and foreign economies are symmetric in terms of preferences and technology, but they can differ in price-setting and monetary policy. The equations describing the foreign economy are therefore the same as for Home, with 'starred' variables and parameters properly substituted. We can define the real exchange rate as:

$$s_t = \frac{e_t P_t^*}{P_t}. \tag{14}$$

Symmetry implies that the foreign real exchange rate $s_t^* = s_t^{-1}$. On the other hand, the terms of trade differ between the two countries by the l.o.p. gaps. The domestic terms of trade, that is, the price of exports in terms of imports measured in domestic currency are

$$q_t = \frac{P_{H,t}}{P_{F,t}}, \tag{15}$$

while the foreign terms of trade are:

$$q_t^* = \frac{P_{F,t}^*}{P_{H,t}^*}. \tag{16}$$

Using the definition of the real exchange rates we can derive the expression:

$$\frac{\psi_{F,t}}{q_t} = \frac{\psi_{H,t}^*}{q_t^*}. \tag{17}$$

Home and foreign terms of trade coincide (inversely) only when passthrough is perfect.

3.5 Risk-sharing, Market Clearing and Equilibrium

Complete international asset markets imply perfect risk-sharing between households in the two countries. In equilibrium, stochastic discount factors in the two countries have to be equalized, which leads to the following condition:

$$\beta \frac{\lambda_{t+1}}{\lambda_t} \frac{P_t}{P_{t+1}} = Q_{t,t+1} = \beta \frac{\lambda_{t+1}^*}{\lambda_t^*} \frac{P_t^*}{P_{t+1}^*} \frac{e_t}{e_{t+1}}. \tag{18}$$

Goods market clearing requires that:

$$Y_{H,t} = C_{H,t} + G_t + C_{H,t}^* \text{ and } Y_{F,t}^* = C_{F,t}^* + G_t^* + C_{F,t}. \tag{19}$$

Moreover, we assume that both countries are of equal size and that initial asset positions are zero. This implies a zero current account in and out of steady state and balanced trade in value terms. That is, there is no net asset accumulation by any country. Although this is a clearly counterfactual assumption, it provides a useful benchmark.

3.6 Linearization

We proceed by (log-) linearizing the model equations around the deterministic steady state. Since the model contains a non-stationary component in form of world-wide productivity growth, we de-trend the affected variables by their specific growth components beforehand. Details on the entire equation system can be found in the Appendix A. In our empirical analysis, we exploit the properties of the model as a variant of the New Keynesian monetary policy model that has attracted a lot of recent interest due its interpretability and tractability. In what follows we therefore briefly discuss some key structural equations. All variables are in log-deviations from the steady state, where $\widetilde{x}_t = \log x_t - \log \overline{x}$.

A linear approximation to the solution of the domestic firms' price-setting problems results in a Phillips-curve type relationship between domestic inflation and marginal cost:

$$\widetilde{\pi}_{H,t} = \beta E_t \widetilde{\pi}_{H,t+1} + \kappa_H \widetilde{mc}_t, \tag{20}$$

where $\kappa_H = \frac{1-\theta_H}{\theta_H}(1-\theta_H\beta)$. Using the condition for labor-leisure choice, the marginal cost term can be expressed as $\widetilde{mc}_t = -\widetilde{\lambda}_t - \alpha\widetilde{q}_t - \widetilde{A}_t$. $\widetilde{\lambda}_t$ is the marginal utility of income, which evolves according to:

$$-\widetilde{\lambda}_t = \frac{\tau}{1-h\beta}\widetilde{\mathcal{C}}_t - \frac{h\beta}{1-h\beta}E_t[\tau\widetilde{\mathcal{C}}_{t+1} + \widetilde{z}_{t+1}], \tag{21}$$

where the law of motion for the habit stock is:

$$(1-h)\,\widetilde{\mathcal{C}}_t = \widetilde{c}_t - h\widetilde{c}_{t-1} + h\widetilde{z}_t. \tag{22}$$

For $h = 0$, the model reduces to standard consumption preferences. Recall that $\widetilde{z}_t = \Delta\widetilde{A}_{W,t}$. World-wide shocks do not affect marginal costs (only country-specific shocks do), but they change the intertemporal consumption trade-off as evidenced by habit dynamics and the Euler-equation:

$$-\widetilde{\lambda}_t = -E_t\widetilde{\lambda}_{t+1} - (\widetilde{R}_t - E_t\widetilde{\pi}_{t+1}) + E_t\widetilde{z}_{t+1}. \tag{23}$$

The price-setting problem of importers reduces to a Phillips-curve type relation between import price inflation and the l.o.p. gap:

$$\widetilde{\pi}_{F,t} = \beta E_t \widetilde{\pi}_{F,t+1} + \kappa_F \widetilde{\psi}_{F,t}, \tag{24}$$

where $\kappa_F = \frac{1-\theta_F}{\theta_F}(1-\theta_F\beta)$. CPI-inflation can be derived using the definition $\widetilde{\pi}_t = \alpha\widetilde{\pi}_{F,t} + (1-\alpha)\widetilde{\pi}_{H,t}$. Inflation dynamics therefore depends on domestic driving forces as well as international relative price movements and endogenous deviations from PPP in the form of imperfect passthrough. The real exchange rate behaves according to $\widetilde{s}_t = \widetilde{\psi}_{F,t} - (1-\alpha)\widetilde{q}_t - \alpha\widetilde{q}_t^*$ and captures the distortions introduced by the l.o.p. gap as well as movements in each country's own terms of trade. Using the definition of the real exchange rate also allows us to derive nominal exchange rate dynamics:

$$\Delta\widetilde{e}_t = \widetilde{\pi}_t - \widetilde{\pi}_t^* + \widetilde{s}_t - \widetilde{s}_{t-1}. \tag{25}$$

For the empirical analysis we add an additional i.i.d. shock $\varepsilon_{E,t}$ to this equation. This PPP-shock is intended to capture exogenous deviations from PPP, and will allows us to assess to what extent exchange rate behavior can be explained by the model's intrinsic dynamics.

The (linearized) asset pricing equation for nominal bonds implies that the interest rate differential is related to expected exchange rate depreciation, in other words, uncovered interest parity (UIP):

$$\widetilde{R}_t - \widetilde{R}_t^* = E_t \Delta\widetilde{e}_{t+1}. \tag{26}$$

Similarly to above, we investigate the effects of deviations from UIP by moving the $\varepsilon_{E,t}$ shock to this equation. The UIP shock is designed to capture time-varying risk-premia or approximation errors in this asset pricing equation. Furthermore international risk-sharing implies a relationship between marginal utilities across countries adjusted for purchasing power:

$$\widetilde{\lambda}_t = \widetilde{\lambda}_t^* - s_t. \tag{27}$$

The goods market clearing condition:

$$\widetilde{y}_{H,t} = \widetilde{c}_t - \widetilde{g}_t - \frac{\alpha}{\tau}\widetilde{s}_t - \alpha(1-\alpha)\eta\left(\widetilde{q}_t - \widetilde{q}_t^*\right) \tag{28}$$

shows how output is affected by demand and relative prices. Demand disturbances in the form of government expenditure shocks $\widetilde{g}_t$ therefore affect output directly and not via changing marginal rates of substitution in consumption and leisure.

The model is closed by specifying monetary policy. We assume that central banks in both countries adjust the nominal interest in response to deviations of inflation, a measure of output, and exchange rate depreciation from their respective targets:

$$\widetilde{R}_t = \rho_R \widetilde{R}_{t-1} + (1-\rho_R)\left[\psi_1 \widetilde{\pi}_t + \psi_2 \widetilde{y}_t + \psi_3 \Delta \widetilde{e}_t\right] + \varepsilon_{R,t}. \tag{29}$$

The monetary policy rule is of the standard Taylor-type and has been studied before in Lubik and Schorfheide (2003). The i.i.d. shock $\varepsilon_{R,t}$ captures the the non-systematic component of monetary policy. We assume that the monetary authorities' target levels are the steady state values of the variables in the rule. Alternatively, we could specify the rule in terms of the output gap $\widetilde{y}_t - \widetilde{y}_t^n$, where $\widetilde{y}_t^n$ is the natural rate of output in the absence of price distortions and full passthrough. This is the model-consistent measure of the output gap.

The model consists of 21 equations in endogenous variables, and 5 equations describing the evolution of the exogenous autoregressive shocks:

$$\begin{aligned}
\widetilde{z}_t &= \gamma(1-\rho_z) + \rho_z \widetilde{z}_{t-1} + \epsilon_{z,t}, \\
\widetilde{A}_t &= \rho_A \widetilde{A}_{t-1} + \epsilon_{A,t}, \\
\widetilde{A}_t^* &= \rho_{A^*} \widetilde{A}_{t-1}^* + \epsilon_{A^*,t}, \\
\widetilde{G}_t &= \rho_G \widetilde{G}_{t-1} + \epsilon_{G,t}, \\
\widetilde{G}_t^* &= \rho_{G^*} \widetilde{G}_{t-1}^* + \epsilon_{G^*,t},
\end{aligned} \tag{30}$$

Moreover, there are innovations in the monetary policy in each country and two measurement errors, deviations from UIP and exogenous deviations from PPP. Given these exogenous process the model is then solved using the methods described in Sims (2002).

4 Why a Bayesian Approach?

The log-linearized DSGE model can be written as a rational expectations (LRE) system of the form

$$\Gamma_0(\theta) s_t = \Gamma_1(\theta) s_{t-1} + \Gamma_\epsilon(\theta)\epsilon_t + \Gamma_\eta(\theta)\eta_t. \tag{31}$$

Here s_t denotes the vector of model variables such as $\widetilde{y}_t$, $\widetilde{\pi}_t$, $\widetilde{R}_t$. The vector ϵ_t stacks the innovations of the exogenous processes and η_t is composed of rational expectations forecast errors.[7] The dynamics of the exogenous shock processes are absorbed in the definition of the Γ matrices and θ collects the structural parameters of the model. The solution to (31) can be expressed as

$$s_t = \Phi_1(\theta) s_{t-1} + \Phi_\epsilon(\theta)\epsilon_t. \tag{32}$$

[7] For instance, one can define $\eta_t^c = \widetilde{c}_t - I\!\!E_{t-1}[\widetilde{c}_t]$ and absorb $I\!\!E_t[\widetilde{c}_{t+1}]$ to represent the model developed in Section 3 in terms of (31).

A measurement equation then relates the model variables s_t to a vector of observables y_t:

$$y_t = A(\theta) + Bs_t. \tag{33}$$

In our application y_t is composed of output growth, inflation, and nominal interest rates for the U.S. and Euro Area, as well as the US$-Euro exchange rate. B does not depend on θ as it merely selects elements of s_t. $A(\theta)$ captures the mean of y_t, which is related to the underlying structural parameters.

If y_t is predicted based on its lagged values, then its forecast error covariance matrix is non-singular. Hence, any DSGE model that generates a rank-deficient covariance matrix for y_t is clearly at odds with the data. Our model has seven shocks (not counting the shock $\varepsilon_{E,t}$ to the PPP relationship), and is indeed able to generate a forecast error covariance matrix that is full rank. The larger the dimension of y_t, the more shocks have to be introduced into the model. For instance, Smets and Wouters (2003) include investment, consumption, hours worked, and wages in addition to output, inflation, and interest rates. As a consequence, they use a high-dimensional vector ϵ_t that includes, for instance, shocks to the mark-up of the monopolistically competitive firms, to the shadow value of installed capital, and the disutility of labor.[8] Other authors, referring to Sargent (1989) have added shocks not to the LRE system (31) but rather to the measurement equation (33), avoiding a structural interpretation of these additional sources of uncertainty. These additional error terms are often called measurement errors, a misnomer, as the shocks are designed to capture an obvious form of model misspecification.

Any estimation method for DSGE models has to confront the following two challenges: model misspecification and identification. We will subsequently discuss how the Bayesian approach copes with misspecification and identification problems. Misspecification and identification are closely related. Relaxing DSGE model restrictions by building bigger models might introduce identification problems.

4.1 Misspecification

DSGE models impose potentially invalid cross-coefficient restrictions on the time series representation of y_t. Such a misspecification manifests itself in poor in-sample and pseudo-out-of-sample fit of the DSGE model compared to say, a VAR for y_t that is estimated with well-designed shrinkage methods, e.g., Sims and Zha (1998), or Del Negro and Schorfheide

[8]In fact, Smets and Wouters (2003) used more shocks and variables to overcome some aspects of model misspecification.

(2004). While large-scale models such as the Smets-Wouters model have had some success in closing the gap between model and reality, misspecification is still a concern as documented in Del Negro, Schorfheide, Smets, and Wouters (2004). Compared to other open economy models in the literature, for instance, Adolfson, Laseen, Linde, and Villani (2004), and the Global Economic Model (GEM) developed at the International Monetary Fund (IMF (2004), Laxton and Pesenti (2003), Pesenti (2004)), our two-country model is fairly stylized and potential misspecification has to be taken seriously. The subsequent discussion will ignore misspecifications due to omitted non-linearities and assume that after suitable transformations the law of motion for y_t can be well approximated by a linear moving average representation.

Let $\Gamma(\theta) = \{\Gamma_0(\theta), \Gamma_1(\theta), \Gamma_\epsilon(\theta), \Gamma_\eta(\theta)\}$. To fix ideas, we will represent model misspecification by assuming that s_t evolves according to $\mathcal{M}_0$ given by $\Gamma(\theta_0) + \Gamma^\Delta$. Here Γ^Δ is such that there exists no $\tilde{\theta}$ for which $\Gamma(\tilde{\theta}) = \Gamma(\theta_0) + \Gamma^\Delta$. We refer to the specification generated by $\Gamma(\theta)$ as approximating model $\mathcal{M}_\theta$. We assume for simplicity that the measurement equation is correctly specified and that the "true" model and the approximating model share the same vector of parameters. This representation is fairly general as it encompasses misspecified structural relationships due to incorrect preferences or technologies, as well as misspecification due to omitted or wrongly-specified exogenous processes. The objects of interest are typically (i) the "true" parameter vector θ_0; (ii) a moving average representation of the time series y_t in terms of the structural shocks ϵ_t; and (iii) the effect of changes in θ_0 on the evolution of y_t.

