AI Regulations and the Indian Sovereign Yield Curve: Empirical Evidence from India

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Abstract

This paper investigates whether AI reggulations has induced structural changes in the determinants of Indian sovereign bond yields across the maturity spectrum. The rapid global adoption of artificial intelligence (AI) in times of macroeconomic turmoil, particularly generative AI technologies since late 2022, has prompted intense debate about its potential macroeconomic consequences, including the measurement issues. Using monthly data from 2000 to 2025 and autoregressive distributed lag (ARDL) models augmented with an AI regulation variable and slope interactions on expected inflation and broad money (M3) growth, we identify significant regime shifts. Results indicate that in the post-AI period, longer-maturity yields exhibit markedly reduced sensitivity to expected inflation and money supply growth. This dampening is statistically significant, with interaction terms largely offsetting baseline positive elasticities. By contrast, short-term yields (91-day Treasury bills) show heightened inflation sensitivity in the AI era, while intermediate yields display mixed patterns. These findings are consistent with theoretical predictions that AI-driven productivity gains could lower equilibrium real interest rates and weaken traditional monetary transmission channels at the long end of the yield curve. For an emerging market like India, where inflation expectations have historically influenced borrowing costs, such changes may enhance monetary policy independence but complicate fiscal-monetary coordination. The paper contributes to the sparse empirical literature on AI regulations and financial market implications in emerging economies. Policy implications include the need for the Reserve Bank of India (RBI) to recalibrate forward guidance and liquidity operations in light of evolving yield dynamics.

JEL Classification Numbers: E43, E44, O33, G12, C22

Keywords: Sovereign bond yields, artificial intelligence, ARDL bounds testing, structural change, monetary transmission, India.

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1. Introduction

The emergence of transformative artificial intelligence technologies, particularly following the public release of large language models in late 2022, has been hailed as a potential general purpose technology.

Theoretical work suggests multiple channels through which AI regulations could affect macroeconomic variables, including interest rates. In India, AI regulations adoption through accelerated rapidly since 2022, with surveys indicating that by 2025 over 85 percent of enterprises were actively deploying AI solutions, driven by both domestic innovation and global integration. Productivity enhancements from AI may raise potential growth, lowering the natural rate of interest via increased investment demand or reduced precautionary savings (Acemoglu and Restrepo, 2018; Aghion et al., 2019). Conversely, displacement effects or uncertainty about transformative AI could raise risk premia (Halperin, 2025). Empirical evidence remains nascent, with most studies focused on advanced economies. Recent event studies find that announcements of major AI model releases are associated with declines in long-term U.S. Treasury yields of over 10 basis points, reflecting revised growth expectations (Babina et al., 2025; MIT Sloan, 2025).

In emerging markets, sovereign bond yields serve as critical benchmarks for borrowing costs and signals of macroeconomic stability. India's government securities market has matured significantly since the early 2000s, with the 10-year GSEC yield becoming a key reference rate. However, yields remain sensitive to domestic fundamentals including fiscal deficits, inflation expectations, monetary aggregates and external factors like capital flows and exchange rates (Chakraborty, 2025). This paper asks whether the AI regulation has altered these relationships. We proxy the structural break with a dummy variable taking the value 1 from September 2022 onwards, coinciding with widespread generative AI regulation in India and globally. Using ARDL models with slope dummies on key transmission variables (expected inflation and M3 growth), we estimate separate equations for 10-year, 5-year, 3-year GSEC, and 91-day Treasury bill yields. Our core finding is a pronounced flattening of the inflation and money-supply sensitivity of longer-term yields post-AI. For the 10-year yield, the baseline inflation elasticity of 1.78 is almost entirely offset by the interaction term (-1.72), rendering the net effect near zero. Similar patterns hold for M3. At the short end, the 91-day T-bill shows the opposite: a large negative baseline inflation coefficient becomes less negative (or positive net) in the AI period. These results align with the hypothesis that AI regulations-induced productivity optimism anchors long term inflation expectations and weakens monetary transmission, while short-term rates remain tied to current policy stance. For policymakers, this suggests enhanced credibility of inflation targeting but potential challenges in steering the yield curve during fiscal expansions.

The paper is organised as follows. Section 2 reviews the literature. Section 3 describes the data. Section 4 outlines the analytical framework and the methodology. Section 5 presents results and discussion. Section 6 concludes with the policy implications.

2. Related Literature

This paper bridges three strands of literature: determinants of sovereign yields in emerging markets, macroeconomic effects of technological change, and emerging evidence on AI's regulations and financial impacts. Central banks play a pivotal role in safeguarding the economic stability of a nation through their monetary policy mandate, principally by ensuring price stability. Since they stand at the intersection of monetary and financial systems, they also bear the concurrent responsibility for ensuring the resilience of the financial system and the efficient functioning of the payments system.

In recent times, Central Banks have been adapting to the rapidly evolving financial landscape characterised by digital transactions, fintech innovation, and increasing systemic complexity. The growing use of artificial intelligence (AI), machine learning (ML) and big data is reshaping financial services by enhancing fraud detection and more effective monitoring of transactions through large-scale data analysis. AI use cases relevant to central banking functions such as economic analysis, forecasting and policy analysis, payment systems, regulation, supervision and oversight, banknote production and distribution, detection of anomalies, risk assessment, customer and corporate services (Bank for International Settlements, 2025). A significant improvement in this area is the application of AI and ML to augment supervisory capabilities, known as 'SupTech', especially for regulatory authorities such as Central Banks. SupTech refers to the technology used by regulators and supervisors to augment and streamline supervisory functions, primarily aimed at seamless data collection and reporting, supporting data analysis, enabling informed decision-making, strengthening market monitoring and surveillance, enhancing oversight of cybersecurity, and promoting evidence-based policy-making (Broeders and Prenio, 2018; Das, 2019). The opportunities for SupTech emerge from the marked expansion in the volume and granularity of available data, supported by advances in digital infrastructure such as cloud computing and Application Programming Interfaces (APIs) that have significantly enhanced the efficiency of data collection, storage and analysis. For regulatory authorities, SupTech can sharpen oversight, enhance surveillance, and expand analytical capability, while generating real-time indicators of risk that support proactive, judgment-based supervision and policy decisions (Financial Stability Board, 2020). The adoption of suptech within central banks is transforming overall supervisory processes by enhancing the detection of anomalies and emerging risks, strengthening analytical capabilities, facilitating decision-making, and enabling timely interventions in response to emerging issues. Therefore, when applied for prudential purposes, AI enhances the monitoring and management of risks, particularly liquidity and credit risks (Bains et al., 2025). Furthermore, for financial stability purposes, leveraging the AI models to predict emerging liquidity problems and to develop forward-looking scenarios to test the resilience of financial institutions.

