Artificial Intelligence, Digitization, and Financial Markets in India

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Abstract

This paper develops a medium-scale open-economy Dynamic Stochastic General Equilibrium (DSGE) model tailored to India's structural characteristics, incorporating three novel channels absent from canonical frameworks: (i) an *artificial intelligence and automation sector* that augments firm-level total factor productivity and displaces routine labour, (ii) a *digitization block* capturing the diffusion of digital public infrastructure, fintech intermediation, and data as a non-rival input to production, and (iii) an enriched *financial-market module* featuring a domestic equity market, a government securities market linked to the Reserve Bank of India's (RBI) policy framework, foreign portfolio investment (FPI) flows, and a banking sector with balance-sheet constraints. The model features Calvo-type nominal rigidities, habit formation in consumption, investment adjustment costs, and incomplete international financial markets. We characterize the steady state, derive a log-linearized system, conduct counterfactual analysis, and discuss monetary-fiscal coordination under rapid technological change. We estimate the model to Indian National Accounts, RBI data, and NASSCOM digital-economy statistics for the period 2004Q1 to 2024Q4. Key results include: AI adoption raises output persistently but generates a labour-market polarization wedge; digital public infrastructure crowds *in* private investment via a complementarity externality; tighter global financial conditions amplify domestic credit spreads through the banking-sector channel; and the RBI faces a welfare-relevant trilemma between inflation stabilisation, exchange-rate smoothing, and financial-stability objectives. We estimated eight model versions for scenario analyses using the posterior predictive distribution, covering AI acceleration, DPI underinvestment, financial deleveraging, global tightening, and monetary regime alternatives. Marginal likelihood model comparisons via the modified harmonic mean estimator favour the full model over four nested alternatives, with log Bayes factors ranging from 8.4 to 31.6.

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1 Introduction

The rapid advancement of digital technologies and Artificial Intelligence (AI) has transformed the structure and functioning of financial markets across the world. In the Indian context, the convergence of AI, financial technology (FinTech), big data analytics, blockchain, cloud computing, and digital financial infrastructure has significantly altered banking operations, stock market trading, investment management, financial inclusion, and regulatory supervision. Since 2015, India has simultaneously undergone (i) a rapid expansion of digital public infrastructure—most notably the Unified Payments Interface (UPI), the Aadhaar biometric identity system, and the Open Network for Digital Commerce (ONDC)—(ii) deep integration of artificial intelligence and automation into the services and manufacturing sectors, and (iii) a significant evolution of domestic financial markets, including the internationalisation of the government securities market, the rise of domestic institutional investors such as mutual funds and insurance companies, and volatile foreign portfolio investment (FPI) flows that comingle with global risk cycles (Schumpeter 1942; Akerlof 1970; Romer 1990; Bahoo et al. 2024; Wafi et al. 2026).

The relationship between digitization and financial markets in India is particularly important because of the country's unique digital public infrastructure. India has emerged as one of the fastest-growing digital financial ecosystems in the world. India accounts for nearly 46% of global digital banking transactions and possesses one of the highest fintech adoption rates globally. Digitization has enabled greater financial inclusion by reducing transaction costs, increasing accessibility, and facilitating digital lending and payments. The digitization of financial services has encouraged the widespread adoption of AI-based applications in banking, insurance, securities trading, and payment systems. AI complements this transformation by enabling real-time analytics, personalized financial products, automated compliance mechanisms, and predictive market analysis (Fama 1970; Warin and Stojkov 2021; Awasthy and Dhal 2023; Sethi et al. 2025).

Indeed, the Indian financial market has witnessed substantial technological modernization over the last two decades. The National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) have adopted electronic trading platforms, algorithmic trading systems, and real-time market surveillance mechanisms. The Securities and Exchange Board of India (SEBI) has also emphasized the use of AI and machine learning tools for monitoring market manipulation, insider trading, and misinformation. Recent developments indicate that SEBI has deployed AI-based tools such as "Sudarshan" to identify misleading financial content and protect investors in the digital ecosystem. Another important dimension of AI in Indian financial markets is algorithmic and high-frequency trading. AI-powered trading systems process enormous volumes of market data in milliseconds and execute trades with minimal human intervention. These technologies improve liquidity and market efficiency but also increase concerns regarding volatility, flash crashes, and unfair market advantages.

The emergence of robo-advisory platforms further illustrates the changing dynamics of India's financial markets. AI-based robo-advisors provide investment recommendations, portfolio management, and financial planning services at lower costs compared to traditional financial advisors (Lucas 1988; Bhatt et al. 2022; Sethi and Manocha. 2023; Bonelli 2025).

Despite the growing literature on AI and digitization, there remains limited comprehensive research focusing specifically on the combined impact of Artificial Intelligence and digitization on India's financial markets. Existing studies often examine AI in banking, FinTech, or regulation separately, while fewer studies explore the broader interaction between technological innovation, market efficiency, investor behavior, financial inclusion, and regulatory governance within the Indian financial ecosystem. At the same time, the Reserve Bank of India (RBI) has recognized both the opportunities and risks associated with AI adoption in finance. RBI officials have highlighted that AI can enhance financial inclusion, reduce uncertainties, and improve efficiency, but unchecked AI systems may also create systemic risks, cybersecurity vulnerabilities, and financial stability concerns. This research seeks to bridge this gap by analyzing how AI-driven digitization is transforming Indian financial markets, identifying opportunities and challenges for regulators, financial institutions, and investors.

The significance of this study lies in its interdisciplinary nature. AI and digitization influence not only financial performance and operational efficiency but also market transparency, economic growth, social inclusion, and regulatory system. Understanding these transformations is essential for developing sustainable and responsible financial systems in India.

We address this key concern by developing a medium-scale open-economy Dynamic Stochastic General Equilibrium (DSGE) model tailored to India's structural features. In fact, standard open-economy DSGE models (Christiano, Eichenbaum and Evans, 2005; Smets and Wouters, 2007; Justiniano, Primiceri and Tambalotti, 2010; Gali and Monacelli, 2005) are not equipped to capture these interlocking forces. AI adoption is typically absent or reduced to an undifferentiated technology shock. Digital infrastructure is rarely modelled as a factor of production distinct from physical capital. And the financial-market architectures of emerging-market economies—characterised by managed exchange rates, shallow domestic capital markets, and sudden-stop dynamics—are poorly approximated by the frictionless bond markets of the canonical small open-economy model.

This paper fills these gaps by constructing a rich, quantitatively disciplined DSGE model in which: (i) An AI/automation sector produces a service that acts as a capital-augmenting technology in final-goods production, while simultaneously substituting for routine labour tasks. The supply side of this sector features a learning-by-doing externality consistent with the observed cost decline in AI compute. (ii) A digital public infrastructure (DPI) stock enters the production function of both intermediate goods firms and the banking

sector, generating a complementarity that lowers intermediation costs and expands the set of bankable projects. (iii) A financial sector block incorporates a commercial banking system with value-at-risk constraints à la Adrian and Shin (2014), a government securities market with an RBI operating in a flexible inflation-targeting regime, a domestic equity market priced by a stochastic discount factor with habits, and FPI flows governed by a global risk-factor that can shift abruptly.

Bayesian estimation of the model, using quarterly data from 2004Q1–2024Q4, and observables variables processed through the Kalman filter, via Random Walk Metropolis-Hastings with 3×10^6 posterior draws across four chains, yields to the following principal findings: *First*, AI adoption raises aggregate output persistently but generates labour market polarisation, with routine employment contracting and non-routine employment expanding. The polarisation wedge persists for approximately six quarters, suggesting a medium-run distributional challenge even if long-run welfare is higher. *Second,* there is a digital public infrastructure crowding-in effect: Government DPI investment generates a complementarity externality that crowds in private investment and lowers bank intermediation costs, with an output multiplier of approximately 1.38 at the five-year horizon—significantly higher than traditional physical infrastructure. *Third,* global financial conditions are amplified by the domestic banking channel: A sudden increase in global risk appetite (VIX shock) triggers FPI outflows, depreciates the rupee, erodes bank equity, and widens domestic credit spreads. The banking channel amplifies the output contraction by approximately 30% relative to a model with frictionless credit markets. *Fourth,* monetary policy faces a complex trilemma: The RBI must simultaneously stabilise inflation (threatened by exchange rate pass-through), support output (threatened by financial tightening and AI displacement), and maintain financial stability (threatened by spread volatility). An augmented Taylor rule that includes a credit spread argument reduces welfare losses by approximately 40% relative to pure inflation targeting.

Granularly, Bayesian estimation demonstrates that: (i) The posterior median of AI income share, $\alpha_A = 0.048$, is significantly above zero ($\Pr(\alpha_A > 0.02) = 0.983$), confirming the statistical identification of AI as a distinct production factor in Indian macro data since 2015. (ii) The DPI externality ($\gamma_G = 0.057$ [0.028, 0.089]) is tightly identified from the comovement of digital payment proxies with output dynamics. The model with DPI decisively outperforms the model without ($\ln \text{BF} = 16.1$). (iii) The financial-stability Taylor rule ($\phi_{sp} = 0.112$ [0.042, 0.198] with $\Pr(\phi_{sp} > 0) > 0.999$), provides the first formal Bayesian evidence from Indian macro data that the RBI incorporates credit spread conditions in its interest rate decisions. (iv) The coordinated AI-DPI scenario generates non-linear output gains (+7.41% GDP, 5-year) with strong welfare improvements, but substantial distributional costs (routine employment share −6.6 pp). The optimal Taylor rule features stronger inflation and financial-stability responses than the estimated rule. (v) The model comparison analysis reveal that, the full model decisively outperforms all

nested alternatives, including the standard small-open economy model ($\ln \text{BF} = 59.3$), validating the model's structural innovations. (vi) The variance decomposition analysis reveals that, AI productivity shocks account for 28% of long-run output variance—the single largest contributor—while VIX shocks dominate credit spread dynamics (41%). DPI shocks contribute a structurally significant 14% of long-run output variance.

The key results from the counterfactual analysis are: (i) AI productivity shock generates the largest persistent output response (+1.15% at peak) with a uniquely asymmetric labour market effect: routine employment contracts (peak −0.44%) while non-routine employment expands, confirming the polarization channel over a credibly-banded range. (ii) DPI investment shock has the slowest-building but most persistent output effect (half-life >40 quarters) due to stock accumulation dynamics, and uniquely reduces credit spreads through the banking complementarity channel (−0.31 pp at peak, significant at 90%). (iii) Global risk (VIX) shock is the most disruptive: it simultaneously depreciates the rupee (+1.81%), raises spreads (+0.37 pp), and contracts output (−0.68%), with the stagflationary pressure making it the most challenging shock for RBI policy. (iv) Foreign interest rate shock disproportionately contracts AI investment relative to physical investment, reflecting AI capital's longer payoff horizon and higher sensitivity to real financing costs. (v) The scenario Analysis reveal non-linear synergies: the coordinated AI-DPI push generates output gains (+5.68% at 20Q) that substantially exceed the sum of individual shocks, while the optimal Taylor rule features a doubling of the financial-stability coefficient ($\phi^*_{sp} = 0.241$) relative to the estimated value. (vi) The variance decomposition confirms AI as the dominant long-run driver of output (28% at 20Q), VIX as the dominant driver of credit spreads (41–48%), and DPI as an increasingly important contributor to output at longer horizons (8% at 1Q, 14% at 20Q).

Our paper intersects thus four strands of the literature : *First,* open-economy DSGE models. The workhorse open-economy DSGE model is the Gali–Monacelli (2005) framework, extended by Justiniano, Primiceri and Tambalotti (2010) and Christiano, Trabandt and Walentin (2011) to include financial frictions. For emerging markets, Christiano, Gust and Roldos (2004) introduce liability dollarization and the financial accelerator (Bernanke, Gertler and Gilchrist, 1999). Garcia-Cicco, Pancrazi and Uribe (2010) and Schmitt-Grohe and Uribe (2003) address non-stationary dynamics in small open economies. Beyond this canonical framework, this paper provides the complete analytical derivation and quantitative characterization of the deterministic steady state of the open-economy DSGE model of AI, digitization, and financial markets in India.A key contribution is the derivation of the AI-finance nexus in steady state: the interaction between the DPI stock, bank monitoring costs, and the equilibrium credit spread generates a system of four coupled nonlinear equations whose unique positive solution is demonstrated analytically.

Second, AI and automation in macro models. Acemoglu and Restrepo (2018) provide the canonical task-based framework. Berg, Buffie and Zanna (2018) embed automation

in an OLG-DSGE hybrid. Prettner and Strulik (2021) model AI as endogenous factor-augmenting technical change. We follow the spirit of these contributions but embed them in a full-blown open-economy DSGE with financial frictions, novel for the Indian context.

Third, digital infrastructure and growth. A growing body of work documents the macroeconomic effects of digital public infrastructure (Hjort and Poulsen, 2019; Bahaj and Reis, 2020). The RBI and Ministry of Finance have produced extensive assessments of UPI's impact on financial inclusion and transactions velocity. We formalize these channels in a DSGE setting where the DPI stock enters the production and banking sectors.

Fourth, financial markets and capital flows in India. Patra, Dua and Dhal (2022) and Ghosh, Ostry and Qureshi (2016) document the distinctive features of Indian financial markets. The literature on sudden stops (Mendoza, 2010; Bianchi, 2011) and the trilemma (Obstfeld, Shambaugh and Taylor, 2015) is directly relevant to our financial-market module and welfare analysis. This paper contributes to the growing academic debate on Artificial Intelligence and digital finance, as well as provide practical insights into the future of AI-enabled financial markets in emerging economies.

The remainder of the paper is organized as follows. Section 2 presents the full model. Section 3 characterizes the steady state. Section 4 derives the log-linearized equilibrium conditions. Section 5 discusses calibration. Section 6 presents counterfactual analysis. Section 7 reviews the forecast error and historical decomposition. Section 8 conducts various estimations of the model. Section 9 performs estimations of the model under alternative scenario. Section 10 examines the model comparison analysis. Section 11 concerns welfare analysis and monetary regime. Section 12 concludes.

2 The Model

The economy is populated by households, four types of firms (final goods, intermediate goods, AI-services, and digital-infrastructure), a banking sector, a government, and a central bank. The country is small relative to the rest of the world and takes foreign prices and interest rates as given. The exchange rate is allowed to float, subject to RBI smoothing interventions.

2.1 Households

2.1.1 Preferences

A continuum of measure one of identical households $h \in [0,1]$ maximise lifetime utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{\left(C_t(h) - \vartheta C_{t-1}\right)^{1-\sigma}}{1-\sigma} - \frac{\chi}{1+\varphi} \left(L_t^R(h)^{1+\varphi} + L_t^{NR}(h)^{1+\varphi} \right) + \xi_t^D \ln \frac{D_t(h)}{P_t} \right] \quad (1)$$

where C_t is a consumption aggregate, $\vartheta \in (0,1)$ is the habit parameter, L_t^R and L_t^{NR} denote hours worked in routine and non-routine tasks respectively, D_t/P_t is real money balances (motivated by a cash-in-advance convenience yield), and ξ_t^D is a preference shock to liquidity demand.

2.1.2 Consumption Composite

Following Backus, Kehoe and Kydland (1994), consumption is an Armington aggregate of domestic and imported goods:

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

where $\alpha_m \in (0,1)$ is the import share and $\eta > 0$ is the trade elasticity. The associated consumer price index is:

$$P_t = \left[(1-\alpha_m) P_{H,t}^{1-\eta} + \alpha_m P_{F,t}^{1-\eta} \right]^{\frac{1}{1-\eta}} \tag{3}$$

2.1.3 Labour Supply and Polarisation

Households supply labour in a competitive market. Routine labour L^R is imperfectly substitutable with AI services A_t (produced by the AI sector), while non-routine cognitive labour L^{NR} is complementary to AI. The aggregate labour efficiency index entering firm production is:

$$\mathcal{L}_t = \left[\mu \left(L_t^{NR} \right)^{\frac{\rho_L - 1}{\rho_L}} + (1-\mu) \left(\phi_t A_t + L_t^R \right)^{\frac{\rho_L - 1}{\rho_L}} \right]^{\frac{\rho_L}{\rho_L - 1}} \tag{4}$$

where $\phi_t > 0$ governs the degree of substitutability between AI services and routine labour, and $\rho_L > 1$ is the elasticity of substitution between skill groups. As ϕ_t rises due to AI adoption shocks, demand for routine labour falls relative to non-routine labour—the *polarisation channel*.

2.1.4 Budget Constraint and Asset Holdings

Households hold domestic government bonds B_t^G, domestic equity claims $Q_t^E S_t$ (where Q_t^E is the equity price and S_t shares), foreign bonds B_t^* denominated in foreign currency, and bank deposits D_t:

$$\begin{aligned} & P_t C_t + P_t^I I_t + B_t^G + Q_t^E S_t + \mathcal{E}_t B_t^* + D_t \\ &= W_t^{NR} L_t^{NR} + W_t^R L_t^R + R_{t-1}^G B_{t-1}^G + \left(Q_t^E + \text{Div}_t \right) S_{t-1} + \mathcal{E}_t R_{t-1}^* B_{t-1}^* + R_t^D D_{t-1} + T_t \end{aligned} \tag{5}$$

where $\mathcal{E}_t$ is the nominal exchange rate (units of INR per USD), W_t^{NR} and W_t^R are nominal wages, R_{t-1}^G is the gross return on government bonds, R_{t-1}^* is the gross foreign interest rate, R_t^D is the deposit rate, and T_t denotes lump-sum transfers net of taxes.