The presence of the misspecification term Γ^Δ complicates econometric inference and decision making. The "true" value θ_0 does not necessarily deliver the approximating model that is most suitable to address questions (ii) and (iii). All formal and informal estimation procedures implicitly use a measure of discrepancy between the "true" law of motion $\mathcal{M}_0$ and the approximating model $\mathcal{M}_\theta$. Not surprisingly, under model misspecification, these different measures of discrepancy tend to deliver different parameter estimates. Likelihood-based methods try to find a value of θ search for values of θ under which the approximating models generates good forecasts of time series generated from $\mathcal{M}_0$. Formally, likelihood-based estimators tend to converge to the $\tilde{\theta}$ that minimizes the Kullback-Leibler discrepancy between $\mathcal{M}_0$ and $\mathcal{M}_\theta$, see for instance, White (1994). Hence, they might give a good approximation of the moving average representation of y_t in terms of the ϵ_t's but, most likely, will not recover θ_0.

One interpretation of the calibration approach advocated by Kydland and Prescott

(1982, 1996) is that there exists ample evidence on θ_0 both through the long-run properties of y_t and from micro econometric studies of household and firm behavior. This evidence translates into calibrated values of θ that are plugged into the DSGE model to address questions (ii) and (iii). In the absence of model misspecification and the presence of abundant out-of-sample evidence[9] on θ_0, likelihood-based estimation methods should generate the same parameter values that calibrators choose, and vice versa, parameter values obtained from a calibration analysis should yield high likelihoods. The experience of two decades of calibration and one decade of estimation has been, unfortunately, that there is neither enough empirical evidence to unambiguously pin down θ_0, nor that parameter values obtained from micro-level studies necessarily lead to large values of likelihood functions.

Bayesian analysis provides a powerful framework for DSGE model estimation and inference that is attractive both at a conceptual level as well as from a practical perspective. Let $Y = \{y_t\}_{t=1}^T$. The likelihood function $\mathcal{L}(\theta|Y)$ is combined with a prior density $p(\theta)$ to form a posterior density $p(\theta|Y)$:

$$p(\theta|Y) \propto \mathcal{L}(\theta|Y)p(\theta), \tag{34}$$

where $\propto$ denotes proportionality. Bayesian procedures do not require the notion of a "true" model and tend to have many desirable statistical properties and allow for coherent inference and decision making under model and parameter uncertainty, discussed in textbooks such as Robert (1994). We want, however, emphasize different aspects of Bayesian inference.

The likelihood function in (34) is re-weighted by the prior density $p(\theta)$ and the prior can bring to bear information that is not contained in the sample Y. Unlike in a maximum likelihood approach that uses some of the extraneous information to fix elements of the parameter vector θ, the prior density allows to weigh information about different parameters according to their reliability. Strong micro econometric evidence about the frequency with which firms change their prices can be captured in a tight prior distribution for the corresponding model parameter, denoted by $p_1(\theta)$. If the likelihood function peaks at a value that is substantially different from the micro-level estimate, then the marginal data density, defined as

$$p_1(Y) = \int \mathcal{L}(\theta|Y)p_1(\theta)d\theta \tag{35}$$

will be substantially lower than the marginal data density computed under an alternative, more diffuse prior $p_2(\theta)$. Marginal data densities can be used to compare different Bayes

[9] By "out-of-sample" evidence here we mean information not contained in the cyclical properties of the time series $\{y_t\}_{t=1}^T$.

models, where a Bayes model consists of a likelihood function and a prior distribution. Illustrating how the marginal data density changes as the prior is modified can highlight tensions between different sources of information. The decision of how much weight to place on different sources of information in the presence of misspecification ultimately depends on the goal of the analysis and the relevant loss function for inference and decision making, a point that has been emphasized in Schorfheide (2000).

Unlike fixing parameters in a maximum likelihood estimation the use of tight yet non-degenerate prior distributions in Bayesian analysis never guarantees a particular posterior distribution. Priors are always subject to revision and the shift from prior to posterior distribution can be another indicator of the tension between the micro-level and time series information.[10]

An alternative to likelihood-based system estimation of the DSGE model is single equation estimation by generalized method of moments (GMM). This approach has been extensively applied to the estimation of consumption Euler equations and more recently in the context of New Keynesian DSGE models to the estimation of price-setting equations and monetary policy rules. These limited information approaches aim to cope with the problem of model misspecification by leaving parts of the system, in particular the law of motion of the exogenous processes, unspecified. By construction, single equation estimates can be more robust to model misspecification and deliver more reliable estimates of particular elements of the vector θ_0. At the same time they tend to ignore a lot of information contained in the cross-coefficient restrictions. Moreover, single equation estimates do not provide an overall measure of time series fit of the DSGE model and hence the reliability of answers to the questions (ii) and (iii) is difficult to assess.

4.2 Identification Issues

In the model outlined in Section 3 it is not possible to separately identify the substitution elasticity for intermediate goods (ω in Footnote 5) and the Calvo parameter θ. This identification problem is well-known as it arises in many New Keynesian models and easily detectable by careful inspection of the linear rational expectation system (31). In our empirical analysis we estimate the Calvo parameters conditional on a substitution elasticity that is fixed at 1/2.

[10] Chang, Gomes, and Schorfheide (2002) illustrate the tension between micro and time series level evidence on learning-by-doing in labor.

Rational expectations models, however, can generate more delicate identification problems that are very difficult to detect in larger systems. Consider the one-equation example

$$y_t = s_t, \quad s_t = \frac{1}{\theta}\mathbb{E}_t[s_{t+1}] + \epsilon_t, \quad \epsilon_t \sim iid(0, \sigma^2). \tag{36}$$

It is straightforward to verify that for $\theta > 1$ the unique (stable) rational expectation solution is $y_t = \epsilon_t$. Hence, it is not possible to point identify the structural parameter. In general, θ is identifiable if no two values of the structural parameter vector lead to the same joint distribution of Y. Unfortunately, the lack of identification in large systems is very difficult to detect since the mapping from θ into the state-space representation (32) and (33) is highly nonlinear and only evaluated numerically.

There is a tension between identification and misspecification in that the more cross-coefficient restrictions in (31) are relaxed and the larger the parameter vector θ, the more difficult it becomes to identify the structural parameters. As the vector of y_t is enlarged and more observations are included in the estimation, the number of identifiable parameters increases but the contamination of the implied law of motion for y_t through the misspecification matrix Γ^Δ above might become more severe again.

A GMM estimation of θ in (36) would be based on the instrumental variable regression

$$y_{t+1} = \theta y_t + \theta\eta_{t+1} + \theta\epsilon_t = \theta y_t + u_{t+1}. \tag{37}$$

Here η_{t+1} captures the rational expectation forecast error for y_{t+1}. The MA(1) structure of u_{t+1} the model suggest to use y_{t-1} as an instrument to estimate θ. According to the *iid* law of motion of y_t the instrumental variable is uncorrelated with the regressor and a properly constructed confidence set would extend over the entire domain $\theta > 1$. While there are econometric methods available that deliver correct answers in the presence of non- or weak identification (see, for instance, Wright (2003) for a test for identification and Stock, Wright and Yogo (2002) for a survey), their application in macroeconomics is rare and researchers typically only report fragile point estimates with large standard errors.

If the model (36) is actually solved, then one obtains a likelihood function that does not depend on θ. In larger systems this lack of identification would imply that the likelihood function is flat in certain directions of the parameter space. A numerical maximization of such a likelihood function is difficult and a characterization of the set of θ's for which the likelihood function attains its maximum, let alone a valid confidence set, pose a computational challenge (though they are conceptually well defined).

While Bayesian analysis and maximum likelihood estimation are based on the same likelihood function, proper priors can introduce curvature into the objective function that facilitates maximization and the use of Markov Chain Monte Carlo methods to generate draws from the posterior distribution. Suppose that $\theta = [\theta_1', \theta_2']'$ and the likelihood function only depends on θ_1: $\mathcal{L}(\theta|Y) = \bar{\mathcal{L}}(\theta_1|Y)$. Straightforward manipulations with Bayes Theorem lead to

$$p(\theta|Y) = p(\theta_1|Y)p(\theta_2|\theta_1). \tag{38}$$

Thus, there is updating of the marginal distribution of θ_1, but not of the conditional distribution of $\theta_2|\theta_1$.[11] Nevertheless, the posterior distribution is well defined as long as the joint prior distribution of θ integrates to one. In our empirical analysis, we are using priors in which the elements of θ are independent. In the context of the simple example $p(\theta_2|Y) = p(\theta_2)$ if the two parameters are independent. Hence, a comparison of priors and posteriors can provide insights about the extent to which the data provide information about the parameters of interest.

5 Data and Priors

5.1 Construction of a Two-Country Dataset

We interpret our theoretical two-country model as representing the economies of the United States and the Euro Area, that is, those member countries of the European Union which share a common currency. As our focus in this paper is on the U.S. economy, the second country in the model should reflect the major trade and policy influences that affect outcomes in the U.S. Ideally, this would be the entire rest of the world. We decided not to go in that direction because of data considerations. A more important issue, however, is the interpretation of the second country in the model as a unified economic area. This criterion is clearly fulfilled by the Euro Area. Even before European Monetary Union, monetary policy in Europe was guided by the Deutsche Bundesbank within a system of fixed exchange rates. Although adding other major trading partners of the U.S., such as Canada or Japan, to our dataset would more closely reflect the real links in the model, the interpretability of the foreign country's monetary policy would be called into question.[12]

[11] This is well-known in Bayesian econometrics, see Poirier (1993) for a discussion, and has been exploited in Lubik and Schorfheide (2004) when estimating DSGE models with potential indeterminacies.

[12] We also constructed a dataset for the G10 economies. Further details and estimation results are available from the authors upon request.

Data for the U.S. were extracted from the FRED 2 database maintained at the Federal Reserve Bank of St. Louis. We utilize data at quarterly frequencies. Monthly series were converted into quarterly series by arithmetic averaging. We use the series Consumer Price Index For All Urban Consumers: All Items ($CPIAUCSL$, monthly) to construct the inflation measure in our model, defined as $400 * ln(CPI_t/CPI_{t-1})$. The Effective Federal Funds Rate ($FEDFUNDS$, monthly) is used as our monetary policy variable, while Real Gross Domestic Product and Total Population are used to define output growth rates as $100 * ln(GDPC96_t * POP_{t-1}/GDPC96_{t-1} * POP_t)$.

Euro data were extracted from the database underlying the Area Wide Model (AWM) of the European Central Bank, which is described in detail Fagan, Henry, and Mestre (2001). The Short Term Nominal Interest Rate (STN) is used as monetary policy variable, while inflation is defined as $400*ln(HICP_t/HICP_{t-1})$, using the Consumer Price Index ($HICP$). In addition to real GDP (YER), we are using a Euro Area population series provided by Raf Wouters. Output growth rates are then defined as $100*ln(YER_t*POP_{t-1}/YER_{t-1}*POP_t)$.

We constructed bilateral exchange rates between the U.S. Dollar and the Euro. They are based on data from the International Financial Statistics database maintained by the IMF. Starting in 1999 we use the reciprocal of the series IFS_EU_NCUUSD, denoted by $USDEUR$. Prior to 1999 we extract national currency to U.S. Dollar exchange rates and take reciprocals to obtain Dollar per unit of national currency. We calculate a fixed-weight average of these rates, using the weights that underlie the construction of the synthetic Euro Area data in the AWM database.[13] We denote this synthetic series by $FXWGTD$. In order to match the levels of the $USDEUR$ and the $FXWGTD$ series we conduct the following transformation:

$$FXWGTD_* = FXWGTD * \frac{E\bar{E}N_{98}}{FXW\bar{G}TD_{98}} * \frac{EUR\bar{U}SD_{99}}{E\bar{E}N_{99}},$$

where EEN is an effective Euro exchange rate from the AWM database and $\bar{X}_{yy}$ denotes a sample average in year yy. To estimate the model, we are using depreciation rates, calculated as $100 * \ln(USDEUR_t/USDEUR_{t-1})$. For the presample analysis to determine some of the priors we compute import shares, which we define as $IMP/(GDP - EXP + IM)$. We are using EXPGSC96 and IMPGSC96 extracted from FRED 2 for the U.S. and MTR and XTR from the AWM database for the Euro Area.

[13] These weights are: BE=0.036; DE=0.283; ES=0.111; FR=0.201; IE=0.015; IT=0.195; LU=0.003; NL=0.060; AT=0.030; PT=0.024; FI=0.017; GR=0.025.

5.2 Presample Analysis and Prior Distributions

The choice of priors in Bayesian estimation is guided by several considerations. At a basic level, priors reflect a researcher's inherent beliefs about, and confidence in the likely location of the structural parameters. Priors can be gleaned from personal introspection to reflect strongly held beliefs about the validity of economic theories. They can also be derived from previous studies, or may sometimes be chosen for expediency in estimation. Priors can also be used to introduce information that is available outside the modelling framework. One example is to choose priors for specific parameters, typically those describing exogenous shocks, based on a pre-sample. Finally, the choice of a prior distribution has to reflect restrictions on the parameters such as non-negativity or interval restrictions. It is convenient to pick a beta-distribution for parameters that are constrained on the unit interval, while a gamma-distribution may be chosen for parameters in $\mathbb{R}^+$. Inverse gamma-distributions are typically chosen for variances. The marginal prior distributions for the parameters of the NOEM model are summarized in Tables 1 and 5. We assume all parameters to be *a priori* independent.