In the Indian context, the Reserve Bank of India (RBI) has taken significant steps toward integrating artificial intelligence (AI) into its regulatory and operational framework, thereby promoting innovation within safeguards, through calibrated guidance, and robust supervisory oversight (Sankar, 2025). As AI continues to reshape the financial landscape, technological progress must advance in tandem with prudence. RBI has

progressively adopted the integration of AI and machine learning tools for supervisory and regulatory technology as early as September 2022 (Economic Times, 2023). The policy discourse on monetary policy and AI has gained traction in the light of the publication of the FREE-AI (Framework for Responsible and Ethical Enablement of AI) Committee Report in August 2025 by the RBI.

The existing literature on the term structure of interest rates in India emphasizes macroeconomic determinants such as short-term policy rates, expected inflation, money supply, fiscal deficit, output gap (Dua and Pandit, 2002; Chakraborty, 2002; Das, 2004; Goyal, 2004; Chakraborty, 2012; Vinod, Chakraborty, and Karun, 2014; Chakraborty, 2024; Chakraborty et al., 2025). This paper attempts to capture the impact of the introduction of AI on the term structure of interest rates in India. Specifically, we extend the Autoregressive Distributed Lag (ARDL) based on the term structure model by incorporating AI slope interaction terms with expected inflation and broad money (M3) to understand the impact of these key variables on yields to vary across the pre- and post-AI regimes.

The contribution of the paper is threefold. Firstly, it provides one of the earliest empirical evidence for India on AI-mediated monetary transmission across the term structure. Secondly, it demonstrates that AI adoption attenuates the inflation and liquidity channels, particularly at longer maturities. Thirdly, it offers policy-relevant insights into how augmenting central banking tools with AI influences the formation of expectations and interest rate dynamics in emerging market economies.

A. Determinants of Emerging Market Sovereign Yields

Classical theories emphasize the role of short-term rates, inflation expectations, and fiscal variables in driving long-term yields (Mishkin, 1995). In India, empirical studies consistently find the policy repo or short-term Treasury bill rate as the dominant long-run driver, consistent with expectations hypothesis augmented for risk premia (Chakraborty, 2016). Using ARDL bounds testing, Singh (2019) shows that while fiscal deficits exert upward pressure in the short run, they are not cointegrating in the long run, with the short rate explaining most variation. Other factors include output gaps (capturing demand pressure), capital flows (external vulnerability), and exchange rates (pass-through effects). Inflation expectations are particularly salient in India due to historical episodes of high inflation. Monetary aggregates like M3 have featured in quantity-theory inspired models, though their importance has waned post-inflation targeting framework adoption in 2016.

B. Technological Change and Interest Rates

Historical general-purpose technologies boosted productivity but had ambiguous effects on real rates, depending on capital deepening versus growth channels. Modern theoretical models predict that automation lowers the natural rate via substitution away from labor (Acemoglu and Restrepo, 2020), while innovation-driven growth raises it (Aghion et al.,

2019). For AI specifically, growth models suggest unbounded productivity gains could substantially lower equilibrium rates if labor displacement dominates, or raise them if investment surges. Halperin (2025) argues existential risks from misaligned AI could increase precautionary demand for safe assets, pushing rates down.

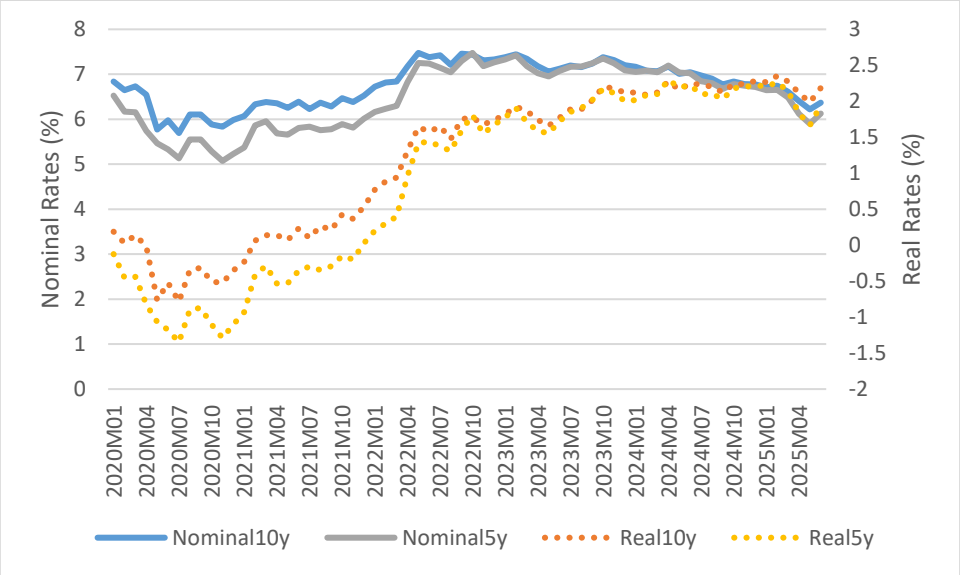
C. Emerging Empirical Evidence on AI and Financial Markets

Financial market reactions provide indirect evidence. Babina et al. (2025) find significant declines in 10-year U.S. Treasury yields following major AI announcements, attributing this to revised higher growth and lower inflation expectations. Micro-level studies document productivity gains from AI adoption of 10–40 percent in specific tasks. Macro estimates vary, Goldman Sachs projects 1.5 percentage point annual productivity growth in advanced economies from generative AI. Similar patterns appear in corporate bond spreads. In India, limited evidence exists, though equity markets reacted positively to AI themes post-2022. This paper extends the literature by providing the first emerging-market evidence of AI-induced structural change in yield determinants, using interaction terms to capture regime shifts in transmission channels.

3. Data on Term Structure in India

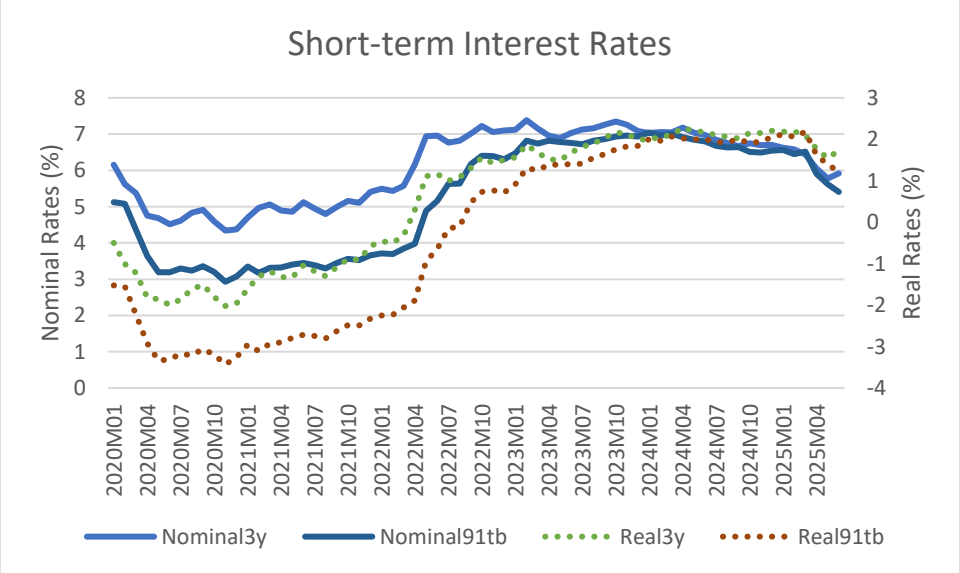
The interest rate dynamics in India post-2020 reflect the monetary policy responses to the COVID-19 pandemic, the subsequent inflationary pressures, and the normalisation of policy rates by the Reserve Bank of India. The behaviour of long-term interest rates is reflected in the evolution of nominal yields but with notable changes during the pandemic period (Figure 1). The long-term interest rates, comprising the 10-year and 5-year government security yields, experienced a modest decline during 2020, reflecting the RBI's accommodative monetary policy stance and abundant liquidity conditions. Thereafter, coinciding with the normalisation of monetary policy in response to elevated inflationary pressures and strengthening of economic activity, the yields improved steadily from early 2021, reaching a peak of 7.2 to 7.4 per cent during 2022-23. From mid-2023 onwards, the long-term nominal yields remained relatively stable at around 7 per cent, before declining towards mid-2025.

