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Policy Predictions If the Model Doesn't Fit

Marco Del Negro and Frank Schorfheide

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Policy Predictions if the Model doesn't Fit

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September, 2004

Abstract

This paper uses a novel method for conducting policy analysis with potentially misspecified DSGE models (Del Negro and Schorfheide 2004b) and applies it to a simple New Keynesian DSGE model. We illustrate the sensitivity of the results to assumptions on the policy invariance of model misspecifications.

JEL CLASSIFICATION: C32, E5

KEY WORDS: Bayesian Analysis, DSGE Models, Misspecification, Policy Analysis.

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1 Introduction

Despite recent successes in improving the empirical performance of dynamic stochastic general equilibrium (DSGE) models, e.g., Smets and Wouters (2003), even large-scale DSGE models suffer to some extent from misspecification (see Del Negro, Schorfheide, Smets, and Wouters 2004). In this paper misspecification means that the DSGE model potentially imposes invalid cross-coefficient restrictions on the moving-average representation of the macroeconomic time series that it aims to explain. As a consequence, one typically observes that the forecasting performance of DSGE models is worse than that of vector autoregressions (VARs) estimated with well-calibrated shrinkage methods. On the other hand, DSGE models have the advantage that one can explicitly assess the effect of policy regime changes on expectation formation and decision rules of private agents. Thus, policy analysis with DSGE models is robust to the Lucas critique and potentially more reliable than conclusions drawn from VARs. This trade-off poses a challenge to policymakers who want to use DSGE models in practice.

Del Negro and Schorfheide (2004a) proposed a framework that combines VARs and DSGE models, extending earlier work by Ingram and Whiteman (1994). In this framework DSGE model restrictions are neither completely ignored as in the unrestricted estimation of VARs, nor are they dogmatically imposed as in the direct estimation of DSGE models. Instead the VAR estimates are tilted toward the restrictions implied by the DSGE model, where the degree of tilting is determined by a Bayesian data-driven procedure that trades off model fit against complexity. Del Negro and Schorfheide (2004a) show that priors arising from the same model used in this paper improve both the in-sample and out-of-sample fit of a VAR.

In ongoing research (Del Negro and Schorfheide, 2004b) we build upon our earlier work and further develop procedures that are suitable to study the effects

of rare regime shifts with potentially misspecified DSGE models. These procedures can be viewed as a Bayesian alternative to the robust control and minimax approaches that recently have been proposed to cope with model misspecification, e.g., Hansen and Sargent (2000) and Onatsky and Stock (2002). One advantage of Bayesian procedures is that the policymaker can learn from existing data about the extent of the DSGE model's misspecification, and consequently adjust her policies. The present paper applies these procedures to a simple New Keynesian DSGE model. We illustrate that conclusions about the effects of changing the response to inflation are sensitive to assumptions about the policy invariance of observed discrepancies between model and reality. Section 2 briefly describes the DSGE model. In Section 3 we outline our framework, Section 4 discusses our findings, and Section 5 concludes.

2 The DSGE Model

Starting point is a DSGE model in log-linearized form. The model used here is a standard New Keynesian DSGE model, e.g., Woodford (2003), which we now briefly describe (see Del Negro and Schorfheide (2004a) for details). The log-linearized equilibrium conditions consist of three equations in nominal interest rates $\tilde{R}_t$, output $\tilde{x}_t$, and inflation $\tilde{\pi}_t$ ($\tilde{}$ denotes percentage deviations from the steady state and Δ is the temporal difference operator):

Monetary Policy Rule:

$$\widetilde{R}_t = \rho_R \widetilde{R}_{t-1} + (1-\rho_R)\left[\psi_1 \widetilde{\pi}_t + \psi_2(\Delta \widetilde{x}_t + \widetilde{z}_t)\right] + \epsilon_{1,t}, \tag{1}$$

Price-setting equation:

$$\widetilde{\pi}_t = \frac{\gamma}{r^*} \mathbb{E}_t[\widetilde{\pi}_{t+1}] + \kappa[\widetilde{x}_t - \widetilde{g}_t], \tag{2}$$

Euler equation:

$$\widetilde{x}_t = \mathbb{E}_t[\widetilde{x}_{t+1}] - \tau^{-1}(\widetilde{R}_t - \mathbb{E}_t[\widetilde{\pi}_{t+1}]) + (1-\rho_g)\widetilde{g}_t + \rho_z \frac{1}{\tau}\widetilde{z}_t. \tag{3}$$

The exogenous processes $\widetilde{z}_t$ and $\widetilde{g}_t$ capture technology growth and government spending, or more broadly speaking, demand shifts. The autoregressive coefficients of the exogenous processes are denoted by ρ_z and ρ_g, while the innovation standard deviations are σ_z and σ_g. A period t corresponds to one quarter.