To choose prior distributions we are calculating some simple statistics based on presamples: 1970:I to 1982:IV for the estimation sample 1983:I to 2002:IV; 1970:I to 1987:II for the estimation sample 1987:III to 2002:IV. For both the US and the Euro Area we are using inflation rates, import shares, and ex post real interest rate to estimate AR(1) models of the form

$$x_t = \mu(1-\rho) + \rho x_{t-1} + u_t.$$

OLS estimates of μ are used to guide the choice of prior means for the steady state real interest r, the import share parameter α, and steady state inflation rates π, and π^*. We also estimate a system of the form

$$\begin{aligned}
\Delta\widetilde{y}_t &= \gamma + \Delta\widetilde{A}_t + z_t, \\
\Delta\widetilde{y}^*_t &= \gamma + \Delta\widetilde{A}^*_t + z_t, \\
\widetilde{A}_t &= \rho_A \widetilde{A}_{t-1} + \epsilon_{A,t}, \quad \widetilde{A}^*_t = \rho_{A^*}\widetilde{A}^*_{t-1} + \epsilon_{A^*,t}, \quad \widetilde{z}_t = \rho_z \widetilde{z}_{t-1} + \epsilon_{z,t},
\end{aligned}$$

using Bayesian methods with fairly diffuse prior distributions. The estimate of γ is used to set the prior mean for γ in the analysis of the DSGE model. We use the estimates of ρ_z and $\sigma(\epsilon_{z,t})$ to set prior means for the corresponding parameters in the DSGE model. The processes $\widetilde{A}_t$ and $\widetilde{A}^*_t$ are not directly comparable to the region specific technology processes in the DSGE model. Nevertheless, we use the estimates to guide the choice of prior for the remaining exogenous processes in the DSGE model. In order to choose a prior for the standard deviation of the monetary policy shock we estimate the following regression by OLS (for the U.S. and the Euro Area):

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 \Delta Y_{t-1} + \epsilon_{R,t}.$$

The priors for the price stickiness parameters θ are chosen based on evidence on the average frequency of price changes. Following Bils and Klenow (2004) an average 26% of U.S. sectoral prices are changed every 3.3 months which translates into a Calvo-adjustment parameter of $\theta_H = 0.5$. Stickiness of import prices is set at the same level. For Euro-area data we use information reported by Angeloni et al. (2004) to set the prior mean at 0.75. Mean and variance of the habit parameter h are based on prior estimates available in the literature, as is the intertemporal substitution elasticity τ. The prior mean for the intratemporal substitution elasticity η is set at 1 with a large standard deviation to account for uncertainty about its location. The priors for the coefficients in the monetary policy rule are centered around values typically associated with the Taylor rule, but we allow for fairly large standard deviations. We allow for the possibility of a small policy response to exchange rate movements in both countries following Lubik and Schorfheide (2003). As a final point, it is well known that linear rational expectations models can have multiple equilibria. While this may be an issue of independent interest (see Lubik and Schorfheide, 2004), we do not pursue this direction in this paper. The prior distribution for the model is therefore truncated at the boundary of the determinacy region.

6 Empirical Analysis

The empirical analysis has three parts. We begin by estimating the two country model developed in Section 3 under a benchmark prior distribution. We then document the sensitivity of the parameter estimates to changes in prior distribution and model specification. The second part studies the dynamics of the estimated NOEM model through impulse response functions. We assess the estimates of the transmission of monetary policy shocks under various prior distributions. Finally we are examining the estimated exchange rate dynamics and the relative importance of the various structural shocks for exchange rate fluctuations.

6.1 Estimation

Markov Chain Monte Carlo Methods described in Appendix B are used to generate draws from the posterior distribution of the model parameters. Based on these draws we compute the summary statistics (posterior means and 90% probability intervals) reported in Tables 2 to 8. The results in Sections 6.2 and 6.3 are obtained by converting the parameter draws into impulse response functions and variance decompositions. Unless otherwise noted the estimation period is 1983:I to 2002:IV.

6.1.1 Estimation of Closed Economy Models

If agents do not value goods produced abroad ($\alpha = 0$) and the exchange of financial assets across country borders is prohibited, our model reduces to the familiar New Keynesian closed economy (CE) DSGE model. Although Bayesian estimates for the CE version have been reported elsewhere in the literature, we re-estimate CE models based on our particular model specification and data set.[14] The estimates for the U.S. and the Euro Area are summarized in Tables 2 and 3, respectively. The posteriors are based on the prior distributions reported in Table 1. For convenience, we reproduce the prior mean and confidence intervals in Tables 2 and 3. Three versions of the CE model are considered. The benchmark specification, a version without stationary technology shocks A_t and A_t^*, and a version that is estimated on demeaned data.

The estimates of the degree of nominal rigidities are fairly stable across specifications: the posterior means of θ range from 0.74 to 0.78. The variation of the point estimates is relatively small compared to the overall uncertainty captured by the probability intervals. There seems to be little information about the preference parameters τ and η in the data as the likelihood function leaves the prior distributions for these parameters virtually unchanged.

The point estimates of the policy parameters are sensitive to the auxiliary assumptions. The estimated coefficient on inflation, ψ_1, increases as we move from the benchmark version

[14] There are typically subtle differences in model specification that makes a direct comparison of estimates difficult. Rabanal and Rubio-Ramirez (2003, 2004) estimate the New Keynesian benchmark model with U.S. and the Euro Area data, respectively. However, they use a stationary version of the model and work with HP-filtered output data. Lubik and Schorfheide (2004) also use HP-filtered output and transform the exogenous technology and government spending processes into a pure shift of the Euler equation and a pure shift of the price setting equations with correlated innovations. Schorfheide (2005) uses output growth data and non-transformed structural shocks estimates the model over longer sample period, ranging from 1960:I to 1997:IV.

of the model to the specification without stationary technology shock estimated with demeaned data. Vice versa, the coefficient on output, ψ_2, decreases. The exogenous processes are fairly persistent, slightly more so when the stationary technology shock is dropped.

The parameter $r^{(A)}$ enters the system through the measurement equation as average real rate, and the dynamics as discount factor $\beta = \exp[r^{(A)}/400]$. If the model is estimated on demeaned data the information in the long-run average of the observed ex-post real rate is removed and the prior of $r^{(A)}$ is essentially not revised, indicating that output growth, inflation, and interest rate dynamics provide little information about this parameter.

The Euro Area estimates are by and large similar to the U.S. estimates. There is a substantial overlap of the confidence sets of the confidence sets of τ, h, γ, and $r^{(A)}$ providing support for the symmetry assumption built into the two-country model. The estimated nominal rigidity for the Euro Area is slightly higher than for the U.S., possibly a reflection of the prior distribution that, based on micro-evidence, assigns slightly more mass to large values of θ.

For the Euro Area the estimate of ψ_2 is more sensitive to auxiliary assumptions due to the particular specification of the monetary policy rule. The central bank reacts to deviations of output from the stochastic trend generated by the non-stationary technology process. The presence of the stationary technology shock A_t^* affects the estimate of the stochastic trend and therefore potentially the estimate of the policy parameters ψ_1 and ψ_2. In the closed economy version of the model there is little scope for trying to distinguish between permanent and transitory shocks to technology. Since neither consumption nor investment data are included in the estimation, the sample does not contain co-trending information that could help to identify permanent technology shifts.

6.1.2 Open versus Closed Economy

Table 4 compares the closed economy estimates to those obtained from the two-country model. The numbers reported in the columns "U.S." and "Euro Area" correspond to the ones labelled "Benchmark" in Tables 2 and 3. The estimated price stickiness in the U.S. drops to 0.47 from 0.78 in the closed economy model, while the corresponding parameter for the Euro Area, θ_F^* remains high. Estimates of the risk aversion parameter τ and the habit persistence h rise to 3.4 and 0.5, respectively. The prior distribution for the import share parameter α is not updated. The estimated substitution elasticity between home and foreign goods, η, is 0.4.

While the estimates of the Euro Area policy parameters obtained from the NOEM model are similar to their closed economy counterparts, the U.S. estimates are markedly different: $\hat{\psi}_1$ rises from 1.7 to 1.93 and $\hat{\psi}_2$ drops from 0.56 to nearly zero. The model implicitly constructs a non-stationary technology process for the U.S. and the Euro Area based on co-movements of output. This process looks different from the ones extracted with the closed economy models and causes a drastic change in $\hat{\psi}_2$. As an alternative to the current specification we also estimated a version of the model in which potential output is defined as the level of output in the world-wide absence of nominal rigidities. However, we found that this specification fits worse in terms of marginal likelihood than our benchmark specification.[15] We included the depreciation rate as an argument into the policy rule but found that the corresponding coefficient estimates for the U.S. and the Euro Area are nearly zero. This finding complements the empirical results reported in Lubik and Schorfheide (2003), who find no evidence of exchange rate responses for a variety of small open economies. In most of the subsequent analysis we fix $\psi_3 = \psi_3^* = 0$.

Finally, our estimated standard deviation of the PPP shock is large. Since the importance of shocks cannot directly be assessed from the magnitude of the associated standard deviation due to normalization issues, we defer the discussion of the PPP shock to Section 6.3, which studies variance decompositions of exchange rate fluctuations.

6.1.3 Estimation under Diffuse Priors

The two-country model is now re-estimated under two alternative prior distribution. The first prior, labelled as "Diffuse Prior (I)" in Table 5, replaces the Beta-priors for the Calvo parameters by uniform distributions. Moreover, we make the priors for the autocorrelations of the exogenous processes less informative by changing them to uniform distributions as well. The estimation results are reported in Table 6. While the estimates of the autocorrelation parameters are not affected by the modification of the prior distribution, the Calvo parameter posteriors shift. Most notably, $\hat{\theta}_H$ falls from 0.47 to 0.31, $\hat{\theta}_F$ rises from 0.66 to 0.87, and $\hat{\theta}_H^*$ drops from 0.43 to 0.12. A comparison of marginal likelihoods indicates that the data favor the diffuse prior. It is important to note that the marginal data density penalizes the likelihood fit by a measure of model complexity. Making a prior distribution more diffuse is equivalent to the removal of restrictions on parameters and increases the

[15] We are still planning to estimate versions of the models with a interest-rate feedback rules that respond to output growth. Its estimates are potentially more robust since the output regressor is fully observable, instead of being a latent variable that might absorb some of the model misspecification.

model complexity (approximately measured by the log determinant of the posterior covariance matrix of the parameters). Hence, making a prior more diffuse does not necessarily increase the marginal data density.[16]

The "Diffuse Prior (II)" relaxes some of the restrictions that we placed on the preference parameters. Most notably, the estimated habit persistence is now close to one, meaning that utility is defined in terms of output growth rather than the level of output. The change of prior also affects the posterior estimates of the policy parameters for the Euro Area. In particular, ψ_1^* rises from about 1 to 1.5. The increased habit persistence also lowers the autocorrelation of A^*. The marginal data density improves from -870.05 to -850.63, indicating that the benchmark prior restricts the parameter estimates from moving into an area of the parameter space that yields a higher likelihood. If one is willing to interpret the benchmark prior as driven by micro-evidence, then there seems to be some tension here. Trying to keep the estimates close to a priori plausible values leads to a deterioration of marginal likelihood.

6.1.4 PPP versus UIP Shocks

Our benchmark specification includes an shock appended to the definitional equation for the exchange rate. We interpret this disturbance as capturing exogenous deviations from PPP on top of model-implied endogenous deviations via imperfect passthrough. This PPP-shock does not have a structural interpretation within the economic framework. Adding this shock, however, improves the fit of the model since it allows the exchange rate equation to not hold perfectly. We use this insight later on to quantify the contributions of our model in explaining exchange rate dynamics. In order to gauge the importance of this shock we re-estimate the benchmark version of the model with a tight prior on σ_E. Results are reported in Table 7. Estimates of the structural parameter are virtually unchanged. More interestingly, the posterior shifts back to a large value of σ_E. This suggests substantial deviations from PPP that are captured by variations in the exogenous shocks, while the cross-equation restrictions implied by the model are unaffected by the exact specification of the exchange rate equation. The overall fit of the model decreases substantially, however, as evidenced by the deterioration of the marginal likelihood. The estimation procedure thus penalizes the specification of the PPP-shock for its tightness.

[16] In fact, given set of observations, we can always construct a more diffuse prior distribution that lowers the marginal data density, a phenomenon referred to as "Lindley's Paradox."

An alternative specification assumes an additive shock in the UIP-equation (26). This disturbance is similarly designed to capture deviations from UIP such as time-varying risk premia. For instance, Bergin (2004) in a related two-country framework shows that this shock explains more than 60% of current account dynamics. We next assess the results from the model with the UIP-shock instead of the PPP-shock, allowing for a wide prior. Overall, this version of the model does not fit well compared to the benchmark (see Table 7). There are also some notable differences with respect to parameter estimates.The import share α increases from 0.13 in the benchmark to 0.48. The relative sizes of the Calvo parameters in the Euro Area are flipped around, implying much more price rigidity in the import sector. Output coefficients in both economies policy rule change, ψ_2^* declines to almost zero, while the U.S. coefficient increases somewhat. The UIP-specification also implies higher volatility of country-specific technology shocks, but lower purchases shocks. Similar to the PPP-specification the variance of this non-structural disturbance is an order of magnitude larger.

In comparison to the benchmark specification, the version with UIP-shocks allows interest-rate differentials and expected depreciation not to line up exactly. This leaves more latitude for different cross-equation restriction to hold, which may result in alternative parameter estimates. This raises concerns about structural identification in the model, and may also be the reason behind the differences with Bergin (2004). Since both types of shocks are a priori similarly plausible, we maintain the PPP-shock specification throughout the rest of the paper due to its superior fit.