Figure 1: Real and Nominal Long-term Interest Rates



Movements in India's short-term nominal and real interest rates are represented by 3-year G-Sec yields over the period 2020 to 2025 as depicted in Figure 2. Compared to the long-term yields, the short-term yields exhibit greater volatility. Initially, both the short-term interest rates show a sharp decline, reaching their lowest in 2020 as the RBI adopted an accommodative policy stance. At the beginning of 2022, nominal short-term interest rates increased in response to rising inflationary pressures, which was followed by subsequent monetary policy tightening.

Figure 2: Real and Nominal Short-Term Interest Rates

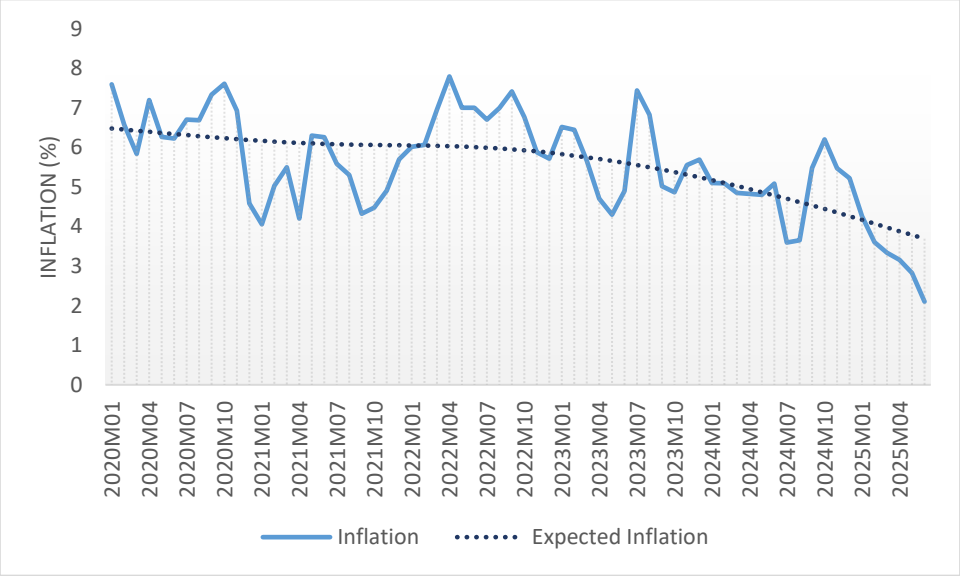


It is further seen that both the 91-day Treasury Bill and 3-year G-Sec yields leapt up to about seven per cent by late 2023, thereafter remaining fairly stable and then moderating towards the end of the study period. The close convergence of the two nominal series in

2023 and 2024 suggests alignment in market expectations regarding the future path of policy rates.

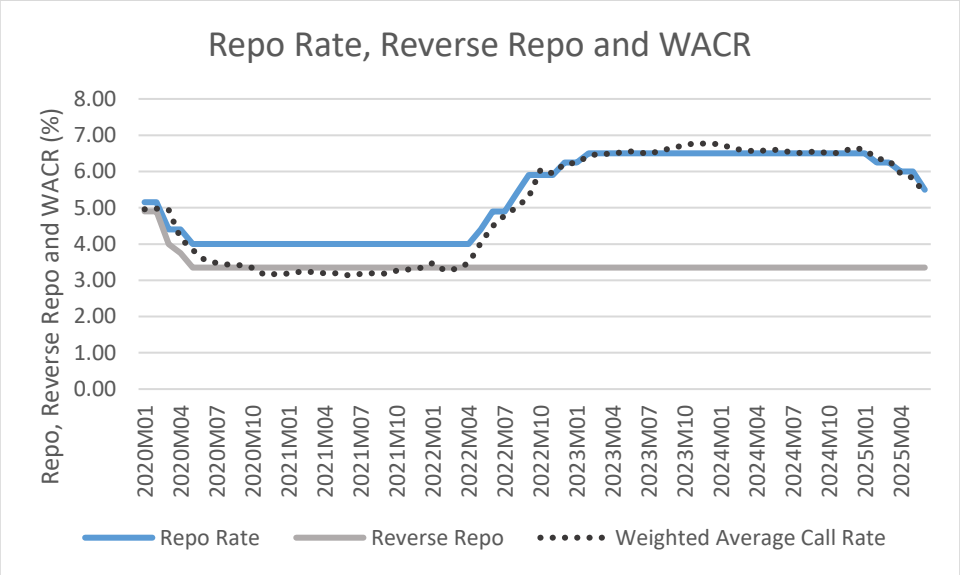
Inflation expectations play a pivotal role in India's macroeconomic dynamics. However, inflation expectations are inherently unobservable and should therefore need to be approximated using a proxy. Although the RBI Inflation Expectations Survey of Households (IESH) provides survey-based estimates, it captures the inflation perception of consumers (which is subject to behavioural biases and influenced by food and fuel prices) rather than the expectation of financial market participants. Additionally, it is bi-monthly data, while we adhere to monthly data. The present study employs the Hodrick-Prescott (HP) filter to extract the persistent component of inflation, removing any transitory fluctuations. Actual and expected inflation in India over the period January 2020 to April 2025 is depicted in Figure 3.

Figure 3: Inflation and Expected Inflation



Actual inflation, which is based on the Consumer Price Index (CPI), exhibits fluctuations over the months during the study period. This is reflective of the initial pandemic-induced supply disruptions and commodity price shocks and subsequent normalisation through policy controls. Inflation remained at elevated levels during the 2020s at about 6-7 per cent, before declining sharply to about 4 per cent in early 2021. Inflation again spiked by the end of 2021 till July 2023, primarily driven by commodity shocks from imported goods, the Russia-Ukraine war, and erratic monsoons impacting agricultural commodity prices. After some intermittent spikes in 2024, the inflation trajectory declined, indicating significant moderation in price pressures, which was reined in by the RBI through an increase in Repo Rates post April 2022, as seen in Figure 4.

