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The Role of Composite Habits in Asset Prices and Business Cycles: A Bayesian Approach

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The Role of Composite Habits in Asset Prices and Business Cycles: A Bayesian Approach

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Abstract

Habit formation defined over a composite measure of consumption and leisure helps align predicted asset pricing and business cycle moments with their observed counterparts. We employ Bayesian maximum-likelihood techniques to assess the empirical significance of generalized composite habits within a production-based asset pricing model. Using U.S. quarterly data on output, consumption, investment, and hours worked, our findings indicate a very high level of habit intensity and a moderate degree of habit persistence, although the data are less informative regarding the latter. Overall, the estimated model successfully matches the observed equity premium and key business cycle moments.

Keywords: composite habits, asset prices, business cycles, Bayesian estimation
JEL Codes: C11, E32, G12

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1 Introduction

Habits, typically defined over consumption or leisure, have proven successful in explaining asset pricing phenomena in both endowment and production economies (Cochrane, 2017). Their success in jointly accounting for asset prices and business cycles is more limited, especially in environments with endogenous labor supply (Boldrin et al., 2001; Kliem and Uhlig, 2016). This paper follows Jaccard (2014), who introduced internal habit formation over a composite of consumption and leisure to jointly account for the sizable equity premium and procyclical labor supply. These composite habits capture the idea that consumers dislike changes in their living standards. In contrast to Jaccard (2014), we empirically examine a more general composite-habit specification by allowing variation in its intensity. The magnitude of this parameter influences business-cycle comovements by affecting the wealth elasticity of labor supply and the substitutability between consumption and leisure (Dmitriev, 2017). Habit intensity has been shown important for other habit specifications (Boldrin et al., 2001). However, how the interplay of the two parameters governing composite-habit formation affects model estimates and quantitative implications remains unanswered.

The contribution of this paper is twofold. First, it estimates the unknown composite-habit parameters in an asset-pricing model with endogenous labor supply using a full-information Bayesian ML approach. Second, it evaluates the estimated model's ability to replicate observed business-cycle and asset-pricing moments. Using U.S. quarterly data on output, consumption, investment, and hours worked over the period 1963:Q1-2024:Q4 our estimation results suggest a very high degree of habit intensity and a more modest degree of habit persistence. The data are more informative on the former rather than the latter. The estimated model predicts a realistically high equity premium, countercyclical conditional expected excess returns, as well as procyclical labor supply. It also matches the empirical second moments of other key macroeconomic aggregates.

Our paper contributes to four strands of literature. First, we build on work using composite habits as a transmission mechanism in general equilibrium models (Jaccard, 2018; Dmitriev, 2017; Jaccard and Smets, 2020). Our Bayesian estimates suggest high habit intensity, reinforcing their relevance for understanding macroeconomic dynamics. Second, we contribute to the literature on DSGE models that jointly account for asset pricing and business cycle regularities (Jermann, 1998; Boldrin et al., 2001). Our work extends Jaccard (2014)'s model and estimates it using full-information likelihood methods, providing empirical validation of their theoretical mechanism. Third, our work relates to Bayesian DSGE analyses of time-nonseparability for asset pricing and cycles (Kliem and Uhlig, 2016). Finally, we add to the empirical literature on the magnitude of habit formation (Havranek et al., 2017).

2 The Baseline Model

Our production-based asset pricing model based on Jaccard (2014) is generalized to permit varying habit persistence and intensity. Like Jermann (1998), we combine habits with capital adjustment costs, but include endogenous labor and composite habits over consumption and leisure.

2.1 Households

A representative household's utility is

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t \Phi(L_t) - \chi H_{t-1})^{1-\sigma} - 1}{1-\sigma}, \tag{1}$$

where $\beta \in (0,1)$ is the discount factor, $\sigma > 0$ is the curvature parameter, and $\Phi(L) \equiv \psi + L^{\nu}$ with $\psi > 0$ and $\nu > 1$ governing the steady-state hours worked and the Frisch elasticity. The habit stock H_t, defined over the composite of consumption C_t and leisure L_t, evolves according to

$$H_t = \lambda H_{t-1} + (1-\lambda) C_t \Phi(L_t). \tag{2}$$

Composite-habit formation depends on two parameters: intensity $\chi \in [0,1)$, capturing habit strength, and persistence $\lambda \in [0,1)$, weighting past versus current habit levels. The household faces a time constraint

$$N_t + L_t = 1, \tag{3}$$

and an intertemporal budget constraint

$$C_t + P_t^e X_t = W_t N_t + X_{t-1} \left(P_t^e + D_t \right), \tag{4}$$

where W_t is the real wage rate per unit of labor N_t, X_t is the end-of-period equity issued by the firm at price P_t^e with dividends D_t per share.

2.2 Firms

The firm produces a single good using capital K_{t-1} and labor N_t:

$$Y_t = \exp(Z_{A,t})\, K_{t-1}^{\alpha} (\Gamma_t N_t)^{1-\alpha}, \tag{5}$$

where Γ_t denotes labor-augmenting productivity, which grows at a constant rate $\gamma > 1$:

$$\Gamma_{t+1} = \gamma \Gamma_t.$$

The log of total factor productivity $Z_{A,t}$ follows a stationary AR(1) process:

$$Z_{A,t} = \rho_A Z_{A,t-1} + \varepsilon_{A,t}, \quad \varepsilon_{A,t} \sim \mathcal{N}(0, \sigma_{\varepsilon_A}^2). \tag{6}$$

Capital accumulation follows

$$K_t = (1-\delta) K_{t-1} + \Omega\left(\frac{I_t}{K_{t-1}} \right) K_{t-1}, \tag{7}$$

where $\delta \in (0, 1)$ is the depreciation rate, I_t is investment, and $\Omega(\cdot)$ is a concave function reflecting the increasing marginal cost of rapid capital adjustment. Following Jaccard (2014), we assume

$$\Omega\left(\frac{I_t}{K_{t-1}}\right) = \omega_2 + \omega_1 \frac{\left(\frac{I_t}{K_{t-1}}\right)^{1-\frac{1}{\xi}}}{1-\frac{1}{\xi}},$$

where ξ denotes the elasticity of the investment–capital ratio with respect to Tobin's q. Parameters ω_1 and ω_2 satisfy $\Omega(I/K) = I/K$ and $\Omega'(I/K) = 1$ to ensure that the steady state is unaffected by adjustment costs.

