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David Meenagh, Patrick Minford and Yongdeng Xu

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Cardiff Business School
Cardiff University
Colum Drive
Cardiff CF10 3EU
United Kingdom
t: +44 (0)29 2087 4000
f: +44 (0)29 2087 4419
business.cardiff.ac.uk

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Why Applied Macroeconomists Should Not Use Bayesian Estimation of DSGE Models

David Meenagh [*] Patrick Minford [‡] Yongdeng Xu [§]

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Abstract

This paper argues that the common practice of Bayesian estimation in applied macroeconomic DSGE modeling can lead to severely biased results when the imposed prior beliefs are misspecified. We demonstrate, through controlled Monte Carlo experiments on two canonical DSGE models (a Real Business Cycle model and a New Keynesian model), that Bayesian estimation may yield misleading parameter estimates, often gravitating toward the researcher's prior at the expense of empirical accuracy. In contrast, we show that Indirect Inference, a simulation-based classical estimation approach, remains largely unbiased and robust even under substantial model uncertainty. These findings suggest that heavy reliance on Bayesian estimation can perpetuate false conclusions (for example, overstating nominal rigidities) and thereby misguide policy analysis. We advocate greater use of robust estimation and model validation techniques, like Indirect Inference, to ensure that model-based policy guidance rests on credible empirical foundations.

JEL Codes: C11, C15, C52, E32

Keywords: Bayesian Estimation; DSGE Models; Indirect Inference; Monte Carlo Simulation; Model Misspecification

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[*]Cardiff Business School, Colum Drive, Cardiff, CF10 3EU, UK. Email: MeenaghD@cardiff.ac.uk

[†]Cardiff Business School, Cardiff University, Cardiff, UK.

[‡]CEPR, UK. Email: MinfordP@cardiff.ac.uk

[§]Corresponding Author: Cardiff Business School, Colum Drive, Cardiff, CF10 3EU, UK. Email: xuy16@cardiff.ac.uk

1 Introduction

Dynamic Stochastic General Equilibrium (DSGE) models have become a workhorse tool for applied macroeconomic analysis and policy evaluation. Over the past two decades, Bayesian estimation has emerged as the dominant method for calibrating DSGE models to data, due in part to user-friendly software (e.g. Dynare, Adjemian et al., 2011) and exemplified by the success of studies like Smets and Wouters (2007). Recent surveys confirm this continued dominance and discuss both the attractions of Bayesian tools and their frontier challenges (identification, prior specification, and computational practice). In particular, Guerrón-Quintana and Nason (2025) emphasise how Bayesian methods have become integral to DSGE work while noting that greater computing power does not resolve fundamental identification issues and that Bayesian practice has its own analogous vulnerabilities. However, a growing body of recent research warns that this Bayesian approach can introduce substantial estimation biases, especially if the model is misspecified or the priors are strongly wrong. By placing too much weight on prior information compared to observed data, Bayesian procedures may effectively force the data to conform to prior beliefs, yielding posterior estimates that confirm the modelers' preconceptions rather than revealing the true data-generating process. In macroeconomics, where rival schools of thought often impose conflicting priors (e.g. New Keynesian vs. Real Business Cycle assumptions), this creates a risk that empirical work simply reproduces prior-driven results instead of resolving debates

A prominent example is the long-standing controversy over nominal rigidity. New Keynesian (NK) models assume that prices and wages adjust only sluggishly, amplifying demand-driven fluctuations and giving monetary policy powerful real effects. In contrast, Real Business Cycle (RBC) or New Classical models assume near full price flexibility, so that markets clear quickly and monetary policy has limited real impact. Which view better characterizes the real economy is ultimately an empirical question with vital policy implications (e.g. the appropriate aggressiveness of central bank interventions). Yet empirical evidence remains inconclusive. Typically, New Keynesian proponents estimate DSGE models using Bayesian methods with tight priors that favour significant nominal rigidity, and unsurprisingly obtain posterior estimates supporting sticky prices. Meanwhile, advocates of flexibility often forgo formal estimation altogether, simply calibrating flexible-price models or imposing price flexibility in estimation by assumption. The result is that the degree of price/wage flexibility has failed to be resolved by empirical

estimation and testing due to the imposition of strong priors on each side. The use of Bayesian estimation, in particular, may be biasing results in favour of the modelers' priors, preventing data from genuinely testing which model is more accurate.

Recent studies have raised serious concerns about this issue. For example, Meenagh, Minford and Wickens (2022) conduct simulation experiments and find that Bayesian estimation of macro models can give very misleading results by placing excessive weight on the prior, potentially drowning out the data signal. Their results suggest that if a researcher's prior strongly favours the New Keynesian paradigm, a Bayesian-estimated DSGE will likely "produce posterior estimates that support the use of New Keynesian models' even if the true economy is closer to an flexible-price world. Complementing this, Marlow (2025) demonstrates that standard posterior summaries can understate joint estimation uncertainty and proposes a decision-theoretic joint Bayesian procedure to correct this, highlighting limitations of current practice. In a similar vein, Chari, Kehoe and McGrattan (2009) argued that standard New Keynesian DSGE models "are not yet useful for policy analysis," partly because their empirical validations were unconvincing when scrutinized without strong prior assumptions. These concerns have only grown in the wake of recent macroeconomic events (such as the 2020–21 inflation surge), where models heavily tuned to prior beliefs struggled to anticipate or explain observed outcomes. The potential for prior misspecification, for example, confidently assuming a high degree of price stickiness when the true economy might have more flexibility, which means that Bayesian estimators can be substantially biased and yield spurious precision. Indeed, if the likelihood function is relatively flat for certain parameters (a common occurrence in DSGE estimation due to weak identification), the posterior will be dominated by the prior, making the inference essentially a self-fulfilling prophecy.

In light of these issues, it is critical to revisit how we estimate DSGE models for applied macroeconomic analysis. This paper contributes to the debate by providing a comprehensive Monte Carlo evaluation of Bayesian vs. classical estimation methods in the context of DSGE models. Specifically, we focus on Bayesian estimation vis-à-vis Indirect Inference (II), which is a simulation-based estimation and testing approach, under scenarios of model uncertainty (i.e. when the researcher's maintained model may be misspecified relative to the true data-generating process). Indirect Inference does not require informative priors; instead, it matches simulated model moments or auxiliary model estimates to those in actual data, letting the data 'speak' more freely.

Meenagh, Minford and Wickens (2022) carried out a similar exercise to the one here, focusing purely on the price rigidity parameters of a single model that otherwise had all the same parameters, imposed as calibrated values. They compared Bayesian estimates of the price rigidity parameters alone, holding the rest fixed. What they found was that the rigidity estimates were strongly biased to the prior values; when the true model was flexible, the rigid priors delivered rigid posteriors, and when the true model was rigid, the flexible priors delivered flexible posteriors. Thus regardless of the true rigidity the estimated rigidity was close to the prior rigidity. In this paper we take matters further and compare two complete models, each with a full set of priors. Each model corresponds to a different and opposed school of thought about the economy: on the one hand a standard NK model and on the other an RBC model in which there is continuous market-clearing. Our design is straightforward. Using a Monte Carlo design, we generate artificial datasets from each model and then estimate them using both correct and incorrect priors. The results are striking. When Bayesian estimation is applied with correct priors, it performs well, recovering parameter values with little bias. But when Bayesian estimation is applied with priors from the wrong paradigm (NK priors on RBC data or RBC priors on NK data), the posteriors become severely biased, in some cases by several hundred or even several thousand percent. By contrast, Indirect Inference proves robust across all scenarios. While somewhat less precise in the correctly specified cases, II avoids the catastrophic distortions that plague Bayesian estimation under false priors and consistently recovers parameters that remain close to their true values.

