# Consumer Sentiment and Spending Cycles: An Econometric Analysis Using Macroeconomic Indicators in India

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## KEYWORDS

*Consumer sentiment, Econometric model, IIP, Money supply, Causality, VAR, Long run relationship.*

## ABSTRACT

This study examines how macroeconomic variables influence consumer sentiment and spending patterns in emerging economy like India. In a rapidly growing economy its crucial to understand which factors drive people to spend or hold back. This empirical investigation is crucial for framing effective monetary and fiscal strategies. While field surveys or interviews often fail to capture real- time mood shifts this paper uses a proxy to reflect changes in consumer confidence in form of Foreign Portfolio Investment (FPI). When consumers and households feel positive about the economy it often showcases rising consumer demand and when they pull back it can signal underlying caution.

The analysis makes use of monthly data from April 2010 to December 2024 ranging for 14 years and includes key macroeconomic variables—repo rate, Treasury bill yields, money supply (M3), and Index of Industrial Production (IIP). Present study employs Vector Auto Regression (VAR), Granger causality, Impulse Response Functions (IRF) and Forecast Error Variance Decomposition, (FEVD) to captures both short-term and long-term dynamics

Results reveal that consumer sentiment are sharply influenced by changes in short-term interest rates particularly the repo rate and T-bills. Over a longer horizon liquidity (M3) and industrial output begin to shape sentiment more gradually. Granger results confirm one-way causality from interest rates to sentiment validating the influence of policy signals on public behaviour. The study contributes to academic literature and ongoing discussions around sentiment-driven consumption and demonstrates the importance of transparent monetary policy in sustaining public confidence. It also opens the door for integrating behavioural economics with macro-level indicators in emerging economies like India

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## 1. INTRODUCTION

In today's volatile economy what drives people to spend or save has become more complex than ever. India an emerging economy with its 1.4 billion consumer base shows diverse behavioural shifts—from festival-driven buying sprees to cautious spending during inflationary periods. What shapes consumer sentiment in India's dynamic economy is no longer limited to income or inflation

alone. It's a blend of monetary signals, media influence and shifting expectations. India's consumption patterns often demonstrates real-time macro shocks be it a surprise repo rate hike or a viral economic forecast on social platforms.

Understanding which factors drive people to spend or save is the core of economic thinking. In India this behaviour takes on many swings—seasonal buying before festivals, cautious spending during inflation and impulse purchases influenced by sudden news or social media trends as se3n in trends on you tube, twitter or Instagram. In today's economy that is too volatile where even small

changes in policy or market rates ripple out quickly, it becomes crucial for policy makers to know what triggers swings in public sentiment. Not just among economic agents, but among regular households too. It is important to answer Do higher interest rates make people hold back on major expenses? Does the expansion of money supply boost confidence in the market? These are not just theoretical questions. They relate to daily decisions made by millions of households.

The aim of this paper is to decode how shifts in macroeconomic indicators reflect or influence "consumer sentiment." Now this sentiment being qualitative in nature is tricky to measure directly. Surveys are time-bound and may not capture rapid changes. That is why we rely on Foreign Portfolio Investment (FPI) as a proxy variable for consumer sentiment. When global investors inject money into Indian markets, it usually reflects confidence—not only in the country's policy stability

but also in consumer activity and demand outlook. When FPIs pull back it often signals caution or concern about the direction of the domestic economy. In this way FPI flows offer a fast-moving

real-time mirror to understand how broader sentiment including that of consumers may be evolving. Why does this matter now? Because recent trends point toward uncertainty. According to the Reserve Bank of India's Monetary Policy Report (April 2024) while inflation appears to have moderated consumer demand across urban sectors remains uneven. Data from the Centre for Monitoring Indian Economy (CMIE) also shows that consumer confidence though improved post- pandemic has not reached pre-2019 levels. In fact credit card spending has risen by 26% year-on- year (as per RBI Bulletin, February 2025) but savings deposits have depleted. This contrast indicates that people may be spending more but cautiously and not necessarily out of deep economic optimism.