6.1.5 Estimation Based on Short Sample

Lastly, we estimate the model over a sub-sample period to detect possible evidence of parameter instability. We restrict our analysis to the period from 1987:3 - 2002:4 which coincides with Alan Greenspan's tenure as Chairman of the Federal Reserve Board. Estimation results are shown in Table 8. As a reference point we first report on the closed economy estimates. The results for the U.S. do not differ substantially. Output and inflation coefficients in the policy rule decrease slightly. This can be explained by the inclusion of the strongly dis-inflationary policy under Paul Volcker in the early years of the full sample. The results for the Euro Area are more striking. There is a slight decrease in price rigidity in the short sample, and a doubling of the habit coefficient from 0.27 to 0.57. The strongest contrast, however, is in the policy rule, where the output coefficient drops to almost zero, whereas ψ_1^* increase to almost two.

These differences are not as pronounced when we compare the estimates for the full two-country model. Preference and technology parameters are broadly similar with the exception of an increase in price stickiness (which stands in contrast to the closed economy results). As in the closed economy, U.S. monetary policy becomes more accommodating in the short sample, while Euro Area becomes more aggressive. Finally, the posterior mean of the correlation between policy shocks is now reasonably large negative, albeit with a wide confidence interval. This could support the notion of a change in policy coordination following the Plaza and Louvre Accords to stem the appreciation of the Dollar. It would certainly be worthwhile to investigate these issue further and more formally, by explicitly incorporating regime switching in the full sample estimation.

6.2 Impulse Response Analysis

We can develop some initial understanding of the inherent dynamics and the relative importance of different shocks by computing impulse response functions. The responses of endogenous variables of interest to one-standard deviations structural shocks are reported in Figure 1. We first discuss results for the benchmark model. We then compare the effects of different priors for selected variables and shocks.

The effects of monetary policy shocks are as expected (first and second row of the panel). Inflation and output decline in response to domestic contractionary policy. The inflation response in the U.S. is stronger than in the Euro Area on account of a higher policy coefficient. Interest rate shocks sharply appreciate the currency as depicted in last column, but the effect quickly dissipates within a few periods. A monetary contraction in the U.S. leads to a rise in European output and inflation to which the monetary authority responds endogenously with an interest rate hike. The transmission of European monetary shocks to the U.S. is weaker and estimated with less precision. The main transmission mechanism of shocks between countries in this model are relative price movements that are consistent with perfect risk sharing. Since the exchange rate response is weaker to Euro Area shocks the terms of trade do not move as much, which reduces the strength of the relative price effect.

U.S. technology shocks are expansionary at home, lower prices and the interest rate, thereby depreciating the Dollar. European technology shocks, on the other hand lead to a fall in output. This somewhat puzzling effect is explained by the strong response to output in the monetary rule. As inflation falls and the expansionary effects of increased productivity take hold, the implied output increase is countermanded by the desire of the monetary authority to stabilize output movements. The interest rate therefore falls by less than it otherwise would and prevents an expansion of output. Appreciation of the Euro exchange rate is therefore driven by a real appreciation on account of the decline in production. Similarly, U.S. technology shocks are transmitted negatively abroad on account of an adverse exchange rate response and the shift of productive activity to the U.S. due to risk-sharing. In a perfectly symmetric model, world-wide productivity shocks would not have any effects on relative prices. In our framework, however, (see the seventh row of the panel) they imply a Dollar appreciation. Since the Euro interest rate does not respond, the positive differential in favor of the U.S. requires an expected depreciation; the dollar therefore falls on impact.

The effects of government purchases are broadly similar in both economies. Output expands, inflation declines, the currency appreciates. Transmission from the U.S. to the Euro Area is positive, while transmission in the other direction is negative. We also report impulse responses to the non-structural PPP-shock. A positive innovation increases the depreciation rate, but dies out after one period since we assumed it to be i.i.d. The PPP-shock is contractionary in the U.S., but expansionary in Europe. The mechanism behind this appears to be the endogenous interest rate response in both countries to exchange rate movements in the benchmark specification. Pure exchange rate shocks can therefore have domestic effects via an endogenous policy response.[17]. This also points toward potential problems with adding measurement errors to structural equations. In our framework, the non-structural PPP-shock appears in isolation from the rest of the model. It is purely designed to capture that part of restriction on endogenous variables that is not explained within the modelling framework. It does not have any meaningful economic interpretation.

The NOEM provides a plausible and consistent framework for the analysis of the effects of monetary policy in the international economy. In order to analyze the mechanism involved in more detail, we trace the effects of variations in the prior distributions. We concentrate on the dynamic effects of monetary policy shocks and on the behavior of exchange rates under various disturbances. Figure 2 contrasts impulse response functions to monetary innovations for the benchmark prior with the two diffuse priors. Diffuse prior (I) relaxes the Calvo parameters and shock correlations, whereas diffuse prior (II) relaxes restrictions on preferences. The main difference that emerges is that both diffuse priors affect the response of U.S. output to monetary shocks. In the benchmark specification, U.S. interest

[17] This issue has been highlighted by Lubik and Schorfheide (2003) in the context of small open economies.

rate surprises are contractionary domestically.

Figure 3 looks at the behavior of the exchange rate under the three priors in response to the model's shocks. The differences in terms of impact and adjustment dynamics are minor. This suggests that exchange rate movements are not sensitive to variations in the parameters in question. In the end, exchange rates are determined by inflation differentials and real exchange rate movements to the extent that variations in the Calvo parameters or the preference parameters are not large enough across prior specification to have an impact. The impulse response also show clearly that contractionary monetary policy shocks lead to a currency appreciation on impact, followed by an expected depreciation as mandated by UIP. Similarly, government purchases reduce the exchange on account of a real appreciation. Technology shocks, on the other hand imply a strong supply response so that the Dollar depreciates. Since transmission of shocks from the Euro Area to the U.S. is stronger than in the other direction, country-specific shocks imply a depreciation no matter their source. Finally, shocks to the common trend appreciate the Dollar, dramatically so in the case of the second diffuse prior. World-wide shocks lead to a positive interest differential in favor of the U.S. after which the logic behind UIP bites.

6.3 What Determines Exchange Rate Dynamics?

Our estimation methodology allows us to decompose exchange rate volatility into individual components explained by the disturbances in the model. The model is driven by seven structural shocks (monetary policy, technology, and government purchases) to which we add an additional disturbance in form of an error term appended to UIP-equation or to the equation defining the nominal depreciation rate. Both types of disturbances are no strictly structural since they are not contained in the model's primitives. The UIP-shock could be interpreted as a risk-premium (Bergin, 2004), while the PPP-shock captures deviations from PPP not already explained endogenously through imperfect passthrough. Both interpretations lack economic content, however, since they are not tied to behavior by the agents in the model.[18] Nevertheless, it is often instructive to add disturbances of this type as they provide a measure to what extent the data are explained by specific features of the model.

[18] A similar criticism applies to the common practice of adding 'demand' shocks to the Euler-equation and 'supply' shocks to the Phillips-curve in New Keynesian models. While both types of disturbances can be modelled a priori, as we do with government expenditure shocks, they do impose cross-equation restrictions on the model's reduced form that are likely to differ from the ex post specification. This issue is discussed in Lubik and Schorfheide (2004).

In a purely econometric sense, introducing these shocks allows a better fit of individual equations since they do not appear anywhere else in the model and do not have to obey any cross-equation restrictions. Without these shocks, the estimation procedure attempts to fit the model's unobservables according to a tightly restricted equation such as the definition of the depreciation rate, which may result in implausible estimates.

We report variance decompositions for the depreciation rate in Table 9. As discussed above, model fit under UIP-shocks is considerably worse than with PPP-shocks. We therefore only present results obtained for the latter. In our benchmark estimation, PPP-shocks explain 82% of the variability of the depreciation rate. This result had already been hinted at by the estimated variance of the PPP-shock which is an order of magnitude larger than those of other disturbances. The second largest component are Euro Area technology shocks, followed by Euro Area government purchases. Monetary policy shocks, perhaps surprisingly, do not have any significant influence at all. The same conclusion emerges from the estimation under diffuse prior (I) which imposes no prior information on the stickiness parameters and the autoregressive coefficients of the structural shocks.

The results change somewhat when we impose the diffuse prior (II), which imposes very weak restrictions on the preference parameters. Recall that this specification also resulted in the best fit. The fraction of exchange rate movements explained by the PPP shock now drops to 78%, while the non-stationary technology shock explains 10% at the expense of the Euro Area shock. The model's dynamics in this case are to a greater extent explained by endogenous forces, mainly habit persistence. Despite symmetry in preferences, world-wide shocks can have an impact on exchange rates because of differential inflation dynamics and monetary policy responses. The substantial role of European government shocks in driving exchange rates is due to their strong effect on European output, which in turn influences the terms of trade.

These relationships are further explored in Figure 4, which depict various exchange rate series. In the upper panel we contrast the depreciation rate in the data with that implied by the model, that is $\Delta\widetilde{e}_t = \widetilde{\pi}_t - \widetilde{\pi}^*_t + \widetilde{s}_t - \widetilde{s}_{t-1}$. The model-implied exchange rate is extracted by using the Kalman smoother. Consequently, the difference between the two series is made up by the exogenous PPP-shock. Visual inspection reveals a reasonably volatile model-implied exchange rate that mostly tracks the turning points in the actual exchange rate. The bottom panel depicts the implied real exchange rate series $\Delta\widetilde{s}_t = \widetilde{s}_t - \widetilde{s}_{t-1}$ which follows closely the nominal series. This is, of course, the well-known observation by Mussa (1985) that nominal and real exchange rates are highly correlated and that they exhibit the same volatility even under floating exchange rates. The flip side of this observation is that inflation differentials do not matter for exchange rate determination. The middle panel shows the model-implied l.o.p. gaps. The Euro Area gap is much smoother and less volatility than the U.S. series, which suggests a higher degree of passthrough into European price levels. L.o.p. gaps also affect terms of trade movements. This suggests that the implied U.S. terms of trade are more volatile than the Euro Area's.

Overall, our results lend support to the notion that exchange rate dynamics are largely driven by real shocks, at least as far the endogenous component are concerned. Our model can thus explain 20% of the movements in the depreciation rate. This result is not immediately comparable to other contributions in the literature mainly because of different methodologies applied. Calibration studies typically only study one shock at a time and attempt to match a small set of statistics with large degrees of freedom in setting parameters. Methodologically comparable results can be found in Bergin (2004). He reports that monetary policy shocks contribute between 50% and 70% to exchange rate movements at longer horizons. His approach differs from ours in various ways, however, the most problematic is the use of UIP shocks that are correlated with the structural shocks in the model. He shows that different orthogonalization schemes change variance decompositions considerably. It is therefore not a priori clear whether the influence attributed to monetary policy shocks is the artefact of an orthogonalization scheme. Using long-run identification restrictions in a VAR framework Ahmed et al. (1993) do not find support for a role of monetary policy shocks in exchange rate dynamics. Our results do point in the same direction on account of the theoretical long-run restrictions imposed by the common productivity trend.

7 Conclusion

This paper has developed and estimated a two-country NOEM model using a Bayesian approach. We provide estimates for various prior distributions and document the extent to which inference is robust and sensitive to the choice of priors. One of the more interesting results to emerge from our analysis is that exchange rate dynamics are determined largely by real factors. Although we are able to explain only a fraction of exchange rate volatility within the model, we regard this as a useful starting point and a benchmark for future research.

The model can be easily extended to an incomplete market setting which could be used to additionally study current account dynamics. Although construction of a bilateral current account data set is not straightforward, the same procedure that we used in constructing the exchange series could be employed. Adding another data series requires the introduction of another disturbance. A likely candidate is a shock to the UIP relationship. Our benchmark estimates rejected that specification in favor of a PPP-shock, but the former may contain information that helps explain current account dynamics as in Bergin (2004). Real exchange rate dynamics in our model exclusively depend on movements in relative prices of traded goods. However, movements in non-traded goods prices are an important component of real exchange rates (see Betts and Kehoe, 2004). The model can be extended to include a non-traded sector that is also subject to nominal rigidities. It is our presumption that this would help improve the overall fit of the model and help explain exchange rate movements endogenously.

It is also plausible to assume that the host of puzzles in international finance cannot satisfactorily be explained by models with fully-rational agents. Attempts to integrate deviations from this benchmark have been made by Duarte and Stockman (2001) and, albeit in a less structural framework, by Gourinchas and Tornell (2004). Moreover, likelihood-based techniques for solving and estimating structural models under deviations from rational expectations. Important steps in this direction has been made by Milani (2005) in a closed economy setting.

The paper also takes great care in implementing Bayesian estimation procedures. These combine information from the likelihood function with prior distributions. The likelihood function moves parameter estimates toward values that deliver good time series fit of the model. The prior distribution can bring to bear additional information that is not contained in the estimation sample. In particular, it can be used to down weigh the likelihood function in regions of the parameter space that are at odds with information contained in other data sets. Both aspects are important and useful, for academic research as well as the use of these models in policy making.

Any procedure that attempts to estimate DSGE model has to face identification and misspecification issues. We have only touched upon these issues by conducting a series of robustness checks. There are more extensive methods available to adjust inference, forecasts, and policy analysis for model misspecification, by evaluating and comparing DSGE models through a reference model (Schorfheide, 2000), or by relaxing the DSGE model restrictions as in Del Negro and Schorfheide (2004, 2005). There is a lot of current research devoted to extending DSGE model specification to improve fit; for instance, Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2003) for the closed economy, Adolfsen, Laseen, Linde, and Villani (2004) for a small open economy. Enriching the model structure may introduce non-identifiabilities, which is where a Bayesian approach can unfold its power: Priors can bring to bear additional information to sharpen inference. We used a log-linear approximation of our two-country and the omission of important non-linearities could potentially be another form of misspecification. Fernandez-Villaverde and Rubio-Ramirez (2002) have made significant progress toward algorithms that enable the likelihood-based estimation of DSGE models solved with nonlinear methods.