Figure 4: Repo Rate, Reverse Repo Rate and the Weighted Average Call Rate



4. The Analytical Framework

This study follows the analytical framework of Sargent (1969), which is extended comprehensively to analyse the macroeconomic factors underlying the determination of interest rates (Chakraborty, 2016). As per the framework proposed by Sargent (1969), the nominal interest rate is conceptualised to comprise three distinct elements, viz., the equilibrium rate of interest, the spread between the market and the equilibrium real rate of interest, and the spread between the nominal rate of interest and the market rate of interest. This relationship can be represented as follows:

$$r_{n(t)} = r_{e(t)} + [r_{m(t)} - r_{e(t)}] + [r_{n(t)} - r_{m(t)}] \quad (1)$$

where, $r_{n(t)}$ denotes the nominal rate of interest, $r_{e(t)}$ is the real rate of interest which equilibrates desired savings and desired investment, and $r_{m(t)}$ represents the nominal rate of interest adjusted for the expected rate of inflation. The present study focuses on examining the financial crowding-out mechanism, rather than evaluating alternative theoretical paradigms.

Within this framework, deficit is treated as a significant determinant of the first term, re(t), while the determinant of the second term, $[r_{m(t)} - r_{e(t)}]$, is specified as a function of the growth rate of high-powered money. In an open economy model, capital flows and the real effective exchange rate also determine the spread between the market rate and the equilibrium real rate of interest.

$$r_{e(t)} = \alpha + \beta_1(def_t) + \mu_t \quad (2)$$

Assuming linearity, we thus have:

$$r_{m(t)} - r_{e(t)} = \lambda + \beta_2(\Delta M_3)_t + \beta_3(K_r)_t + \beta_4(REER_t) + \delta_t \quad (3)$$

where, $(\Delta M_3)_t$ = changes in high-powered money, $REER_t$ = real effective exchange rate.

The last term of equation (1) is assumed to depend linearly and positively on the inflationary expectations.

$$r_{n(t)} - r_{m(t)} = \theta + \beta_5(\pi_t^e) + \upsilon_t \quad (4)$$

where, $\pi_t^e = Expected\ Rate\ of\ Inflation$

Now by substituting equations (2), (3), and (4) into equation (1), we get:

$$r_{n(t)} = \phi + \beta_1(def_t) + \beta_2(\Delta M_3)_t + \beta_3(K_r)_t + \beta_4(REER_t) + \beta_5(\pi_t^e) + \omega_t \quad (5)$$

Equation (5) indicates that the nominal rate of interest is a function of fiscal deficits, changes in high-powered money, capital flows, real effective exchange rate and expected inflation.

While the analytical framework described above adequately captures the conventional macroeconomic determinants of the term structure of interest rates, the recent advances in technology through the adoption of AI are expected to improve efficiency by modifying the strength and speed of transmission channels. Accordingly, this study extends the standard analytical framework by allowing the effects of expected inflation and money supply on interest rates to vary across the pre- and post-AI adoption periods.

4.1 Data and Variable Construction

The data for the empirical analysis consist of high-frequency monthly data spanning January 2020 to June 2025, covering the post-COVID-19 pandemic monetary policy regime, sourced primarily from the Reserve Bank of India (RBI) database. Following the literature on the term structure of interest rates in India, government security yields representing different segments of the yield curve are considered as the independent variables. The sample spans pre- and post-global financial crisis periods while capturing the period of the implementation of AI. The dependent variables constitute the continuously compounded yields on 10-year (ln10y), 5-year (ln5y), 3-year (ln3y) GSEC, and 91-day Treasury bill (lntb) rates, which are considered in their natural log forms.

4.2 Specification of the Empirical Model

Following the analytical framework and the existing literature ((Dua and Pandit, 2002; Chakraborty, 2002; Das, 2004; Goyal, 2004; Chakraborty, 2012; Vinod, Chakraborty, and Karun, 2014; Chakraborty, 2024; Chakraborty et al., 2025(a), Chakraborty et al., 2025(b)), the determination of interest rates is analysed separately for the long-term (LT) and short-term (ST) rates of interest models by the functional form:

1. LT Interest Rate = f (Fiscal Deficit, Capital Flows, ST Interest Rate, Inflation expectations, Output Gap, Money supply, REER, AI)

2. ST Interest Rate = f (Fiscal Deficit, LT Interest Rate, Inflation expectations, Capital Flows, Output Gap, Money supply, REER, AI)

The long-term interest rates could be taken as the interest rates on 10 Year GSEC or 5 Year GSEC. Taking the logarithmic form, the long-term interest rates could be specified as two models:

Model 1: $ln10y_t = \alpha_0 + \beta_1 lnfd_t + \beta_2 ln91tb_t + \beta_3 lneinf_t + \beta_4 lnkflows_t + \beta_5 lnopg_t + \beta_6 lnm3_t + \beta_7 lnreer_t + \beta_8 lnAI_t + \beta_9 (AI_t * lneinf_t) + \beta_{10} (AI_t * lnm3_t) + \varepsilon_t$

Model 2: $\alpha_0 + \beta_1 lnfd_t + \beta_2 ln91tb_t + \beta_3 lneinf_t + \beta_4 lnkflows_t + \beta_5 lnopg_t + \beta_6 lnm3_t + \beta_7 lnreer_t + \beta_8 lnAI_t + \beta_9 (AI_t * lneinf_t) + \beta_{10} (AI_t * lnm3_t) + \varepsilon_t$

where, ln10y (10-year GSEC interest rate) and ln5y (5-Year GSEC interest rate) represents the long-term interest rate, lnfd is the fiscal deficit, ln91tb (interest rate on 91-day treasury bills) represents the short-term interest rate, lneinf is the expected inflation rate derived using the HP filter, lnkflows denote the capital flows, lnopg is the output gap of the economy, and lnreer denotes the real effective exchange rate. The empirical specification extends the conventional term structure model by incorporating an AI regime dummy together with interaction terms to capture whether the transmission of inflation expectations and liquidity conditions changes following the adoption of AI-enabled supervisory technology by the RBI.

Similarly, the short-term interest rate could be taken as the interest rate on 5Year GSEC or 91-day Treasury Bills (91TB). The corresponding models could be specified as:

Model 3: $ln3y_t = \alpha_0 + \beta_1 lnfd_t + \beta_2 ln10y_t + \beta_3 lneinf_t + \beta_4 lnkflows_t + \beta_5 lnopg_t + \beta_6 m3_t + \beta_7 lnreer_t + \beta_8 lnAI_t + \beta_9 (AI_t * lneinf_t) + \beta_{10} (AI_t * lnm3_t) + \varepsilon_t$

Model 4: $ln91tb_t = \beta_1 lnfd_t + \beta_2 ln10y_t + \beta_3 lneinf_t + \beta_4 lnkflows_t + \beta_5 lnopg_t + \beta_6 m3_t + \beta_7 lnreer_t + \beta_8 lnAI_t + \beta_9 (AI_t * lneinf_t) + \beta_{10} (AI_t * lnm3_t) + \varepsilon_t$

4.3 ARDL Representation

Since the variables are integrated I (0) and I (1) the present study follows the ARDL (Autoregressive Distributed Lag) model proposed by Pesaran and Shin (1999), for estimation of the interest rate determination models. The choice of the ARDL model in this study is motivated by the presence of non-stationary variables, and the ability of the error correction models to determine both the short-run and the long-run determinants. To test the long-run relationship between the variables, the study follows the bounds test approach to cointegration (Pesaran, Shin, and Smith; 2001).