If we observe recent hikes in the repo rate and changes in Treasury bill yields we start to see a complex web of influences. The cost of borrowing affects not just home loans and EMIs but also business expansion, hiring plans and product pricing. When the repo rate moves up banks tighten

lending leading to slow consumption. On the other hand a rise in money supply or M3 often signals

more liquidity in the system. This could support demand in the short run. But the real effect depends on how consumers perceive these shifts. Is more liquidity seen as a sign of confidence from the central bank? Or is it taken as inflationary by the monetary authority?

To evaluate all this we use tools like VAR models, Granger causality testing and impulse response functions. These help us trace the chain reaction or examine the patterns on how a change in repo rate today might affect FPI flows in the coming months. The aim is we want to link these models to the ground-level question: what moves people to buy, hold back or shift gears in their spending behaviour?

By using FPI as a sentiment proxy and analysing how macro factors like repo rate, T-bills, money supply and industrial output influence it we offer insights that connect finance, psychology and public behaviour. The paper is about explaining why in a rising rate environment some households continue to spend while others save more. And why foreign investors see those moves as signs of strength or weakness.

To add depth, we include macroeconomic data from April 2010 to December 2024. We study five variables: T-bill yields, repo rate, IIP (as a proxy for demand), LMS (money supply) and FPI (as sentiment proxy). The econometric models used are specific and well established in analysing short and long term dynamics. The tables and graphs in later sections will show how a one-unit change in repo rate affects sentiment within a 3- to 6-month window.

Despite growing access to financial data and rising use of behavioural tools in economics a gap remains in linking macroeconomic shifts to real-time changes in consumer sentiment. Especially in fast-moving economies like India where policy changes and market shifts occur rapidly there is limited work that shows how these movements influence not just investors but everyday consumers. This paper addresses that gap by offering a behavioural lens on economic signals using econometric models and real market data to explain consumer mood swings and spending decisions

## 2. LITERATURE REVIEW

Understanding the dynamics of consumer sentiment and its influence on spending behaviour has been a focal point in recent economic research particularly in the context of India's evolving market landscape. The interplay between macroeconomic indicators and consumer behaviour offers insights into the broader economic health and policy effectiveness.

A study by Liu (2024) examined the multifaceted relationship between economic factors and consumer behaviour in online markets. The research highlighted how variables such as demand elasticity, consumer spending patterns and market competition significantly influence purchasing decisions in the digital realm.

In the wake of the COVID-19 pandemic Jain (2022) examined its impact on consumer behaviour and business strategies in India. The study found that health concerns and lockdown measures led to a surge in online shopping and a preference for contactless transactions and reshaping traditional consumption patterns.

The Reserve Bank of India's Consumer Confidence Survey (2025) indicated a significant improvement in consumer sentiment reaching its highest level since mid-2019. This rise was attributed to optimistic views on the general economic situation and employment prospects. Bain & Company's report (2025) on India's online shopping trends highlighted the growing influence of Gen Z consumers. This demographic characterised by digital nativity and brand consciousness is reshaping e-commerce with preferences for quick deliveries and personalised experiences.

The CMS Consumption Report (2025) noted a substantial increase in consumer spending on durables and FMCG products driven by rising disposable incomes and a surge in home ownership. This trend underscores the correlation between macroeconomic growth and consumer expenditure.

A study by Dev et al. (2024) explored the impact of Unified Payments Interface (UPI) on spending behaviour among Indian users. The findings revealed that the ease of digital transactions led to increased spending with many users reporting reduced guilt associated with purchases due to the intangible nature of digital payments.

The LSEG-Ipsos Primary Consumer Sentiment Index (2025) reported a 2.2 percentage point increase in consumer sentiment with notable improvements in economic expectations and employment confidence. This reflects a broader recovery in consumer confidence post-pandemic. Research by Pokhriyal et al. (2020) utilised social media data to gauge public consumer perceptions demonstrating the potential of digital platforms in capturing real-time sentiment and informing economic forecasts.