A final challenge for researchers is how to communicate the fruits of their labor to a wider public, in particular policymakers. We argue that a Bayesian approach is supremely useful for this. Researchers can report to what extent information comes from the likelihood function, and to what extent it derives from the prior. This leaves it up to the policymaker to decide what value to place on the information conveyed. Finally, implementation has become much easier and more transparent due to available software. We provide GAUSS programs, and the analysis in this paper can be conducted with the user-friendly DYNARE package.

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A The Linearized Equation System

1. Domestic firms' price setting:

$$\widetilde{\pi}_{H,t} = \beta E_t \widetilde{\pi}_{H,t+1} + \kappa_H \left[-\widetilde{\lambda}_t - \alpha \widetilde{q}_t - \widetilde{A}_t \right].$$

2. Domestic habits:

$$(1-h)\,\widetilde{\mathcal{C}}_t = \widetilde{c}_t - h\widetilde{c}_{t-1} + h\widetilde{z}_t.$$

3. Marginal utility of consumption:

$$-\widetilde{\lambda}_t = \frac{\tau}{1-h\beta}\widetilde{\mathcal{C}}_t - \frac{h\beta}{1-h\beta}E_t[\tau\widetilde{C}_{t+1} + \widetilde{z}_{t+1}]$$

4. Domestic importers' price setting:

$$\widetilde{\pi}_{F,t} = \beta E_t \widetilde{\pi}_{F,t+1} + \kappa_F \widetilde{\psi}_{F,t}.$$

5. Definition of CPI:

$$\widetilde{\pi}_t = \alpha \widetilde{\pi}_{F,t} + (1-\alpha)\widetilde{\pi}_{H,t}.$$

6. Terms of trade dynamics:

$$\widetilde{q}_t = \widetilde{q}_{t-1} + \widetilde{\pi}_{H,t} - \widetilde{\pi}_{F,t}.$$

7. Real exchange rate dynamics:

$$\widetilde{s}_t = \widetilde{\psi}_{F,t} - (1-\alpha)\widetilde{q}_t - \alpha \widetilde{q}^*_t.$$

8. Nominal depreciation rate:

$$\Delta\widetilde{e}_t = \widetilde{\pi}_t - \widetilde{\pi}^*_t + \widetilde{s}_t - \widetilde{s}_{t-1}.$$

9. Home goods market clearing:

$$\widetilde{y}_{H,t} = \widetilde{c}_t - \widetilde{g}_t - \frac{\alpha}{\tau}\widetilde{s}_t - \alpha(1-\alpha)\eta\left(\widetilde{q}_t - \widetilde{q}^*_t\right).$$

10. Risk-sharing condition:

$$\widetilde{\lambda}_t = \widetilde{\lambda}^*_t - s_t$$

11. Monetary policy rule:

$$\widetilde{R}_t = \rho_R \widetilde{R}_{t-1} + (1-\rho_R)\left[\psi_1 \widetilde{\pi}_t + \psi_2 \widetilde{y}_t + \psi_3 \Delta\widetilde{e}_t\right] + \varepsilon_{R,t},$$

12. UIP-equation:

$$\widetilde{R}_t - \widetilde{R}_t^* = E_t\widetilde{\pi}_{t+1} - E_t\widetilde{\pi}_{t+1}^* + E_t\widetilde{s}_{t+1} - \widetilde{s}_t.$$

13. Foreign firms' price setting:

$$\widetilde{\pi}_{F,t}^* = \beta E_t\widetilde{\pi}_{F,t+1}^* + \kappa_F^*\left[-\widetilde{\lambda}_t^* - \widetilde{q}_t^* - \widetilde{A}_t^*\right].$$

14. Foreign habits:

$$(1-h)\,\widetilde{C}_t^* = \widetilde{c}_t^* - h\widetilde{c}_{t-1}^* + h\widetilde{z}_t.$$

15. Foreign importers' price setting:

$$\widetilde{\pi}_{H,t}^* = \beta E_t\widetilde{\pi}_{H,t+1}^* + \kappa_H^*\widetilde{\psi}_{H,t}^*.$$

16. Definition of CPI:

$$\widetilde{\pi}_t^* = \alpha\widetilde{\pi}_{H,t}^* + (1-\alpha)\widetilde{\pi}_{F,t}^*.$$

17. Terms of trade dynamics:

$$\widetilde{q}_t^* = \widetilde{q}_{t-1}^* + \widetilde{\pi}_{F,t}^* - \widetilde{\pi}_{H,t}^*.$$

18. Real exchange rate dynamics ($\widetilde{s}_t = -\widetilde{s}_t^*$):

$$\widetilde{s}_t = -\widetilde{\psi}_{H,t}^* + (1-\alpha)\widetilde{q}_t^* + \alpha\widetilde{q}_t.$$

19. Foreign goods market clearing:

$$\widetilde{y}_{F,t}^* = \widetilde{c}_t - \widetilde{g}_t^* - \frac{1-\alpha}{\tau}\widetilde{s}_t + \alpha(1-\alpha)\eta\left(\widetilde{q}_t - \widetilde{q}_t^*\right).$$

20. Monetary policy rule:

$$\widetilde{R}_t^* = \rho_R^*\widetilde{R}_{t-1}^* + (1-\rho_R^*)\left[\psi_1^*\widetilde{\pi}_t^* + \psi_2^*\widetilde{y}_t^* - \psi_3^*\Delta\widetilde{e}_t\right] + \varepsilon_{R,t}^*.$$

21. Euler-equation:

$$-\widetilde{\lambda}_t = -E_t\widetilde{\lambda}_{t+1} - (\widetilde{R}_t - E_t\widetilde{\pi}_{t+1}) + E_t\widetilde{z}_{t+1}.$$

The closed economy version of the model is obtained by setting $\alpha = 0$ and combining the following equations: (1) domestic firms' price setting; (2) domestic habits; (3) marginal utility of consumption; (5) definition of CPI; (9) home goods market clearing; (11) monetary policy rule; and (21) Euler equation.

B Practical Implementation

1. The matrices $\Gamma_0(\theta)$, $\Gamma_1(\theta)$, $\Gamma_\epsilon(\theta)$, and $\Gamma_\eta(\theta)$ in Equation (31) can be derived from the linearized equations presented in Appendix A. The solution algorithm described in Sims (2002) is used to compute the state transition equation (32).

2. Combine (32) with the measurement equation (33) to form a state space model for the observables $\mathbf{y}_t$. The matrix $A(\theta)$ in (33) is composed of

$$A(\theta) = [\gamma, \pi^{(A)}, r^{(A)} + \pi^{(A)}, \gamma, \pi^{*(A)}, r^{(A)} + \pi^{*(A)}, 0]'$$

   where y_t stacks U.S. output growth (percent, quarter-to-quarter), U.S. inflation (percent, quarter-to-quarter annualized), U.S. nominal interest rates (percent, annualized), Euro Area output growth (percent, quarter-to-quarter), Euro Area inflation (percent, quarter-to-quarter annualized), Euro Area nominal interest rates (percent, annualized), depreciation rate (percent, quarter-to-quarter). The matrix B selects and scales the relevant model variables to construct y_t. The steady state real rate is related to the discount factor β through $\beta = 1/\exp(r^{(A)}/400)$.

3. The likelihood function $\mathcal{L}(\theta|Y)$ can be evaluated with the Kalman Filter.

4. A numerical-optimization procedure is used to maximize

$$p(\theta|Y) \propto \mathcal{L}(\theta|Y)p(\theta)$$

   and find the posterior mode. The inverse Hessian is calculated at the posterior mode. For the two-country model the maximization algorithm frequently stopped at the boundary of the determinacy region. In these case, we fixed $\psi_2^* = 1$ and maximized the the posterior with respect to the remaining parameter. In the calculation of the Hessian we set the diagonal element corresponding to ψ_2^* equal the the reciprocal of its prior variance, and the corresponding off-diagonal elements to zero. We then freed the parameter ψ_2^* when running the Metropolis Algorithm.

5. 100,000 draws from $p(\theta|Y)$ are generated with a random-walk Metropolis Algorithm. The scaled inverse Hessian serves as a covariance matrix for the Gaussian proposal distribution used in the Metropolis-Hastings algorithm. The first 10,000 draws are discarded. The parameter draws θ are converted into impulse response functions and variance decompositions to generate the results reported in Section V. Posterior moments are obtained by Monte-Carlo averaging. The marginal data densities for the two

regions are approximated with Geweke's (1999) modified harmonic-mean estimator. Further details of these computations are discussed in Schorfheide (2000).

Table 1: PRIOR DISTRIBUTION (BENCHMARK), PART 1

			Non-truncated		Truncated	
Name	Domain	Density	Para (1)	Para (2)	Mean	90% Interval
θ_H	$[0,1)$	Beta	0.50	0.15	0.50	[0.24, 0.74]
θ_F	$[0,1)$	Beta	0.50	0.15	0.50	[0.26, 0.75]
θ_H^*	$[0,1)$	Beta	0.75	0.15	0.75	[0.53, 0.98]
θ_F^*	$[0,1)$	Beta	0.75	0.15	0.75	[0.52, 0.97]
τ	$\mathbb{R}^+$	Gamma	2.00	0.50	2.00	[1.20, 2.81]
h	$[0,1)$	Beta	0.30	0.10	0.30	[0.14, 0.46]
α	$[0,1)$	Beta	0.12	0.05	0.12	[0.04, 0.20]
η	$\mathbb{R}^+$	Gamma	1.00	0.50	1.00	[0.23, 1.74]
ψ_1	$\mathbb{R}^+$	Gamma	1.50	0.25	1.50	[1.10, 1.90]
ψ_2	$\mathbb{R}^+$	Gamma	0.13	0.10	0.13	[0.00, 0.26]
ψ_3	$\mathbb{R}^+$	Gamma	0.10	0.05	0.10	[0.02, 0.17]
ψ_1^*	$\mathbb{R}^+$	Gamma	1.50	0.25	1.51	[1.09, 1.89]
ψ_2^*	$\mathbb{R}^+$	Gamma	0.13	0.10	0.12	[0.00, 0.26]
ψ_3^*	$\mathbb{R}^+$	Gamma	0.10	0.05	0.10	[0.02, 0.17]
ρ_A	$[0,1)$	Beta	0.80	0.10	0.80	[0.65, 0.96]
ρ_R	$[0,1)$	Beta	0.50	0.20	0.50	[0.18, 0.83]
ρ_G	$[0,1)$	Beta	0.80	0.10	0.80	[0.65, 0.96]
ρ_A^*	$[0,1)$	Beta	0.60	0.20	0.60	[0.29, 0.93]
ρ_R^*	$[0,1)$	Beta	0.50	0.20	0.50	[0.17, 0.82]
ρ_G^*	$[0,1)$	Beta	0.80	0.10	0.80	[0.65, 0.96]
ρ_Z	$[0,1)$	Beta	0.66	0.15	0.66	[0.41, 0.90]

Notes: The prior is truncated at the boundary of the determinacy region. Para (1) and Para (2) list the means and the standard deviations for Beta, Gamma, and Normal distributions; the upper and lower bound of the support for the Uniform distribution; s and ν for the Inverse Gamma distribution, where $p_{\mathcal{IG}}(\sigma|\nu, s) \propto \sigma^{-\nu-1}e^{-\nu s^2/2\sigma^2}$.

Table 1: Prior Distribution (Benchmark), Part 2

			Non-truncated		Truncated	
Name	Domain	Density	Para (1)	Para (2)	Mean	90% Interval
$r^{(A)}$	$\mathbb{R}^+$	Gamma	1.50	1.00	1.51	[0.12, 2.90]
γ	$\mathbb{R}$	Normal	0.70	0.30	0.69	[0.20, 1.19]
$\pi^{(A)}$	$\mathbb{R}^+$	Gamma	7.00	2.00	7.02	[3.71, 10.12]
$\pi^{*(A)}$	$\mathbb{R}^+$	Gamma	8.80	2.00	8.81	[5.54, 12.01]
σ_A	$\mathbb{R}^+$	InvGamma	1.00	4.00	1.25	[0.51, 1.96]
σ_G	$\mathbb{R}^+$	InvGamma	1.00	4.00	1.26	[0.53, 1.98]
σ_R	$\mathbb{R}^+$	InvGamma	0.40	4.00	0.50	[0.21, 0.79]
σ_{A^*}	$\mathbb{R}^+$	InvGamma	0.40	4.00	0.50	[0.21, 0.79]
σ_{G^*}	$\mathbb{R}^+$	InvGamma	1.00	4.00	1.25	[0.54, 1.99]
σ_{R^*}	$\mathbb{R}^+$	InvGamma	0.20	4.00	0.25	[0.11, 0.40]
σ_Z	$\mathbb{R}^+$	InvGamma	0.50	4.00	0.63	[0.27, 0.99]
σ_E	$\mathbb{R}^+$	InvGamma	4.50	4.00	5.61	[2.41, 8.87]
ρ_{RR^*}	$[-1, 1]$	Uniform	0.00	0.00	0.00	[0.00, 0.00]

Notes: The prior is truncated at the boundary of the determinacy region. Para (1) and Para (2) list the means and the standard deviations for Beta, Gamma, and Normal distributions; the upper and lower bound of the support for the Uniform distribution; s and ν for the Inverse Gamma distribution, where $p_{\mathcal{IG}}(\sigma|\nu, s) \propto \sigma^{-\nu-1} e^{-\nu s^2/2\sigma^2}$.

Table 2: Parameter Estimation Results: U.S.