The firm maximizes its value to shareholders, defined as the expected discounted stream of dividends $D_t = Y_t - W_t N_t - I_t$:

$$E_0 \sum_{t=0}^{\infty} (\beta^*)^t \frac{\Lambda_t}{\Lambda_0} D_t, \tag{8}$$

where $\beta^* = \beta\gamma^{1-\sigma}$ is the trend-adjusted discount factor, and $(\beta^*)^t \frac{\Lambda_t}{\Lambda_0}$ the household's intertemporal marginal rate of substitution.

2.3 Market Clearing and Optimality Conditions

Market-clearing conditions require that: (i) aggregate output is allocated between consumption and investment; (ii) labor demand equals labor supply; and (iii) all outstanding equity shares are fully held by shareholders.

To characterize equilibrium dynamics, the model is detrended by dividing non-stationary variables by labor-augmenting productivity, Γ_t. Denoting $c_t \equiv C_t/\Gamma_t$ and applying the same notation to other detrended variables, the planner's optimality conditions are summarized in Table 1.

The standard asset pricing equations are:

$$p_t^e = \beta^* E_t \left[\frac{\Lambda_{t+1}}{\Lambda_t} \left(p_{t+1}^e + d_{t+1}\right)\right],$$

where p_t^e is the share price and Λ_{t+1} is the one-period-ahead marginal utility of consumption. The gross risk-free rate is

$$r_t^f = \frac{1}{\beta^* E_t \left(\frac{\Lambda_{t+1}}{\Lambda_t}\right)},$$

and the (ex ante) equity premium is

$$r_t^{ep} = E_t \left(\frac{p_{t+1}^e + d_{t+1}}{p_t^e}\right) - r_t^f.$$

3 Estimation

Quarterly U.S. data (1963:Q1–2024:Q4) on per capita GDP, consumption, investment, and hours worked are used to estimate the log-linearized model. To avoid stochastic singularity, i.i.d. measurement errors $e_{j,t} \sim \mathcal{N}(0, \sigma_{e_j}^2)$ are added for $j \in y, c, i, N$. Estimated parameters include

Table 1: Summary of the optimality conditions

Eq.	Condition
(i)	$\left[\left(c_t\left(\psi+L_t^{\nu}\right)-\chi h_{t-1}\right)^{-\sigma}+\theta_t\left(1-\lambda\right)\right]\left(\psi+L_t^{\nu}\right)=\Lambda_t$
(ii)	$c_t\frac{\nu(1-N_t)^{\nu-1}}{\psi+(1-N_t)^{\nu}}=w_t$
(iii)	$w_t=\left(1-\alpha\right)\frac{y_t}{N_t}$
(iv)	$y_t=e^{Z_{A,t}}\left(k_{t-1}\right)^{\alpha}N_t^{1-\alpha}$
(v)	$m_t=\tilde{\beta}E_t\left[\Lambda_{t+1}\alpha\frac{y_{t+1}}{k_t}+m_{t+1}\left(1-\delta-\frac{\omega_1}{1-\xi}\left(\frac{i_{t+1}}{k_t}\right)^{1-1/\xi}+\omega_2\right)\right]$
(vi)	$m_t\omega_1\left(\frac{i_t}{k_{t-1}}\right)^{-1/\xi}=\Lambda_t$
(vii)	$\gamma k_t=\left(1-\delta\right)k_{t-1}+\left(\frac{\omega_1}{1-1/\xi}\left(\frac{i_t}{k_{t-1}}\right)^{1-1/\xi}+\omega_2\right)k_{t-1}$
(viii)	$\theta_t=\tilde{\beta}E_t\left[\lambda\theta_{t+1}-\chi\left(c_{t+1}\left(\psi+L_{t+1}^{\nu}\right)-\chi h_t\right)^{-\sigma}\right]$
(ix)	$\gamma h_t=\lambda h_{t-1}+\left(1-\lambda\right)c_t\left(\psi+L_t^{\nu}\right)$
(x)	$d_t=y_t-w_tN_t-i_t$
(xi)	$c_t+i_t=y_t$
(xii)	$N_t+L_t=1$
(xiii)	$Z_{A,t}=\rho_A Z_{A,t-1}+\varepsilon_{A,t}$

Note: $\tilde{\beta}=\beta\gamma^{-\sigma}$, and $\varepsilon_{A,t}\sim\mathcal{N}\left(0,\sigma^2_{\varepsilon_A}\right)$.

habit intensity and persistence, the Frisch elasticity, and the parameters governing the stochastic processes. Remaining parameters are calibrated as shown in Table 2.

3.1 Baseline Results

Several findings are worth highlighting. First, the estimates of composite-habit parameters reported in Table 3 suggest a high level of intensity ($\chi = 0.9666$) and a more moderate level of persistence ($\chi = 0.8545$). The data are less informative on the persistence, as indicated by the larger standard deviation of its posterior distribution (0.0076 vs. 0.0288). Our estimates are consistent with those obtained using simulated method of moments (SMM). For example, Dmitriev (2017) reports that a composite habit intensity of 0.97 maximizes the model's ability to replicate cross-country correlations of macroeconomic aggregates. Existing SMM evidence places composite habit persistence estimates between 0.50 (Jaccard, 2014) and 0.97 (Jaccard, 2024), depending on the model specification and sample used.

Second, the estimated parameters of productivity process are close to the AR(1) estimates of the Solow residuals, typically used in calibrated models. For instance, Jaccard's (2014) estimates of persistence and volatility (0.98 and 0.0069), while exceeding ours (0.9617 and 0.0061), fall within 95% HPD intervals

Third, the priors shown in Figure 1 are highly diffuse, while corresponding posteriors are tightly centered around their modes. An exception is habit persistence with relatively more diffused posterior (95% HPD: 0.737-0.941). This suggests that the data are only weakly informative about persistence, possibly reflecting collinearity with intensity and making it hard to disentan-

Table 2: Calibrated Parameters

Parameter	Description	Value	Source
γ	Gross trend growth	1.004074	U.S. real GDP per capita
α	Capital share of output	0.36	Jaccard (2014)
σ	Utility curvature parameter	1	Jaccard (2014)
β	Subjective discount rate	0.98545	Steady-state Euler equation
ξ	Elasticity of I/K w.r.t. Tobin's q	0.2596	Jaccard (2014)
δ	Depreciation rate	0.009483	Steady-state Euler equation