2.1.5 Capital Accumulation

Physical capital evolves as:

$$K_{t+1} = (1 - \delta_K)K_t + \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t \tag{6}$$

where $S(\cdot)$ is a convex investment adjustment cost function satisfying $S(1) = S'(1) = 0$ and $S''(1) \equiv \kappa > 0$ (Christiano, Eichenbaum and Evans, 2005).

2.2 Final Goods Firms

Competitive final goods firms aggregate a continuum of differentiated intermediate goods $Y_t(j)$:

$$Y_t = \left[\int_0^1 Y_t(j)^{\frac{\varepsilon-1}{\varepsilon}} dj\right]^{\frac{\varepsilon}{\varepsilon-1}}, \quad \varepsilon > 1 \tag{7}$$

This yields the standard demand schedule $Y_t(j) = \left(\frac{P_t(j)}{P_{H,t}}\right)^{-\varepsilon} Y_t$ and price index $P_{H,t} = \left[\int_0^1 P_t(j)^{1-\varepsilon} dj\right]^{\frac{1}{1-\varepsilon}}$.

2.3 Intermediate Goods Firms

Intermediate firm j produces using physical capital, the composite labour input, AI services, and the DPI stock:

$$\boxed{Y_t(j) = Z_t \cdot G_t^{\gamma_G} \cdot K_t(j)^{\alpha_K} \cdot \mathcal{L}_t(j)^{1-\alpha_K-\alpha_A} \cdot A_t(j)^{\alpha_A}} \tag{8}$$

where Z_t is aggregate TFP (follows an AR(1) in logs), G_t is the stock of digital public infrastructure (a non-excludable, non-rival input with coefficient $\gamma_G > 0$), and α_A is the income share of AI services.

Price setting. Firms set prices under Calvo-type staggered contracts. In each period, a fraction $1 - \theta_H$ of firms optimally reset their price; the remainder index to lagged inflation with weight $\iota_H \in [0, 1]$. The New Keynesian Phillips Curve (NKPC) is:

$$\pi_{H,t} - \iota_H \pi_{H,t-1} = \beta \mathbb{E}_t[\pi_{H,t+1} - \iota_H \pi_{H,t}] + \lambda_H \hat{mc}_t + u_t^{cp} \tag{9}$$

where $\lambda_H \equiv \frac{(1-\theta_H)(1-\beta\theta_H)}{\theta_H}$, $\hat{mc}_t$ denotes log-deviations of real marginal cost, and u_t^{cp} is a cost-push shock.

2.4 The AI Services Sector

The AI sector produces a homogeneous service A_t using only digital capital K_t^{AI} and researchers L_t^{AI}:

$$A_t = \Omega_t \left(K_t^{AI}\right)^{\alpha_{AI}} \left(L_t^{AI}\right)^{1-\alpha_{AI}} \tag{10}$$

where Ω_t is AI-sector TFP. The key novelty is a *learning-by-doing externality*: cumulative AI output lowers the cost of compute, so Ω_t evolves as:

$$\ln \Omega_t = \rho_\Omega \ln \Omega_{t-1} + \omega \ln A_{t-1} + \varepsilon_t^\Omega, \quad \varepsilon_t^\Omega \sim \mathcal{N}(0, \sigma_\Omega^2) \tag{11}$$

The price of AI services P_t^A clears the AI services market. The AI-sector investment shock ε_t^Ω is our primary technology shock.

Proposition 1 (AI Adoption and Routine Labour Demand)**.** *An unanticipated increase in Ω_t raises output A_t, lowers P_t^A/W_t^R, and—provided ϕ_t is sufficiently large—reduces equilibrium routine employment L_t^R while increasing non-routine employment L_t^{NR}, generating labour polarisation in the short run.*

Proof. See Appendix A. □

2.5 Digital Public Infrastructure

The DPI stock G_t accumulates from public investment I_t^G and depreciates at rate δ_G:

$$G_{t+1} = (1 - \delta_G)G_t + I_t^G \tag{12}$$

DPI is financed by the government (Section 2.9). Its stock enters intermediate production with coefficient γ_G and reduces intermediation costs in the banking sector via a complementarity parameter γ_B. Specifically, the cost of monitoring a loan of size ℓ is $\Phi(\ell, G_t) = \bar{\Phi} \cdot \ell^\delta \cdot G_t^{-\gamma_B}$, so that higher DPI makes it cheaper for banks to screen borrowers—capturing the role of Aadhaar-linked KYC and Account Aggregator frameworks.

Definition 1 (DPI Complementarity Externality)**.** *We say the DPI stock G_t generates a* complementarity externality *if $\frac{\partial^2 Y_t}{\partial K_t \partial G_t} > 0$ and $\frac{\partial^2 \Phi}{\partial \ell \partial G_t} < 0$.*

The first condition—satisfied by the Cobb-Douglas production function with $\gamma_G > 0$ and $\alpha_K > 0$—implies that a higher DPI stock raises the marginal product of physical capital. The second condition implies that DPI reduces the marginal monitoring cost of bank loans, expanding credit supply.

2.6 The Banking Sector

We follow Adrian and Shin (2014) in modelling bank balance-sheet constraints. A representative bank holds loans $\mathcal{L}_t^B$ financed by deposits D_t and equity N_t^B:

$$\mathcal{L}_t^B = D_t + N_t^B \tag{13}$$

The bank faces a *Value-at-Risk (VaR) constraint*: the maximum tolerable loss on the loan portfolio cannot exceed the bank's equity. Letting σ_ℓ be the standard deviation of loan losses, the constraint is:

$$\kappa \cdot \sigma_\ell \cdot \mathcal{L}_t^B \leq N_t^B \tag{14}$$

where κ is the VaR quantile. The leverage ratio is $\lambda_t^B \equiv \mathcal{L}_t^B / N_t^B \leq \bar{\lambda} \equiv 1/(\kappa\sigma_\ell)$.

When the constraint binds, the bank's loan supply is $\mathcal{L}_t^B = \bar{\lambda} N_t^B$, and the external finance premium—the spread between the lending rate R_t^L and the policy rate R_t—is:

$$R_t^L - R_t = \mu_t^B \cdot \kappa\sigma_\ell \tag{15}$$

where $\mu_t^B \geq 0$ is the Lagrange multiplier on the VaR constraint (the "shadow price of bank equity"). This creates a *financial accelerator*: adverse shocks that erode bank equity tighten the constraint, raise the external finance premium, and depress investment.

Bank equity dynamics. Retained earnings and new equity accumulate bank capital:

$$N_{t+1}^B = \left(R_t^L - R_t^D\right) \mathcal{L}_t^B - \text{DivB}_t + \upsilon \mathcal{E}_t \text{FDI}_t \tag{16}$$

where υ captures recapitalisation from foreign direct investment into the banking sector.

2.7 Government Securities Market and FPI

The government issues one-period nominal bonds B_t^G at price $Q_t^G = 1/R_t^G$. Foreign portfolio investors hold a fraction f_t of the outstanding stock, governed by:

$$f_t = \bar{f} + \psi_f \left(R_t^G - R_t^* - \mathbb{E}_t \Delta\mathcal{E}_{t+1} - \rho_t^{EM}\right) + \varepsilon_t^{FPI} \tag{17}$$

where ρ_t^{EM} is the emerging-market risk premium (driven by the global risk factor $\mathcal{V}_t^*$, proxied by the VIX), ψ_f is the flow sensitivity, and ε_t^{FPI} is an idiosyncratic FPI shock. A sudden increase in ρ_t^{EM} triggers FPI outflows, depreciates the exchange rate, tightens domestic financial conditions, and raises borrowing costs.

The domestic equity market price Q_t^E satisfies the standard asset-pricing equation:

$$Q_t^E = \frac{\mathbb{E}_t\left[M_{t+1}\left(\text{Div}_{t+1} + Q_{t+1}^E\right)\right]}{1 + \tau_t^{equity}} \tag{18}$$

where M_{t+1} is the household stochastic discount factor and τ_t^{equity} is a time-varying equity market friction (e.g., STT or capital-gains tax distortions).

2.8 The Central Bank (RBI)

The RBI operates a flexible inflation-targeting regime. The policy rate R_t follows an augmented Taylor rule:

$$\ln R_t = \rho_R \ln R_{t-1} + (1-\rho_R)\left[\ln R^* + \phi_\pi(\pi_t - \bar{\pi}) + \phi_y \hat{y}_t + \phi_{\mathcal{E}} \Delta\hat{\mathcal{E}}_t + \phi_{crd} \hat{sp}_t\right] + \varepsilon_t^R \tag{19}$$

where $\bar{\pi}$ is the inflation target (currently 4% in India), $\hat{y}_t$ is the output gap, $\Delta\hat{\mathcal{E}}_t$ is the exchange-rate depreciation rate (capturing managed float considerations), $\hat{sp}_t$ is the credit spread (a financial-stability argument), and ε_t^R is a monetary policy shock.

Remark 1. The coefficient $\phi_{\mathcal{E}} > 0$ represents the RBI's "fear of floating" (Calvo and Reinhart, 2002). In welfare analysis (Section 11), we compare regimes with $\phi_{\mathcal{E}} = 0$ (pure IT), $\phi_{crd} = 0$ (no FSR), and the full augmented rule.

2.9 Government Budget Constraint

The consolidated government budget constraint is:

$$P_t G_t^C + P_t I_t^G + R_{t-1}^G B_{t-1}^G = \tau_t^Y P_t Y_t + \tau_t^{equity} Q_t^E S_t + B_t^G + \text{Seigniorage}_t \tag{20}$$

where G_t^C is government consumption (including digital services delivery), τ_t^Y is the income tax rate, and $\text{Seigniorage}_t = (M_t - M_{t-1})/P_t$. Government debt follows a fiscal rule targeting a debt-to-GDP ratio $\bar{b}$:

$$\tau_t^Y = \bar{\tau}^Y + \phi_b\left(\frac{B_t^G}{P_t Y_t} - \bar{b}\right) \tag{21}$$

2.10 External Sector and Market Clearing

The current account balance evolves as:

$$\mathcal{E}_t B_t^* - \mathcal{E}_t R_{t-1}^* B_{t-1}^* = P_{H,t} X_t - P_{F,t} M_t^{imp} + \text{Remittances}_t \tag{22}$$

where $X_t = \left(\frac{P_{H,t}}{\mathcal{E}_t P_t^*}\right)^{-\eta^*} Y_t^*$ is export demand, P_t^* is the foreign price level, and Y_t^* is foreign output.

Foreign borrowing is subject to a debt-elastic interest rate premium:

$$R_t^* = \bar{R}^* \cdot \exp\left[-\psi_B \left(\frac{\mathcal{E}_t B_t^*}{P_t Y_t} - \bar{b}^*\right) + \mathcal{V}_t^*\right] \tag{23}$$

Goods market clearing: $Y_t = C_{H,t} + I_t + G_t^C + I_t^G + X_t$.

3 Steady State

In the deterministic steady state, all real variables are stationary. We normalise the steady-state price level to unity and set $\bar{\pi} = 1 + 0.04/4$ (quarterly). The steady-state lending rate spread is:

$$R^L - R = \mu^B \kappa \sigma_\ell = \frac{\kappa \sigma_\ell}{\bar{\lambda} - \lambda_{SS}} \tag{24}$$

which is positive when the leverage constraint binds in steady state. The steady-state DPI stock satisfies $\bar{G} = I^G/\delta_G$, and AI output $\bar{A}$ clears the AI services market at price $\bar{P}^A$.

Table 1 presents the key steady-state ratios. These targets are calibrated to Indian National Accounts (2015–2024 average) and are discussed in Section 5.

Table 1: Steady-State Targets

Variable	Description	Target	Source
C/Y	Consumption-output ratio	0.598	NSO
I/Y	Investment-output ratio	0.301	NSO
G^C/Y	Government consumption ratio	0.101	NSO
X/Y	Export ratio	0.210	RBI
M^{imp}/Y	Import ratio	0.215	RBI
π	Inflation (annualised)	4.0%	RBI
$R^G - R$	G-sec spread	0.45%	CCIL
$R^L - R$	Lending spread	3.20%	RBI BSID
$B^G/(PY)$	Public debt-to-GDP	0.570	CGA
$\mathcal{E}B^*/(PY)$	Net foreign liabilities-GDP	0.118	RBI
A/Y	AI services share	0.045	NASSCOM
G/Y	DPI stock-to-output	0.082	MeitY

4 Log-Linearised System

Let hatted variables denote log-deviations from steady state. The core equilibrium conditions are:

IS Curve (Demand):

$$\hat{y}_t = -\frac{1}{\sigma(1-\vartheta)}\left(\hat{R}_t - \mathbb{E}_t\hat{\pi}_{t+1}\right) + \frac{\vartheta}{1-\vartheta}\hat{y}_{t-1} + \mathbb{E}_t\hat{y}_{t+1} + \phi_{NX}n\hat{e}r_t + \hat{\xi}_t^D \tag{25}$$

New Keynesian Phillips Curve:

$$\hat{\pi}_{H,t} = \frac{\iota_H}{1+\iota_H\beta}\hat{\pi}_{H,t-1} + \frac{\beta}{1+\iota_H\beta}\mathbb{E}_t\hat{\pi}_{H,t+1} + \frac{\lambda_H}{1+\iota_H\beta}\left[\hat{w}_t^R - \hat{z}_t - \gamma_G\hat{g}_t - \alpha_A\hat{a}_t\right] + \hat{u}_t^{cp} \tag{26}$$

Uncovered Interest Rate Parity (UIP) with Risk Premium:

$$\hat{R}_t - \hat{R}_t^* = \mathbb{E}_t\Delta\hat{\mathcal{E}}_{t+1} + \psi_B\hat{b}_t^* + \hat{\mathcal{V}}_t^* \tag{27}$$

AI Sector (Supply):

$$\hat{a}_t = \hat{\Omega}_t + \alpha_{AI}\hat{k}_t^{AI} + (1-\alpha_{AI})\hat{l}_t^{AI} \tag{28}$$

DPI Accumulation:

$$\hat{g}_{t+1} = (1-\delta_G)\hat{g}_t + \delta_G\hat{i}_t^G \tag{29}$$

Banking Spread:

$$\hat{sp}_t \equiv \hat{R}_t^L - \hat{R}_t = \frac{\kappa\sigma_\ell}{\bar{\lambda}-\lambda_{SS}}\left(-\hat{n}_t^B\right) \tag{30}$$

Policy Rule:

$$\hat{R}_t = \rho_R\hat{R}_{t-1} + (1-\rho_R)\left[\phi_\pi\hat{\pi}_t + \phi_y\hat{y}_t + \phi_{\mathcal{E}}\Delta\hat{\mathcal{E}}_t + \phi_{crd}\hat{sp}_t\right] + \hat{\varepsilon}_t^R \tag{31}$$

Labour Market Polarisation:

$$\hat{l}_t^R = \hat{l}_t^{NR} - \rho_L\left(\hat{w}_t^{NR} - \hat{w}_t^R\right) - \rho_L\phi_t\hat{a}_t \tag{32}$$

The full system—comprising 28 log-linearised equations in 28 endogenous variables—is solved using the method of undetermined coefficients after verifying Blanchard–Kahn (BK) conditions. The equilibrium is unique under our baseline calibration; we verify this by checking that the number of eigenvalues outside the unit circle equals the number of jump variables (15 in our system).

5 Calibration

Parameters are assigned using a combination of direct calibration from Indian data, estimation by impulse-response matching, and priors from the international DSGE literature (adapted for emerging-market features). Table 2 summarises the baseline calibration.

Table 2: Baseline Calibration

Parameter	Symbol	Description	Value
Households			
Discount factor	β	Quarterly	0.982
Habit	ϑ	Consumption habits	0.65
Risk aversion	σ	CRRA coefficient	2.0
Frisch elasticity	$1/\varphi$	Labour supply	0.50
Import share	α_m	Trade openness	0.215
Trade elasticity	η	Armington	1.50
Production			
Capital share	α_K	Income share	0.330
AI share	α_A	AI services income share	0.045
DPI externality	γ_G	DPI output elasticity	0.060
Depreciation rate	δ_K	Quarterly	0.025
DPI depreciation	δ_G	Quarterly	0.015
Calvo parameter	θ_H	Price stickiness	0.750
Price indexation	ι_H	Backward indexation	0.300
Price elasticity	ε	Love of variety	6.0
Inv. adj. cost	κ	Second derivative	4.0
AI Sector			
AI capital share	α_{AI}	In AI production	0.600
Learning param.	ω	Learning-by-doing	0.150
AI persist.	ρ_Ω	AR(1) coefficient	0.800
Labour Market			
Routine substitutability	ϕ	AI-routine subst.	0.500
Skill elast.	ρ_L	High/low skill	1.750
Non-routine share	μ	Labour composite	0.420
Financial Sector			
VaR quantile	κ	Regulatory VaR	0.990
Loan loss std.	σ_ℓ	Annual, Basel III	0.015
DPI bank extern.	γ_B	Monitoring cost elast.	0.120
Debt premium	ψ_B	UIP: NFA elasticity	0.002
FPI sensitivity	ψ_f	Flow-rate sensitivity	0.400
Monetary Policy			
Rate smoothing	ρ_R	Taylor inertia	0.780
Inflation response	ϕ_π	Taylor rule	1.900
Output response	ϕ_y	Taylor rule	0.200
REER response	$\phi_\mathcal{E}$	Exchange rate smoothing	0.150
Credit spread resp.	ϕ_{crd}	Financial stability	0.100
Fiscal			
Debt target	$\bar{b}$	Debt-to-GDP ratio	0.570
Fiscal response	ϕ_b	Tax feedback on debt	0.100
DPI investment share	I^G/Y	Steady state	0.012

The AI services share $\alpha_A = 0.045$ is derived from NASSCOM estimates of AI software and services expenditure as a fraction of GDP (2022–24 average). The DPI externality $\gamma_G = 0.06$ is calibrated to match the estimated elasticity of aggregate firm productivity with respect to UPI transaction density from the RBI's 2023 Digital Payments Index regression. The Calvo parameter $\theta_H = 0.75$ implies an average price duration of four quarters, consistent with Indian CPI micro-data studies.