The unrestricted Error Correction representation of the ARDL model is expressed as:

$$\Delta r_t = \alpha_0 + \lambda r_{t-1} + \delta_1 fd_{t-1} + \delta_2 ir_{t-1} + \delta_3 einf_{t-1} + \delta_4 kflows_{t-1} + \delta_5 opg_{t-1} + \delta_6 m3_{t-1} + \delta_7 reer_{t-1} + \delta_8 AI_{t-1} + \delta_9 (AI_{t-1} * einf_{t-1}) + \delta_{10} (AI_{t-1} * m3_{t-1}) + \sum_{i=1}^{m} \gamma_i \Delta r_{t-i} + \sum_{i=1}^{n} \theta_i \Delta fd_{t-i} + \sum_{i=1}^{p} \eta_i \Delta ir_{t-i} + \sum_{i=1}^{q} \pi_i \Delta einf_{t-i} + \sum_{i=1}^{r} \varphi_i \Delta kflows_{t-i} + \sum_{i=1}^{s} \omega_i \Delta opg_{t-i} + \sum_{i=1}^{t} \phi_i \Delta m3_{t-i} + \sum_{i=1}^{u} \psi_i \Delta reer_{t-i} + \sum_{i=1}^{v} \mu_i \Delta AI_{t-i} + \sum_{i=1}^{w} \rho_i \Delta (AI * einf)_{t-i} + \sum_{i=1}^{x} \tau_i \Delta (AI * m3)_{t-i} + \varepsilon_t$$

where, r is the dependent interest rate, ir represents the corresponding benchmark rate (91-day Treasury Bill rate for long-term models, and 10-year GSEC yield for short-term models), δ_1 , ..., δ_{10} capture the long-run equilibrium relationship. Δ denotes the first-difference operator, and ε is the error term.

5. Empirical Results and Discussion

5.1 Stationarity Tests

Before estimating the model, the variables were checked for stationarity using the Augmented Dickey-Fuller (ADF) test to determine their order of integration. The results (given in Table 1) indicate that the variables are integrated of order zero, I(0), and order one, I(1), with none exhibiting integration at order two, I(2), thereby satisfying the pre-requisite for ARDL bounds testing (Pesaran and Shin, 1999; Pesaran et al., 2001).

Table 1: Stationarity Test (ADF)

Variable Name	Variable Notation	t-stat	Lags	Decision
3Y yield rate	ln3y	-5.3978***	1	I(1), with trend and intercept
5Y yield rate	ln5y	-5.5248***	1	I(1), with trend and intercept
91tbill yield rate	lntb	-4.0080**	1	I(1), with trend and intercept
10Y yield rate	ln10y	-4.4911***	2	I(1), with trend and intercept
Expected inflation	lneinf	-4.7126***	2	I(0), No trend, no intercept
Fiscal deficit	lnfd	-6.4887***	3	I(1), No trend, no intercept
IIP Output_Gap	lnopg	-4.9568***	3	I(0), No trend, no intercept
M3	lnm3	-3.8841**	0	I(1), with trend and intercept
Capital Flows	lnkflow	-4.1398***	3	I(0), with trend and intercept
REER	lnreer	-3.4592*	4	I(0), with trend and intercept

*, **, *** denote significance at 10%, 5% and 1% respectively.

Following the confirmation of the stationarity properties of the variables, the ARDL bounds testing framework is employed in this study to examine both the long-run

equilibrium relationships and the short-run dynamics across the identified maturity segments of government securities.

The results of the bounds test for all the estimated equations given in Table 2 reveal that for all the estimated equations, the null hypothesis of no cointegration is rejected at 1 per cent level of significance since the value of the F statistic lies above the bound I(1), implying the existence of a long-run relationship among the variables.

Table 2: Bounds Test of Interest Rate Determination Models

F-Bounds Test relationship			Null Hypothesis: No levels		
Interest Rate Model	**F-statistic**	**k**	**Signif.**	**I(0)**	**I(1)**
10Y	7.12	10	10%	1.83	2.94
5Y	7.26	10	5%	2.06	3.24
3Y	14.48	10	2.5%	2.28	3.5
91TB	11.63	10	1%	2.54	3.86

5.2 Long-term Interest Rate

The results of the ARDL estimation of long-term interest rates are given in Table 3.

Table 3: Long-Term Interest Rates

Dependent variable: GSEC 10Y yield rate			Dependent variable: GSEC 5Y yield rate		
Variable	**Estimate**	**t-stat**	**t-stat**	**Estimate**	**t-stat**
Long-run Coefficients			**Long-run Coefficients**		
lnfd	-0.001	-1.395	***lnfd***	0.000	1.041
lntb	0.406	4.618***	***lntb***	0.380	4.492***
lneinf	1.781	2.963***	***lneinf***	-0.009	-0.017
lnopg	0.005	3.632***	***lnopg***	0.004	2.112**
lnkflow	0.000	-1.366	***lnkflow***	0.000	-0.099
lnm3	1.601	2.115**	***lnm3***	3.585	3.869***
lnreer	0.332	1.789*	***lnreer***	0.101	0.701
AI	1.067	3.094***	***AI***	0.159	0.426
AI*einf	-1.718	-2.911***	***AI*einf***	-0.209	-0.333
AI*m3	-1.910	-2.277**	***AI*m3***	-3.947	-3.412***
Error Correction Representation			**Error Correction Representation**		
C	-5.343	-10.058***	***C***	-0.922	-10.110***
$\Delta ln10y_{t-1}$	0.305	2.629**	$\Delta ln5y_{t-1}$	0.430	3.720***
$\Delta lnfd_t$	0.000	-0.633	$\Delta lntb_t$	0.329	5.440***
$\Delta lntb_t$	0.385	8.190***	$\Delta lntb_{t-1}$	-0.162	-2.627***
$\Delta lntb_{t-1}$	-0.191	-3.645***	$\Delta lneinf_t$	8.698	8.208***
$\Delta lneinf_t$	31.470	6.474***	$\Delta lnopg_t$	0.003	2.228**
$\Delta lnopg_t$	0.001	0.960	$\Delta lnkflows_t$	-0.001	-2.422**
$\Delta lnopg_{t-1}$	-0.004	-2.502**	$\Delta lnkflows_{t-1}$	-0.001	-2.563**
$\Delta lnm3_t$	0.244	0.671	$\Delta lnm3_t$	1.383	2.972***

$\Delta lnm3_{t-1}$	-0.967	-2.302**	$\Delta lnm3_{t-1}$	-2.345	-3.950***
$\Delta lnreer_t$	0.286	1.430	$\Delta lnreer_t$	0.378	1.607
$\Delta lnreer_{t-1}$	0.430	2.253**	$\Delta lnreer_{t-1}$	0.833	3.587***
ΔAI_t	-141.422	-8.345***	$\Delta AI*einf_t$	-0.540	-7.178***
ΔAI_{t-1}	161.936	8.455***	$\Delta AI*m3_t$	-1.190	-1.864*
$\Delta AI*einf_t$	246.864	8.349***	$\Delta AI*m3_{t-1}$	2.789	3.768***
$\Delta AI*einf_{t-1}$	-281.407	-8.456***	EC_{t-1}	-1.893	-10.075***
$\Delta AI*m3_t$	-0.206	-0.405			
$\Delta AI*m3_{t-1}$	1.594	2.882***			
EC_{t-1}	-2.063	-10.065***			

*, **, *** denote significance at 10%, 5% and 1% respectively.