The vector y_t of observable data is composed of the annualized nominal interest rate, the annualized inflation rate, and the quarterly output growth rate. The relationships between the steady-state deviations and the observables are given by the following measurement equations:

$$\begin{aligned} y_{1,t} &= \ln r_a^* + \ln \pi_a^* + 4\widetilde{R}_t, \\ y_{2_t} &= \begin{bmatrix} \ln \pi_a^* + 4\widetilde{\pi}_t \\ \\ \ln \gamma + \Delta \widetilde{x}_t + \widetilde{z}_t \end{bmatrix}. \end{aligned} \tag{4}$$

where $y_{1,t}$ denotes the policymaker's instrument (the interest rate), and $y_{2,t}$ is a vector that includes the remaining two endogenous variables. Call θ the vector of DSGE model parameters included in equations (1) through (4).

3 Setup and Inference

3.1 A VAR Representation of the DSGE Model

Let us rewrite Eq. (1), which describes the policymaker's behavior, in more general form as:

$$y_{1,t} = x_t' M_1 \beta_1(\theta) + y_{2,t}' M_2 \beta_2(\theta) + \epsilon_{1,t}, \tag{5}$$

where the $k \times 1$ vector x_t is composed of an intercept and lags of y_t. The matrices M_1 and M_2 select the appropriate elements of x_t and $y_{2,t}$ to generate the policy rule. Here, the vector M_1 selects the intercept and the lagged nominal interest rate and the matrix M_2 extracts inflation, and output growth. The functions $\beta_1(\theta)$ and $\beta_2(\theta)$ can be easily derived from (1) and (4). The remainder of the

system is given by the reduced form equations

$$y'_{2,t} = x'_t \Psi^*(\theta) + u'_{2,t}, \tag{6}$$

where $\Psi^*(\cdot)$ relates the DSGE model parameters to the autoregressive coefficients of $y_{2,t}$. The system (6) essentially consists of equations (2) and (3) expressed in terms of observables with the expectational terms solved out. This VAR representation, when it is not exact, can be made arbitrarily precise by including additional lags.

If we substitute for $y_{2,t}$ in Eq. (5) and combine the resulting expression with (6) we obtain the following (restricted) VAR for our endogenous variables:

$$y'_t = x'_t \Phi^*(\theta) + u'_t. \tag{7}$$

where $\Phi^*(\theta) = [M_1\beta_1(\theta) + \Psi^*(\theta)M_2\beta_2(\theta), \Psi^*(\theta)]$, and $u'_t = [u'_{2,t}M_2\beta_2(\theta) + \epsilon_{1,t}, u'_{2,t}]$. We assume that $u_t \sim \mathcal{N}(0, \Sigma^*_{tr}(\theta)\Sigma^*_{tr}(\theta)')$, where $\Sigma_{tr}(\theta)$ is a lower-triangular matrix. The one-step ahead forecast errors u_t are functions of the structural shocks of the DSGE model.[1]

3.2 Misspecification and Bayesian Inference

We make the following assumptions about misspecification of the DSGE model. There is a vector θ and matrices Ψ^Δ and Σ^Δ_{tr} such that data are generated according to

$$y_{1,t} = x'_t M_1\beta_1(\theta) + x'_t(\Psi^*(\theta) + \Psi^\Delta)M_2\beta_2(\theta) + u_{1,t} \tag{8}$$

$$y'_{2,t} = x'_t(\Psi^*(\theta) + \Psi^\Delta) + u'_{2,t} \tag{9}$$

and

$$\mathbb{E}[u_t u'_t] = (\Sigma^*_{tr}(\theta) + \Sigma^\Delta_{tr})(\Sigma^*_{tr}(\theta) + \Sigma^\Delta_{tr})'. \tag{10}$$