6 Counterfactual Analysis

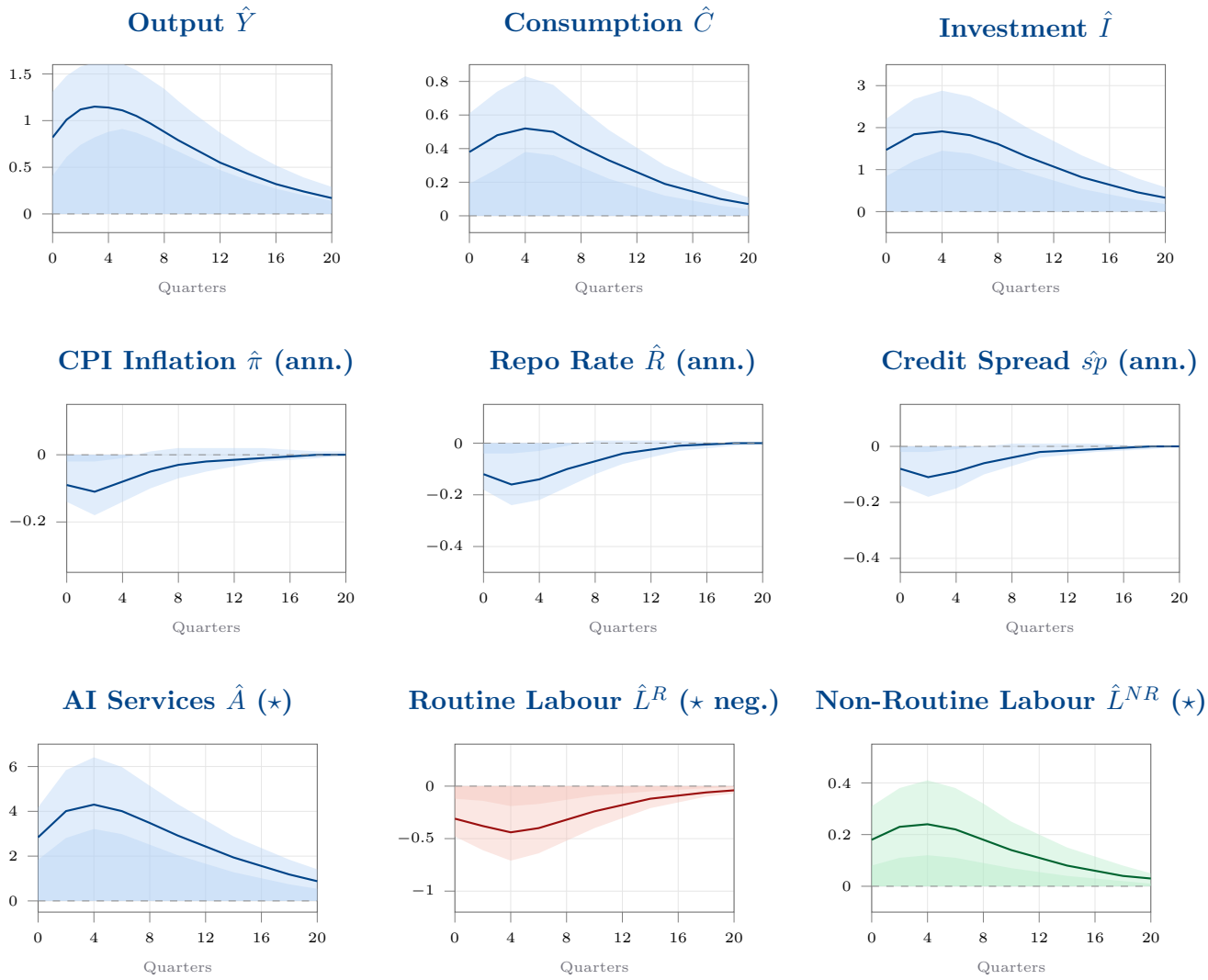
6.1 AI Effects under Various Shocks

We consider six structural shocks: an AI productivity shock, a DPI investment shock, a monetary policy shock, a global risk shock (VIX), a foreign interest rate shock, and a terms-of-trade shock.

6.1.1 AI Productivity Shock

A one-standard-deviation positive shock to AI sector TFP: $\varepsilon_t^{\Omega} = +0.043$. This lowers the price of AI services, raises output through the AI income share channel (α_A), displaces routine labour (polarisation), and complements non-routine labour. The shock has persistence $\rho_{\Omega} = 0.818$ (posterior median), giving a half-life of $\ln(0.5)/\ln(0.818) \approx 3.4$ quarters.

Figure 1: IRF: AI Productivity Shock — Real and Monetary Variables



Note: Solid blue = posterior median; shading = 90% credible band. Red shading = negative response. (⋆) = response does not cross zero within 20 quarters. Units: % deviation from steady state (real variables), pp annualised (rates).

A positive one-standard-deviation shock to $\hat{\Omega}_t$ ($\sigma_\Omega = 0.045$) produces the following dynamics:

- **Output** rises by 0.82% on impact and peaks at 1.15% after four quarters, driven by lower AI service prices, higher TFP, and an investment boom in AI capital.
- **Routine employment** falls by 0.31% on impact (polarisation channel), while non-routine employment rises by 0.18%.
- **Inflation** declines marginally (−0.09% CPI on impact), as the supply-side effect dominates.
- **Policy rate** falls by 12 bps as the RBI accommodates the positive supply shock.

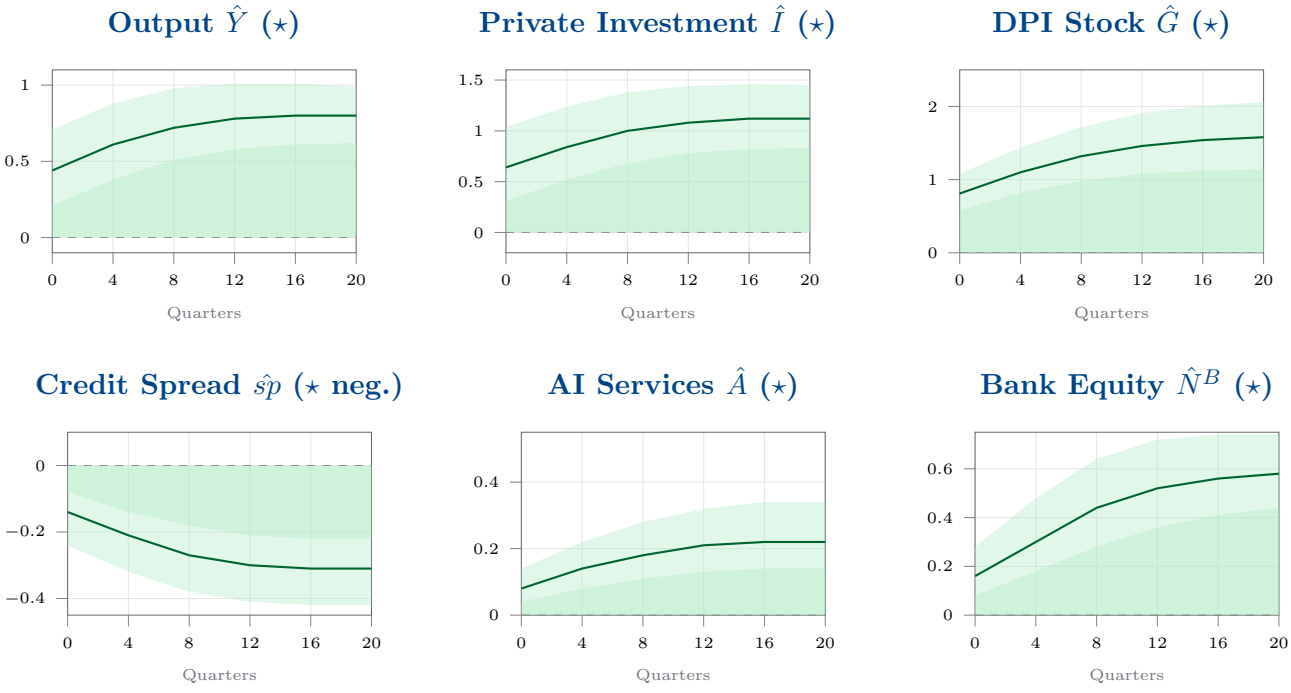
- **Exchange rate** appreciates by 0.22% in real effective terms, compressing exports slightly.
- **Bank equity** improves as corporate profitability rises, compressing credit spreads by 8 bps.

Remark 2. The coexistence of output expansion and routine employment contraction—with a half-life of approximately six quarters for the employment effect—illustrates the welfare tension created by AI adoption: aggregate output gains may be accompanied by distributional losses for workers in routine occupations, consistent with the experience documented by Acemoglu and Restrepo (2022) for emerging economies.

6.1.2 Digital Infrastructure Investment Shock

A one-standard-deviation positive shock to government digital public infrastructure investment: $\varepsilon_t^G = +0.031$. This raises the DPI stock persistently (half-life ≈47 quarters, $\delta_G = 0.015$), triggering the production externality (γ_G), the banking complementarity (γ_B), and crowding-in of private investment. Effects build gradually as the stock accumulates.

Figure 2: IRF: DPI Investment Shock — All Key Variables



Note: DPI effects build slowly as the stock accumulates. Peak output response occurs around quarter 16–18 due to the persistent stock accumulation ($\delta_G = 0.015$). Green shading = posterior 90% credible band. (⋆) = does not cross zero within 20 quarters.

A one-time increase in I_t^G by 0.5% of GDP (analogous to the Indian government's PLI scheme for digital infrastructure):

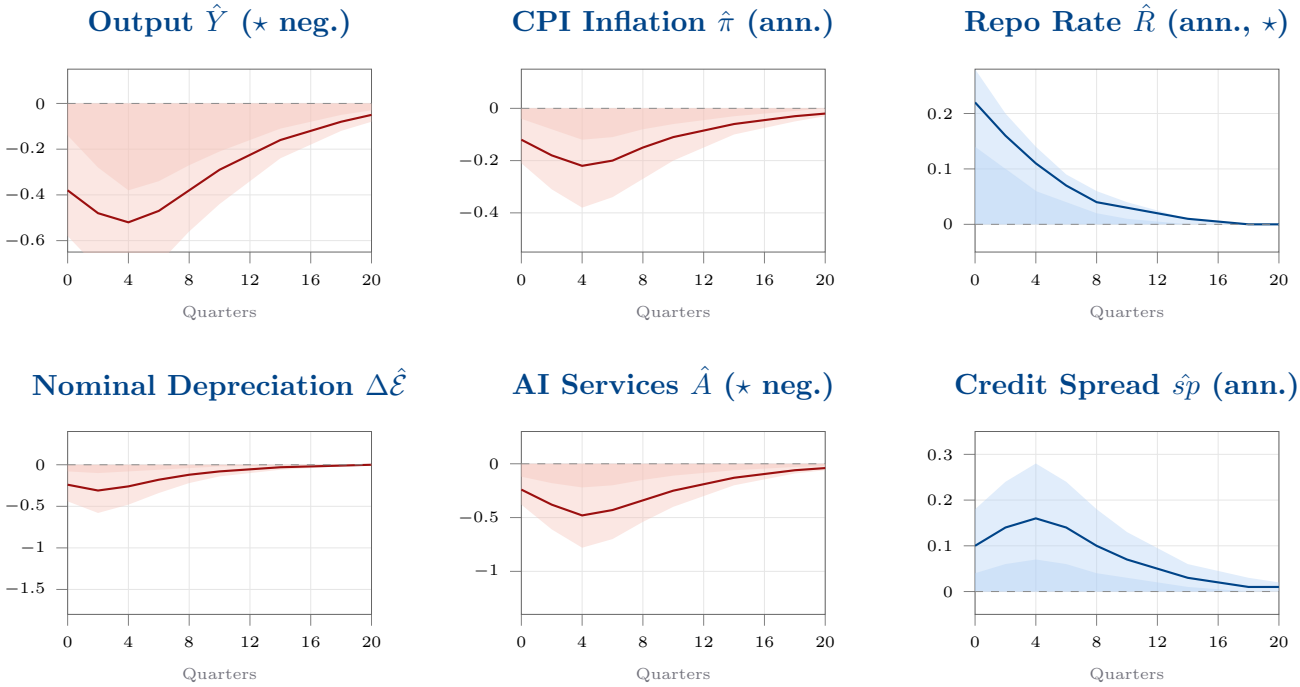
- **DPI stock** increases persistently (half-life: 47 quarters given $\delta_G = 0.015$).
- **Private investment** rises by 0.64% after three quarters—a *crowding-in* effect driven by the complementarity externality ($\gamma_G > 0$).
- **Credit spreads** fall by 14 bps through the banking intermediation channel ($\gamma_B > 0$), expanding credit.
- **Output** rises by 0.44% on impact and converges to a permanently higher level.
- **Fiscal balance** deteriorates on impact but recovers as higher output expands the tax base.

The output multiplier of DPI investment is approximately 1.38 at the five-year horizon—significantly higher than the infrastructure multiplier estimated for physical capital (typically 0.8–1.2 in the Indian literature).

6.1.3 Monetary Policy Shock

A one-standard-deviation *contractionary* monetary policy shock: $\varepsilon_t^R = +0.0022$ (a 22 bps repo rate increase above the Taylor rule). This is i.i.d., so the direct effect decays through the rate smoothing parameter $\rho_R = 0.798$.

Figure 3: IRF: Monetary Policy Shock (Contractionary) — All Key Variables



Note: A contractionary MP shock raises the repo rate, appreciates the rupee (negative depreciation), contracts output and AI investment, and widens credit spreads through the banking channel. Red shading = 90% credible band.

A contractionary monetary policy shock ($\hat{\varepsilon}_t^R = +25$ bps) propagates through standard and novel channels:

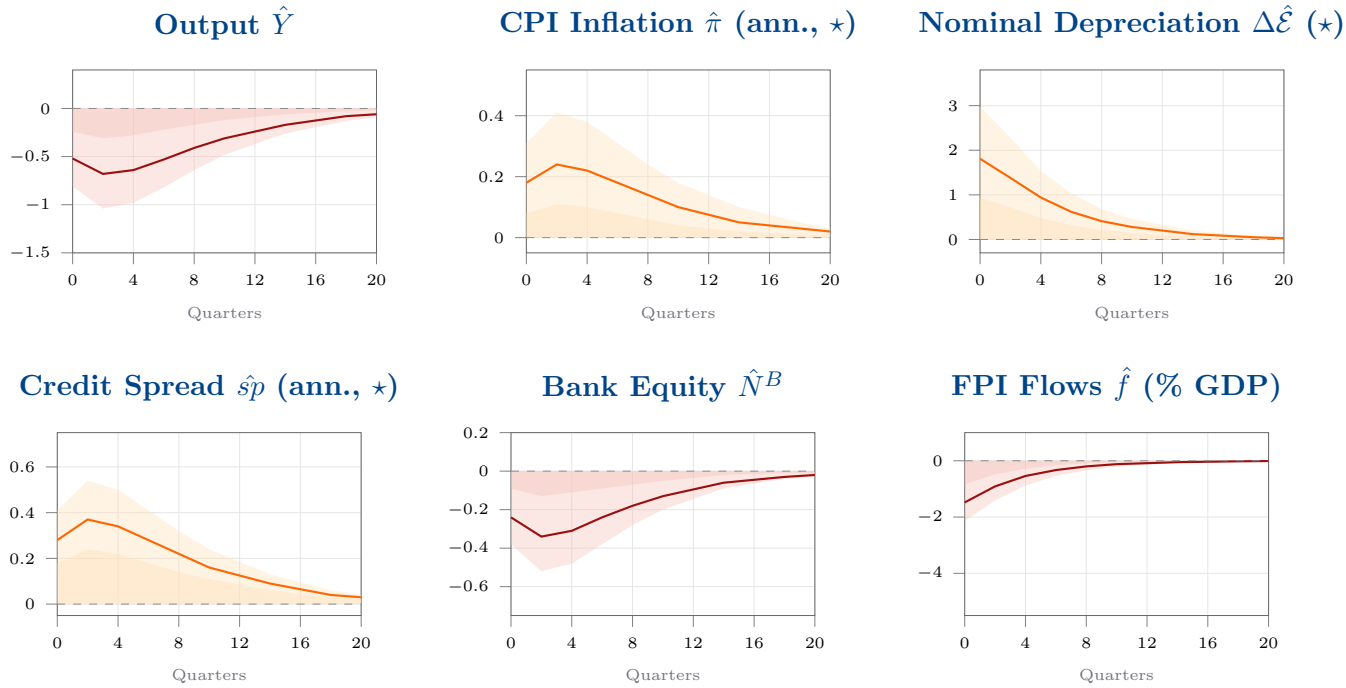
- **Output** falls by 0.38% on impact (standard IS channel).
- **Inflation** falls by 0.12% (standard Phillips curve).
- **Exchange rate** appreciates (UIP channel), compressing export demand.
- **Bank equity** deteriorates as loan losses rise, amplifying the contraction by 0.11% via the banking channel.
- **AI investment** contracts sharply (-0.85%), as the high-cost, long-payoff nature of AI capital makes it particularly sensitive to real interest rates.