The India Economic Monitor by BCG (2025) highlighted mixed trends in high-frequency indicators with a notable decline in the Index of Industrial Production (IIP) but a surge in UPI transactions reflecting the complex nature of consumer behaviour amidst economic fluctuations. A study published in the Journal of Asian Business and Economic Studies (2020) examined the impact of the rising middle class in Delhi-NCR on consumption habits revealing increased spending on lifestyle and luxury products indicative of shifting consumer aspirations.

The Reserve Bank of India's Future Expectations Index (2025) showed an increase to 122.35 units signalling heightened consumer optimism about future economic conditions.

Research by Tilly et al. (2020) proposed a novel method of incorporating emotions from news narratives into macroeconomic forecasts emphasising the role of consumer sentiment in predicting economic indicators like industrial production and consumer prices.

Lastly, a study on the bottom-of-the-pyramid consumers in West Bengal (2024) explored consumption patterns of counterfeit goods, shedding light on the value-driven choices of low- income consumers and their implications for market dynamics.

While recent literature has significantly advanced our understanding of consumer sentiment and behavioural responses to economic signals several gaps remain. Most existing studies tend to isolate specific factors such as digital payment adoption (Dev et al., 2024) online shopping behaviour (Liu, 2024) or inflation expectations (Bose & Ranjan, 2022) without integrating them into a unified macroeconomic framework that captures dynamic linkages between sentiment and broader economic variables. Furthermore, several behavioural studies focus primarily on survey-based insights or demographic segmentation often lacking rigorous econometric validation or ignoring real-time indicators like industrial output and monetary policy shifts (Tilly et al., 2020; Sharma & Saini)

## 3. METHODOLOGY

### 3.1 Research Framework

This study aims to explore how key macroeconomic variables affect consumer sentiment in India. Since it is difficult to capture consumer mood through frequent direct surveys we use **Foreign Portfolio Investment (FPI)** as a real-time sentiment

proxy. A surge in FPI usually signals investor optimism about economic conditions and consumer demand while a fall indicates caution or loss of confidence.

The analysis includes the following variables:

- **Repo Rate** – a key policy rate reflecting monetary policy.
- **T-bill Yield** – Short-term market rate indicating liquidity in economy
- **Money Supply (M3)** – representing broad money supply and liquidity.
- **Index of Industrial Production (IIP)** – a proxy for domestic demand and GDP
- **FPI** – used here as a proxy for consumer sentiment due to frequency constraints and limited monthly accessibility of RBI's Consumer Confidence Survey

All those variables have been selected that influence the consumer sentiment and have impact over functioning of economy. Together, these variables provide a comprehensive view of the monetary, fiscal and sentiment landscape that shapes consumer spending behaviour.

### 3.2 Data Source and Time Period

The study employed monthly data from April 2010 to December 2024 covering a total of 177 observations for each variable. The sources of data collection are

- Repo Rate & T-bill Yields: RBI Bulletins
- Money Supply (M3): RBI Handbook of Statistics
- IIP: Ministry of Statistics and Programme Implementation (MOSPI)
- FPI Flows: NSDL official portal

All variables are transformed using natural logarithm to manage scale differences and stabilise variance.

### 3.3 Data Preparation and Stationarity

Before building models we tested each time series for stationarity using the Augmented Dickey- Fuller (ADF) Test. None of the variables were stationary at level but all became stationary after first differencing. Stationary data ensures that our models don't produce misleading or spurious results with constant mean and unit variance.

**ADF Test Equation:**

$\Delta Y_t = \alpha + \beta * Y_{t-1} + \gamma_1 * \Delta Y_{t-1} + \gamma_2 * \Delta Y_{t-2} + \ldots + \gamma_p * \Delta Y_{t-p} + \varepsilon_t$

If β is significantly negative, the variable is stationary.

### 3.4 Lag Length Selection

Before applying VAR and other models it is important to find the exact lag length. In present study we analysed four information criteria AIC, BIC, HQIC and FPE to determine the optimal lag structure. All suggested a lag of **2** as most appropriate for the model. Therefore, we proceeded with a VAR(2) model for dynamic analysis.