Long Term: 10-year G-Sec yield

The long-run estimates show that the yield of 91-day treasury bill exerts a strong positive influence over the 10-year G-Sec yield. A one per cent increase in the short-term interest rate raises the 10-year yield by about 0.41 per cent in the long-run, indicating a strong transmission from short-term rates to long-term rates, consistent with the expectations hypothesis and Fisher effect. The positive and statistically significant effect of expected inflation (β = 1.781) adheres to the Fisher effect, where higher inflation expectations drive higher nominal long-term yields. The positive coefficient of output gap suggests that a boost in economic activity enhances long-term yields through higher credit demand and expectations of future monetary tightening. Contrary to conventional theory, money supply and real exchange rate exhibit positive effects, reflecting the dominance of inflation expectations and sterilisation policies over pure liquidity and exchange rate channels. The findings further show that fiscal deficit is statistically insignificant, implying that government borrowing does not independently raise long-term interest rates and thereby providing little evidence of financial crowding out (see Chakraborty, 2002; Das, 2004; Chakraborty, 2024; Chakraborty et al., 2025).

The positive and significant AI term suggests that the initial phase of AI adoption coincided with enhanced policy credibility and tightening measures. However, the negative and significant interaction terms between AI and both inflation expectations and money supply indicate that AI adoption suggests strengthened monetary transmission by moderating the influence of inflationary and liquidity shocks on long-term yields.

The error correction coefficient is highly significant and negative, confirming rapid adjustment towards long-run equilibrium following temporary deviations. The rapid adjustment towards long-run equilibrium implies strong market efficiency in the government securities market. Short-run dynamics reveal that inflation and policy rate shocks transmit quickly, while fiscal and output effects remain largely long-term in nature.

Long Term: 5-year G-Sec yield

The ARDL estimates for the 5-year G-Sec yield reveal strong transmission from short-term interest rates and business cycle conditions, indicating effective monetary policy pass-through. The positive and significant effect of money supply reflects the dominance of

inflation and risk premia channels over traditional liquidity effects. The output gap is significant and positive, in coherence with results of the 10-year G-sec yield.

Fiscal deficit is insignificant in accordance with the reviewed empirical literature (Chakraborty, 2002; Das, 2004; Goyal, 2004; Chakraborty, 2012; Vinod, Chakraborty, and Karun, 2014; Chakraborty, 2024; Chakraborty et al., 2025). The real effective exchange rate does not exert a significant long-run effect, highlighting the relative insulation of the domestic bond market.

Further, the insignificant AI term implies that AI adoption does not influence the term structure. However, the significant negative interaction between AI and money supply confirms that AI-enhanced liquidity management shows a strengthening effect. The error correction coefficient (-1.89) is negative and highly significant, confirming rapid adjustment to inflation and policy rate shocks.

Table 4 exhibits the results of the ARDL estimation of the short-term interest rates.

Table 4: Short Term Interest Rates

Dependent variable: GSEC 3Y yield rate			**Dependent variable: 91TB yield rate**		
Variable	**Estimate**	**t-stat**	**t-stat**	**Estimate**	**t-stat**
Long-run Coefficients			**Long-run Coefficients**		
lnfd	0.000	-0.164	***lnfd***	-0.001	-1.329
ln10y	1.366	8.842***	***ln10y***	1.282	5.147***
lneinf	2.395	2.473**	***lneinf***	-5.161	-6.731***
lnopg	-0.011	-3.288***	***lnopg***	-0.007	-1.946**
lnkflow	0.001	1.623	***lnkflow***	0.000	0.814
lnm3	4.782	3.004***	***lnm3***	-2.161	-2.169**
lnreer	-0.317	-0.805	***lnreer***	-1.309	-3.569***
AI	1.383	2.211**	***AI***	-3.099	-5.449***
AI*einf	-2.806	-2.461**	***AI*einf***	4.939	4.870***
AI*m3	-3.230	-2.947***	***AI*m3***	-1.304	-1.331
Error Correction Representation			**Error Correction Representation**		
C	0.239	9.599***	***C***	11.847	12.594***
$\Delta ln10y_t$	0.976	12.493***	$\Delta ln10y_t$	0.904	8.220***
$\Delta lneinf_t$	2319.897	6.265***	$\Delta lneinf_t$	-34.878	-4.658***
$\Delta lneinf_{t-1}$	-4857.092	-6.342***	$\Delta lnopg_t$	0.006	3.117***
$\Delta lneinf_{t-2}$	2658.382	6.508***	$\Delta lnopg_{t-1}$	0.008	3.417***
$\Delta lnopg_t$	-0.005	-4.249***	$\Delta lnm3_t$	-0.518	-1.453
$\Delta lnkflows_t$	0.000	-1.739*	$\Delta lnreer_t$	-0.570	-1.773*
$\Delta lnkflows_{t-1}$	-0.001	-3.037***	ΔAI_t	366.674	10.404***
$\Delta lnkflows_{t-2}$	-0.001	-2.884***	ΔAI_{t-1}	-392.415	-10.206***
$\Delta lnm3_t$	1.310	3.846***	$\Delta AI*einf_t$	-639.796	-10.403***
$\Delta lnm3_{t-1}$	-2.188	-5.531***	$\Delta AI*einf_{t-1}$	681.916	10.207***
$\Delta lnm3_{t-2}$	-0.889	-2.935***	EC_{t-1}	-1.300	-12.587***
$\Delta lnreer_t$	0.026	0.127			

$\Delta lnreer_{t-1}$	0.178	0.827
$\Delta lnreer_{t-2}$	-0.637	-3.229***
ΔAI_t	992.187	3.329***
ΔAI_{t-1}	-1834.342	-2.920***
ΔAI_{t-2}	902.533	2.688**
$\Delta AI*einf_t$	-1730.814	-3.329***
$\Delta AI*einf_{t-1}$	3192.440	2.919***
$\Delta AI*einf_{t-2}$	-1568.160	-2.688**
$\Delta AI*m3_t$	-1.597	-3.948***
EC_{t-1}	-1.274	-14.634***

*, **, *** denote significance at 10%, 5% and 1% respectively.