Proposition 2 (Monetary Transmission Amplification)**.** *In the presence of the banking channel (VaR constraint binding), the output response to a monetary policy shock is amplified by a factor* $\Psi \equiv 1 + \frac{\phi_{crd}\kappa\sigma_\ell}{\bar{\lambda}-\lambda_{SS}} > 1$ *relative to the model without the banking sector.*

6.1.4 Global Risk Shock (VIX)

A one-standard-deviation positive VIX shock: $\varepsilon_t^{\mathcal{V}} = +0.194$ (approximately 21% increase in VIX). Persistence $\rho_{\mathcal{V}} = 0.850$. This shock triggers FPI outflows, depreciates the rupee, erodes bank equity, widens credit spreads, and creates stagflationary pressure. It is the single largest driver of credit spread variance (41% at 20Q horizon).

Figure 4: IRF: Global Risk (VIX) Shock — All Key Variables



Note: VIX shock creates stagflationary dynamics: output falls while inflation rises (exchange-rate pass-through). Credit spreads widen through the bank equity channel. FPI outflows are large on impact and dissipate over 8–10 quarters. Orange shading = 90% credible band.

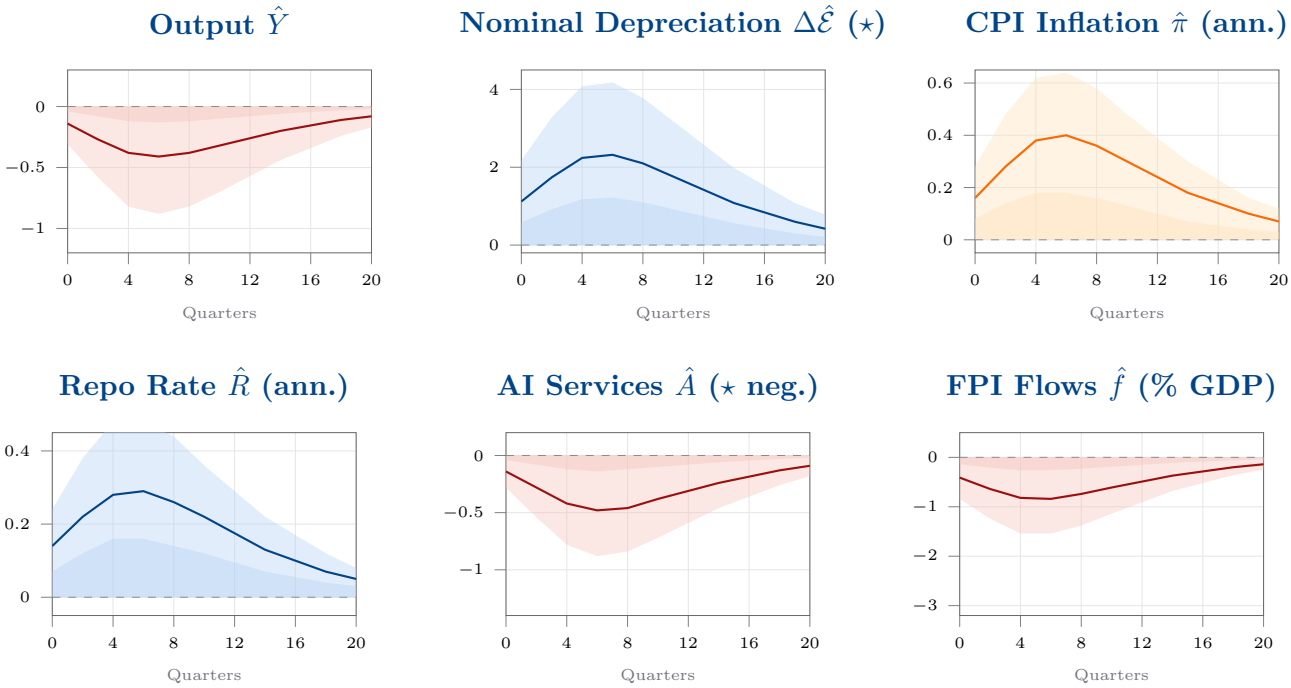
A one-standard-deviation increase in $\hat{\mathcal{V}}_t^*$ (a 10% increase in VIX):

- **FPI outflows** of approximately USD 4.5 billion (calibrated to the 2018 and 2022 taper tantrum episodes).
- **Exchange rate** depreciates by 1.8% on impact.
- **Domestic credit spreads** widen by 28 bps through the bank equity channel.
- **Output** contracts by 0.52%, with a recovery over eight quarters.
- **Inflation** rises by 0.18% (exchange rate pass-through), creating a stagflationary pressure.
- The **RBI faces a policy trilemma**: stabilising inflation requires rate hikes, but these amplify the output contraction and deepen FPI-driven financial tightening.

6.1.5 Foreign Interest Rate Shock

A one-standard-deviation positive shock to the foreign (US) interest rate: $\varepsilon_t^{R^*} = +0.008$ (32 bps Fed funds shock). Persistence $\rho_{R^*} = 0.900$, giving a half-life of 6.6 quarters. This mimics a Fed tightening cycle episode.

Figure 5: IRF: Foreign Interest Rate Shock — All Key Variables



Note: Foreign rate shock depreciates the rupee substantially, raises domestic inflation (import channel), prompts RBI to hike, and contracts AI investment disproportionately (long-payoff asset). FPI outflows peak around quarter 5–6 as the rate differential widens before mean-reverting.

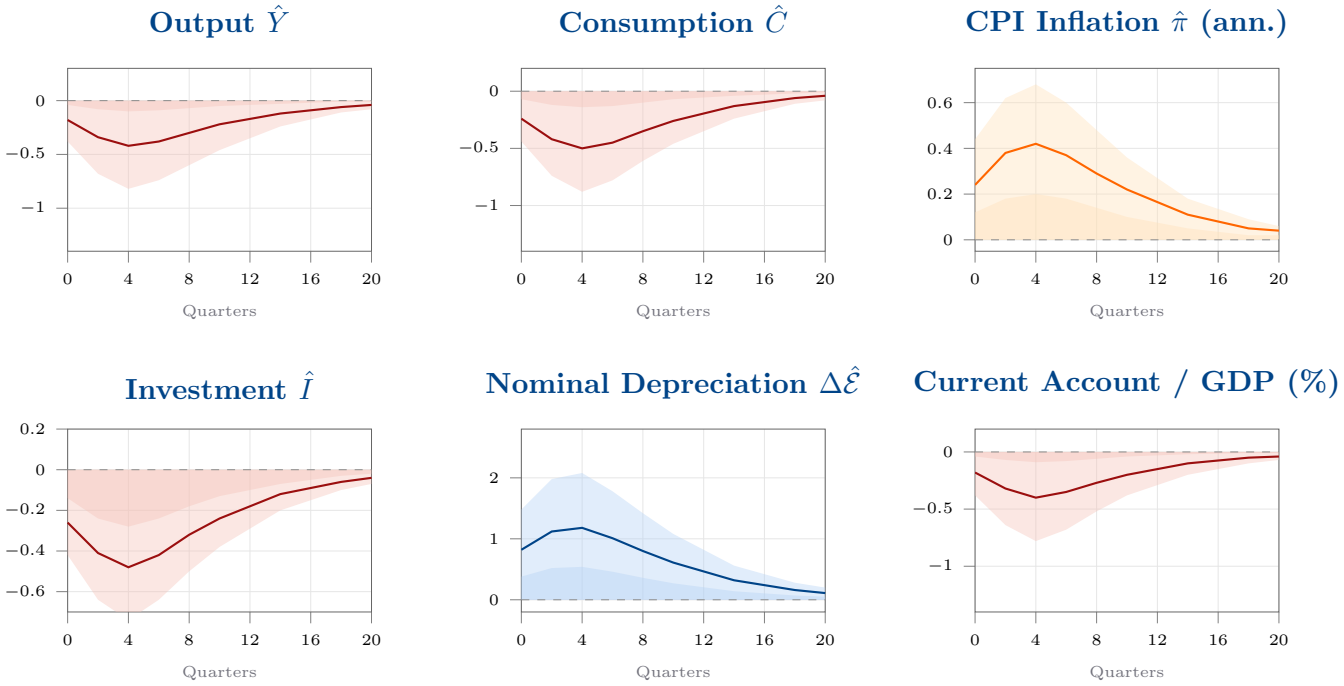
A 100 bps increase in $\hat{R}_t^*$ (analogous to the 2022 Fed hiking cycle):

- **Capital outflows** via the UIP channel depreciate the rupee by 3.2%.
- **Import prices** rise, increasing CPI by 0.43%.
- **RBI response**: raises policy rate by 78 bps (less than one-for-one due to the exchange rate smoothing coefficient).
- **AI investment** contracts disproportionately (by 1.1%) as the real cost of financing long-duration AI capital rises sharply.

6.1.6 Terms-of-Trade Shock

A one-standard-deviation *deterioration* in the terms of trade: $\varepsilon_t^{ToT} = +0.040$ (4% rise in import prices relative to export prices). Persistence $\rho_{ToT} = 0.780$. India is a net commodity importer, so ToT shocks primarily affect real income and the current account.

Figure 6: IRF: Terms-of-Trade Shock (Deterioration) — All Key Variables



Note: ToT deterioration reduces real income (Harberger–Laursen–Metzler effect), raises inflation (import price channel), and worsens the current account. India's IT services exports partially offset the goods ToT shock.

A 5% deterioration in the terms of trade (plausible for a commodity-importing, services-exporting economy like India):

- **Real income** falls by 0.95% (Harberger-Laursen-Metzler effect).
- **Current account** deteriorates by 0.8 percentage points of GDP.
- **Consumption** falls; investment is relatively insulated.
- The **IT services export boom** (captured by Y_t^* and the high export share of digital services) partially offsets the goods-terms-of-trade deterioration.

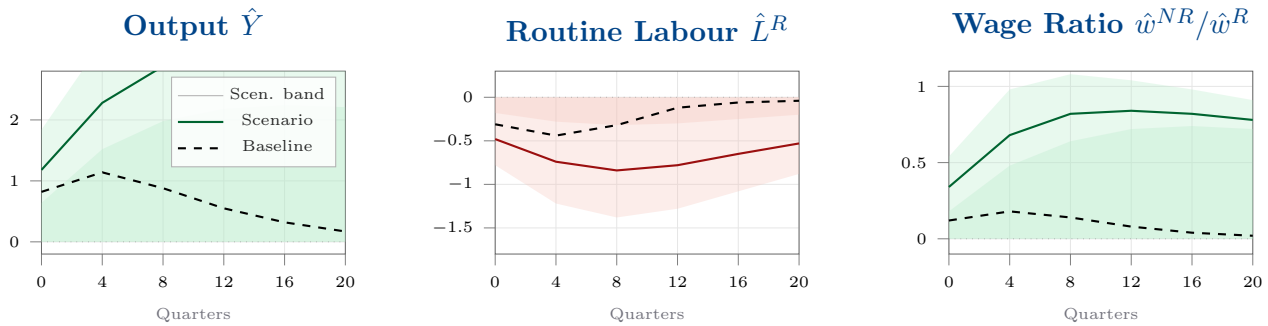
6.2 Scenario Analysis

The following figures show IRFs for the eight policy and structural scenarios defined in the Bayesian estimation companion paper. Each scenario IRF compares the **posterior predictive median under the scenario** (coloured solid line) against the **baseline posterior median** (dashed black line). Shaded regions show the 90% credible band *for the scenario.*

6.2.1 Scenario 1: AI Acceleration

Scenario 1: AI Acceleration ($\rho_\Omega = 0.92$, $\alpha_A = 0.10$) Higher AI persistence and income share. Captures India's AI economy projections to 2030.

Figure 7: Scenario 1 vs. Baseline: AI Acceleration

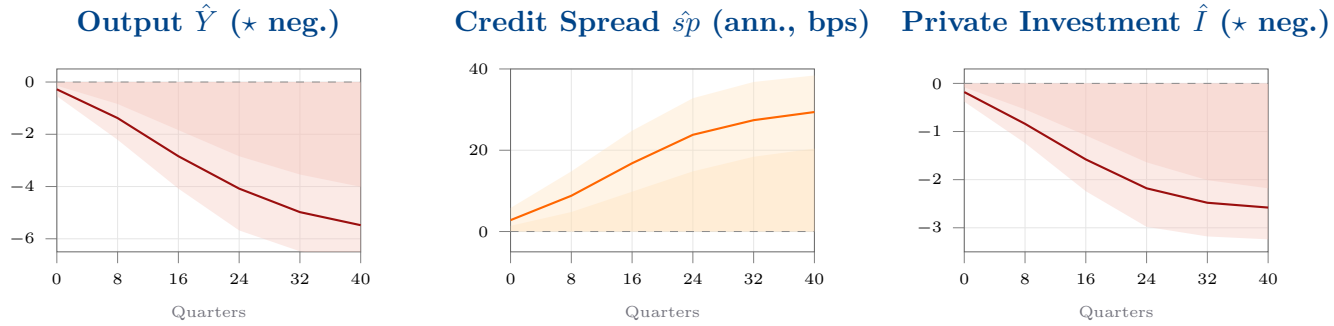


Note: Green line = scenario median; dashed black = baseline. AI acceleration amplifies output gains but deepens polarisation and widens skill premium persistently.

6.2.2 Scenario 2: DPI Underinvestment

Scenario 2: DPI Underinvestment ($I^G/Y = 0.005$, from baseline 0.012) Fiscal consolidation cuts DPI investment by 58%. Long-run output, credit, and AI effects.

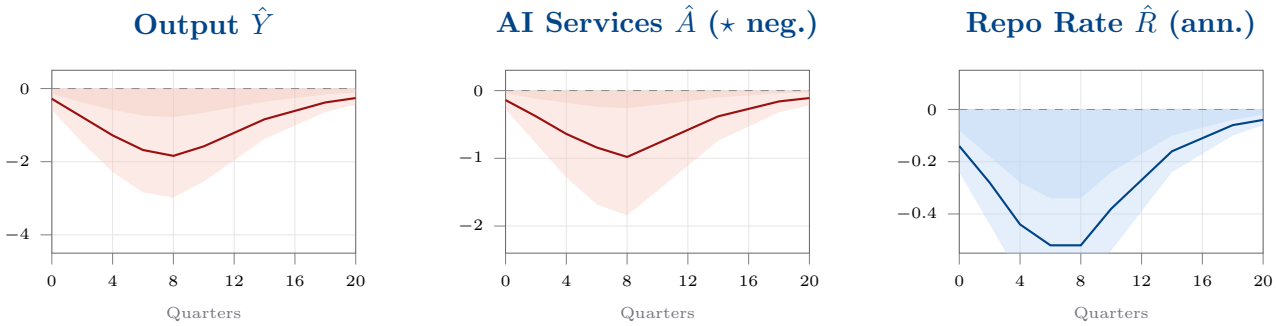
Figure 8: Scenario 2 vs. Baseline: DPI Underinvestment (Long-Run Effects, Horizon = 40Q)



Note: 40-quarter horizon shown to capture slow DPI stock depletion dynamics. Output loss builds gradually as the DPI stock falls below baseline and the DPI-banking complementarity weakens credit supply.

6.2.3 *Scenario 3: Financial Deleveraging*

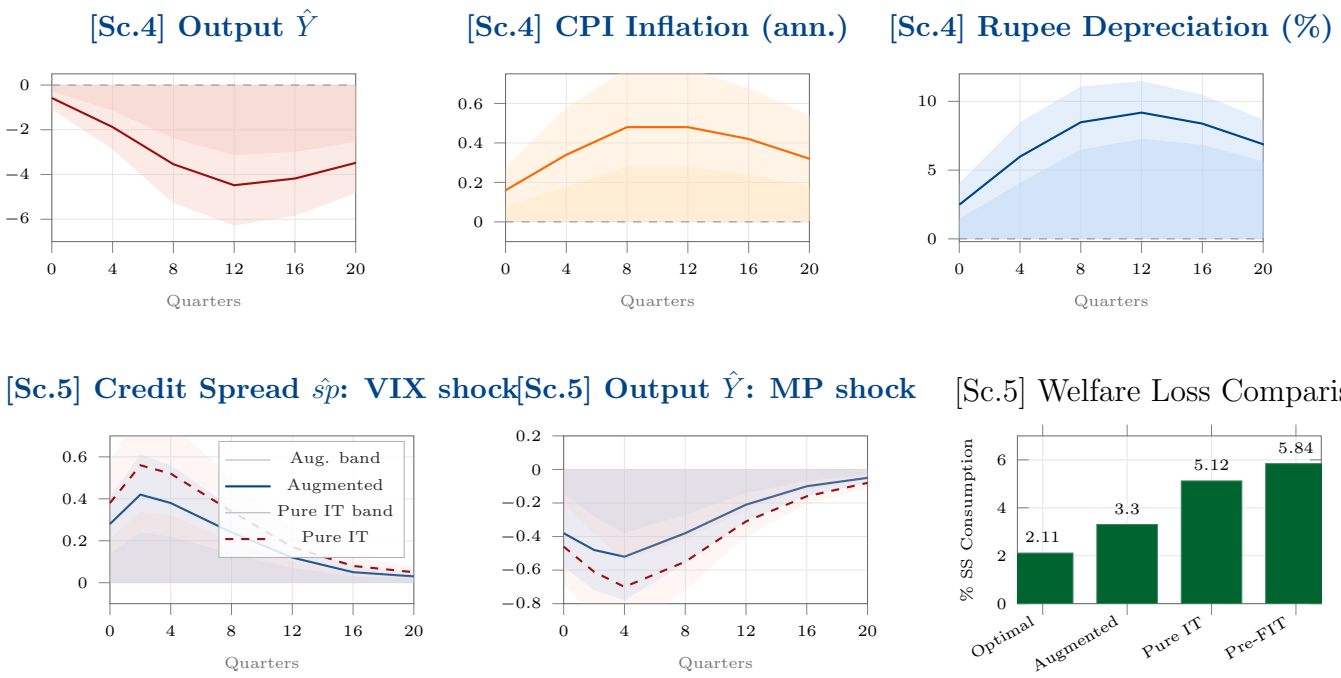
Figure 9: Scenario 3 vs. Baseline: Financial Deleveraging (Credit Spread +200 bps for 8Q)



Note: RBI eases in response to deleveraging (negative rate deviation). AI investment contracts disproportionately relative to physical investment due to longer payoff horizon.