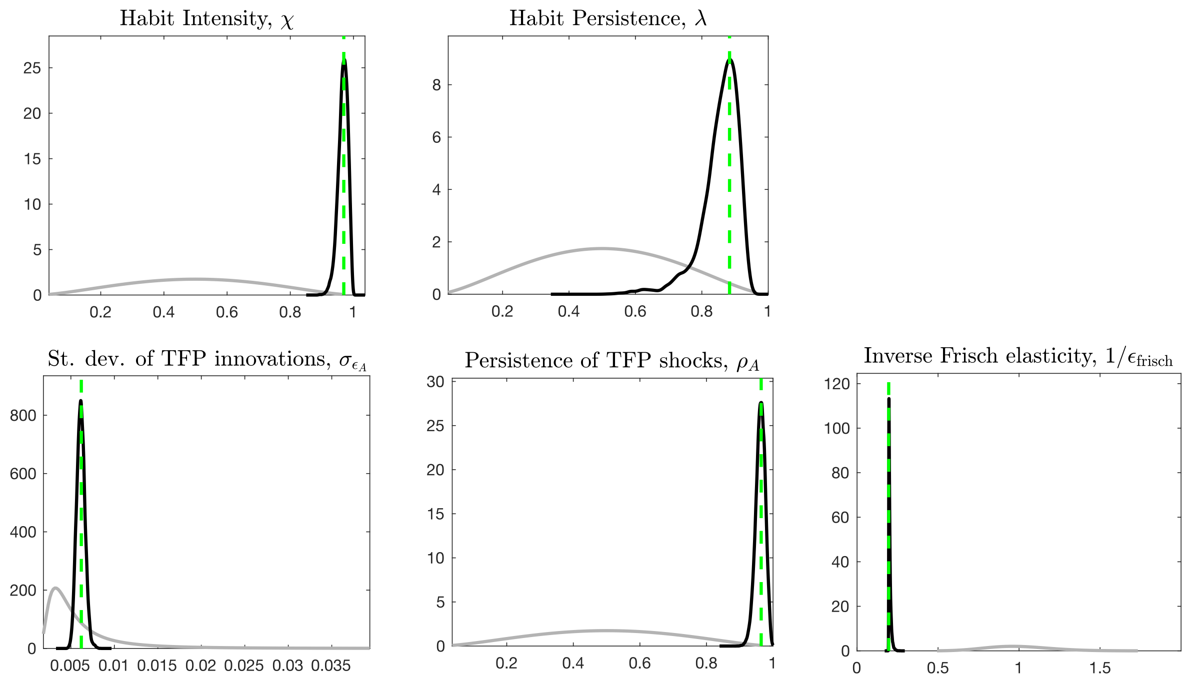
Note: The model period is one quarter. Utility parameters ν and ψ are determined by: (i) steady-state hours worked $N = 0.2$; (ii) the estimated Frisch elasticity of labor supply $\varepsilon_{\text{Frisch}}$; and (iii) the estimated habit parameters χ (intensity) and λ (persistence).

Table 3: Prior and Posterior Distributions for the Estimated Model

	Bayesian Estimation						
	Prior			Posterior			
	Distribution	Mean	SD	Mode	SD	Mean	[5%, 95%]
(a) Structural parameters							
Habit intensity, χ	Beta	0.5000	0.2000	0.9694	0.0076	0.9666	[0.9373, 0.9944]
Habit persistence, λ	Beta	0.5000	0.2000	0.8835	0.0288	0.8543	[0.7371, 0.9405]
Inverse Frisch elasticity, $\epsilon_{\text{frisch}}^{-1}$	Gamma	1.0000	0.2000	0.1954	0.0070	0.2022	[0.1954, 0.2164]
Persistence of TFP shocks, ρ_A	Beta	0.5000	0.2000	0.9643	0.0176	0.9617	[0.9341, 0.9889]
St. dev. of TFP innovations, σ_{ε_A}	Inv. Gamma	0.0070	0.2000	0.0062	0.0002	0.0061	[0.0052, 0.0071]
(b) Measurement errors (standard deviations)							
$\sigma_{\varepsilon_{e_y}}$	Inv. Gamma	0.0007	0.2000	0.0003	0.0010	0.0013	[0.0002, 0.0028]
$\sigma_{\varepsilon_{e_i}}$	Inv. Gamma	0.0007	0.2000	0.0189	0.0013	0.0188	[0.0166, 0.0210]
$\sigma_{\varepsilon_{e_N}}$	Inv. Gamma	0.0007	0.2000	0.0084	0.0004	0.0085	[0.0075, 0.0094]
$\sigma_{\varepsilon_{e_c}}$	Inv. Gamma	0.0007	0.2000	0.0059	0.0003	0.0058	[0.0053, 0.0064]

Note: Using Bayesian likelihood methods, the log-linearized baseline model with measurement errors is estimated on four U.S. quarterly macroeconomic data series from 1963Q1 to 2024Q4. Parameters ρ and σ represent, respectively, the persistence of the stochastic processes and the standard deviations of their innovations.

Figure 1: Priors and Posteriors of the Estimated Model



Note: The grey solid line represents the prior density, the black solid line represents the posterior density, and the green dashed line represents the posterior mode.

gle their individual effects. To address this, we re-estimate the model by holding the persistence fixed at several points in its admissible range. Figure 2 shows that the posterior mean and HPD intervals for intensity are largely invariant to the choice of λ.

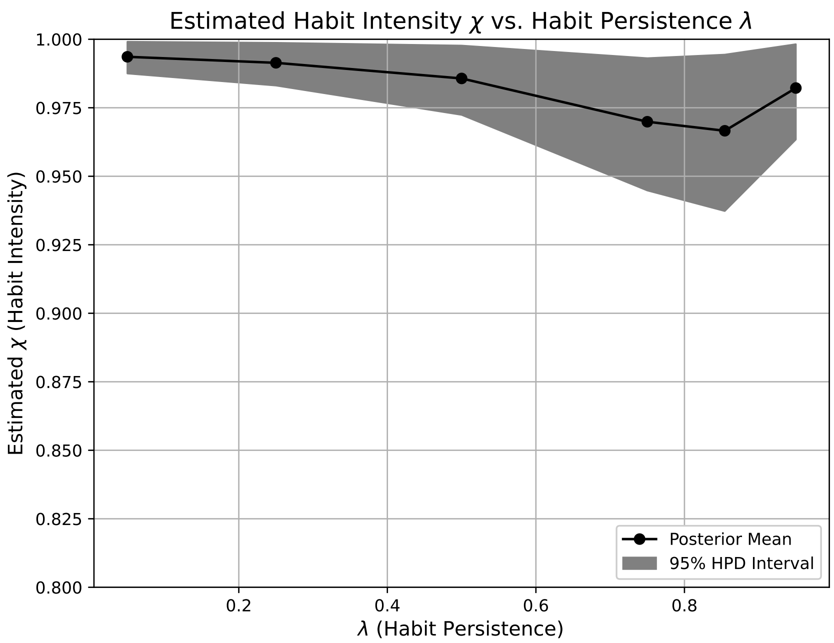


Figure 2: Estimated habit intensity χ as a function of fixed habit persistence λ.