5.3 Short-term Interest Rate

Short Term: 3-year G-Sec yield

The ARDL estimates for the 3-year G-Sec yield indicate the strong operation of the term structure, as reflected by the highly significant long-term yield rate. Inflation expectations exert a pronounced influence on short maturities, highlighting their sensitivity to monetary policy credibility. Contrary to conventional liquidity theory, money supply expansion is associated with higher yields, reflecting inflation and risk-premium channels.

The positive and significant AI dummy possibly implies transitional tightening and enhanced policy discipline following AI adoption. However, the negative interaction terms with inflation and money supply confirm that AI has strengthened policy effectiveness by moderating the transmission of macroeconomic shocks. The short-run dynamics reveal strong persistence and rapid adjustment to inflation and policy signals, supported by a highly significant error correction term.

Short Term: 91-day Treasury bill yield

The ARDL estimates for the 91-day Treasury bill yield highlight the dominance of monetary policy credibility and liquidity management in shaping short-term interest rates. The strong influence of the 10-year yield reflects the operation of the term structure. Contrary to conventional theory, expected inflation exhibits a significant negative effect, indicating that inflation expectations are effectively anchored through forward-looking monetary policy.

Money supply and real exchange rate exert stabilising effects on short-term yields, confirming the importance of liquidity accommodation and exchange rate management in the money market. The negative and significant AI dummy suggests that artificial intelligence adoption has improved liquidity forecasting and reduced rate volatility at the short end of the yield curve.

However, the positive interaction between AI and inflation indicates that AI-enhanced systems increase the responsiveness of money market rates to inflation signals, thereby

strengthening policy transmission. Short-run dynamics reveal rapid adjustment and strong responsiveness to macroeconomic news, supported by a highly significant error correction term, implying high efficiency in India's Treasury bill market. The stability diagnostics of the analysis are given in the Appendix.

5.4 Stability Diagnostics

We checked for any potential bias or misspecification in the executed model. To check the stability of the model, plots of the Cumulative Sum of Recursive Residuals (CUSUM) and the CUSUM of squares (CUSUMSQ) are examined. CUSUM and CUSUMSQ tests, which are based on the cumulative sum of recursive residuals, plot the cumulative sum along with standard error bands indicating the level of significance limits. If the cumulative sum falls outside the level of significance limits, it indicates instability of parameters. In Figure 4 and 5, which give the stability of long-term interest rates, the plot of CUSUM and CUSUMQ statistics of the estimated model lies within the critical bounds at 5% level of significance, showing that the estimated parameters of the model are stable over the sample period.