This evidence highlights both the strengths and the fragility of Bayesian estimation. It can deliver precise results when priors happen to be correct, but it cannot protect against the risks of prior misspecification. Since there is no consensus on the true structure of the economy, the risk of false priors is ever-present. Indirect Inference, by contrast, offers a safeguard: it forces the model to match the behaviour of the data and provides a formal test of model adequacy, rather than simply reproducing the modeller's prior beliefs.

To summarise, our study makes several contributions to the literature. First, we provide a head-to-head comparison of Bayesian and Indirect Inference estimation in a controlled setting involving two canonical DSGE models (RBC and NK). Second, we quantify the potential bias introduced by 'whole-model' priors, showing how imposing the wrong paradigm can distort inference on key structural features. Third, we extend previous work that focused on single-parameter priors (e.g. rigidity) to the broader and more consequential issue of full-model

selection. Finally, we draw out the policy implications: if Bayesian estimation tends to confirm prior beliefs even when they are wrong, it risks misleading policymakers. Indirect Inference, by contrast, offers a more reliable route, ensuring that DSGE models used for policy guidance are tested against the data rather than against the modeller's preconceptions.

The remainder of the paper is organized as follows. Section 2 describes the two DSGE models used in our experiments. Section 3 presents the simulation results, including quantitative evidence of Bayesian estimation bias under prior misspecification and the superior robustness of Indirect Inference. In Section 4, we summarise the findings and discuss their implications for macroeconomic policy modeling. Section 5 concludes.

2 Models

We consider two well-established structural models that represent opposing schools of macroeconomic thought. The first is a Real Business Cycle (RBC) model characterised by continuous market clearing, price flexibility, and supply-driven fluctuations. The second is a New Keynesian (NK) model, which incorporates sticky wages and prices and is driven largely by nominal rigidities and demand shocks. Both models are estimated in log-linear form and solved using standard Dynare procedures. A complete description of the model equations is provided in Appendix A.

Real Business Cycle (RBC)

RBC models assume perfectly competitive markets and instantaneous price adjustment, so the decentralised choices of households and firms can be represented as the solution to a social–planner problem. A standard formulation maximises discounted utility

$$\max_{\{C_t, N_t\}} \; E_t \sum_{i=0}^{\infty} \beta^i (U(C_{t+i}) - V(N_{t+i}))$$

subject to the resource constraint and capital accumulation,

$$Y_t \;=\; C_t + I_t \;=\; A_t K_{t-1}^{\alpha} N_t^{1-\alpha}, \qquad K_t \;=\; I_t + (1-\delta) K_{t-1},$$

and a stochastic process for technology,

$$\log A_t \;=\; (1-\rho)\log \bar{A} \;+\; \rho \log A_{t-1} \;+\; \varepsilon_t.$$

With flexible prices and wages, the model exhibits monetary neutrality and market clearing each period; business-cycle comovements are driven by real (e.g. technology) shocks.

New Keynesian (NK)

NK models retain the RBC core (intertemporal optimisation by households and firms, rational expectations) but introduce nominal frictions, typically Calvo-type price and/or wage stickiness. These frictions break monetary neutrality so that policy rates affect real allocations. In the canonical log-linearised representation this yields an intertemporal IS curve, a New Keynesian Phillips curve, and a monetary policy rule. Demand shocks (including belief or 'animal spirits' disturbances) and policy shocks can have persistent real effects precisely because prices and wages adjust sluggishly.

These two paradigms provide the contrasting maintained hypotheses we exploit in our Monte Carlo design. The RBC model delivers a flexible-price benchmark in which policy has no real effects; the NK model embeds nominal rigidities that amplify demand disturbances and render monetary policy powerful. Our experiment asks how estimation behaves when the prior embodies one paradigm but the data are generated by the other.

Bayesian estimation

Let θ denote the structural parameter vector and let Y collect the observed data (e.g. output, inflation, interest rates). Bayesian estimation combines a prior density $p(\theta)$ with the model-implied likelihood $p(Y \mid \theta)$ to form the posterior density via Bayes' rule:

$$p(\theta \mid Y) = \frac{p(Y \mid \theta)\, p(\theta)}{p(Y)} \;\propto\; p(Y \mid \theta)\, p(\theta), \tag{1}$$

$$p(Y) = \int p(Y \mid \theta)\, p(\theta)\, d\theta \quad \text{(marginal likelihood)}. \tag{2}$$

Equivalently, in logs,

$$\log p(\theta \mid Y) = \log p(Y \mid \theta) + \log p(\theta) - \log p(Y). \tag{3}$$

For point estimation, the *posterior mode* (MAP) solves

$$\hat{\theta}_{\mathrm{MAP}} \in \arg\max_{\theta} \left\{ \log p(Y \mid \theta) + \log p(\theta) \right\}, \tag{4}$$

so that the prior acts as an explicit regulariser on the likelihood. When the likelihood is flat or weakly identified in some directions (a common feature in DSGE applications), $\log p(\theta)$ can dominate (3), tilting $\hat{\theta}_{\mathrm{MAP}}$ toward the prior. Posterior uncertainty is then summarised by (marginal) credible sets derived from $p(\theta \mid Y)$, typically computed via MCMC.

For model comparison, the marginal likelihood (2) yields Bayes factors. In practice, we report both posterior objects (modes/means and credible sets) and frequentist diagnostics (via Indirect Inference) to assess whether a given parameterisation can replicate reduced-form data behaviour.

In what follows, we implement Bayesian estimation under two prior systems corresponding to each paradigm (RBC and NK). This allows us to evaluate directly how prior information interacts with the likelihood in our models, and to compare these outcomes with Indirect Inference, which dispenses with informative priors and instead matches simulated model behaviour to the data.

3 Monte Carlo Experiment

In this section, we conduct a Monte Carlo experiment to examine the consequences of estimating a model using Bayesian priors derived from a different theoretical paradigm than the true data-generating process (DGP). While earlier work focused on a limited parameter subset, typically the degree of price rigidity, our experiment compares full-model priors across two distinct DSGE structures.

We take each model, the RBC and the NK, in turn as the true DGP. For each case, we generate 1,000 artificial samples of simulated data. We then estimate both models using Bayesian methods, once using priors consistent with the true model and once using priors drawn from the rival framework. This allows us to assess the extent to which the posterior distribution is influenced by the prior, even when the prior is inconsistent with the underlying economic process.

For the NK prior, we follow the Smets and Wouters (2007) tradition, assigning high weight to nominal rigidities. For the RBC prior, we adopt flexible-price priors consistent with the

calibration literature initiated by Kydland and Prescott (1982). In all experiments, parameters that are not central to the divide between the two paradigms are given priors centered on their true values. This ensures that any observed bias is due to the model-defining parameters.

3.1 RBC as the True Model

We begin with the RBC model as the true DGP. Artificial data are simulated using the RBC model and its corresponding parameter set. In the Bayesian estimation stage, we estimate the model under two prior configurations: one with prior means equal to the true RBC parameters, and one with prior means taken from the NK model. In both cases, the prior distributions are normal, with a standard deviation set at 30% of the prior mean for each parameter Z_1 to Z_{18}.