	Prior		Posterior Distributions: Benchmark		No A-shock		Demeaned Data	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
θ	0.50	[0.25, 0.75]	0.78	[0.71, 0.86]	0.76	[0.68, 0.84]	0.74	[0.65, 0.83]
τ	2.00	[1.19, 2.81]	2.19	[1.37, 2.96]	2.05	[1.28, 2.85]	2.07	[1.31, 2.85]
h	0.30	[0.13, 0.46]	0.33	[0.16, 0.50]	0.30	[0.16, 0.43]	0.30	[0.14, 0.43]
ψ_1	1.50	[1.09, 1.87]	1.69	[1.23, 2.11]	1.76	[1.38, 2.13]	1.85	[1.42, 2.27]
ψ_2	0.12	[0.00, 0.25]	0.56	[0.19, 0.94]	0.45	[0.22, 0.69]	0.40	[0.20, 0.61]
ρ_A	0.80	[0.65, 0.96]	0.88	[0.79, 0.97]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
ρ_R	0.50	[0.18, 0.83]	0.84	[0.79, 0.88]	0.84	[0.79, 0.88]	0.83	[0.79, 0.87]
ρ_G	0.80	[0.65, 0.95]	0.86	[0.77, 0.95]	0.94	[0.91, 0.98]	0.93	[0.90, 0.97]
ρ_Z	0.66	[0.42, 0.90]	0.90	[0.84, 0.96]	0.93	[0.89, 0.96]	0.92	[0.89, 0.96]
$r^{(A)}$	1.49	[0.07, 2.85]	2.58	[1.58, 3.58]	2.51	[1.47, 3.62]	1.48	[0.10, 3.10]
γ	0.70	[0.22, 1.21]	0.66	[0.34, 0.98]	0.65	[0.31, 1.00]	0.69	[0.19, 1.14]
$\pi^{(A)}$	7.04	[3.82, 10.21]	4.28	[2.83, 5.80]	4.76	[2.97, 6.66]	6.52	[3.88, 9.21]
σ_A	1.25	[0.54, 1.96]	1.10	[0.59, 1.62]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
σ_G	1.26	[0.54, 1.99]	0.52	[0.40, 0.63]	0.55	[0.46, 0.64]	0.55	[0.47, 0.63]
σ_R	0.50	[0.21, 0.79]	0.15	[0.13, 0.18]	0.16	[0.13, 0.18]	0.16	[0.14, 0.18]
σ_Z	0.63	[0.27, 1.00]	0.25	[0.19, 0.31]	0.23	[0.19, 0.28]	0.24	[0.19, 0.29]

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator.

Table 3: PARAMETER ESTIMATION RESULTS: EURO AREA

	Prior		Posterior Distributions: Benchmark		Posterior Distributions: No A-shock		Posterior Distributions: Demeaned Data	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
θ	0.75	[0.53, 0.97]	0.84	[0.78, 0.89]	0.83	[0.76, 0.91]	0.81	[0.74, 0.88]
τ	2.00	[1.20, 2.81]	2.48	[1.71, 3.21]	2.67	[1.82, 3.50]	2.45	[1.68, 3.32]
h	0.30	[0.13, 0.45]	0.26	[0.10, 0.42]	0.30	[0.11, 0.50]	0.29	[0.13, 0.49]
ψ_1	1.51	[1.09, 1.86]	1.18	[0.97, 1.39]	1.40	[1.08, 1.70]	1.42	[1.10, 1.74]
ψ_2	0.12	[0.00, 0.25]	0.75	[0.45, 1.04]	0.24	[0.09, 0.37]	0.23	[0.09, 0.37]
ρ_A	0.80	[0.65, 0.96]	0.97	[0.96, 0.99]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
ρ_R	0.51	[0.18, 0.84]	0.85	[0.80, 0.90]	0.89	[0.85, 0.93]	0.88	[0.85, 0.92]
ρ_G	0.80	[0.66, 0.96]	0.86	[0.80, 0.91]	0.98	[0.97, 0.99]	0.98	[0.97, 0.99]
ρ_Z	0.66	[0.43, 0.92]	0.55	[0.33, 0.76]	0.76	[0.56, 0.94]	0.74	[0.57, 0.91]
$r^{(A)}$	1.50	[0.14, 2.93]	3.18	[2.13, 4.21]	3.10	[2.15, 4.02]	2.33	[0.66, 4.14]
γ	0.69	[0.22, 1.21]	0.48	[0.35, 0.61]	0.47	[0.19, 0.77]	0.65	[0.32, 1.01]
$\pi^{(A)}$	8.84	[5.51, 12.09]	7.41	[5.53, 9.77]	7.74	[6.02, 10.00]	7.12	[4.98, 9.90]
σ_A	0.50	[0.21, 0.78]	0.49	[0.24, 0.74]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
σ_G	1.26	[0.57, 2.03]	0.73	[0.55, 0.91]	0.59	[0.45, 0.72]	0.58	[0.47, 0.69]
σ_R	0.25	[0.11, 0.39]	0.11	[0.10, 0.13]	0.14	[0.12, 0.16]	0.15	[0.13, 0.17]
σ_Z	0.63	[0.26, 0.99]	0.31	[0.23, 0.40]	0.37	[0.24, 0.51]	0.38	[0.24, 0.52]

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator.

Table 4: Open and Closed Economy Estimates, Part 1

			Posterior Distributions					
	Prior		U.S. - Euro Area		U.S.		Euro Area	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval		
θ_H	0.50	[0.24, 0.74]	0.47	[0.32, 0.63]	0.78	[0.71, 0.86]		
θ_F	0.50	[0.26, 0.75]	0.66	[0.43, 0.90]				
θ_H^*	0.75	[0.53, 0.98]	0.43	[0.15, 0.74]				
θ_F^*	0.75	[0.52, 0.97]	0.90	[0.85, 0.95]			0.84	[0.78, 0.89]
τ	2.00	[1.20, 2.81]	3.42	[2.51, 4.27]	2.19	[1.37, 2.96]	2.48	[1.71, 3.21]
h	0.30	[0.14, 0.46]	0.50	[0.29, 0.71]	0.33	[0.16, 0.50]	0.26	[0.10, 0.42]
α	0.12	[0.04, 0.20]	0.13	[0.06, 0.20]				
η	1.00	[0.23, 1.74]	0.40	[0.08, 0.72]				
ψ_1	1.50	[1.10, 1.90]	1.93	[1.56, 2.32]	1.69	[1.23, 2.11]		
ψ_2	0.13	[0.00, 0.26]	0.01	[0.00, 0.03]	0.56	[0.19, 0.94]		
ψ_3	0.10	[0.02, 0.17]	0.03	[0.01, 0.05]				
ψ_1^*	1.51	[1.09, 1.89]	1.07	[0.86, 1.28]			1.18	[0.97, 1.39]
ψ_2^*	0.12	[0.00, 0.26]	0.73	[0.42, 1.02]			0.75	[0.45, 1.04]
ψ_3^*	0.10	[0.02, 0.17]	0.02	[0.01, 0.04]				
ρ_A	0.80	[0.65, 0.96]	0.85	[0.80, 0.91]	0.88	[0.79, 0.97]		
ρ_R	0.50	[0.18, 0.83]	0.74	[0.67, 0.81]	0.84	[0.79, 0.88]		
ρ_G	0.80	[0.65, 0.96]	0.96	[0.93, 0.99]	0.86	[0.77, 0.95]		
ρ_A^*	0.60	[0.29, 0.93]	0.98	[0.97, 1.00]			0.97	[0.96, 0.99]
ρ_R^*	0.50	[0.17, 0.82]	0.86	[0.82, 0.91]			0.85	[0.80, 0.90]
ρ_G^*	0.80	[0.65, 0.96]	0.89	[0.84, 0.94]			0.86	[0.80, 0.91]
ρ_Z	0.66	[0.41, 0.90]	0.55	[0.32, 0.78]	0.90	[0.84, 0.96]	0.55	[0.33, 0.76]

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator.

Table 4: Open and Closed Economy Estimates, Part 2

			Posterior Distributions					
	Prior		U.S. - Euro Area		U.S.		Euro Area	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval		
$r^{(A)}$	1.51	[0.12, 2.90]	2.96	[2.41, 3.51]	2.58	[1.58, 3.58]	3.18	[2.13, 4.21]
γ	0.69	[0.20, 1.19]	0.51	[0.39, 0.63]	0.66	[0.34, 0.98]	0.48	[0.35, 0.61]
$\pi^{(A)}$	7.02	[3.71, 10.12]	3.48	[2.89, 4.05]	4.28	[2.83, 5.80]		
$\pi^{*(A)}$	8.81	[5.54, 12.01]	6.55	[6.51, 6.59]			7.41	[5.53, 9.77]
σ_A	1.25	[0.51, 1.96]	1.28	[0.87, 1.67]	1.10	[0.59, 1.62]		
σ_G	1.26	[0.53, 1.98]	0.68	[0.58, 0.78]	0.52	[0.40, 0.63]		
σ_R	0.50	[0.21, 0.79]	0.22	[0.17, 0.26]	0.15	[0.13, 0.18]		
σ_{A^*}	0.50	[0.21, 0.79]	0.56	[0.24, 0.88]			0.49	[0.24, 0.74]
σ_{G^*}	1.25	[0.54, 1.99]	0.91	[0.70, 1.11]			0.73	[0.55, 0.91]
σ_{R^*}	0.25	[0.11, 0.40]	0.12	[0.10, 0.13]			0.11	[0.10, 0.13]
σ_Z	0.63	[0.27, 0.99]	0.28	[0.19, 0.36]	0.25	[0.19, 0.31]	0.31	[0.23, 0.40]
σ_E	5.61	[2.41, 8.87]	4.40	[3.83, 4.97]				
ρ_{RR^*}	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]				

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator.

Table 5: DIFFUSE PRIOR DISTRIBUTIONS

Name	Domain	Density	Para (1)	Para (2)
Diffuse Prior (I)				
θ_H	$[0,1)$	Uniform	0.00	1.00
θ_F	$[0,1)$	Uniform	0.00	1.00
θ^*_H	$[0,1)$	Uniform	0.00	1.00
θ^*_F	$[0,1)$	Uniform	0.00	1.00
ρ_A	$[0,1)$	Uniform	0.00	1.00
ρ_R	$[0,1)$	Uniform	0.00	1.00
ρ_G	$[0,1)$	Uniform	0.00	1.00
ρ^*_A	$[0,1)$	Uniform	0.00	1.00
ρ^*_R	$[0,1)$	Uniform	0.00	1.00
ρ^*_G	$[0,1)$	Uniform	0.00	1.00
Diffuse Prior (II)				
τ	$\mathbb{R}^+$	Gamma	2.00	2.00
h	$[0,1)$	Uniform	0.00	1.00
α	$[0,1)$	Uniform	0.00	1.00
η	$\mathbb{R}^+$	Gamma	1.00	1.00

Notes: Para (1) and Para (2) list the means and the standard deviations for Beta, Gamma, and Normal distributions; the upper and lower bound of the support for the Uniform distribution.

Table 6: POSTERIOR ESTIMATES UNDER DIFFUSE PRIORS, PART 1

	Benchmark		Diffuse Prior (I)		Diffuse Prior (II)	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
θ_H	0.47	[0.32, 0.63]	0.31	[0.08, 0.56]	0.39	[0.25, 0.53]
θ_F	0.66	[0.43, 0.90]	0.87	[0.69, 1.00]	0.48	[0.23, 0.74]
θ_H^*	0.43	[0.15, 0.74]	0.12	[0.00, 0.24]	0.29	[0.14, 0.51]
θ_F^*	0.90	[0.85, 0.95]	0.92	[0.88, 0.96]	0.97	[0.96, 0.97]
τ	3.42	[2.51, 4.27]	3.36	[2.35, 4.52]	4.40	[4.09, 4.73]
h	0.50	[0.29, 0.71]	0.59	[0.38, 0.81]	0.99	[0.99, 0.99]
α	0.13	[0.06, 0.20]	0.13	[0.08, 0.18]	0.15	[0.10, 0.20]
η	0.40	[0.08, 0.72]	0.45	[0.06, 0.82]	0.24	[0.01, 0.41]
ψ_1	1.93	[1.56, 2.32]	1.98	[1.66, 2.37]	2.00	[1.65, 2.38]
ψ_2	0.01	[0.00, 0.03]	0.01	[0.00, 0.03]	0.01	[0.00, 0.02]
ψ_3	0.03	[0.01, 0.05]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
ψ_1^*	1.07	[0.86, 1.28]	0.95	[0.76, 1.12]	1.52	[1.15, 1.81]
ψ_2^*	0.73	[0.42, 1.02]	0.62	[0.33, 0.95]	0.50	[0.35, 0.65]
ψ_3^*	0.02	[0.01, 0.04]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
ρ_A	0.85	[0.80, 0.91]	0.89	[0.84, 0.93]	0.91	[0.87, 0.95]
ρ_R	0.74	[0.67, 0.81]	0.66	[0.49, 0.79]	0.72	[0.64, 0.81]
ρ_G	0.96	[0.93, 0.99]	0.97	[0.94, 1.00]	0.96	[0.94, 0.99]
ρ_A^*	0.98	[0.97, 1.00]	0.98	[0.96, 1.00]	0.62	[0.31, 0.93]
ρ_R^*	0.86	[0.82, 0.91]	0.82	[0.76, 0.87]	0.87	[0.84, 0.90]
ρ_G^*	0.89	[0.84, 0.94]	0.89	[0.84, 0.94]	0.92	[0.89, 0.94]
ρ_Z	0.55	[0.32, 0.78]	0.18	[0.00, 0.43]	0.26	[0.11, 0.44]

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator. We fixed $\psi_3 = \psi_3^* = 0$ under the diffuse priors.