[1] To specify $\Psi^*(\theta)$ and $\Sigma^*_{tr}(\theta)$ define the population moments $\Gamma_{XX}(\theta) = \mathbb{E}_\theta[x_t x'_t]$ and $\Gamma_{XY}(\theta) = \mathbb{E}_\theta[x_t y'_t]$, which can be calculated based on the DSGE model solution. Then let Ψ^* be columns 2 through n of $\Gamma^{-1}_{XX}\Gamma_{XY}$ and Σ^*_{tr} the Cholesky decomposition of $\Gamma_{YY} - \Gamma'_{XY}\Gamma^{-1}_{XX}\Gamma_{XY}$.

Our econometric analysis is casted in a Bayesian framework that can be interpreted as follows. At the beginning of time "nature" draws the vector of structural parameters θ and the degree of DSGE model misspecification λ. Given θ and λ, nature draws the misspecification matrices Ψ^{Δ} and Σ_{tr}^{Δ}. The misspecification parameter λ scales the variance of the distribution that generates Ψ^{Δ} and Σ_{tr}^{Δ}. If λ is close to zero, the prior variance of the discrepancies Ψ^{Δ} and Σ_{tr}^{Δ} is large. Large values of λ, on the other hand, correspond to small model misspecification and for $\lambda = \infty$ the misspecification disappears. The joint distribution used by nature (the prior) can then be decomposed as follows:

$$p(\Psi^{\Delta}, \Sigma_u^{\Delta}, \theta, \lambda) = p(\Psi^{\Delta}|\Sigma_u^{\Delta}, \theta, \lambda)p(\Sigma_u^{\Delta}|\theta, \lambda)p(\theta)p(\lambda). \tag{11}$$

Based on the sample $y_1, \ldots, y_T$ the policymaker's task is to learn about (form a posterior distribution on) θ, Ψ^{Δ}, Σ_{tr}^{Δ}, and λ. Markov Chain Monte Carlo methods can be used to implement posterior inference and policy analysis. Details on prior and posterior distributions can be found in Del Negro and Schorfheide (2004b). We refer to the resulting specification as DSGE-VAR.

3.3 Policy Analysis

At time $t = T$ the policymaker seeks to replace the existing policy rule with one that minimizes the following loss function[2]

$$L(\theta_p, \theta_s, \Psi^{\Delta}, \Sigma_{tr}^{\Delta}) = \min \left\{ \mathcal{B}, \mathbb{E} \left[(1-\delta) \sum_{t=T}^{\infty} \delta^{t-T} (y_t - \bar{y})' \mathcal{W} (y_t - \bar{y}) \right] \right\}, \tag{12}$$

where δ is a discount factor, θ is partitioned into policy rule parameters θ_p and taste-and-technology parameters θ_s, and $\mathcal{B}$ is a positive constant that ensures that

[2] We make the simplifying assumption that the public believes the new policy to be in place indefinitely after being announced credibly. This assumption is a short-cut to a more realistic scenario in which there are two types of policy shifts - normal policy making and rare regime shifts (using the terminology of Sims, 1982). In addition we assume that the expectation in (12) is unconditional. The policymaker does not exploit the fact that the public has formed its time $T-1$ expectations based on the $T-1$ policy rule.

the loss is bounded even if the VAR coefficients imply non-stationary or explosive behavior of the endogenous variables. The loss function encompasses popular ad-hoc loss functions that penalize inflation, output, and interest rate variability.

The policymaker minimizes the loss $L(\theta_p, \theta_s, \Psi^\Delta, \Sigma_{tr}^\Delta)$ as a function of the policy parameter θ_p. She has imperfect knowledge about: (i) the policy invariant private sectors' taste and technology parameters θ_s; and (ii) the degree of model misspecification captured by λ, Ψ^Δ and Σ_{tr}^Δ. The uncertainty is summarized in the posterior distribution.

We consider four different scenarios for the policy invariance of the misspecification matrices Φ^Δ and Σ^Δ. Then we calculate the posterior expected loss associated with different policies according to each scenario. If the DSGE model does not suffer from serious misspecification all scenarios collapse to Scenario 1.