For comparison, we also estimate the model using Indirect Inference (II). This is implemented in a manner directly comparable to the Bayesian setup. We use Matlab's `fmincon` algorithm to minimise the weighted distance between the data and the model-implied outcomes. The objective function is based on the coefficients of a three-variable unrestricted VAR, estimated on output, inflation, and interest rate dynamics. Following Le et al. (2016), we choose a three-variable VAR as it offers a good trade-off between statistical power and reliability of inference. For the II estimation, which relies on numerical optimization, the choice of starting values is crucial. To improve robustness and avoid local minima, we initialize the optimization using the RBC and NK priors, along with ten equally spaced grid points between them, resulting in a total of twelve deterministic starting values. For each starting point, we solve a bound-constrained nonlinear optimization problem using `fmincon`, where the objective function is the II Wald criterion. The structural parameters are estimated by minimizing this criterion across all starting values, and the final II estimator is taken as the solution corresponding to the smallest objective value.

Estimation with RBC Priors: Baseline Case of Correct Specification

We begin by examining the baseline case in which the data are generated by the RBC model and the estimation is conducted using Bayesian priors drawn from the same RBC framework. Table 1 presents the parameter estimates obtained using both Bayesian estimation (BS) and Indirect Inference (II).

In this benchmark setting, where the prior, model, and data-generating process are all consistent, Bayesian estimation performs as expected. Posterior means are tightly clustered around

the true parameter values, and bias is uniformly low across all parameters. Notably, key structural parameters such as the intertemporal elasticity of substitution (Z_2), capital adjustment costs (Z_1), and the production function elasticity (Z_{10}) show minimal deviation, with biases generally below 3%. Standard deviations are small, reflecting the precision that comes from incorporating informative priors based on the correct model.

Indirect Inference also performs well in this setting, though with slightly larger standard deviations due to the absence of informative priors. Importantly, the point estimates under II remain close to their true values. For example, Z_2, Z_3, and Z_{10} are all estimated with less than 1% bias, while other parameters such as Z_5 and Z_{15} deviate only marginally. The slightly wider dispersion of II estimates is to be expected, as this method does not benefit from prior-based regularisation. Nonetheless, it exhibits strong accuracy and consistency.

These results confirm that both Bayesian estimation and Indirect Inference can recover the true parameter values when the model and priors align with the data-generating process. However, while Bayesian estimation enjoys greater precision in this correctly specified case, it remains to be seen how it behaves when the priors are drawn from a different and inconsistent theoretical model — a question we turn to next.

Table 1: Parameter Estimation (RBC prior, RBC model)

	True	Prior	BS Mean	BS Std	BS Bias (%)	II Mean	II Std	II Bias (%)
Z_1	9.931	9.931	9.963	0.345	+0.32%	10.140	0.919	+2.10%
Z_2	1.270	1.270	1.306	0.204	+2.88%	1.267	0.061	-0.22%
Z_3	0.896	0.896	0.896	0.002	+0.02%	0.889	0.015	-0.68%
Z_4	0.703	0.703	0.703	0.000	-0.00%	0.701	0.032	-0.20%
Z_5	2.301	2.301	2.308	0.059	+0.32%	2.287	0.093	-0.59%
Z_6	0.583	0.583	0.583	0.000	-0.00%	0.583	0.027	+0.05%
Z_7	0.433	0.433	0.433	0.000	+0.00%	0.433	0.018	-0.01%
Z_8	0.041	0.041	0.041	0.000	+0.00%	0.041	0.001	+0.26%
Z_9	0.163	0.163	0.163	0.001	+0.06%	0.163	0.006	+0.16%
Z_{10}	1.500	1.500	1.521	0.097	+1.37%	1.502	0.055	+0.13%
Z_{11}	2.573	2.573	2.573	0.000	-0.00%	2.565	0.099	-0.34%
Z_{12}	0.873	0.873	0.873	0.000	-0.00%	0.864	0.032	-0.98%
Z_{13}	0.009	0.009	0.009	0.000	-0.00%	0.009	0.000	+0.23%
Z_{14}	0.011	0.011	0.011	0.000	+0.00%	0.011	0.000	+0.23%
Z_{15}	0.336	0.336	0.334	0.017	-0.39%	0.336	0.011	+0.05%
Z_{17}	0.967	0.967	0.967	0.000	-0.00%	0.937	0.071	-3.05%
Z_{18}	0.015	0.015	0.015	0.000	-0.00%	0.015	0.001	+0.37%

Note: "BS" denotes Bayesian Estimation; "Mean" gives the average estimate across the simulation runs, "Std" gives the standard deviation of those estimates, "Bias (%)" reports the percentage deviation of the mean estimate from the true value.

Estimation with NK Priors: Bias under Misspecified Beliefs

We now consider the case where the data continue to be generated by the RBC model, but the estimation is conducted using priors drawn from the NK model. This represents a situation in which the econometrician imposes a belief system inconsistent with the true economic structure. The results are shown in Table 2.

Bayesian estimation under these misspecified priors performs very poorly. The bias is substantial and widespread across parameters, with many estimates deviating dramatically from their true values. In general, the Bayesian posterior is pulled toward the prior, but the direction and magnitude of bias vary widely. For instance, Z_1 (capital adjustment cost) is pulled downward toward the lower NK prior, showing a –24% bias, while Z_5 (labour share) collapses by more than –70%. Some parameters move dramatically in the direction of the prior — such as Z_3 (intertemporal elasticity of substitution), which falls by –38% — while others exhibit extreme and seemingly random distortions. Price stickiness parameters such as Z_8, Z_{13}, and Z_{14} illustrate this problem vividly, with biases of +3800%, +2100%, and +15400% respectively. Moreover, structural parameters such as Z_9 (returns to scale) are not merely biased but become implausible, with Bayesian estimates turning negative. This shows that when priors are structurally inconsistent with the true model, the Bayesian procedure can generate posteriors that are not only wrong but economically nonsensical.

In contrast, the Indirect Inference (II) method produces considerably more stable and accurate estimates. Interestingly, although we use different starting values for the II estimation, the optimization consistently converges to the same solution as in the initial case. This occurs because the `fmincon` algorithm selects the starting values and parameter estimates that minimise the Wald statistic.

These findings reinforce a key conclusion: when priors are misspecified, Bayesian estimation is not just biased toward the prior but can also generate extreme and erratic distortions. The apparent precision of the Bayesian posterior in these cases is misleading, as the results are driven more by the false prior than by the data. Indirect Inference, by contrast, avoids these pitfalls. By allowing the data rather than the priors to drive estimation, II produces results that remain broadly consistent with the true data-generating process, even when the starting priors are far from correct.

Table 2: Parameter Estimation (NK prior, RBC model)

	True	Prior	BS Mean	BS Std	BS Bias %	II Mean	II Std	II Bias (%)
Z_1	9.931	5.993	7.513	9.601	-24.45%	10.140	0.919	+2.10%
Z_2	1.270	1.254	1.100	1.525	-13.36%	1.267	0.061	-0.22%
Z_3	0.896	0.511	0.558	0.188	-37.68%	0.889	0.015	-0.68%
Z_4	0.703	0.639	0.640	0.022	-8.86%	0.701	0.032	-0.20%
Z_5	2.301	2.709	0.626	0.045	-72.81%	2.287	0.093	-0.59%
Z_6	0.583	0.384	0.955	0.001	+63.83%	0.583	0.027	+0.05%
Z_7	0.433	0.239	0.967	0.001	+123.13%	0.433	0.018	-0.01%
Z_8	0.041	0.032	1.606	3.008	+3801.79%	0.041	0.001	+0.26%
Z_9	0.163	0.207	-2.469	1.399	-1613.26%	0.163	0.006	+0.16%
Z_{10}	1.500	1.870	0.384	0.013	-74.42%	1.502	0.055	+0.13%
Z_{11}	2.573	1.754	0.238	0.039	-90.75%	2.565	0.099	-0.34%
Z_{12}	0.873	0.628	0.033	0.029	-96.18%	0.864	0.032	-0.98%
Z_{13}	0.009	0.012	0.198	0.021	+2123.07%	0.009	0.000	+0.23%
Z_{14}	0.011	0.008	1.754	0.000	+15472.58%	0.011	0.000	+0.23%
Z_{15}	0.336	0.277	0.012	0.008	-96.35%	0.336	0.011	+0.05%
Z_{17}	0.967	0.967	0.439	0.206	-54.58%	0.937	0.071	-3.05%
Z_{18}	0.015	0.024	0.025	0.019	+68.54%	0.015	0.001	+0.37%

Note: See Table 1.