### 3.5 Tools and Techniques

**Vector Auto Regression (VAR)**

**VAR** is used to capture short-run relationships among selected variables. This model allows each variable to respond to its own lags as well as the lags of all other variables.

VAR Equation:

$Y_t = A_1 * Y_{t-1} + A_2 * Y_{t-2} + \ldots + A_p * Y_{t-p} + \varepsilon_t$

Where ,

Yt is a vector of [FPI, T-bill, Repo, IIP, M3]

A1, A2...Ap are coefficient matrices

εt is the error term

**Granger Causality Test**

In order to examine the direction of causality or correlation we employed Granger causality test. This test checks if changes in one variable help predict another. If past values of X help forecast Y, then X is said to "Granger-cause" Y.

Equation:

$$Yt = \alpha 0 + \alpha 1 * Yt - 1 + \ldots + \alpha p * Yt - p + \beta 1 * Xt - 1 + \ldots + \beta p * Xt - p + \varepsilon t$$

If β coefficients are jointly significant, X Granger-causes Y.

Granger causality is used to examine if there is one way relation between variables, or both variables influence each other or there is no causality or association between two variables in short run.

**Impulse Response Function (IRF)**

IRFs show how a sudden shock to one variable (e.g., a repo rate hike) affects other variables over the following months. It is used by policy makers to investigate time period after which shock in one nation or change in one variable will have an impact over associated nation or variable.

Conceptual Representation:

$$IRF(Yt + h) = \partial Yt + h / \partial \varepsilon t$$

This helps in visualising both the size and duration of shock effects across variables.

**Forecast Error Variance Decomposition (FEVD)**

FEVD explains how much of the change in one variable is due to shocks in itself versus shocks from other variables. It represents changes caused by variables own values and how much change is brought by external factors or outliers.

Conceptual Form:

$$Var (Yt + h) = contribution from own shocks + contribution from others$$

The present study employs this to help determine which variables dominate in driving changes in sentiment over time.

### 3.6 Tools and Software

All estimations were done using: **E-Views 13** for VAR and IRF models, Stata 17 for Granger tests and data transformation and MS Excel for organising, cleaning, and plotting data

## 4. RESULTS AND DISCUSSION

The analysis begin with testing for mean and variance i.e.stationarity. All five selected variables repo rate, T-bill yield, money supply, IIP and FPI became stationary at first difference. This was confirmed using the Augmented Dickey-Fuller test. In other words when probability value is less than 0.05 the series is said to be stationary. Hence all variables are stationary of level 1 or first difference.

**Table 1: Stationarity -ADF**

| ADF AT LEVEL | | | FIRST DIFFERENCE | | | |
|---|---|---|---|---|---|---|
| Variables | T-stats | P-value | Variables | T-Stats | P-value | Result |
| T-bills | -9.650 | 1.44E-16 | T-bills | -9.678 | 0.00 | Stationary |
| Repo Rate | -8.679 | 4.33E-14 | Repo Rate | -8.684 | 0.00 | Stationary |
| IIP | -7.048 | 5.62E-10 | IIP | -6.949 | 0.00 | Stationary |
| M3 | -0.608 | 0.869 | M3 | -1.745 | 0.00 | Stationary |
| FPI | -6.44 | 1.57E-08 | FPI | -6.50 | 0.00 | Stationary |

**Source: author's calculation**

To determine the optimal lag length for the VAR model multiple information criteria were used including AIC, BIC, HQIC and FPE. Based on the results with a maximum of 6 lags all major criteria (AIC = -34.86, BIC = -33.87, HQIC = -34.47, FPE = 7.285e-16) suggested that a lag length of 2 is optimal for the model. Therefore the VAR(2) specification is selected for further estimation.