In linearized DSGE model estimated by Bayesian ML methods, local identification arises from the mapping of parameters to the model-implied first and second moments of the observables. Hence, habit parameters are identified insofar as they generate distinct second-moment patterns. Specifically, intensity χ primarily shifts the level of the habit wedge in the Euler equation, scaling the wealth effect on labor supply and thus the response of hours worked to shocks. By contrast, persistence λ governs the habit stock's evolution, reallocating spectral mass to lower frequencies and longer lags and determining the decay of autocovariances and the hump-shaped impulse IRFs for the composite good (see Figure 4). To address potential identification concerns, we perform additional diagnostics reported in the Supplementary Appendix.

4 Model Evaluation

Bayesian approach allows us to perform model comparison even when the models are misspecified. In addition to the baseline, we estimate two nested alternatives featuring non-persistent composite habits ($\lambda = 0$), and time-separable preferences ($\chi = 0$) . Using the Modified Harmonic Mean estimates of log data density, we find strong evidence in favor of the composite-habit specification without the slow-moving component.

Relative to the baseline model, the Bayes factor (the ratio of posterior to prior odds) is $e^{16.63}$, indicating overwhelming support for non-persistent specification. Against the time-separable benchmark, the non-persistent specification achieves $e^{123.32}$, while the baseline model dominates time-separability with $e^{106.69}$.

Next, we evaluate the performance of the baseline model in comparison with two nested alternatives, each parameterized using posterior mode estimates of the non-calibrated parameters. The numerical simulations, based on a third-order perturbation solution, are summarized in Table 4.

Both composite-habit models replicate the unconditional second moments of key macroeconomic aggregates. In contrast to time-separable preferences, they generate a plausible equity premium while maintaining the positive comovement between output and hours worked. This feature is important because, as Boldrin et al. (2001) highlight, combining capital adjustment costs with endogenous labor supply often leads to countercyclical hours. Figure 4 demonstrates this for the time-separable case.

As explained in Jaccard (2014), composite habits scale down the wealth effect on labor supply, ensuring procyclical hours even under costly capital adjustment. Our generalized specification builds on this mechanism. Relative to the baseline, the non-persistent habit variant produces a higher equity premium, a lower risk-free rate consistent with data, and a stronger hours response to TFP shocks, reflecting reduced wealth effects.

Composite-habit models capable of producing realistic equity premia also exhibit countercyclical conditional expected excess returns, $E_t(r^e_{t+1} - r^f_t)$, documented in the literature (Jaccard, 2014). Generalized IRFs in Figure 3 show that $E_t(r^e_{t+1} - r^f_t)$ increases following a one-standard deviation negative TFP shock at the ergodic mean. While the baseline model generates a more persistent response, allowing fast depreciation of habit stock leads to higher volatility of the conditional expected excess returns.

Table 4: Data vs. Model Predictions

	Empirical Moments	Simulated Moments			
		Baseline Model	No measurement error	Non-persistent habits	Time separable preferences
Panel A: Standard deviations (percent)					
Δy	1.07	1.09	1.07	1.10	1.09
Δc	0.98	0.97	0.77	0.91	0.98
Δi	2.08	3.10	2.44	3.42	1.95
ΔN	1.33	1.10	0.71	1.17	1.39
Panel B: Contemporaneous correlations with Δy					
$\Delta c,\ \Delta y$	0.7944	0.7963	0.9997	0.7561	0.8089
$\Delta i,\ \Delta y$	0.6630	0.7965	0.9984	0.7928	0.1340
$\Delta N,\ \Delta y$	0.8367	0.6582	0.9971	0.7524	-0.0491
Panel C: Asset pricing (annualized, percent)					
$E(r^f)$	1.31	3.2671	3.5272	2.7042	5.8703
$E(r^e - r^f)$	6.36	4.1249	4.1324	5.0573	0.0472
$\rho(r^f, \Delta y)$	-0.1146	-0.2154	-0.1693	-0.2334	-0.1352

Note: The macroeconomic series include quarterly, real, per capita growth rates of output (Δy), consumption (Δc), investment (Δi), and hours worked (ΔN), covering 1963Q1–2024Q4. The average risk-free rate $E(r^f)$ and equity premium $E(r^e - r^f)$ are taken from Mehra and Prescott (2008).

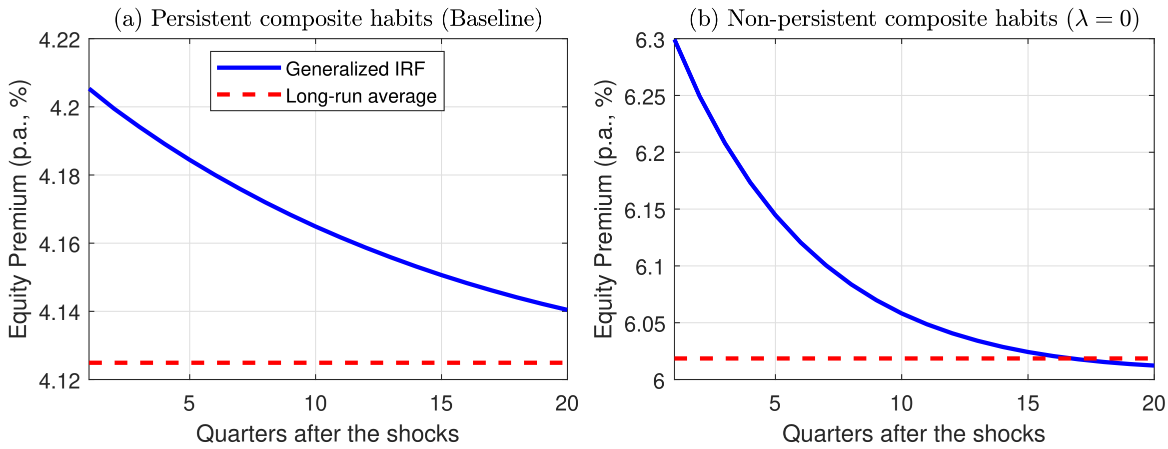
Measurement errors do not influence asset pricing results and only marginally affect the second moments of quantities.