Table 6: Posterior Estimates under Diffuse Priors, Part 2

	Benchmark		Diffuse Prior (I)		Diffuse Prior (II)	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
$r^{(A)}$	2.96	[2.41, 3.51]	3.11	[2.60, 3.66]	2.89	[2.19, 3.46]
γ	0.51	[0.39, 0.63]	0.51	[0.42, 0.61]	0.58	[0.55, 0.60]
$\pi^{(A)}$	3.48	[2.89, 4.05]	3.53	[2.75, 4.41]	3.42	[2.66, 4.07]
$\pi^{*(A)}$	6.55	[6.51, 6.59]	6.40	[6.37, 6.44]	6.25	[4.69, 8.01]
σ_A	1.28	[0.87, 1.67]	1.14	[0.78, 1.54]	1.48	[1.08, 1.88]
σ_G	0.68	[0.58, 0.78]	0.67	[0.57, 0.77]	0.62	[0.54, 0.69]
σ_R	0.22	[0.17, 0.26]	0.25	[0.16, 0.35]	0.23	[0.17, 0.30]
σ_{A^*}	0.56	[0.24, 0.88]	0.60	[0.26, 0.99]	0.48	[0.23, 0.73]
σ_{G^*}	0.91	[0.70, 1.11]	0.87	[0.68, 1.08]	0.77	[0.65, 0.88]
σ_{R^*}	0.12	[0.10, 0.13]	0.11	[0.09, 0.13]	0.12	[0.10, 0.13]
σ_Z	0.28	[0.19, 0.36]	0.40	[0.28, 0.52]	0.33	[0.23, 0.44]
σ_E	4.40	[3.83, 4.97]	4.39	[3.82, 4.95]	4.44	[3.84, 5.02]
ρ_{RR^*}	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
$\ln p(Y)$	−870.05		−860.44		−850.63	

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator. We report marginal data densities in the last row, denoted by $\ln p(Y)$.

Table 7: PPP versus UIP Shocks, Part 1

	Benchmark		Tight Prior on σ_E		UIP Shock	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
θ_H	0.47	[0.32, 0.63]	0.44	[0.28, 0.57]	0.45	[0.30, 0.60]
θ_F	0.66	[0.43, 0.90]	0.66	[0.41, 0.91]	0.84	[0.60, 0.96]
θ_H^*	0.43	[0.15, 0.74]	0.37	[0.18, 0.57]	0.85	[0.78, 0.91]
θ_F^*	0.90	[0.85, 0.95]	0.91	[0.86, 0.95]	0.51	[0.34, 0.68]
τ	3.42	[2.51, 4.27]	3.46	[2.61, 4.38]	3.60	[2.67, 4.54]
h	0.50	[0.29, 0.71]	0.45	[0.25, 0.67]	0.65	[0.49, 0.79]
α	0.13	[0.06, 0.20]	0.15	[0.08, 0.20]	0.48	[0.34, 0.63]
η	0.40	[0.08, 0.72]	0.43	[0.09, 0.78]	0.32	[0.15, 0.43]
ψ_1	1.93	[1.56, 2.32]	1.90	[1.52, 2.25]	1.69	[1.41, 2.00]
ψ_2	0.01	[0.00, 0.03]	0.01	[0.00, 0.03]	0.12	[0.00, 0.23]
ψ_3	0.03	[0.01, 0.05]	0.00	[0.00, 0.00]	0.04	[0.02, 0.07]
ψ_1^*	1.07	[0.86, 1.28]	1.03	[0.87, 1.22]	1.07	[0.97, 1.17]
ψ_2^*	0.73	[0.42, 1.02]	0.67	[0.41, 0.94]	0.06	[0.00, 0.13]
ψ_3^*	0.02	[0.01, 0.04]	0.00	[0.00, 0.00]	0.02	[0.01, 0.04]
ρ_A	0.85	[0.80, 0.91]	0.87	[0.83, 0.92]	0.94	[0.89, 0.97]
ρ_R	0.74	[0.67, 0.81]	0.73	[0.65, 0.80]	0.77	[0.71, 0.82]
ρ_G	0.96	[0.93, 0.99]	0.96	[0.93, 0.99]	0.95	[0.92, 0.98]
ρ_A^*	0.98	[0.97, 1.00]	0.98	[0.96, 0.99]	0.95	[0.91, 0.98]
ρ_R^*	0.86	[0.82, 0.91]	0.85	[0.81, 0.89]	0.80	[0.76, 0.84]
ρ_G^*	0.89	[0.84, 0.94]	0.90	[0.85, 0.94]	0.92	[0.87, 0.97]
ρ_Z	0.55	[0.32, 0.78]	0.58	[0.34, 0.80]	0.51	[0.30, 0.73]

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator. For the "tight" prior on σ_E we use an Inverse Gamma distribution with $s = 0.5$ and $\nu = 50$. For the UIP shock specification we use an Inverse Gamma prior with $s = 1$ and $\nu = 4$.

Table 7: Parameter Estimation Results, Part 2

	Benchmark		Tight Prior on σ_E		UIP Shock	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
$r^{(A)}$	2.96	[2.41, 3.51]	2.99	[2.52, 3.50]	3.90	[3.47, 4.35]
γ	0.51	[0.39, 0.63]	0.51	[0.38, 0.62]	0.50	[0.32, 0.66]
$\pi^{(A)}$	3.48	[2.89, 4.05]	3.50	[2.95, 4.11]	4.49	[3.97, 5.15]
$\pi^{*(A)}$	6.55	[6.51, 6.59]	5.96	[5.94, 5.99]	5.63	[5.55, 5.72]
σ_A	1.28	[0.87, 1.67]	1.22	[0.87, 1.55]	2.12	[1.47, 2.87]
σ_G	0.68	[0.58, 0.78]	0.68	[0.57, 0.78]	0.56	[0.50, 0.64]
σ_R	0.22	[0.17, 0.26]	0.21	[0.16, 0.27]	0.19	[0.16, 0.23]
σ_{A^*}	0.56	[0.24, 0.88]	0.64	[0.32, 0.97]	1.24	[0.80, 1.78]
σ_{G^*}	0.91	[0.70, 1.11]	0.90	[0.68, 1.10]	0.56	[0.50, 0.64]
σ_{R^*}	0.12	[0.10, 0.13]	0.11	[0.09, 0.13]	0.16	[0.14, 0.19]
σ_Z	0.28	[0.19, 0.36]	0.26	[0.19, 0.34]	0.37	[0.25, 0.50]
σ_E	4.40	[3.83, 4.97]	3.44	[3.07, 3.79]	4.28	[3.75, 4.72]
ρ_{RR^*}	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
$\ln p(Y)$	−870.05		−942.22		−907.81	

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator. For the "tight" prior on σ_E we use an Inverse Gamma distribution with $s = 0.5$ and $\nu = 50$. For the UIP shock specification we use an Inverse Gamma prior with $s = 1$ and $\nu = 4$. We report marginal data densities in the last row, denoted by $\ln p(Y)$.

Table 8: Short Sample Estimates, Part 1

	1983:1 - 2002:4		1987:3 - 2002:4					
	U.S. - Euro Area		U.S. - Euro Area		U.S.		Euro Area	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval		
θ_H	0.47	[0.32, 0.63]	0.62	[0.45, 0.79]	0.74	[0.59, 0.89]		
θ_F	0.66	[0.43, 0.90]	0.63	[0.41, 0.88]				
θ_H^*	0.43	[0.15, 0.74]	0.66	[0.34, 0.96]				
θ_F^*	0.90	[0.85, 0.95]	0.84	[0.78, 0.90]			0.62	[0.46, 0.80]
τ	3.42	[2.51, 4.27]	3.26	[2.36, 4.15]	2.35	[1.41, 3.32]	2.87	[2.01, 3.79]
h	0.50	[0.29, 0.71]	0.44	[0.23, 0.62]	0.33	[0.13, 0.51]	0.57	[0.40, 0.78]
α	0.13	[0.06, 0.20]	0.11	[0.03, 0.19]				
η	0.40	[0.08, 0.72]	0.58	[0.11, 1.05]				
ψ_1	1.93	[1.56, 2.32]	1.67	[1.23, 2.09]	1.59	[1.18, 2.00]		
ψ_2	0.01	[0.00, 0.03]	0.04	[0.00, 0.07]	0.39	[0.00, 0.79]		
ψ_3	0.03	[0.01, 0.05]	0.03	[0.01, 0.05]				
ψ_1^*	1.07	[0.86, 1.28]	1.23	[0.97, 1.50]			1.95	[1.60, 2.34]
ψ_2^*	0.73	[0.42, 1.02]	1.14	[0.70, 1.62]			0.04	[0.00, 0.08]
ψ_3^*	0.02	[0.01, 0.04]	0.03	[0.01, 0.06]				
ρ_A	0.85	[0.80, 0.91]	0.83	[0.74, 0.92]	0.91	[0.84, 0.99]		
ρ_R	0.74	[0.67, 0.81]	0.72	[0.65, 0.81]	0.78	[0.70, 0.87]		
ρ_G	0.96	[0.93, 0.99]	0.92	[0.87, 0.97]	0.81	[0.71, 0.92]		
ρ_A^*	0.98	[0.97, 1.00]	0.96	[0.94, 0.99]			0.89	[0.84, 0.94]
ρ_R^*	0.86	[0.82, 0.91]	0.86	[0.82, 0.90]			0.81	[0.74, 0.87]
ρ_G^*	0.89	[0.84, 0.94]	0.85	[0.79, 0.90]			0.88	[0.79, 0.98]
ρ_Z	0.55	[0.32, 0.78]	0.86	[0.78, 0.94]	0.67	[0.44, 0.87]	0.53	[0.33, 0.71]

Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator.

Table 8: Short Sample Estimates, Part 2

	1983:1 - 2002:4		1987:3 - 2002:4					
	U.S. - Euro Area		U.S. - Euro Area		U.S.		Euro Area	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval		
$r^{(A)}$	2.96	[2.41, 3.51]	2.62	[2.04, 3.23]	2.11	[1.38, 2.92]	3.98	[3.16, 4.83]
γ	0.51	[0.39, 0.63]	0.61	[0.39, 0.82]	0.50	[0.27, 0.67]	0.49	[0.33, 0.66]
$\pi^{(A)}$	3.48	[2.89, 4.05]	3.46	[2.65, 4.30]	4.08	[2.47, 5.93]		
$\pi^{*(A)}$	6.55	[6.51, 6.59]	5.54	[3.78, 7.12]			3.30	[2.44, 4.20]
σ_A	1.28	[0.87, 1.67]	0.95	[0.61, 1.28]	1.02	[0.59, 1.41]		
σ_G	0.68	[0.58, 0.78]	0.63	[0.53, 0.71]	0.53	[0.42, 0.65]		
σ_R	0.22	[0.17, 0.26]	0.19	[0.15, 0.24]	0.16	[0.12, 0.19]		
σ_{A^*}	0.56	[0.24, 0.88]	0.47	[0.25, 0.67]			1.73	[0.96, 2.43]
σ_{G^*}	0.91	[0.70, 1.11]	0.85	[0.63, 1.03]			0.45	[0.37, 0.55]
σ_{R^*}	0.12	[0.10, 0.13]	0.13	[0.10, 0.16]			0.16	[0.13, 0.20]
σ_Z	0.28	[0.19, 0.36]	0.21	[0.17, 0.25]	0.35	[0.22, 0.49]	0.42	[0.26, 0.57]
σ_E	4.40	[3.83, 4.97]	4.24	[3.62, 4.87]				
ρ_{RR^*}	0.00	[0.00, 0.00]	-0.31	[-0.91, 0.31]				

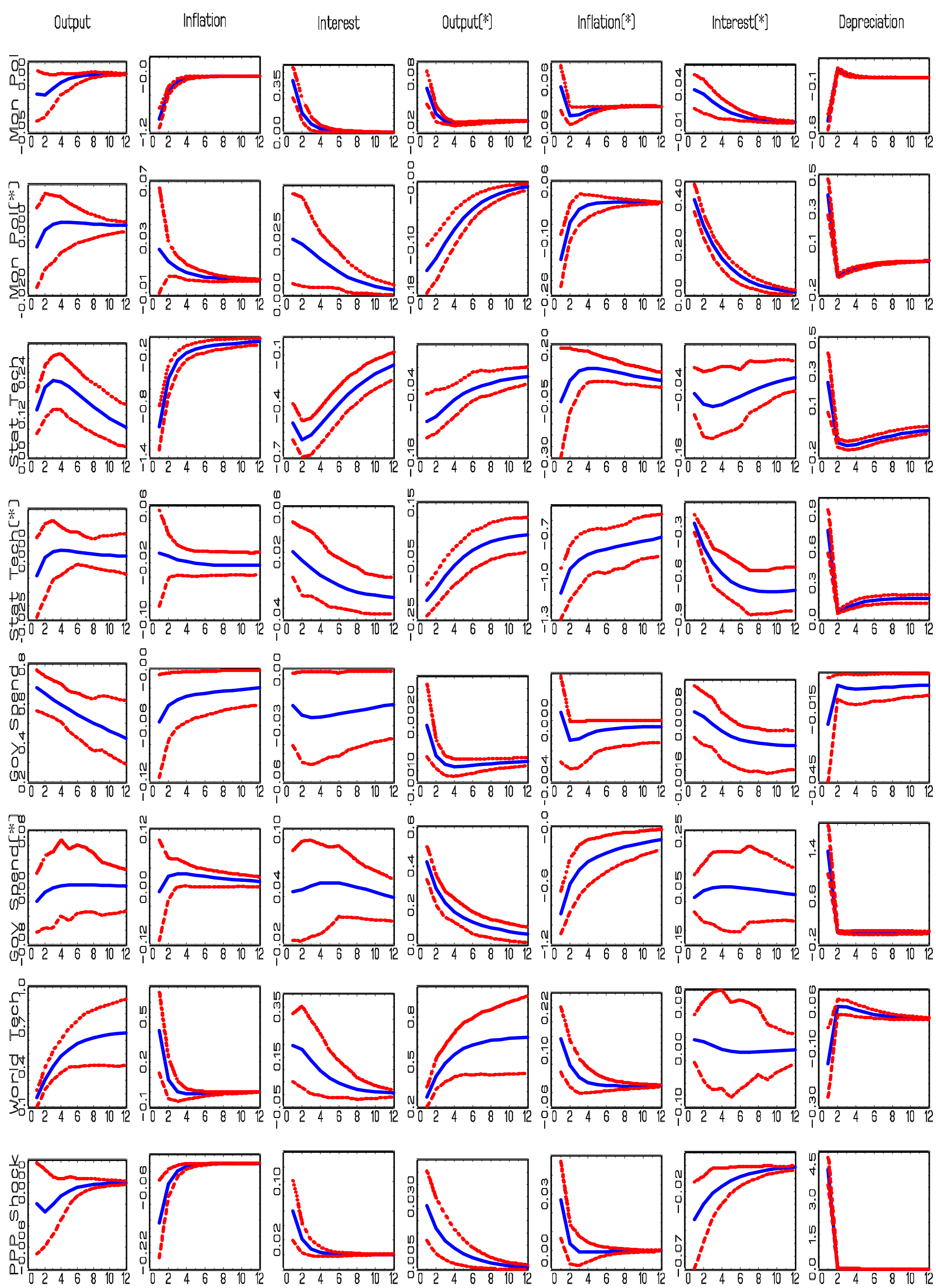
Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator.