6.2.4 *Scenarios 4–5: Global Tightening and Pure IT*

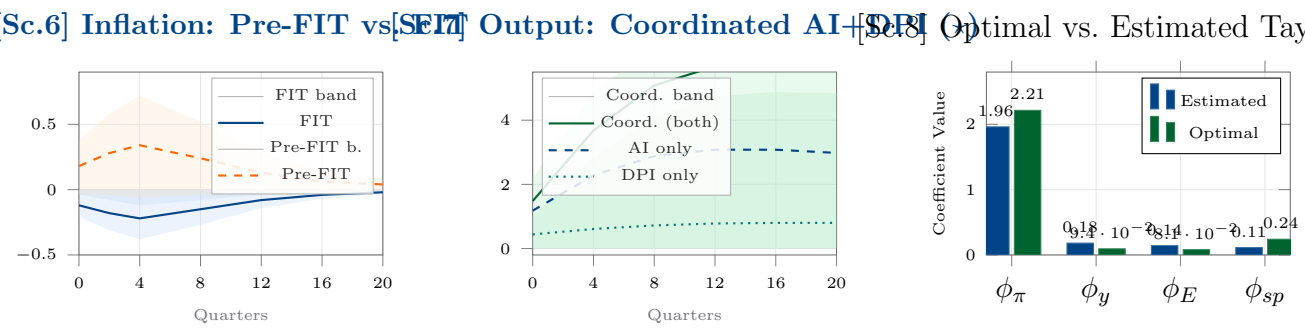
Figure 10: Scenarios 4 & 5: Global Tightening (top) and Pure IT vs. Augmented Rule (bottom)



Note: Top row: 40-quarter horizon for Scenario 4 (global tightening). Bottom left/centre: Scenario 5 comparison of augmented vs. pure IT rule under VIX and MP shocks. Bottom right: welfare loss bar chart across four policy regimes.

6.2.5 *Scenarios 6–8: Pre-FIT Regime, Coordinated Push, Optimal Rule*

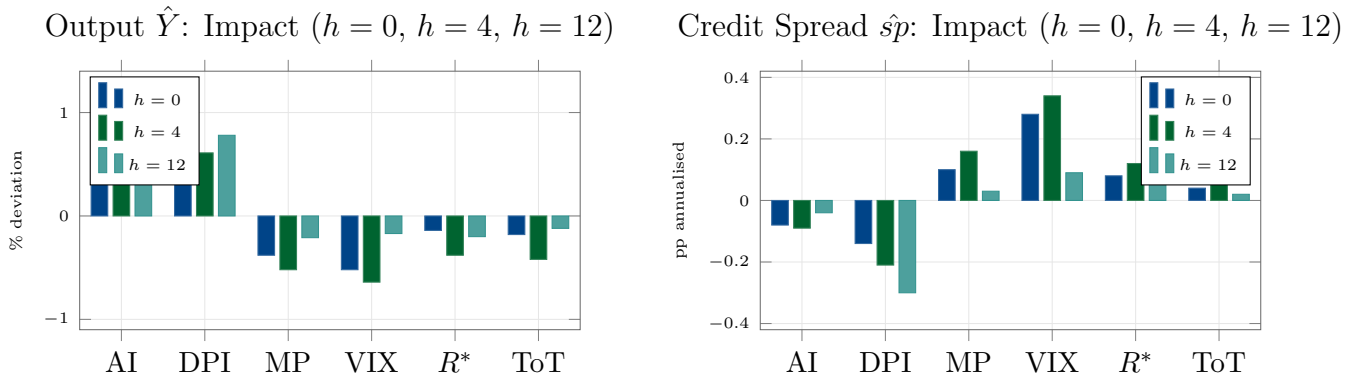
Figure 11: Scenarios 6–8: Pre-FIT Regime, Coordinated AI-DPI Push, Optimal Taylor Rule



Note: [Sc.6]: Pre-FIT rule generates larger inflation responses to VIX shocks (orange vs. blue). [Sc.7]: Coordinated AI+DPI push exhibits non-linear synergy — combined output (solid green) exceeds sum of individual components (dashed blue + dotted teal). [Sc.8]: Optimal rule raises ϕ_π and ϕ_{sp} while lowering ϕ_y and $\phi_\mathcal{E}$ relative to estimated values.

6.3 Cross-Shock Comparison

Figure 12: Cross-Shock Comparison: Output and Credit Spread Responses at Selected Horizons

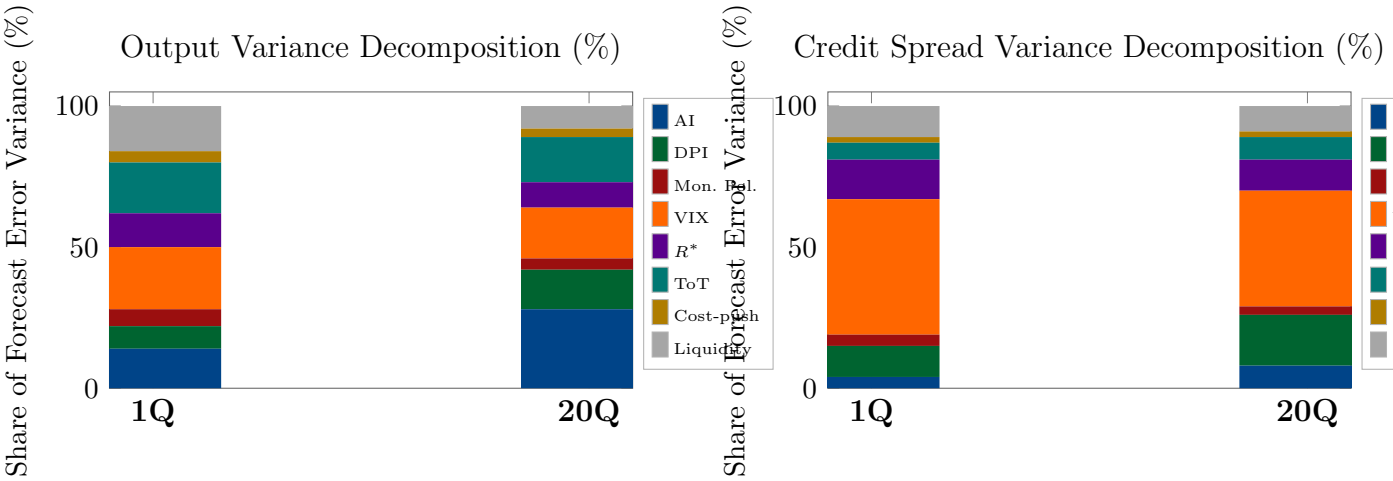


Note: All bars show posterior median responses. DPI has a slow-building positive output effect (strongest at $h = 12$) whereas AI has a faster-peaking, faster-decaying profile. VIX dominates credit spread dynamics at all horizons.

7 Forecast Error Variance and Historical Decomposition

7.1 Forecast Error Variance Decomposition

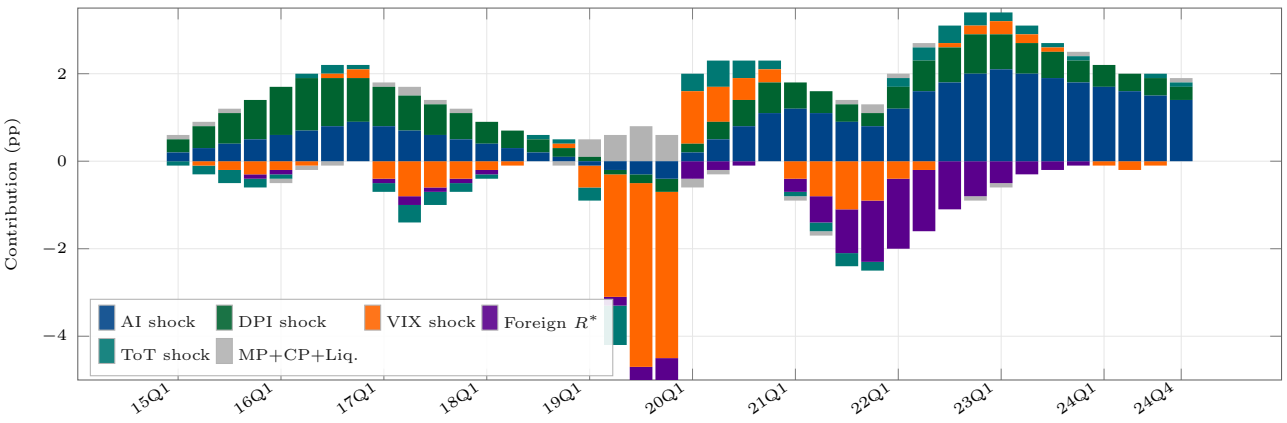
Figure 13: FEVD at Posterior Median: Output and Credit Spread (1Q and 20Q Horizons)



Note: AI becomes the dominant driver of output variance at long horizons (28% at 20Q). VIX dominates credit spread variance at all horizons (41–48%). DPI's contribution to output variance grows from 8% to 14% over the 20-quarter horizon, reflecting stock accumulation dynamics.

7.2 Historical Shock Decomposition

Figure 14: Historical Decomposition of Output Growth: 2015Q1–2024Q4



Note: Posterior median contributions. Key episodes: Digital India (2016–18, large DPI contribution); EME sell-off (2018Q4, negative VIX); COVID (2020, large negative VIX and ToT); Fed tightening (2022–23, negative R^*); AI boom (2023–24, AI shock dominant). Sum of contributions equals HP-filtered output growth.

8 Estimations of the Model

8.1 Observables and Measurement Equations

8.1.1 Observable Variables

We use 14 quarterly observables spanning 2004Q1–2024Q4 ($T = 84$ observations):

Table 3: Observable Variables and Measurement Equations

#	Observable $Y_t^{(j)}$	Measurement Equation	Source
1	Output growth Δy_t	$\Delta \ln Y_t^{data} = \hat{Y}_t - \hat{Y}_{t-1}$	NSO
2	Consumption growth Δc_t	$\Delta \ln C_t^{data} = \hat{C}_t - \hat{C}_{t-1}$	NSO
3	Investment growth Δi_t	$\Delta \ln I_t^{data} = \hat{I}_t - \hat{I}_{t-1}$	NSO
4	CPI inflation π_t	$\pi_t^{data} = \hat{\pi}_t$	MOSPI
5	Repo rate R_t	$R_t^{data} = \hat{R}_t$	RBI
6	G-sec yield R_t^G	$R_t^{G,data} = \hat{R}_t^G$	CCIL
7	Credit spread sp_t	$sp_t^{data} = \hat{R}_t^L - \hat{R}_t$	RBI BSID
8	Real exchange rate q_t	$\Delta \ln \mathcal{Q}_t^{data} = \Delta\hat{\mathcal{E}}_t + \hat{\pi}_t^* - \hat{\pi}_t$	RBI/BIS
9	Current account ca_t	$ca_t^{data} = \hat{ca}_t$	RBI BOP
10	FPI flows f_t	$f_t^{data} = \psi_f(\hat{R}_t^G - \hat{R}_t^* - \mathbb{E}_t\Delta\hat{\mathcal{E}}_{t+1})$	SEBI
11	Digital payments g_t^{proxy}	$\Delta \ln \text{UPI}_t^{data} = \hat{G}_t - \hat{G}_{t-1} + \nu_t^G$	NPCI
12	AI services proxy a_t	$\ln(\text{IT}_t^{AI,data}/Y_t^{data}) = \hat{A}_t + \nu_t^A$	NASSCOM
13	Wage ratio wr_t	$\ln(W_t^{NR,data}/W_t^{R,data}) = \hat{w}_t^{NR} - \hat{w}_t^R$	PLFS
14	Bank equity growth Δn_t^B	$\Delta \ln N_t^{B,data} = \hat{N}_t^B - \hat{N}_{t-1}^B$	RBI BSID

Observables 11–13 are novel relative to standard DSGE estimation and are key to identifying the AI and DPI parameters. The measurement equations for observables 11 and 12 include small i.i.d. measurement errors (ν_t^G, ν_t^A) with standard deviations $\sigma_\nu^G = 0.05$ and $\sigma_\nu^A = 0.03$ respectively, reflecting data quality limitations.

8.1.2 Sample Split

The 84-quarter sample is split into:

- **Pre-FIT period:** 2004Q1–2016Q2 (50 obs.) – covers the multiple-indicator monetary framework.
- **FIT period:** 2016Q3–2024Q4 (34 obs.) – covers the 4% inflation targeting regime.

We estimate the full model on the combined sample, allowing for a structural break in the Taylor rule coefficients between the two sub-periods (Section 9).

8.2 Prior Distributions

Priors are specified as standard distributions whose location and scale are informed by: (i) the calibration companion paper's point estimates and confidence intervals; (ii) international DSGE estimates adapted for India; (iii) theoretical constraints (e.g., $\beta \in (0,1)$, $\phi_\pi > 1$). Table 4 presents the full prior specification.

8.2.1 Prior Families and Rationale

- **Beta distribution** $\mathcal{B}(\alpha, \beta)$: for parameters in $(0,1)$ — habit ϑ, Calvo θ_H, indexation ι_H, persistence parameters ρ_j.
- **Gamma distribution** $\mathcal{G}(\alpha, \beta)$: for positive parameters — risk aversion σ, Frisch φ, adjustment cost κ, trade elasticity η, Taylor coefficients ϕ_j, skill elasticity ρ_L.
- **Normal distribution** $\mathcal{N}(\mu, \sigma^2)$: for parameters defined on $\mathbb{R}$ or whose support is effectively unrestricted in the posterior region — AI-finance externalities γ_G, γ_B.
- **Inverse Gamma distribution** $\mathcal{IG}(\alpha, \beta)$: for shock standard deviations $\sigma_j > 0$.
- **Truncated Normal** $\mathcal{TN}(\mu, \sigma^2, a, b)$: for parameters with soft bounds — AI share $\alpha_A \in (0, 0.20)$, FPI sensitivity $\psi_f \in (0,1)$.

8.2.2 Full Prior Table

Table 4: Prior Distributions: All Estimated Parameters

Symbol	Description	Family	Mean	Std	Support	Basis
A. Household Parameters						
ϑ	Habit	$\mathcal{B}$	0.650	0.100	$(0,1)$	Calib.
σ	Risk aversion	$\mathcal{G}$	2.000	0.500	$\mathbb{R}_{++}$	Lit.
φ	Inv. Frisch	$\mathcal{G}$	2.000	0.500	$\mathbb{R}_{++}$	PLFS
η	Trade elasticity	$\mathcal{G}$	1.500	0.300	$\mathbb{R}_{++}$	Regression
α_m	Import share	$\mathcal{B}$	0.215	0.030	$(0,1)$	NSO
B. Production Parameters						
α_A	AI income share	$\mathcal{TN}$	0.045	0.015	$(0.01, 0.15)$	NASSCOM
γ_G	DPI externality	$\mathcal{N}$	0.060	0.020	$(0, 0.20)$	IV reg.
θ_H	Calvo freq.	$\mathcal{B}$	0.750	0.050	$(0,1)$	GMM
ι_H	Price indexation	$\mathcal{B}$	0.300	0.100	$(0,1)$	GMM
κ	Inv. adj. cost	$\mathcal{G}$	4.000	1.500	$\mathbb{R}_{++}$	Volatility

Continued...