5 Concluding Remarks

Using Bayesian methods, this paper estimates a production-based asset pricing model with generalized composite-habit preferences. The results, that suggest a high degree of habit intensity and a modest degree of habit persistence, have implications for both monetary and fiscal policy. Under strong composite habits, fiscal expansions simultaneously increase consumption and leisure owing to their complementarity, generating larger fiscal multipliers and inducing a positive consumption response—contrasting with the crowding-out effect under standard preferences (Christoffel et al., 2013). On the monetary side, composite habits dampen consumers' short-run sensitivity to interest rate changes, as they initially adjust leisure or other margins to maintain habitual consumption levels. As the habit reference gradually shifts, consumption responds more fully, producing gradual, hump-shaped impulse responses to policy changes (Jaccard, 2024).

This study is the first to estimate generalized composite habits using Bayesian methods, extending the quantitative insights of Jaccard (2014). Our small-scale model provides limited internal propagation, but special cases of composite habits have been embedded in medium-scale models with richer dynamics. These models help explain financial imbalances in the Eurozone (Jaccard and Smets, 2020), asymmetric monetary policy transmission (Jaccard, 2024), and housing price volatility. Our results offer empirical support for these theoretical mechanisms.

Figure 3: Generalized Impulse Responses to a negative TFP shock



Note: Responses of conditional expected excess return, $E_t(r^e_{t+1} - r^f_t)$, to a one-standard-deviation negative TFP shock at the ergodic mean.

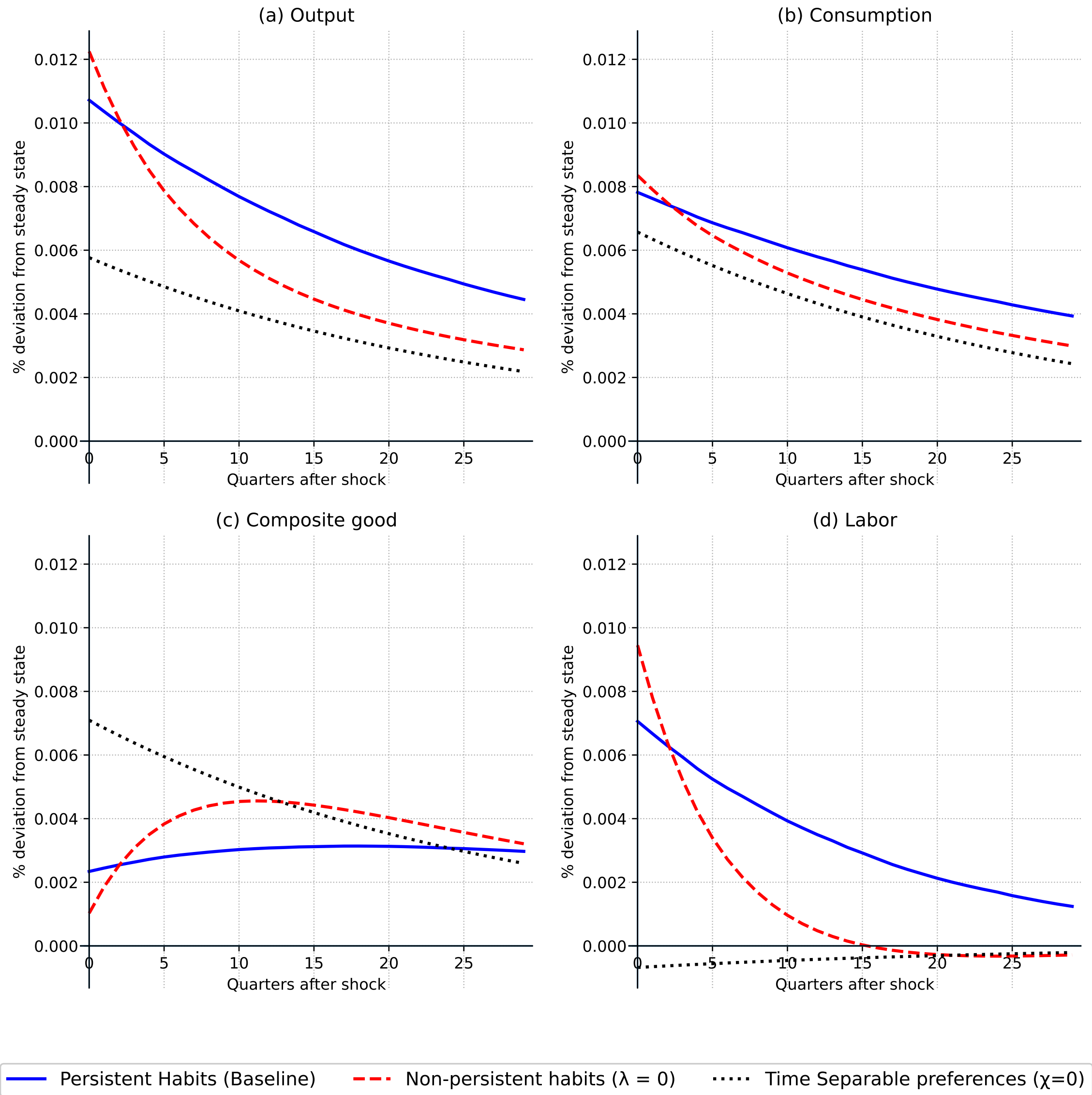
6 Disclosure statement

No potential conflict of interest was reported by the authors.

7 Funding

No funding was received.

Figure 4: Responses to a positive TFP shock



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Supplementary Appendix to The Role of Composite Habits in Asset Prices and Business Cycles: A Bayesian Approach

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Abstract

This Supplementary Appendix is divided into three parts. Part A outlines the data sources and defines the variables used in the estimation. Part B presents the optimization problems of the stationary model, along with the corresponding equilibrium conditions, steady-state relationships, and log-linearized equations. Part C provides additional estimation results.

Keywords: composite habits, asset prices, business cycles, Bayesian estimation
JEL Codes: C11, E32, G12

Appendix A: Data Sources and Construction

The measures of output, consumption, investment, and hours worked are used to construct observed variables for the model estimation. The sample period ranges from 1963:Q1 to 2024:Q4. All time series are quarterly. Nominal data on consumption and investment are transformed into real terms using GDP deflator data. Data on output and hours worked are real quantities. All quarterly real data are transformed into per-capita quantities using population data. The demeaned first-differenced logarithms of these transformed time series are used for the estimation.

All data are from two sources: the U.S. Bureau of Economic Analysis (BEA) and the U.S. Bureau of Labor Statistics (BLS). The measures of the aforementioned variables, together with their data sources, are as follows.