Table 9: Variance Decomposition of Depreciation Rate

	Benchmark		Diffuse Prior (I)		Diffuse Prior (II)	
	Mean	90% Interval	Mean	90% Interval	Mean	90% Interval
Monetary Policy	0.01	[0.01, 0.01]	0.01	[0.01, 0.01]	0.01	[0.01, 0.01]
Monetary Policy (*)	0.00	[0.00, 0.01]	0.01	[0.01, 0.01]	0.01	[0.01, 0.01]
Stat Technology	0.01	[0.00, 0.01]	0.01	[0.01, 0.01]	0.01	[0.01, 0.01]
Stat Technology (*)	0.09	[0.14, 0.11]	0.09	[0.09, 0.07]	0.00	[0.00, 0.00]
Gov Spending	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]	0.00	[0.00, 0.00]
Gov Spending (*)	0.06	[0.12, 0.05]	0.05	[0.07, 0.05]	0.09	[0.09, 0.09]
World Technology	0.01	[0.00, 0.00]	0.00	[0.00, 0.00]	0.10	[0.10, 0.14]
PPP Shock	0.82	[0.73, 0.81]	0.84	[0.82, 0.85]	0.78	[0.78, 0.75]

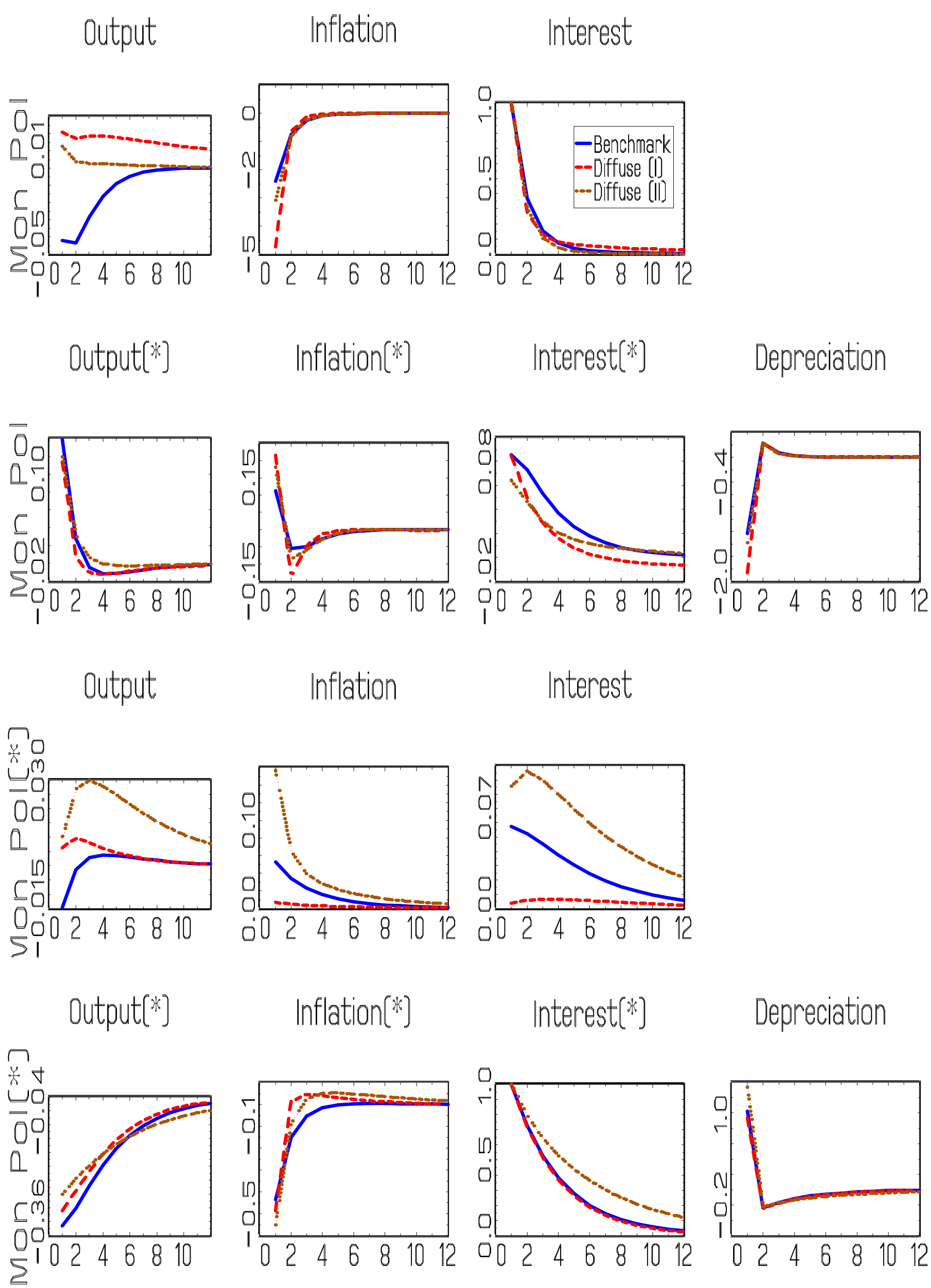
Notes: The table reports posterior means and 90 percent probability intervals (in brackets). The posterior summary statistics are calculated from the output of the posterior simulator. We report marginal data densities in the last row, denoted by $\ln p(Y)$.

Figure 1: Impulse Response Functions for Benchmark Estimation



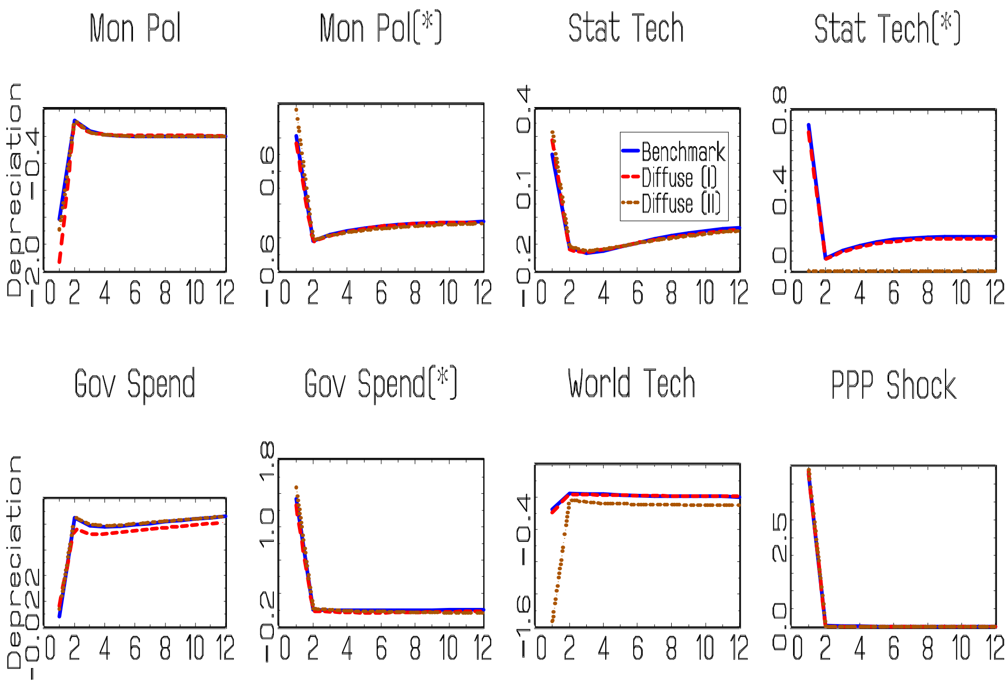
Notes: Figure depicts posterior means (solid lines) and pointwise 90% posterior probability intervals (dashed lines) for impulse responses of endogenous variables to one-standard deviation structural shocks.

Figure 2: Impulse Response Functions to Monetary Policy Shocks



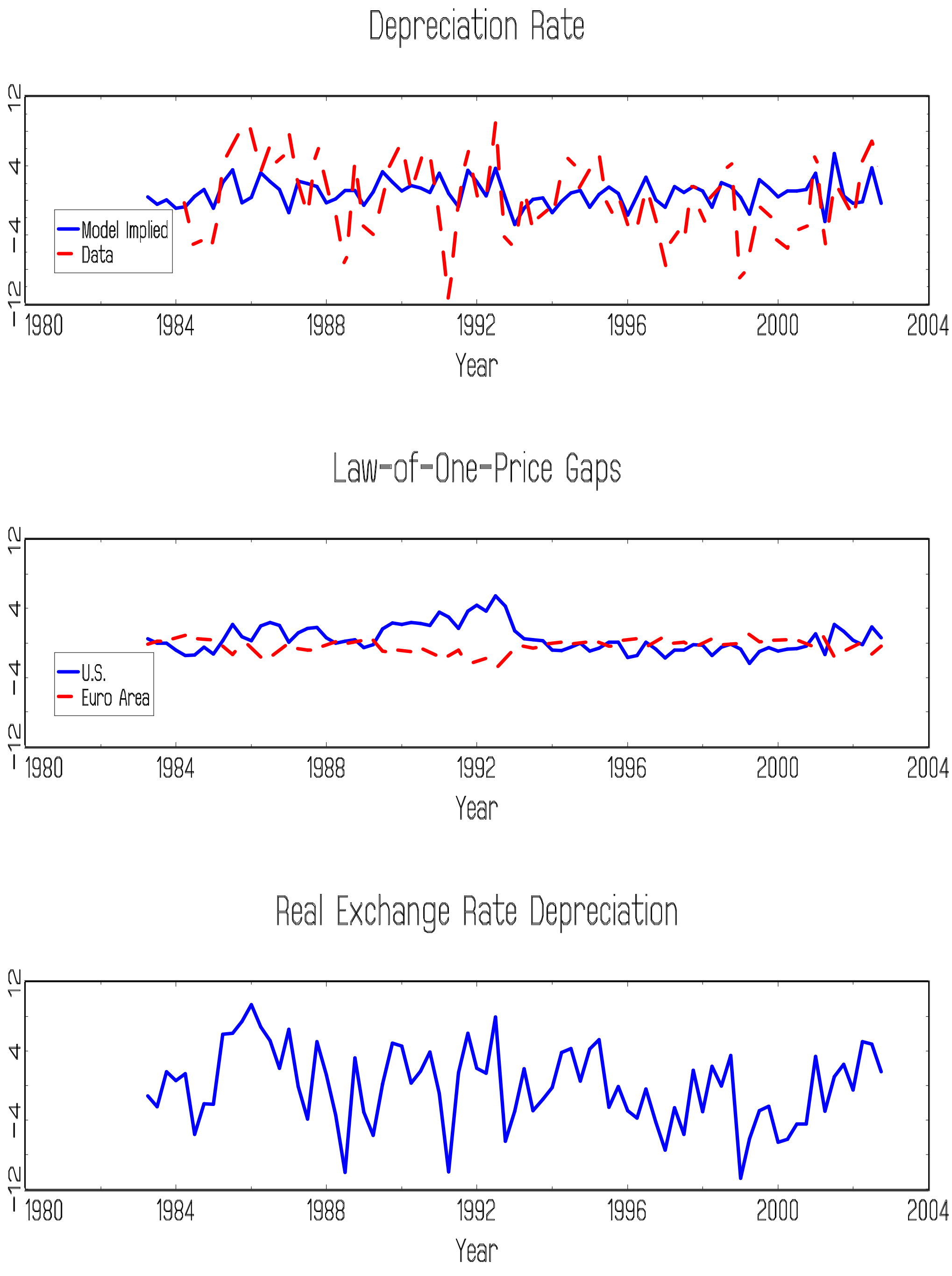
Notes: Figure depicts posterior mean impulse responses of endogenous variables to U.S. and Euro-Area monetary policy shocks that raise the respective nominal interest rate by 100 basis points.

Figure 3: Impulse Response Functions for the Depreciation Rate



Notes: Figure depicts posterior mean impulse responses of depreciation rate to the eight structural shocks.

Figure 4: Exchange Rate Dynamics



Notes: Model implied exchange rates and law-of-one-price gaps are computed with the Kalman smoother. Figure depicts posterior means.