Figure 5: CUSUM and CUSUM of Squares of the GSEC10Y model

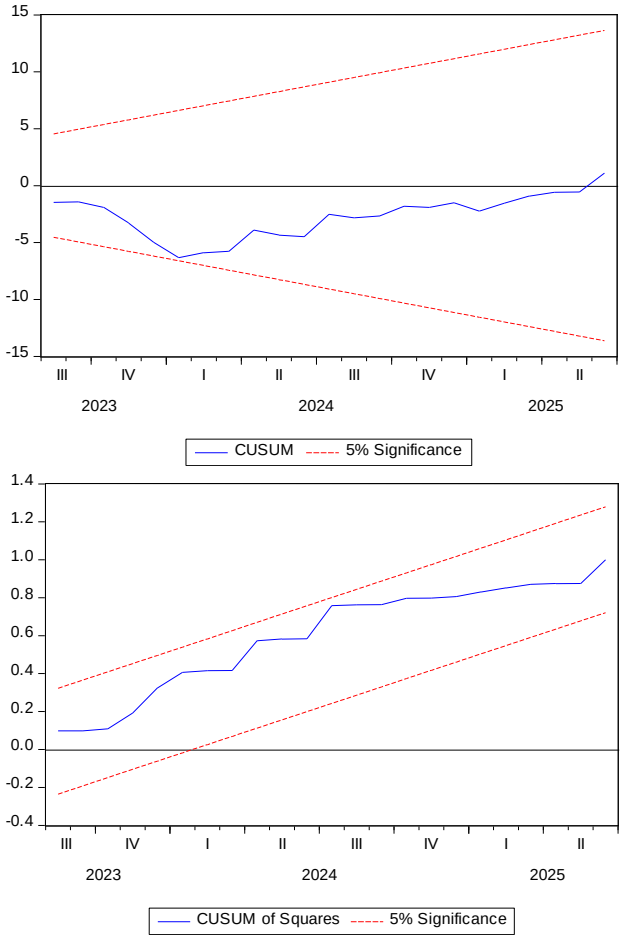


Figure 6: CUSUM and CUSUM of Squares of the GSEC 5Y model

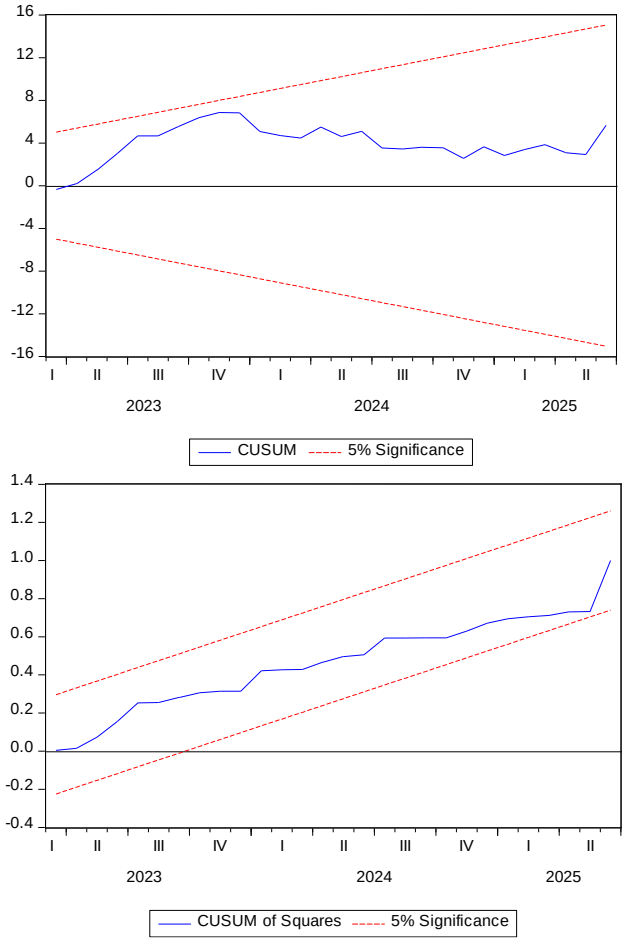


Figure 7: CUSUM and CUSUM of Squares of the GSEC 3Y model

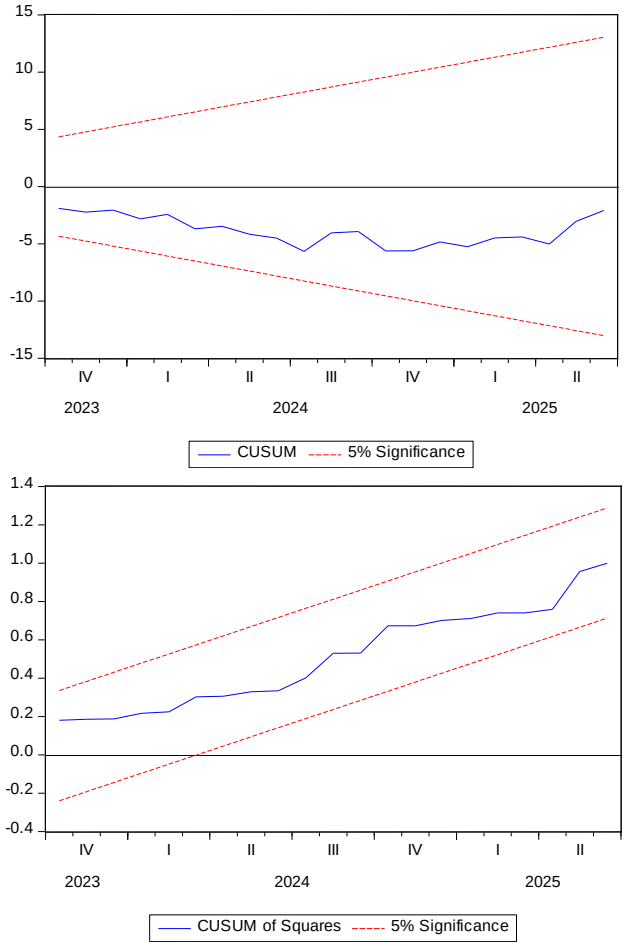
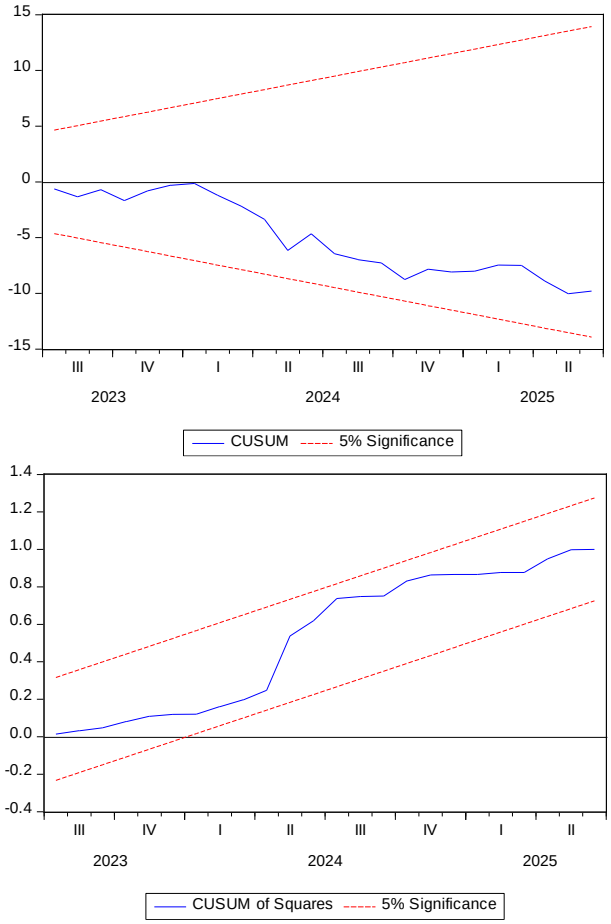


Figure 8: CUSUM and CUSUM of Squares of the 91TB model



6. Conclusions

This paper assessed whether the adoption of AI regulations within the RBI's framework of supervisory and regulatory functions has altered the transmission of monetary policy across the term structure of interest rates. The empirical findings indicate that the traditional macroeconomic determinants of the yield curve continue to remain relevant. Considering the impact across maturities, the long-run estimates suggest that the adoption of AI regulations has a significant impact on the responsiveness of the interest rates to macroeconomic conditions. For longer term government securities, the negatively significant interaction between AI regulations and expected inflation indicate that AI-enhanced supervisory capabilities reduce the sensitivity of the long-term yields to inflationary pressures. The analysis reveals that at shorter maturities, while AI appears to dampen the effects of liquidity shocks across the yield curve, the positive interaction between AI and inflation expectations suggests that the AI regulations enabled supervision technology has improved the responsiveness of money market to the inflation signals. This suggests that rather than weakening the monetary transmission, AI appears to have sharpened the informational efficiency of short-term markets by faster incorporation of macroeconomic information into asset prices. The highly significant error correction terms across all the specifications are indicative of the rapid adjustment

towards long-run equilibrium, reflecting a well-functioning government securities market and effective transmission of monetary policy.

In summary, the findings suggest that artificial intelligence regulations does not replace conventional monetary policy instruments, rather it enhances the effectiveness with which these instruments operate. AI regulations improves supervisory oversight, risk identification and liquidity forecasting, thereby strengthening the overall informational infrastructure of the monetary policy. Subsequently, the transmission of monetary policy becomes more efficient. These results assume importance in emerging economies where imperfect information and structural rigidities often weaken monetary policy transmission.

The present study makes three important contributions to the existing body of literature. Firstly, it extends the conventional term structure framework by introducing AI as a structural policy variable, thereby incorporating technological change into empirical models of monetary policy transmission. Secondly, the study demonstrates that AI affects not only the level of interest rates but also the sensitivity of financial markets to inflation expectations and liquidity conditions through interaction effects. Thirdly, it provides new empirical evidence from India, contributing to the limited but rapidly growing literature on AI adoption within central banking and its macroeconomic impact.

The AI regulations variable employed in the study captures the structural shift associated with the adoption of AI-enabled supervisory and regulatory technologies by the Reserve Bank of India but does not measure the intensity or the sophistication that could arise due to deployment of AI across individual functions. Further, it is understood that as AI adoption continues to evolve, expensive measures incorporating expenditure on digital infrastructure, SupTech implementation indices, and the application of machine learning techniques may provide deeper insights into the channels through which AI influences monetary policy.

Overall, the empirical evidence suggests that artificial intelligence regulations assumes heightened importance, complementing the conventional monetary policy frameworks. As central banks further integrate AI into forecasting, research, supervision, surveillance, and policy analysis, technological capability is likely to become an integral component of monetary policy effectiveness. For emerging economies such as India, which seeks to strengthen policy credibility amid an increasingly complex financial landscape, AI regulations represents not merely an operational innovation but an institutional mechanism capable of enhancing the efficiency and resilience of monetary policy transmission.

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Appendix:

Diagnostic Tests:

Diagnostic Test	Test Statistic	10-Year	5-Year
Serial Correlation (Breusch–Godfrey LM Test)	F-statistic	0.499	1.162
	prob. F	0.612	0.324
	Obs*R^2	1.905	3.924
	prob (Chi-Square)	0.386	0.141
Heteroskedasticity (Breusch–Pagan–Godfrey Test)	F-statistic	0.558	1.56
	Prob. F	0.94	0.107
	Obs*R^2	18.957	32.331
	prob (Chi-Square)	0.872	0.1486