GDP Deflator: The ratio of Gross Domestic Product (line 1, NIPA Table 1.1.5, BEA, billions of dollars, seasonally adjusted at annual rates) to Real Gross Domestic Product (line 1, NIPA Table 1.1.6, BEA, billions of chained 2017 dollars, seasonally adjusted at annual rates).

Output: Real Gross Domestic Product (line 1, NIPA Table 1.1.6, BEA, billions of chained 2017 dollars, seasonally adjusted at annual rates).

Consumption: The sum of Personal Consumption Expenditures on Nondurable Goods (line 5, NIPA Table 1.1.5, BEA) and on Services (line 6, NIPA Table 1.1.5, BEA), both in billions of dollars, seasonally adjusted at annual rates.

Investment: Gross Private Domestic Investment on Fixed Investment (line 8, NIPA Table 1.1.5, BEA, billions of dollars, seasonally adjusted at annual rates).

Population: Civilian Noninstitutional Population, 16 Years and Over (Series ID: LNU00000000Q, BLS). The data are converted from thousands to billions of persons.

Hours Worked: Nonfarm Business Hours Worked (Series ID: PRS85006033, BLS).

Appendix B: Model Solution

This section details the optimization problems for the stationary model and the corresponding equilibrium first-order conditions. Based on these optimality conditions, we derive steady-state relations and the log-linearized equations describing the model's equilibrium dynamics, which constitute the version estimated in the paper.

The Baseline Model

To render the baseline model with trend growth stationary, variables that inherit the trend from labor-augmenting productivity need to be detrended. The transformation of the non-stationary variables involves dividing them — Y, C, I, K, H, W, D, and P^e — by their growth component Γ, such that $y(s^t) = \frac{Y(s^t)}{\Gamma(s^t)}$, $c(s^t) = \frac{C(s^t)}{\Gamma(s^t)}$, $i(s^t) = \frac{I(s^t)}{\Gamma(s^t)}$, $k(s^{t-1}) = \frac{K(s^{t-1})}{\Gamma(s^t)}$, $h(s^{t-1}) = \frac{H(s^{t-1})}{\Gamma(s^t)}$, $w(s^t) = \frac{W(s^t)}{\Gamma(s^t)}$, $d(s^t) = \frac{D(s^t)}{\Gamma(s^t)}$, $p^e(s^t) = \frac{P^e(s^t)}{\Gamma(s^t)}$.

The Representative Household

The representative household solves

$$\max_{\{c(s^t),L(s^t),h(s^t),X(s^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \left(\beta\gamma^{1-\sigma}\right)^t \sum_{s^t \in S^t} \pi(s^t) \frac{\left(c(s^t)\Phi(L(s^t)) - \chi h(s^{t-1})\right)^{1-\sigma}}{1-\sigma} \tag{1}$$

subject to

$$c(s^t) + p^e(s^t)X(s^t) = w(s^t)N(s^t) + X(s^{t-1})\left(p^e(s^t) + d(s^t)\right), \tag{2}$$

$$\gamma\, h(s^t) = \lambda h(s^{t-1}) + (1-\lambda)c(s^t)\Phi(L(s^t)), \tag{3}$$

and

$$N(s^t) + L(s^t) = 1. \tag{4}$$

Applying the Lagrangian method, the household's problem implies the following first-order (necessary) conditions:

$$c(s^t): \quad \left[\left(c(s^t)\Phi(L(s^t)) - \chi h(s^{t-1})\right)^{-\sigma} + \theta(s^t)(1-\lambda)\right]\Phi(L(s^t)) = \Lambda(s^t), \tag{5}$$

$$N(s^t): \quad \left[\theta(s^t)(1-\lambda) + \left(c(s^t)\Phi(L(s^t)) - \chi h(s^{t-1})\right)^{-\sigma}\right] c(s^t)\Phi'(L(s^t)) = \Lambda(s^t)w(s^t), \tag{6}$$

$$h(s^t): \quad \beta^*\gamma^{-1}\textstyle\sum_{s_{t+1}\in S}\pi(s^t,s_{t+1})\Big[-\chi\left(c(s^t,s_{t+1})\Phi(L(s^t,s_{t+1})) - \chi h(s^t)\right)^{-\sigma} + \theta(s^t,s_{t+1})\lambda\Big] = \theta(s^t), \tag{7}$$

$$X(s^t): \quad \beta^*\textstyle\sum_{s_{t+1}\in S}\pi(s^t,s_{t+1})\dfrac{\Lambda(s^t,s_{t+1})}{\Lambda(s^t)}\dfrac{p^e(s^t,s_{t+1}) + d(s^t,s_{t+1})}{p^e(s^t)} = 1, \tag{8}$$

$$\Lambda(s^t): \quad c(s^t) + p^e(s^t)X(s^t) = w(s^t)N(s^t) + X(s^{t-1})\left(p^e(s^t) + d(s^t)\right), \tag{9}$$

$$\theta(s^t): \quad \gamma\, h(s^t) = \lambda h(s^{t-1}) + (1-\lambda)c(s^t)\Phi(L(s^t)). \tag{10}$$

where $\Gamma(s^0) = 1$, $\Phi'[L(s^t)] = \nu L(s^t)^{\nu-1} = \nu(1-N(s^t))^{\nu-1}$, and Λ and θ are the Lagrange multipliers related to (2) and (3), respectively.

The Representative Firm

The representative firm solves

$$\max_{\{k(s^t),i(s^t),N(s^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty}(\beta^*)^t \sum_{s^t\in S^t} \pi(s^t)\frac{\Lambda(s^t)}{\Lambda(s^0)}d(s^t) \tag{11}$$

subject to

$$d(s^t) = e^{Z_A(s^t)}k(s^{t-1})^{\alpha}N(s^t)^{1-\alpha} - w(s^t)N(s^t) - i(s^t), \tag{12}$$

and

$$\gamma\, k(s^t) = (1-\delta)k(s^{t-1}) + \Omega\left(\frac{i(s^t)}{k(s^{t-1})}\right)k(s^{t-1}). \tag{13}$$