3.2 NK as the True Model

We then repeat the procedure using the NK model as the true DGP. As before, we generate 1000 samples of artificial data from the NK model, using parameter values consistent with the literature. In the Bayesian estimation, we again consider two priors: one based on the NK model (true prior) and one based on the RBC model (false prior). Each prior distribution is normal with a standard deviation equal to 30% of the prior mean.

Indirect Inference is applied using the same estimation approach described above. The objective function is based on the same three-variable VAR and the same estimation routine. This like-for-like comparison allows us to assess the robustness of II relative to Bayesian estimation in recovering the true model structure.

Estimation with NK Priors: Baseline Case of Correct Specification

We first examine the baseline case where the NK model is the true data-generating process and estimation is conducted using priors consistent with the NK tradition. The results are shown in Table 3.

In this setting, both Bayesian estimation (BS) and Indirect Inference (II) perform well. Bayesian posterior means are tightly clustered around the true parameter values, with biases typically below 3%. For example, Z_1, Z_2, and Z_{10} are all recovered with negligible error, while nominal rigidity parameters such as Z_3 and Z_4 are estimated with biases of less than 1%. This

outcome confirms that when priors and the true model are aligned, Bayesian estimation delivers precise and accurate results.

Indirect Inference also performs strongly, albeit with slightly larger standard deviations than the Bayesian case. Nevertheless, the point estimates are consistently close to the true values, and in many cases the II estimates exhibit almost no bias, for instance, Z_2, Z_7, and Z_{10} show deviations of less than 0.3%. These results demonstrate that II provides an accurate alternative even without reliance on prior distributions.

Overall, when the true model corresponds to the priors, both methods are able to recover the parameter values with little bias. Bayesian estimation enjoys greater precision due to the use of informative priors, but Indirect Inference proves competitive in terms of accuracy and remains free from prior-driven influence.

Table 3: Parameter Estimation (NK prior, NK model)

	True	Prior	BS Mean	BS Std	BS Bias %	II Mean	II Std	II Bias %
Z_1	5.993	5.993	5.989	0.261	-0.07%	6.054	0.367	+1.03%
Z_2	1.254	1.254	1.253	0.051	-0.07%	1.258	0.034	+0.29%
Z_3	0.511	0.511	0.508	0.018	-0.61%	0.513	0.016	+0.47%
Z_4	0.639	0.639	0.638	0.011	-0.30%	0.641	0.015	+0.20%
Z_5	2.709	2.709	2.628	0.012	-2.99%	2.712	0.048	+0.13%
Z_6	0.384	0.384	0.355	0.000	-7.63%	0.385	0.007	+0.21%
Z_7	0.239	0.239	0.240	0.021	+0.40%	0.239	0.004	+0.07%
Z_8	0.032	0.032	0.034	0.055	+4.00%	0.032	0.001	+0.04%
Z_9	0.207	0.207	0.221	0.131	+6.72%	0.208	0.004	+0.12%
Z_{10}	1.870	1.870	1.885	0.019	+0.78%	1.874	0.035	+0.21%
Z_{11}	1.754	1.754	1.738	0.035	-0.89%	1.762	0.037	+0.45%
Z_{12}	0.628	0.628	0.632	0.002	+0.69%	0.629	0.015	+0.26%
Z_{13}	0.012	0.012	0.012	0.013	-1.80%	0.012	0.000	+0.06%
Z_{14}	0.008	0.008	0.008	0.061	-8.73%	0.008	0.000	+0.08%
Z_{15}	0.277	0.277	0.262	0.002	-5.14%	0.277	0.006	+0.15%
Z_{17}	0.967	0.967	0.969	0.037	+0.24%	0.947	0.050	-2.09%
Z_{18}	0.024	0.024	0.024	0.000	+0.00%	0.024	0.000	-0.02%

Note: See Table 1.

Estimation with RBC Priors: Bias under Misspecified Beliefs

We now turn to the case in which the NK model is the true data-generating process but estimation is conducted using priors taken from the RBC tradition. The results, reported in Table 4, reveal a stark contrast.

Under these false priors, Bayesian estimation becomes heavily distorted. In general, the posterior is pulled in the direction of the RBC priors, but the magnitude of the bias varies enormously and often in a seemingly erratic fashion. For example, Z_1 is drawn upward toward

the higher RBC prior, producing a +35% bias, while Z_5 and Z_{10} collapse by more than 70%. At the same time, certain parameters explode to extreme and implausible levels: Z_8 is inflated by over 5500%, Z_9 is biased upward by more than 1200%, and Z_{14} shows an extraordinary bias exceeding 20000%. Other NK-specific parameters, such as Z_{13} and Z_{16}, are also badly distorted. The pattern here mirrors the RBC DGP with NK priors: when the prior structure is inconsistent with the true model, Bayesian posteriors are dominated by the prior, with some biases that look systematic (moving toward the prior mean) and others that are wildly random in scale.

By contrast, the Indirect Inference approach demonstrates considerably greater robustness. Although some biases remain, they are generally small and consistent with the results from the previous setting.

These results reinforce the central conclusion of our experiment. Bayesian estimation performs well only when priors are consistent with the true model; once priors are drawn from a structurally different paradigm, the posteriors not only become severely biased toward those priors but also display random and extreme distortions. Indirect Inference, by contrast, remains robust in both cases. Although less precise when compared to Bayesian estimation with correct priors, II avoids the catastrophic distortions induced by false priors and provides parameter estimates that remain broadly consistent with the true data-generating process.

Table 4: Parameter Estimation (RBC prior, NK model true)

	True	Prior	BS Mean	BS Std	BS Bias %	II Mean	II Std	II Bias %
Z_1	5.993	9.931	8.073	0.286	+34.71%	6.054	0.367	+1.03%
Z_2	1.254	1.270	1.241	0.046	-1.06%	1.258	0.034	+0.29%
Z_3	0.511	0.896	0.483	0.016	-5.46%	0.513	0.016	+0.47%
Z_4	0.639	0.703	0.630	0.041	-1.48%	0.641	0.015	+0.20%
Z_5	2.709	2.301	0.621	0.011	-77.07%	2.712	0.048	+0.13%
Z_6	0.384	0.583	0.955	0.001	+148.62%	0.385	0.007	+0.21%
Z_7	0.239	0.433	0.878	0.006	+267.58%	0.239	0.004	+0.07%
Z_8	0.032	0.041	1.849	0.012	+5598.32%	0.032	0.001	+0.04%
Z_9	0.207	0.163	2.708	0.154	+1205.49%	0.208	0.004	+0.12%
Z_{10}	1.870	1.500	0.417	0.009	-77.70%	1.874	0.035	+0.21%
Z_{11}	1.754	2.573	0.295	0.037	-83.16%	1.762	0.037	+0.45%
Z_{12}	0.628	0.873	0.042	0.002	-93.23%	0.629	0.015	+0.26%
Z_{13}	0.012	0.009	0.192	0.014	+1460.69%	0.012	0.000	+0.06%
Z_{14}	0.008	0.011	1.750	0.054	+20984.31%	0.008	0.000	+0.08%
Z_{15}	0.277	0.336	0.009	0.001	-96.64%	0.277	0.006	+0.15%
Z_{17}	0.967	0.967	0.308	0.017	-68.19%	0.947	0.050	-2.09%
Z_{18}	0.024	0.015	0.015	0.001	-36.15%	0.024	0.000	-0.02%

Note: See Table 1.