Scenario 1: The DSGE model is estimated directly and its potential misspecification is ignored. The policymaker does, however, take the uncertainty with respect to the non-policy parameters into account when calculating the expected loss. This scenario dates back at least to Brainard (1967) and serves as a benchmark. More recent examples in the context of DSGE models include Laforte (2003) and Onatski and Williams (2004).

Scenario 2: The policymaker believes that the sample (hence the posterior) provides no information about potential misspecification after a regime shift has been implemented. This scepticism about the relevance of sample information is shared by the robust control approaches of Hansen and Sargent (2000) and Onatski and Stock (2002). Here, instead of using a minimax argument, our Bayesian policymaker relies on her prior distribution $p(\Psi^\Delta, \Sigma_{tr}^\Delta | \theta, \lambda)$ to cope with uncertainty about model misspecification. She still uses the sample to learn about θ_s and λ, however.

Scenario 3: Ψ^Δ and Σ_{tr}^Δ are invariant to changes in policy. The sample

information is used to learn about the model misspecification via the posterior distribution. Looking forward, the information is used to adjust the policy predictions derived from the DSGE model, $\Psi^*(\tilde{\theta})$ and $\Sigma^*_{tr}(\tilde{\theta})$. Here $\tilde{\theta}$ denotes the vector of structural parameters that is obtained when θ_p is replaced by a new set of policy parameters $\tilde{\theta}_p$.

Scenario 4: Nature generates a new set of draws from the posterior distribution of Ψ^Δ and Σ^Δ_{tr} conditional on the post-intervention DSGE model parameters $\tilde{\theta}$ instead of the pre-intervention parameters as in Scenario 3. For small values of λ the conditional posterior distribution of $\Psi^*(\theta) + \Psi^\Delta$ and $\Sigma^*_{tr}(\theta) + \Sigma^\Delta_{tr}$ given θ is effectively insensitive to θ. In this case Scenario 4 corresponds to analyzing policy effects with a VAR by simply changing the coefficients in the policy rule.

4 Empirical Results

Table 1 describes the posterior of the misspecification parameter λ. The Table reports log marginal densities for the directly estimated DSGE model and DSGE-VAR based on different values of λ. The results in Table 1 imply that over the historical sample period the DSGE model is strongly dominated by DSGE-VARs with a small value of λ and indicate that the DSGE model is to some extent misspecified.[3]

Columns 2 and 3 of Table 2 contain prior means and 90% probability intervals.

[3]The data for real output growth come from the Bureau of Economic Analysis (Gross Domestic Product-SAAR, Billions Chained 1996$). The data for inflation come from the Bureau of Labor Statistics (CPI-U: All Items, seasonally adjusted, 1982-84=100). For each quarter the interest rate is computed as the average federal funds rate (source: Haver Analytics) during the first month of the quarter, including business days only. Our sample ranges from 1982:I to 2001:III. We reserve the first two observations to initialize VAR lags. The results are based on a DSGE-VAR with 2 lags. We also estimate the DSGE model directly, using the techniques described in Schorfheide (2000).

The specification of the prior is taken from Del Negro and Schorfheide (2004a). Columns 4 through 7 of Table 2 contain posterior means and probability intervals for the DSGE model and the DSGE-VAR with $\lambda = 0.5$. The two specifications lead to somewhat different parameter estimates. For $\lambda = 0.5$ the central bank's reaction to inflation and lagged interest rates is more aggressive, whereas the response to output growth is weaker. The estimated slope of the Phillips curve which determines the real effect of monetary policy is slightly larger than reported elsewhere in the literature, in particular for $\lambda = 0.5$.

Based on the parameter estimates we calculate expected policy losses. The loss is based on Eq. (12) where the weighting matrix $\mathcal{W}$ is diagonal with elements $\frac{1}{4}$ (interest rates, annualized), 1 (inflation, annualized), and $\frac{1}{4}$ (output growth, quarter-to-quarter). Our weight on output growth is somewhat larger than in Woodford (2003, Table 6.1) reflecting a larger estimate of κ. Moreover, we place considerable weight on the nominal interest rate, which could be justified by a large interest elasticity of money demand and an important role of real money balances for transactions. The upper bound $\mathcal{B}$ of the loss is set to 20, which is about 5 times larger than the weighted sample variance of the three series. We evaluate the expected loss as a function of ψ_1, the central bank's response to inflation. The other two parameters of the policy rule are set approximately to their respective posterior mean estimates for $\lambda = 0.5$: $\psi_2 = 0.2$, $\rho_R = 0.75$. The results are summarized in Figure 1, which depicts expected loss differentials relative to the benchmark $\psi_1 = 1.9$. Negative differentials indicate an improvement relative to the benchmark.