Applying the Lagrangian method, the firm's problem implies the following first-order conditions:

$$\begin{aligned} k(s^t):\quad q(s^t) = \beta^*\gamma^{-1}\textstyle\sum_{s_{t+1}\in S}\pi(s^t,s_{t+1})\frac{\Lambda(s^t,s_{t+1})}{\Lambda(s^t)}q(s^t,s_{t+1})\left[1-\delta+\left(\frac{\omega_1(1/\xi)}{1-1/\xi}\right)\left(\frac{i(s^t,s_{t+1})}{k(s^t)}\right)^{1-1/\xi}+\omega_2\right] \\ +\beta^*\gamma^{-1}\textstyle\sum_{s_{t+1}\in S}\pi(s^t,s_{t+1})\frac{\Lambda(s^t,s_{t+1})}{\Lambda(s^t)}\alpha\frac{y(s^t,s_{t+1})}{k(s^t)}, \end{aligned} \tag{14}$$

$$i(s^t):\quad 1 = q(s^t)\,\Omega'\left(\tfrac{i(s^t)}{k(s^{t-1})}\right), \tag{15}$$

$$N(s^t):\quad w(s^t) = (1-\alpha)\tfrac{y(s^t)}{N(s^t)}, \tag{16}$$

$$q(s^t):\quad \gamma\, k(s^t) = (1-\delta)k(s^{t-1}) + \Omega\left(\tfrac{i(s^t)}{k(s^{t-1})}\right)k(s^{t-1}). \tag{17}$$

where $\Gamma(s^0)=1$, $\Omega(\iota(s^t)) = \omega_2 + \omega_1\dfrac{\iota(s^t)^{1-1/\xi}}{1-1/\xi}$, $\Omega'(\iota(s^t)) = \omega_1\iota(s^t)^{-1/\xi}$, $\iota(s^t) = \dfrac{i(s^t)}{k(s^{t-1})}$, and $q(s^t)$ is the Lagrange multiplier associated with (13).

Market-Clearing Conditions

In equilibrium, the following market-clearing conditions hold: (i) goods market, $y(s^t) = c(s^t) + i(s^t)$; (ii) labor market, labor supply (N_s) equals labor demand (N_d), i.e., $N_s(s^t) = N_d(s^t) = N(s^t)$; and (iii) financial market, $X(s^t) = 1$.

Steady-State Relations

Let c denote steady-state consumption, and apply the same rule of notation to other stationary variables. Given that $\Omega\left(\dfrac{i}{k}\right) = \dfrac{i}{k}$, $\Omega'\left(\dfrac{i}{k}\right) = 1$, $\varepsilon_A = 0$, and $Z_A = 0$, the system implies the following steady-state relations:

The steady-state labor supply equation implies

$$c\,\nu(1-N)^{\nu-1} = (\psi + (1-N)^{\nu})\,(1-\alpha)\frac{y}{N}. \tag{18}$$

Let $\eta_\Phi \equiv \dfrac{\nu L^\nu}{\psi + L^\nu}$. Equation (18) can be rewritten as

$$\eta_\Phi = (1-\alpha)\frac{y}{N}\frac{1}{c}(1-N).$$

Let $\widetilde{\beta} \equiv \beta\gamma^{-\sigma}$. The FOC for the habit stock in the steady state implies

$$\theta = \frac{-\widetilde{\beta}\chi\left[c(\psi + L^\nu) - \chi h\right]^{-\sigma}}{1-\tilde{\beta}\lambda}. \tag{19}$$

The steady-state value of Tobin's q is

$$q = 1. \tag{20}$$

Given $q = 1$, the steady-state marginal product of capital is

$$\alpha\frac{y}{k} = \frac{1}{\widetilde{\beta}} - 1 + \delta. \tag{21}$$

The steady-state investment-to-capital ratio is

$$\frac{i}{k} = \gamma - 1 + \delta. \tag{22}$$

The steady-state value of consumption is

$$c = k^\alpha N^{1-\alpha} - i. \tag{23}$$

The steady-state level of output is

$$y = k^\alpha N^{1-\alpha}. \tag{24}$$

The steady-state habit stock is

$$h = \frac{(1-\lambda)c(\psi + L^\nu)}{\gamma - \lambda}. \tag{25}$$

Log-linearized System

Let a hat (ˆ) on a stationary variable denote its percentage deviation from the deterministic steady state; define $u = c(\psi + L^\nu) - \chi h$, $\omega_u = \dfrac{u^{-\sigma}}{u^{-\sigma} + \theta(1-\lambda)}$, and $\eta_\Phi = \dfrac{\nu L^\nu}{\psi + L^\nu}$. Given $\Omega(\frac{i}{k}) = \frac{i}{k}$, $\Omega'(\frac{i}{k}) = 1$, and $q = \frac{1}{\Omega'(i/k)} = 1$, it follows that

$$R^k = \frac{1}{q}\Big[q\big(1 - \delta - \Omega'(\tfrac{i}{k})\tfrac{i}{k} + \Omega(\tfrac{i}{k})\big) + R\Big] = \alpha\frac{y}{k} + 1 - \delta.$$

For notational simplicity, let a stationary variable with subscript t denote the variable in state s^t (e.g., c_t). The system of log-linearized equations determines the logarithmic deviations of $\hat{\Lambda}_t$, $\hat{N}_t$, $\hat{\theta}_t$, $\hat{k}_t$, $\hat{q}_t$, $\hat{i}_t$, $\hat{h}_t$, $\hat{y}_t$, $\hat{c}_t$, and $\hat{w}_t$:

$$\hat{\Lambda}_t = -\eta_\Phi\frac{N}{1-N}\hat{N}_t - \sigma\omega_u\left(\frac{c(\psi + L^\nu)}{u}\hat{c}_t - \frac{c\nu L^\nu}{u}\frac{N}{1-N}\hat{N}_t - \frac{\chi h}{u}\hat{h}_{t-1}\right) + \frac{\theta(1-\lambda)}{u^{-\sigma} + \theta(1-\lambda)}\hat{\theta}_t, \tag{26}$$

$$\hat{w}_t = \hat{c}_t - \frac{N}{1-N}\hat{N}_t(\nu - 1 - \eta_\Phi), \tag{27}$$

$$\hat{\theta}_t = E_t\left[\lambda\widetilde{\beta}\hat{\theta}_{t+1} - \sigma(1-\widetilde{\beta}\lambda)\left(\frac{c(\psi+L^\nu)}{u}\hat{c}_{t+1} - \frac{c\nu L^\nu}{u}\frac{N}{1-N}\hat{N}_{t+1} - \frac{\chi h}{u}\hat{h}_t\right)\right], \tag{28}$$

$$\hat{\Lambda}_t = \hat{\Lambda}_{t+1} + \frac{(\alpha y/k)}{R^k}(\hat{y}_{t+1} - \hat{k}_t) + \frac{(i/k)}{\xi R^k}(\hat{i}_{t+1} - \hat{k}_t) + \frac{1-\delta}{R^k}\hat{q}_{t+1} - \hat{q}_t, \tag{29}$$