3.3 II Wald test

An additional advantage of the II approach is that it allows formal testing of model adequacy. The minimised value of II Wald is the test statistic. Under the null that the structural model is correctly specified, it is asymptotically χ^2-distributed with degrees of freedom equal to the number of (independent) auxiliary statistics used in the test (less any exact identifying restrictions). We report the corresponding p-value and make decisions using standard critical values. As shown by Le et al. (2016), II provides a powerful framework for testing macroeconomic models. A well-specified model should pass the II-based test at the 5% significance level.

We apply the II Wald test to the four model–prior configurations, using 1,000 artificial datasets and the corresponding 1,000 Bayesian and II estimates obtained from the previous simulation. The empirical sizes (or, equivalently, the rejection rates under the null) are reported in Table 5.

When the true model is RBC and the prior corresponds to the true prior, the size of the II Wald test is 6.8%, which is very close to the nominal 5% level. After re-estimation using the Bayesian method, the size becomes 6.6%, and with II re-estimation it is 5.4% — both very close to the nominal level. Similarly, when the NK model and prior correspond to the true data-generating process, the sizes of the II Wald tests remain close to 5%, regardless of whether the prior, Bayesian, or II estimates are used.

A different picture emerges under model misspecification. For instance, when the true model and data follow RBC dynamics but the researcher incorrectly assumes an NK model and uses an NK prior, the II Wald test rejects the null 100% of the time. Even after Bayesian re-estimation under this incorrect prior, the rejection rate remains high at 94.2%. However, when the II estimation is applied without imposing any prior restrictions, the estimated parameters converge to values close to the true ones, resulting in a rejection rate near the nominal 5%.

A similar pattern arises when the true data are generated by the NK model but the researcher incorrectly adopts an RBC prior. The II Wald test and the Bayesian-based estimation both yield nearly 100% rejection rates, reflecting the model's misspecification. In contrast, the II estimation successfully recovers the correct parameters through optimization, and the corresponding II Wald test exhibits a rejection rate close to the nominal 5% level.

Table 5: II Wald test rejection rate

	Prior	BS estimates	II estimates
RBC prior, RBC model	0.068	0.066	0.054
NK prior, RBC model	1.000	0.942	0.054
NK prior, NK model	0.052	0.046	0.051
RBC prior, NK model	1.000	0.990	0.051

3.4 Potential pitfalls with II estimation

We have seen above how II estimation implies very low bias. It should be emphasised that this low bias requires that II search over the parameter space include the whole paradigm-parameter space, with search starting points spanning it in its entirety. This ensures that it can find the minimum of the Wald criterion (i.e. the point closest to the true model). If it searches only around the prior starting point, it will find the point closest within that area of search, which may still lie far from the true parameter vector but not far enough to be sure of rejection, given the test power. This can also account for the fact that paradigms as different as NK and RBC can coexist in macroeconomics, being used persistently by rival schools of thought, even though indirect estimation may be used.

We can illustrate this by showing how fairly large II bias results when the sole starting point for search is the false paradigm. The detailed results are now presented in Appendix B, for example, when the true model is NK but the II search starts only from RBC priors, and similarly when the true model is RBC but the search starts only from NK priors. In this case, the II estimates produce relatively large bias, with some parameters as large as 64%; this is likely due to local minimisation around the starting values. Although present, this bias is still significantly smaller than that of Bayesian estimation.

What these results illustrate is that II estimation needs to be carried out across the full potential parameter range from the theoretical models under contention. Thus, when, as assumed here, there is uncertainty about the paradigm itself, this uncertainty must be mirrored in the search range for the parameters. If the search is limited to the range around the priors, treated as the starting point, II suffers from an analogous problem to that of Bayesian bias, albeit not on such a large scale.

4 Summary and Policy Implications

The Monte Carlo experiments provide clear evidence on the behaviour of Bayesian and Indirect Inference (II) estimation methods under conditions of correct and incorrect prior beliefs. Across both data-generating processes (RBC and NK), the results point to two robust conclusions.

First, Bayesian estimation performs well only when the priors are consistent with the true underlying model. In the benchmark cases where an RBC model is estimated with RBC priors and an NK model is estimated with NK priors, Bayesian posteriors are tightly centred on the true parameter values, with low bias and small standard deviations. In these settings the use of informative priors sharpens inference and delivers precise estimates. However, this performance is entirely conditional on the correctness of those priors.

Second, once priors are taken from the wrong model, Bayesian estimation breaks down. The posterior distributions are strongly biased toward the incorrect priors, with parameter estimates that diverge sharply from the true values. In some cases, the distortions are extreme: biases of several hundred percent and even orders of magnitude larger are observed for key structural parameters. The reason is that economists who take different positions on priors will obtain posterior estimates close to these, even if the true model is closer to that of their opponents. Our Monte Carlo experiments illustrate this directly: when we postulate a true model and then estimate it using priors set by economists from the opposing paradigm, the resulting estimates are pulled strongly toward those false priors. These results illustrate the fundamental vulnerability of Bayesian DSGE estimation: rather than allowing the data to discipline the priors, the estimation outcome is often dominated by the prior belief, especially when the model is misspecified. In practical terms, this means that Bayesian methods can give the appearance of precise and coherent estimates even when they are systematically wrong.

By contrast, Indirect Inference, when appropriately implemented with a comprehensive search procedure, demonstrates greater robustness across all scenarios. While less precise than Bayesian estimation in the correctly specified cases, II is largely unaffected by the imposition of false priors. When the priors are wrong, II continues to recover parameters that are broadly consistent with the true model, avoiding the catastrophic distortions seen under Bayesian methods. In this sense, II provides a built-in safeguard: it lets the data rather than the priors guide estimation, and therefore resists being pulled toward a false model structure.

4.1 Why applied macroeconomists should not use Bayesian estimation of DSGE models

Bayesian estimation is widespread in applied DSGE work, not least because software such as Dynare makes it convenient. Our results indicate it is not appropriate unless the priors on parameter values are uncontroversially agreed to be correct. When prior beliefs differ across schools (NK vs. RBC), researchers will obtain posterior estimates close to their own priors even if the true model is closer to that of their opponents. The Monte Carlo evidence here illustrates this directly: imposing NK priors on an RBC DGP (and vice versa) yields posteriors heavily biased toward the false priors, sometimes to economically implausible values.

This is not surprising, since the whole point of Bayesian priors is to influence the posterior estimates. The grounds for doing this are scientific prior knowledge which create a presumption that in a given new sample the estimated parameters should be within a reasonable range of what is already known. It has been argued by macroeconomists that economics being a science, such prior economic knowledge should play a similar role in economic estimation. The problem however with this argument is that in macroeconomics controversy rages without cease on what is known. This may well also be true in other branches of economics, but the focus of this paper is solely on macroeconomics.

For research where all participants are confident about such prior knowledge this is an attractive procedure. All sciences aspire to create a body of knowledge that is agreed so that the job of new researchers is to take it as given and add to it at the margins. However one has to be realistic about the state of one's science. In macroeconomics there is widespread and bitter controversy about the most basic mechanisms governing the economy. Thus there are New Classical, New Keynesian, New Information, Real Business Cycle and yet other 'schools of thought' about these mechanisms. Hence the construction of priors is fraught with controversy. Therefore any evaluation of a model's probability based on such priors will only be accepted by those who agree with those priors; so there will be no evaluation that can be regarded as objective. This is illustrated in Figure 1.