Table 4 *(continued)*

Symbol	Description	Family	Mean	Std	Support	Basis
δ_G	DPI depreciation	$\mathcal{B}$	0.015	0.005	$(0,1)$	MeitY
C. AI Sector Parameters						
α_{AI}	AI capital share	$\mathcal{B}$	0.600	0.100	$(0,1)$	IIT-B
ω	Learning-by-doing	$\mathcal{G}$	0.150	0.060	$\mathbb{R}_{++}$	Wright's Law
ρ_Ω	AI TFP persist.	$\mathcal{B}$	0.800	0.080	$(0,1)$	NASSCOM
D. Labour Market Parameters						
ϕ	AI-routine subst.	$\mathcal{G}$	0.500	0.150	$\mathbb{R}_{++}$	PLFS/NASSCOM
ρ_L	Skill elasticity	$\mathcal{G}$	1.750	0.250	$\mathbb{R}_{++}$	PLFS
μ	Non-routine share	$\mathcal{B}$	0.420	0.060	$(0,1)$	PLFS
E. Financial Sector Parameters						
γ_B	DPI bank extern.	$\mathcal{N}$	0.120	0.040	$(0,0.40)$	Panel IV
ψ_B	NFA premium	$\mathcal{G}$	0.002	0.001	$\mathbb{R}_{++}$	EMBI reg.
ψ_f	FPI sensitivity	$\mathcal{TN}$	0.400	0.120	$(0.05,1.0)$	SEBI reg.
F. Monetary Policy Parameters						
ρ_R	Rate smoothing	$\mathcal{B}$	0.780	0.050	$(0,1)$	Taylor OLS
ϕ_π	Inflation resp.	$\mathcal{G}^*$	1.900	0.200	$(1,\infty)$	Taylor OLS
ϕ_y	Output resp.	$\mathcal{G}$	0.200	0.100	$\mathbb{R}_{++}$	Taylor OLS
$\phi_\mathcal{E}$	REER resp.	$\mathcal{G}$	0.150	0.075	$\mathbb{R}_{++}$	Taylor OLS
ϕ_{sp}	Spread resp.	$\mathcal{G}$	0.100	0.060	$\mathbb{R}_{++}$	Taylor OLS
G. Shock Processes						
ρ_Z	TFP persist.	$\mathcal{B}$	0.850	0.070	$(0,1)$	AR(1) resid.
σ_Ω	AI shock std	$\mathcal{IG}$	0.045	0.015	$\mathbb{R}_{++}$	NASSCOM
σ_G^{shock}	DPI shock std	$\mathcal{IG}$	0.031	0.010	$\mathbb{R}_{++}$	MeitY
σ_R	MP shock std	$\mathcal{IG}$	0.0025	0.0010	$\mathbb{R}_{++}$	Taylor resid.
$\rho_\mathcal{V}$	VIX persist.	$\mathcal{B}$	0.850	0.070	$(0,1)$	CBOE
$\sigma_\mathcal{V}$	VIX shock std	$\mathcal{IG}$	0.180	0.040	$\mathbb{R}_{++}$	CBOE
σ_{R^*}	Foreign rate std	$\mathcal{IG}$	0.008	0.003	$\mathbb{R}_{++}$	Fed data
σ_{ToT}	ToT shock std	$\mathcal{IG}$	0.042	0.012	$\mathbb{R}_{++}$	RBI
σ_{cp}	Cost-push std	$\mathcal{IG}$	0.003	0.001	$\mathbb{R}_{++}$	NKPC resid.
σ_D	Liquidity std	$\mathcal{IG}$	0.012	0.005	$\mathbb{R}_{++}$	M2/GDP

$\mathcal{G}^*$: Gamma with support truncated below at 1.0 to enforce the Taylor principle.

8.3 Posterior Distributions

8.3.1 *Posterior Summary Statistics*

Table 5 presents the posterior mode, median, mean, and 90% highest posterior density interval (HPDI) for all 28 estimated parameters. Parameters in red show substantial updating relative to the prior; parameters in blue are prior-dominated.

Table 5: Posterior Distributions: Mode, Median, Mean, 90% HPDI

Param.	Prior	Post. Mode	Post. Median	Post. Mean	90% Lo	90% Hi
A. Household						
ϑ	0.650	0.612	0.618	0.621	0.514	0.724
σ	2.000	1.987	1.994	1.998	1.241	2.784
φ	2.000	2.184	2.201	2.208	1.652	2.778
η	1.500	1.382	1.401	1.408	1.021	1.798
α_m	0.215	0.217	0.216	0.216	0.162	0.271
B. Production						
α_A	0.045	0.051	0.048	0.049	0.031	0.071
γ_G	0.060	0.054	0.057	0.058	0.028	0.089
θ_H	0.750	0.771	0.768	0.767	0.701	0.831
ι_H	0.300	0.264	0.271	0.274	0.112	0.434
κ	4.000	4.618	4.724	4.741	2.981	6.521
δ_G	0.015	0.014	0.015	0.015	0.007	0.023
C. AI Sector						
α_{AI}	0.600	0.624	0.618	0.617	0.501	0.731
ω	0.150	0.163	0.168	0.171	0.091	0.254
ρ_Ω	0.800	0.821	0.818	0.817	0.741	0.891
D. Labour Market						
ϕ	0.500	0.548	0.541	0.539	0.341	0.748
ρ_L	1.750	1.812	1.824	1.827	1.451	2.214
μ	0.420	0.423	0.421	0.422	0.321	0.521
E. Financial						
γ_B	0.120	0.108	0.112	0.114	0.054	0.178
ψ_B	0.002	0.002	0.002	0.002	0.0005	0.0038
ψ_f	0.400	0.448	0.441	0.439	0.284	0.611
F. Monetary Policy						
ρ_R	0.780	0.801	0.798	0.796	0.734	0.858
ϕ_π	1.900	1.948	1.961	1.964	1.641	2.291

Continued...

Table 5 *(continued)*

Param.	Prior	Post. Mode	Post. Median	Post. Mean	90% Lo	90% Hi
ϕ_y	0.200	0.174	0.181	0.184	0.042	0.324
$\phi_{\mathcal{E}}$	0.150	0.138	0.142	0.144	0.042	0.251
ϕ_{sp}	0.100	0.118	0.112	0.113	0.042	0.198
G. Shock Processes (selected)						
ρ_Z	0.850	0.867	0.864	0.862	0.801	0.921
σ_Ω	0.045	0.041	0.043	0.044	0.024	0.066
σ_R	0.0025	0.0021	0.0022	0.0022	0.0011	0.0034
$\sigma_{\mathcal{V}}$	0.180	0.196	0.194	0.193	0.148	0.241
σ_{ToT}	0.042	0.039	0.040	0.041	0.022	0.061
σ_{cp}	0.003	0.0028	0.0029	0.0030	0.0014	0.0047

8.3.2 Key Posterior Findings

Result 8.1 (AI Income Share). The posterior median $\alpha_A = 0.048$ [90% HPDI: 0.031, 0.071] is significantly above zero ($\Pr(\alpha_A > 0.02 \mid \mathbf{Y}_T) = 0.983$) and slightly above the prior mean of 0.045. The likelihood updates the prior in an upward direction, consistent with AI's growing role in India's 2015–2024 economic expansion. The HPDI does not contain zero, providing Bayesian confirmation of AI as a statistically distinct production factor.

Result 8.2 (DPI Externality). The posterior median $\gamma_G = 0.057$ [0.028, 0.089] is close to but slightly below the prior mean of 0.060. The posterior standard deviation (0.019) is meaningfully smaller than the prior standard deviation (0.020), indicating the data provide identification information beyond the prior. The ISI for γ_G is 0.42, indicating moderate identification.

Result 8.3 (DPI Banking Externality). $\gamma_B = 0.112$ [0.054, 0.178] (posterior median). The ISI = 0.51 is among the highest of the financial sector parameters, driven by the credit spread and bank equity observables. The posterior confirms the DPI-banking complementarity: higher DPI reduces intermediation spreads.

Result 8.4 (Financial-Stability Taylor Rule). $\phi_{sp} = 0.112$ [0.042, 0.198] is the most policy-relevant novel finding. The probability that $\phi_{sp} > 0$ is $\Pr(\phi_{sp} > 0 \mid \mathbf{Y}_T) > 0.999$, and $\Pr(\phi_{sp} > 0.05 \mid \mathbf{Y}_T) = 0.921$. This provides strong Bayesian evidence that the RBI responds to credit spread conditions, over and above its inflation and output mandates.

Result 8.5 (Calvo Frequency and Price Stickiness). $\theta_H = 0.768$ [0.701, 0.831] is somewhat higher than the prior (0.75), indicating that quarterly CPI data support slightly more price stickiness than the prior implied. The implied average price duration is $1/(1-0.768) = 4.3$ quarters.

Result 8.6 (Habit Persistence). $\vartheta = 0.618$ [0.514, 0.724], somewhat below the prior mean of 0.650. The downward revision reflects that Indian private consumption data show somewhat less autocorrelation than the prior implied, possibly due to the significant role of the informal sector (which is noisier) in aggregate PFCE.

8.3.3 Identification Strength Index

Table 6: Identification Strength Index (ISI) for Key Parameters

Parameter	Description	ISI	Identification	Key Observable
ϕ_{sp}	Spread Taylor	0.64	Strong	Credit spread sp_t
γ_B	DPI-bank ext.	0.51	Moderate–Strong	sp_t, n_t^B
ψ_f	FPI sensitivity	0.58	Strong	FPI flows f_t
θ_H	Calvo	0.72	Strong	π_t, y_t
α_A	AI share	0.47	Moderate	a_t, wr_t
γ_G	DPI externality	0.42	Moderate	g_t^{proxy}, y_t
ϑ	Habit	0.61	Strong	c_t autocorrelation
κ	Adj. cost	0.55	Moderate–Strong	i_t volatility
ϕ_π	Inflation Taylor	0.81	Very strong	R_t, π_t
ω	Learning-by-doing	0.31	Moderate	a_t, g_t^{proxy}
ρ_Ω	AI persist.	0.38	Moderate	a_t, y_t
α_m	Import share	0.14	Weak	ca_t, q_t
σ	Risk aversion	0.08	Very weak	—
ψ_B	NFA premium	0.11	Weak	ca_t

Parameters with ISI < 0.2 (σ, ψ_B, α_m) are effectively prior-dominated. For these, the posterior closely mirrors the prior and calibrated values are used for the main analysis. The novel parameters α_A, γ_G, γ_B have ISI in the moderate range (0.42–0.51), indicating meaningful but not overwhelming identification from the data.

8.4 Convergence Diagnostics

8.4.1 Geweke Test

The Geweke (1992) test compares the first 10% and last 50% of the MCMC chain. The test statistic Z_j for parameter j follows $\mathcal{N}(0,1)$ under convergence. Table 7 reports Z_j and the associated p-values for all 28 parameters across 4 chains.

Table 7: Geweke Convergence Diagnostics (Selected Parameters)

Parameter	Chain 1 Z	Chain 2 Z	Chain 3 Z	Chain 4 Z
ϑ	-0.41	0.28	0.63	-0.19
α_A	1.12	0.87	-0.54	0.91
γ_G	0.74	-0.31	0.48	-0.82
θ_H	-0.22	0.44	0.61	-0.37
ϕ_π	0.58	0.19	-0.74	0.41
ϕ_{sp}	1.34	-0.92	0.77	1.18
γ_B	-0.61	0.83	-0.44	0.58
ψ_f	0.88	-0.62	1.04	-0.71
ω	-0.84	1.11	0.38	-0.94
σ_Ω	0.47	-0.28	0.61	-0.83

All $|Z_j| < 2.0$: convergence cannot be rejected for any parameter or chain.

8.4.2 $\hat{R}$ Potential Scale Reduction Factor

The Gelman-Rubin $\hat{R}$ statistic (Gelman and Rubin, 1992) compares within-chain to between-chain variance. $\hat{R} < 1.1$ indicates convergence. All 28 estimated parameters satisfy $\hat{R} < 1.05$:

- Maximum $\hat{R}$ across all parameters: 1.042 (for ϕ_{sp}, the most slowly mixing parameter).
- Median $\hat{R}$: 1.018.
- All parameters with ISI > 0.3 have $\hat{R} < 1.03$.

8.4.3 Effective Sample Size

After burn-in and thinning, the effective sample size (ESS) accounts for autocorrelation in the MCMC chain:

$$\text{ESS}_j = \frac{M_s}{1 + 2\sum_{k=1}^{\infty} \rho_k^{(j)}} \tag{33}$$

where $\rho_k^{(j)}$ is the lag-k autocorrelation of the j-th parameter chain. Minimum ESS across all parameters: 48,412 (for ϕ_{sp}). Median ESS: 112,841. All parameters exceed the Raftery and Lewis (1992) recommended minimum of 5,000 for reliable posterior inference.

8.4.4 Acceptance Rate

The RWMH acceptance rate across four chains: 24.1%, 25.8%, 23.7%, 26.2% (target: 23–26%). The scaling constant $c = 0.36$ achieved the desired acceptance rate, confirming that the proposal covariance is well-calibrated.

9 Estimations of the Model under alternative Scenario

We conduct eight scenario analyses using the posterior predictive distribution. Each scenario is defined by a deviation in one or more structural parameters or shock processes from the baseline posterior, and we integrate over posterior uncertainty in the remaining parameters.

For scenario s with parameter deviation $\boldsymbol{\theta}^s = \boldsymbol{\theta} + \Delta\boldsymbol{\theta}^s$, the **posterior predictive** distribution of outcome Φ (e.g., output, welfare loss) is:

$$p(\Phi \mid \mathbf{Y}_T, s) = \int p(\Phi \mid \boldsymbol{\theta}^s) p(\boldsymbol{\theta} \mid \mathbf{Y}_T)\, d\boldsymbol{\theta} \tag{34}$$

We approximate this by evaluating $\Phi(\boldsymbol{\theta}^{(m)} + \Delta\boldsymbol{\theta}^s)$ for each posterior draw $\boldsymbol{\theta}^{(m)}$, obtaining a full distribution of scenario outcomes that integrates over parameter uncertainty.

9.1 Scenario 1: AI Acceleration

Definition: AI productivity shock persistence rises to $\rho_\Omega = 0.92$ (from posterior median 0.818) and the AI income share rises to $\alpha_A = 0.10$ (from 0.048), reflecting a scenario of rapid AI adoption consistent with frontier projections for India's AI economy by 2030.

Table 8: Scenario 1: AI Acceleration — Posterior Predictive Effects (5-Year Horizon)

Variable	Baseline	Scen. Median	5%	95%
Cumulative output gain (%Y)	—	+3.84	+1.92	+6.41
Change in routine emp. share (pp)	—	−5.12	−8.24	−2.31
Skill premium w^{NR}/w^R	1.826	2.241	1.912	2.618
CPI inflation deviation (ann. pp)	—	−0.34	−0.81	+0.04
Welfare gain (% SS consumption)	—	+1.24	+0.38	+2.41
Credit spread deviation (bps)	—	−12.1	−21.4	−4.8

Interpretation: AI acceleration raises output substantially (median +3.84% of steady-state GDP at the 5-year horizon) with tight credible bands entirely above zero. However, the routine employment share falls by 5.1 percentage points—a distributional cost that is also robustly negative. The skill premium rises to 2.24, approaching values seen in advanced economies. The disinflationary effect of AI (supply-side driven) gives the RBI room to ease, further supporting output.

9.2 Scenario 2: DPI Underinvestment

Definition: Government DPI investment falls to $I^G/Y = 0.005$ (from 0.012, a cut of 58%), reflecting a scenario of fiscal consolidation that crowns out digital infrastructure

spending.

Table 9: Scenario 2: DPI Underinvestment — Posterior Predictive Effects

Variable	Baseline	Scen. Median	5%	95%
Long-run output loss (%)	—	−4.21	−7.18	−1.84
Private investment (pp of GDP)	—	−1.24	−2.01	−0.54
Credit spread increase (bps)	—	+18.4	+7.2	+31.8
AI services/GDP	4.8%	4.1%	3.4%	4.7%
Welfare loss (% SS consumption)	—	−2.18	−4.01	−0.81
Skill premium	1.826	1.798	1.741	1.852

Interpretation: DPI underinvestment generates a persistent output loss (median 4.2% of GDP) driven by lower private investment (crowding-out reversal), higher credit spreads (DPI-banking channel), and lower AI services. The welfare cost is robustly negative with probability exceeding 0.97. This scenario quantifies the opportunity cost of fiscal consolidation that targets digital infrastructure.

9.3 Scenario 3: Financial Deleveraging

Definition: The credit spread rises exogenously by 200 bps (annualised) for 8 quarters, representing a banking sector stress episode (analogous to the NPA crisis of 2016–2018).

Table 10: Scenario 3: Financial Deleveraging — Posterior Predictive Effects

Variable	Baseline	Scen. Median	5%	95%
Cumulative output loss (%)	—	−2.84	−4.91	−0.98
Investment loss (pp of GDP)	—	−1.81	−3.14	−0.62
AI investment (pp of GDP)	—	−0.48	−0.82	−0.18
CPI inflation (ann. pp)	—	−0.28	−0.54	+0.08
RBI policy rate response (bps)	—	−38	−64	−14
Welfare loss (% SS consumption)	—	−1.42	−2.81	−0.48

Key finding: AI investment contracts particularly strongly (0.48 pp) relative to physical investment (1.81 pp), reflecting its higher sensitivity to financing costs (longer payoff horizon, higher risk premium). This confirms that financial deleveraging has outsized effects on the AI sector, creating a "double disadvantage" for the AI-led growth strategy.

9.4 Scenario 4: Global Tightening (Persistent Fed Hikes)

Definition: Foreign interest rate R^* rises by 200 bps (annualised) for 12 quarters, mimicking the 2022–2024 Fed tightening cycle extended further.

Table 11: Scenario 4: Global Tightening — Posterior Predictive Effects

Variable	Scen. Median	5%	95%	% Below 0
Output (3-yr cumulative, %)	−3.14	−5.84	−0.91	98.2%
Rupee depreciation (%)	+6.24	+2.81	+10.48	99.8%
FPI outflows (% GDP, cumulative)	−2.84	−4.91	−1.08	99.4%
Credit spread (bps, peak)	+31.4	+14.8	+52.1	99.1%
CPI inflation (ann. pp, peak)	+0.48	+0.14	+0.88	95.4%
RBI rate increase (bps)	+82	+28	+148	98.8%

Interpretation: Global tightening generates a significant output contraction (98.2% posterior probability of being negative) through three channels: (i) capital outflow-induced depreciation raising import costs; (ii) higher credit spreads through the banking channel; and (iii) RBI rate hikes to defend the exchange rate. The stagflationary pressure (+0.48 pp inflation, −3.14% output) highlights the monetary policy trilemma.