$$\hat{q}_t = \frac{1}{\xi}(\hat{i}_t - \hat{k}_{t-1}), \tag{30}$$

$$\hat{k}_t = \frac{1-\delta}{\gamma}\hat{k}_{t-1} + \frac{i}{\gamma k}\hat{i}_t, \tag{31}$$

$$\gamma\,\hat{h}_t = \lambda\hat{h}_{t-1} + (\gamma - \lambda)\hat{c}_t - \frac{N\eta_\Phi}{1-N}\hat{N}_t(\gamma - \lambda), \tag{32}$$

$$\hat{y}_t = Z_{A,t} + \alpha\hat{k}_{t-1} + (1-\alpha)\hat{N}_t, \tag{33}$$

$$y\,\hat{y}_t = c\,\hat{c}_t + i\,\hat{i}_t, \tag{34}$$

$$\hat{w}_t = \hat{y}_t - \hat{N}_t. \tag{35}$$

Appendix C: Additional Estimation Results

Identification

To address potential identification concerns, we perform two further diagnostics. First, we apply a local identification test, which verifies that marginal parameter changes induce distinct variations in the autocovariance structure of observables (Iskrev, 2010). Second, we implement an identifiability test advocated by Schmitt-Grohé and Uribe (2012), which examines the ability of estimation strategy to recover the underlying parameters of the DSGE model from the simulated data. We set the model's non-calibrated parameters to the posterior means from the estimation on actual data, simulate artificial data for the full set of observables with the same length as the original sample, and re-estimate the model using the identical Bayesian procedure. Table C1 reports the true parameters alongside their likelihood-based estimates. Given the sample of 247 observations, the Bayesian estimator recovers the underlying parameters reasonably well.

Table C1: Estimation of the Baseline Model on Simulated Data

	True Parameter Value	Bayesian Estimation						
		Prior			Posterior			
		Dist.	Mean	SD	Mode	SD	Mean	[5%, 95%]
(a) Structural parameters								
Habit intensity, χ	**0.9666**	Beta	0.5000	0.2000	0.9433	0.0154	0.9436	[0.9144, 0.9732]
Habit persistence, λ	**0.8543**	Beta	0.5000	0.2000	0.7954	0.0736	0.7740	[0.6237, 0.9108]
Inverse Frisch elasticity, $\epsilon_{\text{frisch}}^{-1}$	**0.2055**	Gamma	1.0000	0.2000	0.3243	0.0601	0.3318	[0.2397, 0.4345]
Persistence of TFP shocks, ρ_A	**0.9617**	Beta	0.5000	0.2000	0.9500	0.0181	0.9467	[0.9125, 0.9791]
St. dev. of TFP innovations, σ_{ε_A}	**0.0061**	IG	0.0070	0.2000	0.0070	0.0005	0.0071	[0.0062, 0.0080]
(b) Measurement errors (standard deviations)								
$\sigma_{\varepsilon_{e_y}}$	**0.0013**	IG	0.0007	0.2000	0.0003	0.0004	0.0005	[0.0002, 0.0012]
$\sigma_{\varepsilon_{e_i}}$	**0.0188**	IG	0.0007	0.2000	0.0198	0.0009	0.0198	[0.0181, 0.0217]
$\sigma_{\varepsilon_{e_N}}$	**0.0085**	IG	0.0007	0.2000	0.0084	0.0004	0.0084	[0.0077, 0.0092]
$\sigma_{\varepsilon_{e_c}}$	**0.0058**	IG	0.0007	0.2000	0.0059	0.0003	0.0059	[0.0054, 0.0065]

Note: The true parameter values correspond to the posterior means obtained from the estimation based on U.S. data, as presented in Table **??**.

Measurement Errors

As a robustness check, we introduce serially correlated measurement errors, specified as AR(1) processes (see Khorunzhina, 2015, and references therein). This specification helps capture persistence in the data that the structural model alone cannot reproduce, thereby reducing the risk of biased parameter estimates. The corresponding estimation results, provided in Table C2 show that our main findings remain unchanged.

Table C2: Estimated Baseline Model with Correlated Measurement Errors

	Bayesian Estimation						
	Prior			Posterior			
	Distribution	Mean	SD	Mode	SD	Mean	[5%, 95%]
(a) Structural parameters							
Habit intensity, χ	Beta	0.5000	0.2000	0.9667	0.0184	0.9610	[0.9283, 0.9919]
Habit persistence, λ	Beta	0.5000	0.2000	0.8846	0.0347	0.8645	[0.7640, 0.9482]
Inverse Frisch elasticity, $\epsilon_{\text{frisch}}^{-1}$	Gamma	1.0000	0.2000	0.1954	0.0093	0.2021	[0.1954, 0.2153]
Persistence of TFP shocks, ρ_A	Beta	0.5000	0.2000	0.9651	0.0169	0.9621	[0.9339, 0.9886]
St. dev. of TFP innovations, σ_{ε_A}	Inv. Gamma	0.0070	0.2000	0.0063	0.0005	0.0064	[0.0055, 0.0073]
(b) Measurement errors							
ρ_{me_y}	Beta	0.5000	0.2000	0.4749	0.0947	0.4366	[0.0687, 0.7931]
$\sigma_{\varepsilon_{me_y}}$	Inv. Gamma	0.0007	0.2000	0.0003	0.0002	0.0006	[0.0002, 0.0014]
ρ_{me_i}	Beta	0.5000	0.2000	0.0386	0.0354	0.0561	[0.0064, 0.1168]
$\sigma_{\varepsilon_{me_i}}$	Inv. Gamma	0.0007	0.2000	0.0189	0.0010	0.0190	[0.0169, 0.0211]
ρ_{me_N}	Beta	0.5000	0.2000	0.1272	0.0584	0.1357	[0.0394, 0.2365]
$\sigma_{\varepsilon_{me_N}}$	Inv. Gamma	0.0007	0.2000	0.0085	0.0005	0.0086	[0.0077, 0.0096]
ρ_{me_c}	Beta	0.5000	0.2000	0.0203	0.0187	0.0290	[0.0025, 0.0604]
$\sigma_{\varepsilon_{me_c}}$	Inv. Gamma	0.0007	0.2000	0.0059	0.0002	0.0059	[0.0054, 0.0065]

Note: The table reports prior and posterior distributions of parameters for the augmented model with correlated measurement errors. Estimated using Bayesian likelihood methods with U.S. quarterly data from 1963Q2 to 2024Q4. Parameters ρ denote autoregressive coefficients, and σ denote standard deviations of innovations.

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