Figure 1 can be understood as follows. There are two possible models, NK or RBC, whose parameters are represented by the vector, θ, summarised here by a single value; these constitute two separate and contrasting sets of priors. The log-likelihood of θ given by these priors is shown as the L curves; they increase the closer θ is to the priors. The log-likelihood of the data

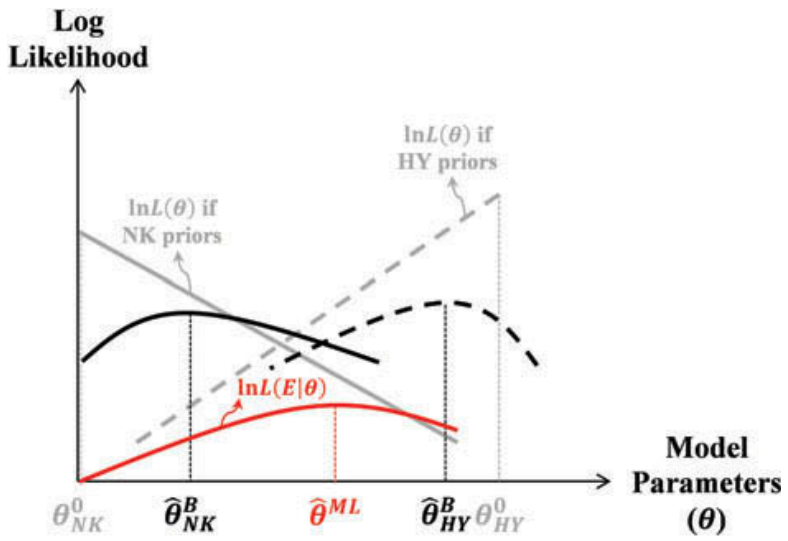


Figure 1: Bayesian evaluation of rival models

conditional on θ is shown by the L(E, θ) curve. The total log-likelihood is shown as the sum of the prior and the data log-likelihood and it differs according to which set of priors is used plainly. If the NK priors are used for example the total log-likelihood of RBC model is very low compared with that of NK; and if the RBC priors are used vice versa. It follows that which model is most probable depends on the priors. Economists with different priors cannot agree in selecting the most probable model.

Of course one may still use Bayesian methods with 'flat priors', where these simply act as initial points for the estimation process; but this is Bayesian only in form, as the posterior then coincides with the likelihood and the estimator is (quasi-)maximum likelihood/Full-Information ML.

Consider now how deeply opposed different groups of economists are on the way that macroeconomic models should be specified. After WWII the reigning macro paradigm was the Keynesian model of price/wage rigidity where output was demand-induced. Empirical estimation of these various models was led by Keynesian modellers after WWII. For 'Old Keynesian' models the main example is Project Link (Klein, 1976) where models were estimated by a wide variety of methods: OLS/IV single equation, FIML, 3SLS. In this estimation process, Keynesian theory, including wage/price rigidity, was simply imposed on the data.

In later New Keynesian models (e.g. Smets and Wouters, 2007), Bayesian NK priors have been imposed in estimation instead.

On the other hand, models with price flexibility were generally calibrated from micro data estimates, not estimated on macro data — just imposed. The main examples of this can be

found in Kydland and Prescott-type RBC models, such as Kydland and Prescott (1982).

Neither side of the price rigidity debate therefore tests its own prior beliefs; each estimates or calibrates models imposing these beliefs. Both sides reject the other; for example Chari et al. (2009) say trenchantly: "Some think New Keynesian models are ready to be used for quarter-to-quarter quantitative policy advice. We do not. Focusing on the state-of-the-art version of these models, we argue that some of its shocks and other features are not structural or consistent with microeconomic evidence. Since an accurate structural model is essential to reliably evaluate the effects of policies, we conclude that New Keynesian models are not yet useful for policy analysis."

Yet it has been shown that neither side's model fits the data. Le et al. (2011) estimated both a flexible price model and a New Keynesian model of the US on postwar US data from the 1950s. Both were strongly rejected on the indirect inference test, meaning that they failed to match reduced form data behaviour at a probability level above the usual 5% threshold. Both models failed to replicate the sample's data behaviour from their massive failure to mirror inflation experience alone. The flexible price model showed heavily excessive inflation variance, NK showed far too little. The failure of each to reflect the joint behaviour of the three central variables, output, inflation and interest rates is revealed by the overall p-values of each model version being close to zero.

The situation has not been changed by the arrival of micro-founded models since Lucas' (1976) critique was taken to heart. These DSGE models have simply been specified either within a sticky-price or a flexible price environment, with again no testing in either case. In these models' specification, this environment is the key driver of behaviour; the parameters of consumption, investment and monetary policy are of secondary importance, it turns out according to the findings of Le et al. (2011) that the Bayesian estimated New Keynesian model of Smets and Wouters (2007) is strongly rejected by a powerful indirect inference test because of its assumptions on price rigidity. Hence it seems to be of great importance to establish good estimates of the degree of price rigidity in macro models. Previous work, Meenagh et al. (2022), carried out an analysis of how this could best be done and showed that Bayesian estimates of price rigidity parameters were highly biased by Bayesian prior. Examples of macro model estimation include Smets and Wouters(2007)'s use of Bayesian methods, Ireland (2011)'s use of FIML (where he reports finding very high rigidity which he overrules in the final version), and Le et al. (2011)'s use of Indirect Inference. In this paper we examined the consequences of

using each method, using an extended Monte Carlo experiment.

4.2 Policy Implications

The policy implications of these findings are significant. Modern monetary policy analysis relies heavily on Bayesian estimation of New Keynesian DSGE models. Our results show that this approach is highly sensitive to the choice of priors: when priors are misaligned with the true structure of the economy, Bayesian methods can produce highly misleading parameter estimates. If policymakers take these estimates at face value, they risk basing policy on models that are fundamentally incorrect. For instance, if an RBC-style economy were wrongly interpreted through the lens of an NK prior, the model would imply rigidities and demand-driven dynamics that do not exist in reality, leading to policy prescriptions that could destabilise rather than stabilise the economy.

Indirect Inference, by contrast, offers a more reliable alternative. Because it places less weight on prior assumptions and instead matches model behaviour directly to the data, it provides a natural check against model misspecification. In practical terms, this means that II can serve as a safeguard in policy analysis: before adopting a Bayesian-estimated DSGE model for forecasting or evaluation, policymakers can test whether the model is rejected by II. If it is, then reliance on that model's policy prescriptions would be unsafe.

More broadly, the results underline the importance of recognising model uncertainty in macroeconomic policymaking. Since there is no consensus on the correct structural model of the economy and the RBC and NK frameworks continue to embody sharply opposed views, relying solely on Bayesian estimation is inherently risky. By incorporating complementary methods such as Indirect Inference, policymakers can better guard against the danger of taking model-based results at face value when they are driven more by prior belief than by empirical reality.

In sum, our study highlights a critical lesson for policy-oriented macroeconomics: estimation methods matter as much as model specification. Bayesian estimation, though dominant in practice, cannot be relied upon when priors are contested or uncertain. Indirect Inference provides a powerful complement, ensuring that policy is informed by models that can genuinely replicate the behaviour of the economy rather than those that simply reflect the modeller's prior assumptions.