In Scenario 1 the policymaker calculates the policy loss with the DSGE model, ignoring misspecification. It is well known that as the response to inflation increases, inflation variability drops and the loss decreases. The inference about the misspecification parameter λ in Table 1 casts some doubts on the reliability of

DSGE model predictions, however.

In Scenario 2 the policymaker still uses the DSGE model to compute the mean response of the endogenous variables to the change in ψ_1, but recognizes that nature may be injecting noise around these mean responses using the prior distribution. Not surprisingly for larger values of λ (low misspecification) the shape of the loss does not change relative to Scenario 1. For smaller values of λ (high misspecification) the loss profile becomes flatter for values of ψ_1 larger than 2. A decomposition of the loss into its three components indicates that interest rate and output growth variability actually rise as the central bank responds more strongly to inflation. However, this rise is off-set by a substantial drop in inflation variability.

In Scenario 3 the policymaker uses sample information to learn about the size of the discrepancies, unlike in the previous scenarios. More specifically, she believes that the historically observed discrepancies Ψ^{Δ} and Σ_{tr}^{Δ} are policy invariant. For $\lambda = 5$ the loss is still a decreasing function of ψ_1, as in the Scenario 1, but for $\lambda = 1$ and $\lambda = 0.5$ the slope switches sign around $\psi_2 = 1.5$. The large expected losses under policies that respond strongly to inflation are a reflection of a predictive distribution that assigns substantial mass to parameter values that imply non-stationary dynamics.

Finally, under Scenario 4 the policymaker again uses sample information to learn about potential model misspecification. Unlike in Scenario 3, the policymaker now asks the question: what is the estimate of the discrepancy if the new policy had been in place during the sample period. For small values of λ inflation and output growth are essentially being forecasted using an unrestricted VAR as changes of agents' decision rules derived from the DSGE models are deemed unreliable. Only the policy equation reflects the change in ψ_1, thereby generating a higher interest rate volatility which leads to the slight positive slope of the loss

functions depicted in the fourth panel of Figure 1. Even for $\lambda = 5$ the shape of the loss function differs from Scenario 1. The overall magnitude of the loss differentials is much smaller than in the previous scenarios.

In summary, we show that the implications of the policy experiment are markedly different depending on: (i) whether the policymaker relies on the data to assess the degree of misspecifications, i.e., learns about λ; and (ii) the assumption she makes on the process driving the discrepancies between the DSGE model and the data in the aftermath of the policy intervention.

5 Conclusion

Current DSGE models are to some extent misspecified, even large-scale models such as the one in Smets and Wouters (2003). While they allow policymakers to assess the effects of rare policy changes on the expectation formation and decision rules of private agents, their fit is typically worse than the fit of alternative econometric models, such as VARs estimated with well-calibrated shrinkage methods. The DSGE-VARs studied in Del Negro and Schorfheide (2004a,b) provide a framework that allows researchers to account for model misspecification. We applied some of the techniques to a simple New Keynesian DSGE model and studied the effect of changing the response to inflation under an ad-hoc loss function that penalizes inflation, output growth, and interest rate variability. We view our framework as an attractive alternative to robust control approaches to model misspecification that deserves to be explored in future research.

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Table 1: Log Marginal Data Densities and Posterior Odds

Specification	$\ln p(Y\|\lambda)$	Posterior Odds
DSGE Model	-321.16	1.000
DSGE-VAR, $\lambda = 5.0$	-313.58	1967
DSGE-VAR, $\lambda = 1.0$	-297.59	1.7E9
DSGE-VAR, $\lambda = 0.5$	-289.75	4E13