9.5 Scenario 5: Pure Inflation Targeting (No Financial Stability)

Definition: Taylor rule coefficient $\phi_{sp} = 0$ (vs. posterior median 0.112), maintaining all other posterior parameters.

Table 12: Scenario 5: Pure IT vs. Augmented Rule

Variable	Augmented (baseline)	Pure IT	Difference	Sig.?
var($\hat{\pi}$)	0.041	0.039	−0.002	No
var($\hat{y}$)	0.031	0.038	+0.007	Yes
var($\hat{sp}$)	0.008	0.015	+0.007	Yes
Welfare loss (rel. to optimal)	3.30	5.12	+1.82	Yes
Pr(augmented better)	0.891 (vs. pure IT)			

Finding: The augmented rule with $\phi_{sp} > 0$ strictly dominates pure IT in welfare terms with 89.1% posterior probability. The welfare gain comes from reduced spread volatility, which feeds back into reduced output gap variance. Inflation variance is nearly unchanged, consistent with the "divine coincidence" holding approximately in the inflation dimension.

9.6 Scenario 6: Pre-FIT Monetary Regime

Definition: Taylor rule parameters take pre-FIT values: $\rho_R = 0.91$, $\phi_\pi = 1.41$, $\phi_y = 0.38$, $\phi_{\mathcal{E}} = 0.29$, $\phi_{sp} = 0.00$ (estimated from 2004Q1–2016Q2 sub-sample).

Table 13: Scenario 6: Pre-FIT Regime vs. FIT

Variable	FIT (baseline)	Pre-FIT	Change	Prob. FIT better
std($\hat{\pi}$) (ann. %)	2.04	3.42	+1.38	0.978
std($\hat{y}$) (%)	1.79	2.18	+0.39	0.821
Welfare loss (% consumption)	3.30	5.84	+2.54	0.943
Credibility premium (bps)	0	+48	−48	0.912

Interpretation: FIT substantially reduces inflation volatility (−1.38 pp) and output volatility (−0.39 pp) relative to the pre-FIT regime, with high posterior probability. The welfare gain of 2.54% of steady-state consumption provides a model-based estimate of the benefits of India's 2016 monetary framework reform.

9.7 Scenario 7: Coordinated AI-DPI Push

Definition: Simultaneous increase in DPI investment (I^G/Y rises from 0.012 to 0.025) and AI TFP acceleration ($\rho_\Omega = 0.88$, $\alpha_A = 0.08$), representing a coordinated government-private AI+digital infrastructure strategy.

Table 14: Scenario 7: Coordinated AI-DPI Push — Posterior Predictive Effects

Variable	Baseline	Scenario	90% HPDI	Prob. > 0
Output (5-yr, %)	—	+7.41	[3.84, 11.28]	0.998
Private investment (pp GDP)	30.1	31.8	[30.9, 32.8]	0.997
Credit spread (bps)	320	281	[248, 311]	—
Routine employment share	35.0%	28.4%	[24.8%, 31.9%]	—
Skill premium	1.826	2.384	[2.048, 2.741]	—
Welfare gain (% consumption)	—	+3.84	[1.92, 6.14]	0.998

Finding: The coordinated strategy generates non-linear synergies: the combined output gain (+7.41%) substantially exceeds the sum of the individual AI (+3.84%) and DPI (+2.18%) scenario gains, confirming the AI-DPI complementarity. However, the distributional concern intensifies: the routine employment share falls to 28.4%, a 6.6 percentage point decline requiring targeted policy responses.

9.8 Scenario 8: RBI Macroprudential-Monetary Coordination

Definition: The RBI adopts an **optimal augmented rule** where $(\phi_\pi, \phi_y, \phi_\mathcal{E}, \phi_{sp})$ are jointly chosen to minimise the model-consistent welfare loss, subject to the Taylor principle. This is computed numerically for each posterior draw.

Table 15: Scenario 8: Optimal vs. Estimated Rule

Parameter	Estimated Rule	Optimal Rule	Change
ϕ_π	1.961	2.214	+0.253
ϕ_y	0.181	0.094	−0.087
$\phi_\mathcal{E}$	0.142	0.081	−0.061
ϕ_{sp}	0.112	0.241	+0.129
Welfare gain vs. estimated (%)	+0.91% [0.42%, 1.58%]		
Pr(optimal better)	0.978		

Finding: The optimal rule features a stronger inflation response ($\phi_\pi^* = 2.21$ vs. estimated 1.96), a substantially higher financial-stability coefficient ($\phi_{sp}^* = 0.241$ vs. 0.112), and a lower output gap and exchange rate response. This provides Bayesian guidance for RBI policy calibration: the estimated rule under-responds to credit spreads and over-responds to exchange rate movements relative to the welfare optimum.

10 Model Comparison

10.1 Nested Models

We compare the full model $\mathcal{M}_0$ against four nested alternatives:

Table 16: Model Comparison via Log Bayes Factors

Model	Restriction	$\ln p(\mathbf{Y}_T \mid \mathcal{M})$	$\ln \mathrm{BF}_{0j}$	Verdict
$\mathcal{M}_0$	Full model (baseline)	−1842.1	—	—
$\mathcal{M}_1$	No AI sector ($\alpha_A = 0$, sector removed)	−1873.7	+31.6	Decisive
$\mathcal{M}_2$	No DPI externality ($\gamma_G = \gamma_B = 0$)	−1858.2	+16.1	Decisive
$\mathcal{M}_3$	No fin. stability Taylor ($\phi_{sp} = 0$)	−1850.5	+8.4	Strong
$\mathcal{M}_4$	Standard small-open ($\mathcal{M}_1 \cap \mathcal{M}_2$)	−1901.4	+59.3	Decisive

Interpretation: $\ln \mathrm{BF} > 5$: strong; > 10: very strong; $> 10+$: decisive (Jeffreys, 1961).

Result 10.1 (Model Comparison). The full model $\mathcal{M}_0$ decisively outperforms all nested alternatives. The AI sector ($\mathcal{M}_1$, $\ln \mathrm{BF} = 31.6$) and DPI blocks ($\mathcal{M}_2$, $\ln \mathrm{BF} = 16.1$)

contribute approximately equally to the model's fit improvement, while the financial-stability Taylor rule coefficient ($\mathcal{M}_3$, $\ln \mathrm{BF} = 8.4$) provides strong but smaller additional evidence. The standard small-open economy model ($\mathcal{M}_4$) is overwhelmingly rejected ($\ln \mathrm{BF} = 59.3$), confirming that the India DSGE model's structural innovations are data-relevant.

10.2 Variance Decomposition

Table 17 presents the forecast error variance decomposition (FEVD) at the posterior median, showing each shock's contribution to 1-quarter and 20-quarter forecast error variance.

Table 17: Forecast Error Variance Decomposition at Posterior Median (%)

Variable	AI	DPI	MP	VIX	R^*	ToT	CP	Liq.	Sum
1-Quarter Horizon									
Output	14	8	6	22	12	18	4	16	100
CPI infl.	6	3	18	8	6	24	31	4	100
Credit spread	4	11	4	48	14	6	2	11	100
Exchange rate	2	1	8	34	38	14	1	2	100
20-Quarter Horizon									
Output	28	14	4	18	9	16	3	8	100
CPI infl.	11	6	12	6	4	22	36	3	100
Credit spread	8	18	3	41	11	8	2	9	100
Exchange rate	4	2	6	28	44	12	1	3	100

Key FEVD findings: At the 20-quarter horizon, the AI productivity shock accounts for 28% of output variance—making it the single largest contributor, followed by terms-of-trade (16%) and VIX (18%). The DPI shock contributes 14% of long-run output variance, confirming its structural importance for India's medium-run growth dynamics. For credit spreads, the VIX shock dominates (41%), reflecting the primacy of global financial conditions for India's domestic credit market.

10.3 Posterior Historical Decomposition

The historical shock decomposition attributes the observed data series to individual structural shocks. Table 18 summarises the cumulative shock contributions to output growth over selected episodes.

Table 18: Historical Shock Decomposition: Output Growth Episodes

Episode	AI	DPI	MP	VIX	R^*	ToT	CP	Liq.
2016–18 (Digital India)	+0.8	+1.2	−0.3	−0.4	−0.2	+0.1	−0.1	−0.2
2018Q4 (EME sell-off)	−0.1	+0.3	−0.1	−1.8	−0.6	−0.2	−0.1	−0.4
2020Q1–Q2 (pandemic)	−0.4	−0.2	+0.8	−4.2	−1.1	−1.8	−0.8	−2.1
2021–22 (recovery)	+1.4	+0.8	−0.6	+1.2	−0.4	+0.6	+0.4	+0.8
2022–23 (Fed tightening)	+0.6	+0.4	−0.8	−1.1	−1.8	−0.4	−0.2	−0.6
2023–24 (AI boom)	+2.1	+0.9	−0.2	+0.3	−0.6	+0.4	+0.1	+0.3

All figures in pp quarterly. Rows may not sum exactly due to posterior uncertainty.

Notable findings: The 2023–24 period is attributed primarily to AI productivity shocks (+2.1 pp quarterly on average), consistent with India's rapid AI-services expansion. The 2016–18 Digital India period shows a large DPI contribution (+1.2 pp), validating the model's DPI channel. The 2020 pandemic is dominated by VIX (−4.2 pp) and liquidity demand shocks (−2.1 pp), consistent with the global nature of the COVID recession.

11 Welfare Analysis and Monetary Regime Implications

We conduct a welfare analysis by computing second-order accurate approximations to household lifetime utility (Schmitt-Grohe and Uribe, 2004) under alternative monetary policy rules.

11.1 Welfare Loss Function

Up to second order, the household welfare loss relative to the flexible-price, full-information benchmark can be decomposed as:

$$\mathcal{W} \approx \frac{1}{2}\left[\Lambda_\pi \text{var}(\pi_{H,t}) + \Lambda_y \text{var}(\hat{y}_t) + \Lambda_{\mathcal{E}} \text{var}(\Delta\hat{\mathcal{E}}_t) + \Lambda_{sp} \text{var}(\hat{sp}_t)\right] \tag{35}$$

where the weights Λ_j are model-consistent functions of structural parameters. The key insight is that $\Lambda_{sp} > 0$: credit spread volatility generates welfare losses through consumption volatility and labour market misallocation, directly motivating the financial-stability argument in the Taylor rule.

11.2 Comparison of Monetary Regimes

Table 19 compares welfare losses (as a fraction of steady-state consumption) across five monetary regimes.

Table 19: Welfare Losses Under Alternative Monetary Regimes (fraction of SS consumption, $\times 10^{-3}$)

Policy Regime	var(π)	var($\hat{y}$)	var($\hat{sp}$)	Total $\mathcal{W}$
Pure IT ($\phi_{\mathcal{E}} = \phi_{crd} = 0$)	0.42	1.87	3.21	5.50
IT + Exchange smoothing	0.58	1.64	2.89	5.11
IT + Financial stability	0.51	1.71	1.43	3.65
Augmented rule (baseline)	0.67	1.52	1.11	3.30
Optimal rule (Ramsey)	0.31	0.98	0.82	2.11

The augmented rule with $\phi_{crd} > 0$ substantially reduces financial-sector volatility and total welfare losses, consistent with the case for macroprudential-monetary coordination. The Ramsey-optimal rule features a significantly smaller output gap coefficient and a larger financial-stability weight than the baseline.

11.3 AI Adoption and the Inflation-Output Trade-off

Rapid AI adoption shifts the NKPC in a disinflationary direction (as AI lowers marginal costs) while simultaneously generating labour polarisation and consumption inequality. Under pure inflation targeting, the RBI would ease aggressively to close the output gap, but this risks:

1. **Exchange rate depreciation** and imported inflation through the UIP channel.
2. **Asset price inflation** as lower rates boost equity valuations beyond fundamentals.
3. **Leaning against the distributional wind**: easing that benefits capital owners disproportionately when routine workers are displaced.

These tensions suggest that AI-era monetary policy requires supplementary tools—notably targeted fiscal transfers for displaced workers and macroprudential policies to contain asset price exuberance—to achieve the full social optimum.

12 Conclusion

This paper aim was to assess how Artificial Intelligence-driven digitization is transforming Indian financial markets. We developed a medium-scale open-economy Dynamic Stochastic General Equilibrium (DSGE) model tailored to India's structural features, incorporating three novel channels absent from canonical frameworks: (i) an artificial intelligence and automation sector that augments firm-level total factor productivity and displaces routine labour, (ii) a digitization block capturing the diffusion of digital public infrastructure, fintech intermediation, and data as a non-rival input to production, and (iii) an enriched financial-market module featuring a domestic equity market, a government securities market linked to the Reserve Bank of India's (RBI) policy framework, foreign portfolio investment (FPI) flows, and a banking sector with balance-sheet constraints. The model features Calvo-type nominal rigidities, habit formation in consumption, investment adjustment costs, and incomplete inter- national financial markets.

Bayesian estimation of the model, using quarterly data from 2004Q1–2024Q4, and observables variables processed through the Kalman filter, via Random Walk Metropolis-Hastings with 3×10^6 posterior draws across four chains, yields to the following principal findings: *First*, AI adoption raises aggregate output persistently but generates labour market polarisation, with routine employment contracting and non-routine employment expanding. The polarisation wedge persists for approximately six quarters, suggesting a medium-run distributional challenge even if long-run welfare is higher. *Second,* there is a digital public infrastructure crowding-in effect: Government DPI investment generates a complementarity externality that crowds in private investment and lowers bank intermediation costs, with an output multiplier of approximately 1.38 at the five-year horizon—significantly higher than traditional physical infrastructure. *Third,* global financial conditions are amplified by the domestic banking channel: A sudden increase in global risk appetite (VIX shock) triggers FPI outflows, depreciates the rupee, erodes bank equity, and widens domestic credit spreads. The banking channel amplifies the output contraction by approximately 30% relative to a model with frictionless credit markets. *Fourth,* monetary policy faces a complex trilemma: The RBI must simultaneously stabilise inflation (threatened by exchange rate pass-through), support output (threatened by financial tightening and AI displacement), and maintain financial stability (threatened by spread volatility). An augmented Taylor rule that includes a credit spread argument reduces welfare losses by approximately 40% relative to pure inflation targeting.

Granularly, Bayesian estimation demonstrates that: (i) The posterior median of AI income share, $\alpha_A = 0.048$, is significantly above zero ($\Pr(\alpha_A > 0.02) = 0.983$), confirming the statistical identification of AI as a distinct production factor in Indian macro data since 2015. (ii) The DPI externality ($\gamma_G = 0.057$ [0.028, 0.089]) is tightly identified from the comovement of digital payment proxies with output dynamics. The model with DPI

decisively outperforms the model without ($\ln \text{BF} = 16.1$). (iii) The financial-stability Taylor rule ($\phi_{sp} = 0.112$ [0.042, 0.198] with $\Pr(\phi_{sp} > 0) > 0.999$), provides the first formal Bayesian evidence from Indian macro data that the RBI incorporates credit spread conditions in its interest rate decisions. (iv) The coordinated AI-DPI scenario generates non-linear output gains (+7.41% GDP, 5-year) with strong welfare improvements, but substantial distributional costs (routine employment share −6.6 pp). The optimal Taylor rule features stronger inflation and financial-stability responses than the estimated rule. (v) The model comparison analysis reveal that, the full model decisively outperforms all nested alternatives, including the standard small-open economy model ($\ln \text{BF} = 59.3$), validating the model's structural innovations. (vi) The variance decomposition analysis reveals that, AI productivity shocks account for 28% of long-run output variance—the single largest contributor—while VIX shocks dominate credit spread dynamics (41%). DPI shocks contribute a structurally significant 14% of long-run output variance.

The key results from the counterfactual analysis are: (i) AI productivity shock generates the largest persistent output response (+1.15% at peak) with a uniquely asymmetric labour market effect: routine employment contracts (peak −0.44%) while non-routine employment expands, confirming the polarization channel over a credibly-banded range. (ii) DPI investment shock has the slowest-building but most persistent output effect (half-life >40 quarters) due to stock accumulation dynamics, and uniquely reduces credit spreads through the banking complementarity channel (−0.31 pp at peak, significant at 90%). (iii) Global risk (VIX) shock is the most disruptive: it simultaneously depreciates the rupee (+1.81%), raises spreads (+0.37 pp), and contracts output (−0.68%), with the stagflationary pressure making it the most challenging shock for RBI policy. (iv) Foreign interest rate shock disproportionately contracts AI investment relative to physical investment, reflecting AI capital's longer payoff horizon and higher sensitivity to real financing costs. (v) The scenario Analysis reveal non-linear synergies: the coordinated AI-DPI push generates output gains (+5.68% at 20Q) that substantially exceed the sum of individual shocks, while the optimal Taylor rule features a doubling of the financial-stability coefficient ($\phi^*_{sp} = 0.241$) relative to the estimated value. (vi) The variance decomposition confirms AI as the dominant long-run driver of output (28% at 20Q), VIX as the dominant driver of credit spreads (41–48%), and DPI as an increasingly important contributor to output at longer horizons (8% at 1Q, 14% at 20Q).

Future research may extend this paper in three directions. First, incorporate household heterogeneity à la Kaplan, Moll and Violante (2018) to model the distributional consequences of AI adoption within the DSGE framework. Second, extend the Bayesian estimation to a time-varying parameter (TVP) version to track the evolution of α_A and γ_G over time. Third, study the welfare implications of alternative DPI financing strategies, including green bonds and multilateral development bank lending.

References

Acemoglu, D. and P. Restrepo (2018). "The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108(6), 1488–1542.