5 Conclusion

This paper has argued that Bayesian estimation of DSGE models is reliable only when prior beliefs are correct and widely shared. When they are not, the posterior is drawn toward those priors and can become severely biased, sometimes to economically implausible values. Our Monte Carlo experiments, conducted on two contrasting paradigms (RBC and NK), make this point clear: applying NK priors to RBC data, or RBC priors to NK data, produces posteriors that reflect the false paradigm rather than the data. In contrast, Indirect Inference, when the search is allowed to range across the full parameter space, remains largely unbiased and robust. It recovers parameters close to their true values and combines estimation with an explicit adequacy test through the Wald criterion. These results help explain why long-standing debates, particularly over nominal rigidity, have remained unresolved when estimation depends too heavily on priors rather than on the data itself.

The implication for applied macroeconomists is practical rather than doctrinal. Bayesian tools need not be abandoned; they perform well when identification is strong or prior consensus exists. However, in contested environments they should be complemented by Indirect Inference as a routine cross-check. In practice, researchers should report prior sensitivity alongside Bayesian estimates, use Indirect Inference with broad starting grids to guard against prior-driven distortions, and treat agreement between the two approaches as a credibility signal while treating divergence as a warning. Given the widespread use of Bayesian workflows in DSGE analysis (for example, in the Smets and Wouters model) and the maturity of the Indirect Inference framework, adopting this combined approach is a straightforward way to ensure that policy guidance reflects the data rather than the modeller's prior convictions.

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Appendix A: Models

Real Business Cycle (RBC) Model

$$R_t = \rho_\pi \pi_t + \frac{1}{\frac{1-\frac{Z_3}{\gamma}}{Z_2(1+Z_3/\gamma)}} \Bigg[\frac{Z_3/\gamma}{1+Z_3/\gamma} C_{t-1} + \frac{1}{1+Z_3/\gamma} C_{t+1} + \frac{(Z_2-1)C^{whlc}}{Z_2(1+Z_3/\gamma)} (LAB_t - LAB_{t+1}) + SH_{1,t} - C_t \Bigg], \tag{5}$$

$$INV_t = \frac{1}{1+\bar{\beta}\gamma} \Big(INV_{t-1} + \bar{\beta}\gamma RK_{t+1} + \tfrac{1}{\gamma^2 Z_1} PK_t \Big) + SH_{2,t}, \tag{6}$$

$$PK_t = -(R_t - \rho_\pi \pi_t) + \frac{CRK}{CRK + (1-\tau)} W_{t+1} + \frac{1-\tau}{CRK + (1-\tau)} PK_{t+1}, \tag{7}$$

$$KP_t = (1-\kappa) KP_{t-1} + \kappa\, INV_t + \kappa \gamma^2 Z_1 SH_{2,t}, \tag{8}$$

$$\pi_t = \rho_\pi \pi_{t-1} + \varepsilon_t^\pi, \tag{9}$$

$$W_t = Z_5 LAB_t + \frac{1}{1-Z_3/\gamma} C_t - \frac{Z_3/\gamma}{1-Z_3/\gamma} C_{t-1} - (\pi_t - \rho_\pi \pi_{t-1}) + SH_{6,t}, \tag{10}$$

$$C_t = \frac{Y_t - CIY \cdot INV_t - SH_{G,t} - CRKKY \cdot \frac{1}{Z_9/(1-Z_9)} RK_t}{CCY}, \tag{11}$$

$$Y_t = Z_{10} \Big(Z_{15} (KP_{t-1} + \tfrac{1}{Z_9/(1-Z_9)} RK_t) + (1-Z_{15}) LAB_t + SH_{4,t} \Big), \tag{12}$$

$$LAB_t = RK_t - W_t + (KP_{t-1} + \tfrac{1}{Z_9/(1-Z_9)} RK_t), \tag{13}$$

$$RK_t = R_t - \rho_\pi \pi_t. \tag{14}$$

Shock Processes:

$$SH_{G,t} = SH_{G,t-1} + \rho_1(SH_{G,t-1} - SH_{G,t-2}) + \varepsilon_t^G, \tag{15}$$

$$SH_{1,t} = \rho_2 SH_{1,t-1} + \varepsilon_t^1, \tag{16}$$

$$SH_{2,t} = \rho_3 SH_{2,t-1} + \varepsilon_t^2, \tag{17}$$

$$SH_{3,t} = \rho_4 SH_{3,t-1} + \varepsilon_t^3, \tag{18}$$

$$SH_{4,t} = SH_{4,t-1} + \rho_5(SH_{4,t-1} - SH_{4,t-2}) + \varepsilon_t^4, \tag{19}$$

$$SH_{5,t} = \rho_6 SH_{5,t-1} + \varepsilon_t^5, \tag{20}$$

$$SH_{6,t} = \rho_7 SH_{6,t-1} + \varepsilon_t^6. \tag{21}$$

New Keynesian (NK) Model

$$R_t = \pi_{t+1} + \frac{1}{\frac{1-Z_3/\gamma}{Z_2(1+Z_3/\gamma)}}\Bigg[\frac{Z_3/\gamma}{1+Z_3/\gamma}C_{t-1} + \frac{1}{1+Z_3/\gamma}C_{t+1} + \frac{(Z_2-1)C^{whlc}}{Z_2(1+Z_3/\gamma)}(LAB_t - LAB_{t+1}) + SH_{1,t} - C_t\Bigg], \tag{22}$$

$$INV_t = \frac{1}{1+\bar{\beta}\gamma}\Big(INV_{t-1} + \bar{\beta}\gamma RK_{t+1} + \tfrac{1}{\gamma^2 Z_1}PK_t\Big) + SH_{2,t}, \tag{23}$$

$$PK_t = -(R_t - \pi_{t+1}) + \frac{CRK}{CRK+(1-\tau)}W_{t+1} + \frac{1-\tau}{CRK+(1-\tau)}PK_{t+1}, \tag{24}$$

$$KP_t = (1-\kappa)KP_{t-1} + \kappa\, INV_t + \kappa\gamma^2 Z_1 SH_{2,t}, \tag{25}$$

$$\pi_t = \frac{R_t - Z_{12}R_{t-1} - Z_{13}(1-Z_{12})Y_t - Z_{14}(Y_t - Y_{t-1}) - SH_{3,t}}{Z_{11}(1-Z_{12})}, \tag{26}$$

$$W_t = \frac{1}{1+(1-Z_4)\big(\frac{1-\bar{\beta}\gamma Z_4}{(1+\bar{\beta}\gamma)Z_4}\big)\big(\frac{1}{(\Lambda_w-1)CURV_w+1}\big)}\Bigg[\frac{1}{1+\bar{\beta}\gamma}W_{t-1} + \frac{\bar{\beta}\gamma}{1+\bar{\beta}\gamma}W_{t+1} + \frac{Z_7}{1+\bar{\beta}\gamma}\pi_{t-1} - \frac{1+\bar{\beta}\gamma Z_7}{1+\bar{\beta}\gamma}\pi_t + \frac{\bar{\beta}\gamma}{1+\bar{\beta}\gamma}\pi_{t+1} + \Big((1-Z_4)\tfrac{1-\bar{\beta}\gamma Z_4}{(1+\bar{\beta}\gamma)Z_4}\tfrac{1}{(\Lambda_w-1)CURV_w+1}\Big)\Big(Z_5 LAB_t + \tfrac{1}{1-Z_3/\gamma}C_t - \tfrac{Z_3/\gamma}{1-Z_3/\gamma}C_{t-1}\Big) + SH_{6,t}\Bigg], \tag{27}$$

$$C_t = \frac{Y_t - CIY\cdot INV_t - SH_{G,t} - CRKKY\cdot\frac{1}{Z_9/(1-Z_9)}RK_t}{CCY}, \tag{28}$$

$$Y_t = Z_{10}\Big(Z_{15}(KP_{t-1} + \tfrac{1}{Z_9/(1-Z_9)}RK_t) + (1-Z_{15})LAB_t + SH_{4,t}\Big), \tag{29}$$

$$LAB_t = RK_t - W_t + (KP_{t-1} + \tfrac{1}{Z_9/(1-Z_9)}RK_t), \tag{30}$$

$$RK_t = Z_{17}\Bigg[\frac{\big((\pi_t - SH_{5,t})/(1/(1+\bar{\beta}\gamma Z_8)) - (\bar{\beta}\gamma\pi_{t+1} + Z_8\pi_{t-1})\big)}{\frac{(1-Z_6)(1-\bar{\beta}\gamma Z_6)/Z_6}{(Z_{10}-1)CURV_p+1}} - (1-Z_{15})W_t + SH_{4,t}\Bigg]\frac{1}{Z_{15}} + (1-Z_{17})\Big(\tfrac{1-Z_{15}}{Z_{15}}(-W_t) + \tfrac{SH_{4,t}}{Z_{15}}\Big). \tag{31}$$