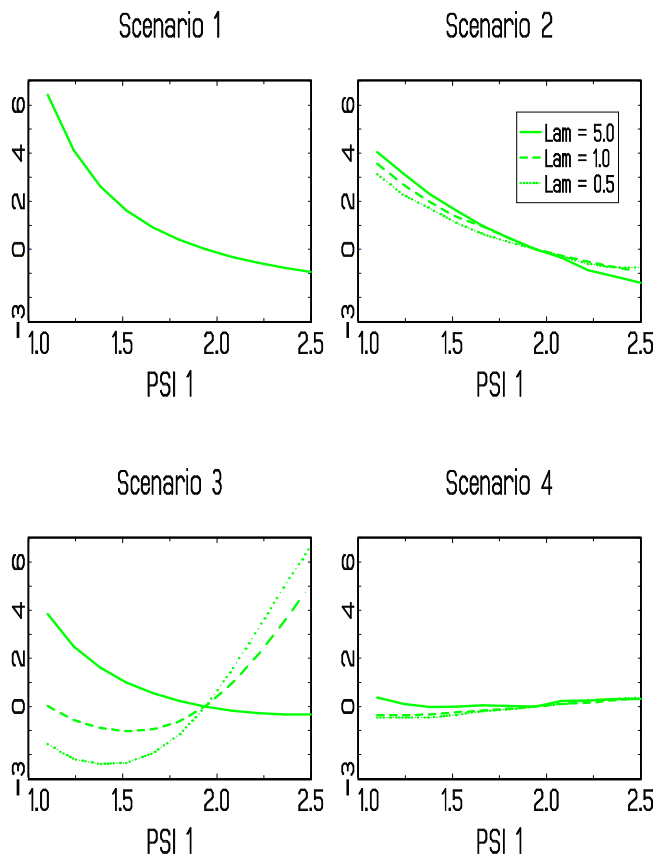
Notes: The marginal data densities are obtained by integrating the likelihood function with respect to the model parameters, weighted by the prior density conditional on λ. The ratio of marginal data densities can be interpreted as posterior odds under the assumption of that the two specifications have equal prior probabilities.

Table 2: Parameter Estimation Results

	Prior		DSGE Model		DSGE-VAR $\lambda = 0.5$	
	Mean	Prob Interval	Mean	Prob Interval	Mean	Prob Interval
ψ_1	1.51	[1.10, 1.90]	1.44	[1.13, 1.72]	1.87	[1.54, 2.22]
ψ_2	0.13	[0.00, 0.26]	0.37	[0.17, 0.55]	0.23	[0.01, 0.44]
ρ_R	0.50	[0.19, 0.84]	0.72	[0.66, 0.79]	0.74	[0.67, 0.82]
$\ln \gamma_a$	2.00	[0.35, 3.62]	2.45	[1.26, 3.56]	2.57	[1.42, 3.75]
$\ln \pi_a^*$	4.01	[0.85, 7.32]	2.84	[2.22, 3.50]	2.60	[1.53, 3.69]
$\ln r_a^*$	1.99	[0.55, 3.52]	2.45	[1.73, 3.14]	2.16	[1.09, 3.15]
κ	0.30	[0.07, 0.52]	0.65	[0.42, 0.88]	0.90	[0.58, 1.25]
τ	2.00	[1.21, 2.82]	1.97	[1.09, 2.78]	1.56	[0.79, 2.29]
ρ_g	0.80	[0.65, 0.96]	0.96	[0.93, 0.99]	0.90	[0.82, 0.98]
ρ_z	0.30	[0.12, 0.45]	0.86	[0.81, 0.91]	0.66	[0.55, 0.76]
σ_R	0.25	[0.11, 0.40]	0.17	[0.13, 0.20]	0.17	[0.12, 0.21]
σ_g	0.63	[0.27, 1.00]	0.86	[0.70, 1.00]	0.54	[0.40, 0.68]
σ_z	0.88	[0.38, 1.40]	0.29	[0.23, 0.35]	0.36	[0.27, 0.44]

Notes: The table reports prior and posterior means and 90 percent probability intervals in brackets. The model parameters $\ln \gamma$, $\ln \pi^*$, $\ln r^*$, σ_R, σ_g, and σ_z are scaled by 100 to convert their units into percentage points. The parameters $\ln \gamma_a$, $\ln \pi_a^*$, and $\ln r_a^*$ are annualized.

Figure 1: Expected Policy Loss Differentials



Notes: Mean policy loss differentials relative to baseline policy rule $\psi_1 = 1.9$, $\psi_2 = 0.2$, $\rho_R = 0.75$. Negative differentials signify an improvement relative to baseline rule.