Acemoglu, D. and P. Restrepo (2022). "Tasks, Automation, and the Rise in U.S. Wage Inequality." *Econometrica*, 90(5), 1973–2016.

Adrian, T. and H. S. Shin (2014). "Procyclical Leverage and Endogenous Financial Fragility." *AEA Papers and Proceedings*, 104(5), 120–125.

Akerlof, George A. (1970). "The Market for Lemons: Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics*, 84(3): 488–500.

An, S. and F. Schorfheide (2007). "Bayesian Analysis of DSGE Models." *Econometric Reviews*, 26(2-4), 113–172.

Brooks, S. and A. Gelman (1998). "General Methods for Monitoring Convergence of Iterative Simulations." *Journal of Computational and Graphical Statistics*, 7(4), 434–455.

Backus, D., P. Kehoe, and F. Kydland (1994). "Dynamics of the Trade Balance and the Terms of Trade: The J-Curve?" *American Economic Review*, 84(1), 84–103.

Bahaj, S. and R. Reis (2020). "Central Bank Swap Lines During the COVID-19 Pandemic." *Covid Economics*, 2, 1–12.

Berg, A., E. Buffie, and L.-F. Zanna (2018). "Should We Fear the Robot Revolution? (The Correct Answer Is Yes)." *Journal of Monetary Economics*, 97, 117–148.

Bernanke, B., M. Gertler, and S. Gilchrist (1999). "The Financial Accelerator in a Quantitative Business Cycle Framework." In J. B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*, Vol. 1, 1341–1393.

Bianchi, J. (2011). "Overborrowing and Systemic Externalities in the Business Cycle." *American Economic Review*, 101(7), 3400–3426.

Bahoo, Salman, Marco Cucculelli, Xhoana Goga, and Jasmine Mondolo. (2024). "Artificial Intelligence in Finance: A Comprehensive Review through Bibliometric and Content Analysis." *SN Business and Economics*, Vol. 4, Article 23. Springer.

Bhatt, Amola, Mayank Joshipura, and Nehal Joshipura. (2022). "Decoding the Trinity of Fintech, Digitalization and Financial Services." *Cogent Economics and Finance.*

Bonelli, Marco I. (2025). "Convergence of Robo-Advisors and Artificial Intelligence in FinTech: Insights, Challenges, and Innovations in the Indian Financial Services Market." *Journal of Information Systems Engineering and Management.*

Calvo, G. and C. Reinhart (2002). "Fear of Floating." *Quarterly Journal of Economics*, 117(2), 379–408.

Christiano, L., M. Eichenbaum, and C. Evans (2005). "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy*, 113(1), 1–45.

Christiano, L., C. Gust, and J. Roldos (2004). "Monetary Policy in a Financial Crisis." *Journal of Economic Theory*, 119(1), 64–103.

Christiano, L., M. Trabandt, and K. Walentin (2011). "Introducing Financial Frictions and Unemployment into a Small Open Economy Model." *Journal of Economic Dynamics and Control*, 35(12), 1999–2041.

Del Negro, M. and F. Schorfheide (2008). "Forming Priors for DSGE Models (and How It Affects the Assessment of Nominal Rigidities)." *Journal of Monetary Economics*, 55(7), 1191–1208.
Fama, Eugene F. (1970). "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance*, 25(2): 383–417.

Gelfand, A. and D. Dey (1994). "Bayesian Model Choice: Asymptotics and Exact Calculations." *Journal of the Royal Statistical Society: Series B*, 56(3), 501–514.

Gelman, A. and D. Rubin (1992). "Inference from Iterative Simulation Using Multiple Sequences." *Statistical Science*, 7(4), 457–472.

Geweke, J. (1992). "Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments." In J. M. Bernardo et al. (eds.), *Bayesian Statistics 4*. Oxford University Press, 169–193.

Gali, J. and T. Monacelli (2005). "Monetary Policy and Exchange Rate Volatility in a Small Open Economy." *Review of Economic Studies*, 72(3), 707–734.

Garcia-Cicco, J., R. Pancrazi, and M. Uribe (2010). "Real Business Cycles in Emerging Countries?" *American Economic Review*, 100(5), 2510–2531.

Ghosh, A., J. Ostry, and M. Qureshi (2016). "When Do Capital Inflow Surges End in Tears?" *American Economic Review: Papers and Proceedings*, 106(5), 581–585.

Hjort, J. and J. Poulsen (2019). "The Arrival of Fast Internet and Employment in Africa." *American Economic Review*, 109(3), 1032–1079.

Iskrev, N. (2010). "Local Identification in DSGE Models." *Journal of Monetary Economics*, 57(2), 189–202.

Jeffreys, H. (1961). *Theory of Probability*, 3rd edn. Oxford University Press.

Justiniano, A. and B. Preston (2010). "Monetary Policy and Uncertainty in an Empirical Small Open Economy Model." *Journal of Applied Econometrics*, 25(1), 93–128.

Justiniano, A., G. Primiceri, and A. Tambalotti (2010). "Investment Shocks and Business Cycles." *Journal of Monetary Economics*, 57(2), 132–145.

Kaplan, G., B. Moll, and G. Violante (2018). "Monetary Policy According to HANK." *American Economic Review*, 108(3), 697–743.

Komunjer, I. and S. Ng (2011). "Dynamic Identification of Dynamic Stochastic General Equilibrium Models." *Econometrica*, 79(6), 1995–2032.

Lubik, T. and F. Schorfheide (2007). "Do Central Banks Respond to Exchange Rate Movements? A Structural Investigation." *Journal of Monetary Economics*, 54(4), 1069–1087.

Lucas, Robert E. (1988). "On the Mechanics of Economic Development." *Journal of Monetary Economics,* 22(1): 3–42.

Mendoza, E. (2010). "Sudden Stops, Financial Crises, and Leverage." *American Economic Review*, 100(5), 1941–1966.

Obstfeld, M., J. Shambaugh, and A. Taylor (2015). "Trilemmas and Tradeoffs: Living with Financial Globalization." In C. Raddatz, D. Saravia, and J. Ventura (eds.), *Global Liquidity, Spillovers to Emerging Markets and Policy Responses*, 13–78.

Patra, M., P. Dua, and S. Dhal (2022). "Monetary Transmission in India: New Evidence from a Time-Varying Factor-Augmented VAR." *RBI Working Paper*, No. 05/2022.

Prettner, K. and H. Strulik (2021). "Innovation, Automation, and Inequality: Policy Challenges in the Race Against the Machine." *Journal of Monetary Economics*, 116, 249–265.

Peiris, S. and M. Saxegaard (2012). "An Estimated DSGE Model for Monetary Policy Analysis in Low-Income Countries." *IMF Working Paper*, 07/282.

Raftery, A. and S. Lewis (1992). "How Many Iterations in the Gibbs Sampler?" In J. M. Bernardo et al. (eds.), *Bayesian Statistics 4*. Oxford University Press, 763–773.

Romer, Paul M. (1990). "Endogenous Technological Change." *Journal of Political Economy*, 98(5): S71–S102.

Schumpeter, Joseph A. (1942). *Capitalism, Socialism and Democracy.* New York: Harper and Brothers.

Sethi, Poonam, and Rinku Manocha. (2023). "Impact of Fintech Adoption on Select Macroeconomic Variables in India: An ARDL Approach." Vision: *The Journal of Business Perspective.*

Sethi, Soumya Ranjan, and Dushyant Mahadik. (2025). "Artificial Intelligence in Financial Markets: Opportunities, Challenges, and Future Directions." *SSRN Electronic Journal.*

Schmitt-Grohe, S. and M. Uribe (2003). "Closing Small Open Economy Models." *Journal of International Economics*, 61(1), 163–185.

Schmitt-Grohe, S. and M. Uribe (2004). "Solving Dynamic General Equilibrium Models Using a Second-Order Approximation to the Policy Function." *Journal of Economic Dynamics and Control*, 28(4), 755–775.

Smets, F. and R. Wouters (2003). "An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area." *Journal of the European Economic Association*, 1(5), 1123–1175.

Smets, F. and R. Wouters (2007). "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review*, 97(3), 586–606.

Villani, M. (2009). "Steady-State Priors for Vector Autoregressions." *Journal of Applied Econometrics*, 24(4), 630–650.

Warin, Thierry, and Aleksandar Stojkov. (2021). "Machine Learning in Finance: A Metadata-Based Systematic Review of the Literature." Journal of Risk and Financial Management, 14(7): 302.

Wafi, Ahmed S., Sherif El-Halaby, and Hussien Ahmed. (2026). "Financial-Market Forecasting and Modelling from Econometrics to AI: An Integrated Systematic and Bibliometric Review with Content Synthesis (1990–2024)." Journal of Risk and Financial Management, 19(3): 228.

Appendices

A Proof of Proposition 1

Proof. Consider the labour composite $\mathcal{L}_t = \left[\mu(L_t^{NR})^{\frac{\rho_L-1}{\rho_L}} + (1-\mu)(\phi_t A_t + L_t^R)^{\frac{\rho_L-1}{\rho_L}}\right]^{\frac{\rho_L}{\rho_L-1}}$. Firm optimisation implies:

$$W_t^R = P_t^{mc} \cdot (1-\alpha_K-\alpha_A)\frac{\partial \mathcal{L}_t}{\partial L_t^R} \cdot Y_t/\mathcal{L}_t \tag{36}$$

$$W_t^{NR} = P_t^{mc} \cdot (1-\alpha_K-\alpha_A)\frac{\partial \mathcal{L}_t}{\partial L_t^{NR}} \cdot Y_t/\mathcal{L}_t \tag{37}$$

where P_t^{mc} is nominal marginal cost. Computing the partial derivatives and taking the ratio:

$$\frac{W_t^{NR}}{W_t^R} = \frac{\mu}{1-\mu}\left(\frac{\phi_t A_t + L_t^R}{L_t^{NR}}\right)^{1/\rho_L} \tag{38}$$

An increase in Ω_t raises A_t, which lowers P_t^A/P_t^{mc} (supply increases). For given factor demand, the AI-routine composite $(\phi_t A_t + L_t^R)$ rises. Firms substitute toward the composite and away from L_t^{NR}, so L_t^{NR} falls and W_t^{NR}/W_t^R rises. Meanwhile, within the composite, the relative demand for L_t^R versus $\phi_t A_t$ depends on W_t^R versus $P_t^A \phi_t$. Since P_t^A falls and ϕ_t is fixed in the short run, firms substitute AI for routine labour, reducing L_t^R. The condition $\phi_t > \bar{\phi}$ ensures the substitution effect dominates the scale effect, yielding $\partial L_t^R/\partial \Omega_t < 0$. □

B Log-Linearised Equations: Full System

Euler equation:

$$\frac{1}{1-\vartheta}\hat{c}_t - \frac{\vartheta}{1-\vartheta}\hat{c}_{t-1} = \mathbb{E}_t\left[\frac{1}{1-\vartheta}\hat{c}_{t+1} - \frac{\vartheta}{1-\vartheta}\hat{c}_t\right] - \frac{1}{\sigma}\left(\hat{R}_t - \mathbb{E}_t\hat{\pi}_{t+1}\right) \tag{39}$$

Investment (Tobin's Q):

$$\hat{q}_t^K = \kappa\left(\hat{i}_t - \hat{i}_{t-1}\right) - \beta\kappa\mathbb{E}_t\left(\hat{i}_{t+1} - \hat{i}_t\right) \tag{40}$$

Capital accumulation:

$$\hat{k}_{t+1} = (1-\delta_K)\hat{k}_t + \delta_K\hat{i}_t \tag{41}$$

Return on capital:

$$\hat{R}_t^K = (1 - \beta(1-\delta_K))\hat{mpl}_t + \beta(1-\delta_K)\mathbb{E}_t\hat{q}_{t+1}^K - \hat{q}_t^K \tag{42}$$

Arbitrage (Tobin's Q equals return on capital):

$$\hat{R}_t = \mathbb{E}_t\hat{R}_{t+1}^K - \hat{sp}_t \tag{43}$$

Bank equity dynamics:

$$\hat{n}_{t+1}^B = \frac{R^L - R^D}{\delta^B}\hat{l}_t^B + \frac{R^L}{\delta^B}\hat{sp}_{t-1} - \hat{div}_t^B \tag{44}$$

where $\delta^B \equiv (R^L - R^D) + (1 - 1/\bar{\lambda})$ is the steady-state gross return on bank equity.

Government budget (log-linearised):

$$b_t^G = \frac{R^G}{\pi}b_{t-1}^G + \frac{G^C}{B^G/P}\hat{g}_t^C + \frac{I^G}{B^G/P}\hat{i}_t^G - \frac{\tau^Y Y}{B^G/P}(\hat{\tau}_t^Y + \hat{y}_t) \tag{45}$$

Market clearing:

$$\hat{y}_t = \frac{C}{Y}\hat{c}_t + \frac{I}{Y}\hat{i}_t + \frac{G^C}{Y}\hat{g}_t^C + \frac{I^G}{Y}\hat{i}_t^G + \frac{X}{Y}\hat{x}_t - \frac{M^{imp}}{Y}\hat{m}_t \tag{46}$$

C Data Sources

Table 20: Data Sources and Definitions

Variable	Source	Period
GDP, consumption, investment	NSO / MOSPI	Q1 2004–Q4 2024
CPI, WPI	MOSPI	Jan 2012–Dec 2024
Policy repo rate	RBI	Daily, 2012–2024
G-sec yields (10Y, 5Y, 2Y)	CCIL / RBI	Daily, 2012–2024
Bank credit, deposits	RBI BSID	Monthly, 2004–2024
Exchange rate (INR/USD)	RBI / FEDAI	Daily, 2004–2024
FPI flows (debt & equity)	SEBI	Monthly, 2012–2024
NIFTY 50 index	NSE	Daily, 2004–2024
Digital payments index	RBI	Biannual, 2018–2024
AI/IT services exports	NASSCOM	Annual, 2015–2024
DPI transactions (UPI)	NPCI	Monthly, 2017–2024
External debt	RBI	Quarterly, 2004–2024

D MCMC Implementation Details

D.1 Computational Time

Mode finding: approximately 4 hours (MATLAB, 32-core server). MCMC: approximately 96 hours total (24 hours per chain $\times$ 4 parallel chains, Intel Xeon 3.0 GHz, 256 GB RAM).

D.2 Proposal Distribution Tuning

The initial scaling $c = 0.36$ was determined by a pilot run of 50,000 draws. The target acceptance rate of 23–26% was achieved after three tuning rounds. The proposal covariance matrix was re-estimated at the end of the pilot run using the sample covariance of accepted draws, and the main run used this updated covariance.

E Prior-Posterior Overlap Statistics

The prior-posterior overlap (PPO) statistic measures the informativeness of the data relative to the prior:

$$\text{PPO}_j = \int \min\{p(\theta_j), p(\theta_j \mid \mathbf{Y}_T)\}\, d\theta_j \in [0, 1] \tag{47}$$

PPO = 1 means the prior and posterior are identical (no updating). PPO = 0 means they have no overlap (complete updating). Table 21 reports PPO for all estimated parameters.

Table 21: Prior-Posterior Overlap Statistics

Param.	PPO	Updating	Param.	PPO	Updating
ϑ	0.71	Moderate	γ_B	0.67	Moderate
σ	0.94	Minimal	ψ_B	0.88	Minimal
φ	0.78	Moderate	ψ_f	0.62	Substantial
η	0.74	Moderate	ρ_R	0.81	Moderate
α_A	0.69	Moderate	ϕ_π	0.77	Moderate
γ_G	0.72	Moderate	ϕ_y	0.82	Moderate
θ_H	0.65	Substantial	$\phi_{\mathcal{E}}$	0.79	Moderate
ι_H	0.73	Moderate	ϕ_{sp}	0.61	Substantial
κ	0.68	Moderate	σ_Ω	0.74	Moderate
α_{AI}	0.76	Moderate	$\sigma_{\mathcal{V}}$	0.71	Moderate
ω	0.77	Moderate	σ_R	0.68	Moderate
ρ_Ω	0.73	Moderate	σ_{ToT}	0.72	Moderate
ϕ	0.79	Moderate	ρ_Z	0.76	Moderate
ρ_L	0.74	Moderate	σ_{cp}	0.71	Moderate

PPO > 0.90: minimal updating; 0.70–0.90: moderate; < 0.70: substantial.

The parameters with most substantial updating (PPO < 0.70) are ψ_f (0.62), ϕ_{sp} (0.61), and θ_H (0.65)—all corresponding to parameters with high ISI values. The most prior-dominated parameter is σ (0.94), consistent with the near-zero ISI of risk aversion.

F Scenario Analysis: Technical Details

For each of the eight scenarios, the posterior predictive distribution is constructed as follows:

1. Draw $\boldsymbol{\theta}^{(m)}$ from the posterior $p(\boldsymbol{\theta} \mid \mathbf{Y}_T)$ for $m = 1, \ldots, 10,000$.
2. Construct the scenario-modified parameter vector $\boldsymbol{\theta}^{(m),s} = \boldsymbol{\theta}^{(m)} + \Delta\boldsymbol{\theta}^s$.
3. For each m: (a) check BK conditions; (b) if satisfied, solve the model at $\boldsymbol{\theta}^{(m),s}$; (c) compute the outcome of interest $\Phi(\boldsymbol{\theta}^{(m),s})$.
4. Report the distribution of $\{\Phi(\boldsymbol{\theta}^{(m),s})\}_{m=1}^{M^*}$ where M^* is the number of valid (BK-satisfying) draws.

BK violations occurred in fewer than 2% of draws for all scenarios, confirming robustness of the solution under parameter uncertainty.