Shock Processes:

$$SH_{G,t} = SH_{G,t-1} + \rho_1(SH_{G,t-1} - SH_{G,t-2}) + \varepsilon_t^G, \tag{32}$$

$$SH_{1,t} = \rho_2 SH_{1,t-1} + \varepsilon_t^1, \tag{33}$$

$$SH_{2,t} = \rho_3 SH_{2,t-1} + \varepsilon_t^2, \tag{34}$$

$$SH_{3,t} = \rho_4 SH_{3,t-1} + \varepsilon_t^3, \tag{35}$$

$$SH_{4,t} = SH_{4,t-1} + \rho_5(SH_{4,t-1} - SH_{4,t-2}) + \varepsilon_t^4, \tag{36}$$

$$SH_{5,t} = \rho_6 SH_{5,t-1} + \varepsilon_t^5, \tag{37}$$

$$SH_{6,t} = \rho_7 SH_{6,t-1} + \varepsilon_t^6. \tag{38}$$

True Parameters Used in Simulations

Table 6 reports the true parameter values (Z_1–Z_{18}) used to generate artificial data in the Monte Carlo experiments for both the RBC and NK models.

Table 6: True parameters used in simulations)

Parameter	RBC Value	NK Value
Z_1	9.931	5.993
Z_2	1.270	1.254
Z_3	0.896	0.511
Z_4	0.703	0.639
Z_5	2.301	2.709
Z_6	0.583	0.384
Z_7	0.433	0.239
Z_8	0.041	0.032
Z_9	0.163	0.207
Z_{10}	1.500	1.870
Z_{11}	2.573	1.754
Z_{12}	0.873	0.628
Z_{13}	0.009	0.012
Z_{14}	0.011	0.008
Z_{15}	0.336	0.277
Z_{17}	0.967	0.967
Z_{18}	0.015	0.024

The table illustrates how the two model traditions embody different assumptions about key structural features of the U.S. economy. For example, Z_1 (capital adjustment costs) is much higher in the RBC model, consistent with strong investment frictions in flexible-price environments, whereas the NK value is lower, reflecting a model with nominal rigidities absorbing more of the adjustment. Similarly, parameters related to wage and price stickiness (Z_3, Z_4, Z_6–Z_8)

are substantially smaller in the NK calibration, capturing sluggish adjustment of wages and prices. By contrast, the RBC calibration assumes near-flexibility, with higher elasticities of substitution. Differences also emerge in production structure: Z_{10} (production elasticity) and Z_{11} (price Phillips curve parameter) are larger in the NK model, while the RBC model relies more on capital share (Z_{15}). Both models use highly persistent shock processes (Z_{16}–Z_{17}), reflecting the empirical persistence in U.S. quarterly data up to 2017. These contrasts highlight the extent to which prior beliefs about rigidity and market clearing shape the model dynamics.

Appendix B: Additional tables

Table 7: Parameter Estimation (NK prior, RBC model)

	True	Prior	BS Mean	BS Std	BS Bias %	II Mean	II Std	II Bias %
Z_1	9.931	5.993	7.513	9.601	-24.45%	8.532	4.128	-14.09%
Z_2	1.270	1.254	1.100	1.525	-13.36%	1.299	0.194	+2.34%
Z_3	0.896	0.511	0.558	0.188	-37.68%	0.620	0.155	-30.83%
Z_4	0.703	0.639	0.640	0.022	-8.86%	0.673	0.127	-4.25%
Z_5	2.301	2.709	0.626	0.045	-72.81%	2.724	0.273	+18.38%
Z_6	0.583	0.384	0.955	0.000	+63.83%	0.401	0.073	-31.17%
Z_7	0.433	0.239	0.967	0.000	+123.13%	0.249	0.043	-42.45%
Z_8	0.041	0.032	1.606	3.008	+3801.79%	0.034	0.006	-17.65%
Z_9	0.163	0.207	-2.469	1.399	-1613.26%	0.216	0.037	+32.68%
Z_{10}	1.500	1.870	0.384	0.013	-74.42%	1.916	0.212	+27.71%
Z_{11}	2.573	1.754	0.238	0.039	-90.75%	1.797	0.223	-30.18%
Z_{12}	0.873	0.628	0.033	0.029	-96.18%	0.664	0.134	-23.92%
Z_{13}	0.009	0.012	0.198	0.021	+2123.07%	0.013	0.002	+45.25%
Z_{14}	0.011	0.008	1.754	0.000	+15472.58%	0.009	0.002	-22.92%
Z_{15}	0.336	0.277	0.012	0.008	-96.35%	0.292	0.050	-13.02%
Z_{17}	0.967	0.967	0.439	0.206	-54.58%	0.910	0.135	-5.83%
Z_{18}	0.015	0.024	0.025	0.019	+68.54%	0.025	0.004	+64.64%

Table 8: Parameter Estimation (RBC prior and II search starting point, NK model)

	True	Prior	BS Mean	BS Std	BS Bias %	II Mean	II Std	II Bias %
Z_1	5.993	9.931	8.073	0.286	+34.71%	7.429	1.196	+23.96%
Z_2	1.254	1.270	1.241	0.046	-1.06%	1.175	0.176	-6.33%
Z_3	0.511	0.896	0.483	0.016	-5.46%	0.796	0.124	+55.74%
Z_4	0.639	0.703	0.630	0.041	-1.48%	0.638	0.084	-0.21%
Z_5	2.709	2.301	0.621	0.011	-77.07%	2.223	0.239	-17.95%
Z_6	0.384	0.583	0.955	0.000	+148.62%	0.547	0.082	+42.36%
Z_7	0.239	0.433	0.878	0.006	+267.58%	0.408	0.062	+71.09%
Z_8	0.032	0.041	1.849	0.012	+5598.32%	0.039	0.006	+21.28%
Z_9	0.207	0.163	2.708	0.154	+1205.49%	0.157	0.022	-24.35%
Z_{10}	1.870	1.500	0.417	0.009	-77.70%	1.458	0.138	-22.07%
Z_{11}	1.754	2.573	0.295	0.037	-83.16%	2.473	0.255	+41.02%
Z_{12}	0.628	0.873	0.042	0.002	-93.23%	0.776	0.119	+23.69%
Z_{13}	0.012	0.009	0.192	0.014	+1460.69%	0.008	0.001	-31.28%
Z_{14}	0.008	0.011	1.750	0.054	+20984.31%	0.011	0.002	+30.01%
Z_{15}	0.277	0.336	0.009	0.001	-96.64%	0.319	0.051	+15.20%
Z_{17}	0.967	0.967	0.308	0.017	-68.19%	0.821	0.173	-15.05%
Z_{18}	0.024	0.015	0.015	0.000	-36.15%	0.014	0.002	-39.18%