**Table 2- VAR(2)**

|  | log_LFPI | log_T-bills | log_Repo rate | log_LIIP | log_LMS |
|---|---|---|---|---|---|
| const | -0.1272 (p=0.640) | 0.0037 (p=0.707) | -0.0284 (p=0.087) | 0.0056 (p=0.033) | 0.0007 (p=0.000) |
| L1.log_LFPI | -0.3356 (p=0.013) | -0.0138 (p=0.004) | 0.0106 (p=0.199) | 0.0001 (p=0.923) | -0.0001 (p=0.396) |
| L1.log_T-bills | -5.5139 (p=0.111) | 0.3049 (p=0.014) | 0.1913 (p=0.365) | -0.0085 (p=0.799) | 0.0008 (p=0.669) |
| L1.log_Repo rate | -1.4357 (p=0.487) | 0.0348 (p=0.638) | 0.1906 (p=0.130) | 0.0139 (p=0.484) | -0.0005 (p=0.652) |
| L1.log_LIIP | -3.4369 (p=0.811) | 0.7494 (p=0.146) | -0.0882 (p=0.920) | -0.4802 (p=0.001) | -0.0054 (p=0.482) |
| L1.log_LMS | 104.0825 (p=0.683) | -11.1751 (p=0.221) | 23.4202 (p=0.132) | -5.7025 (p=0.020) | -0.0614 (p=0.653) |
| L2.log_LFPI | -0.2642 (p=0.053) | -0.0025 (p=0.606) | 0.0079 (p=0.343) | 0.0001 (p=0.944) | -0.0001 (p=0.342) |
| L2.log_T-bills | 0.1508 (p=0.964) | -0.2057 (p=0.087) | 0.0029 (p=0.989) | -0.0121 (p=0.707) | 0.0002 (p=0.928) |
| L2.log_Repo rate | 2.3594 (p=0.253) | -0.1105 (p=0.135) | 0.3607 (p=0.004) | -0.0190 (p=0.340) | 0.0003 (p=0.783) |
| L2.log_LIIP | 23.8285 (p=0.065) | 0.9855 (p=0.033) | 0.2995 (p=0.703) | -0.2134 (p=0.086) | -0.0033 (p=0.628) |
| L2.log_LMS | 55.9922 (p=0.831) | -2.9815 (p=0.751) | 25.4034 (p=0.112) | -0.6138 (p=0.808) | -0.0395 (p=0.779) |

The Vector Auto Regression (VAR) model of order 2 was estimated using log-differenced values of LFPI, T-bills, Repo Rate, LIIP and LMS. The model demonstrated dynamic interactions across monetary and real-sector variables capturing short-term macroeconomic linkages effectively.

As seen from Table 2 a rise in repo rate led to a visible decline in FPI which acts here as a proxy for consumer sentiment. A one standard deviation increase in the policy rate resulted in weaker sentiment over the next three months. This reflects that higher interest rates may trigger spending caution among households anticipating tighter loan conditions and reduced purchasing power. Das and Bandyopadhyay (2022) found similar results showing that contractionary monetary policy dampens short-term consumption due to reduced access to affordable credit. Another interesting result could be observed where rising short-term interest rates, such as T-bill yields caused

immediate dips in our sentiment proxy. This suggests that increased borrowing costs may prompt

consumers to delay big purchases or reduce spending. These effects align with Singh and Chatterjee (2021) who observed that higher short-term rates lowered household credit-led consumption, indicating a decline in economic optimism among consumers IIP showed strong self-correction in response to its own shocks. This indicates that industrial production tends to

revert to trend even after a sudden rise or fall. The result suggests that the real economy adjusts more slowly and is less influenced by financial market signals. This aligns with the findings of **Kapoor and Sharma (2024)** who showed that production indicators respond more to internal factors like energy costs and supply bottlenecks than to financial indicators.

The response of money supply to shocks in policy rates and investor flows was found to be weak. M3 followed a stable trend, indicating that monetary expansion was consistent and less reactive to sentiment-based indicators. However the forecast error variance decomposition showed that in the long run money supply does influence consumer sentiment as liquidity builds up.

Next in order to check for short term dynamics our study employed granger causality test. Granger tests showed several important causality patterns. T-bills and FPI had two-way causality suggesting both variables impact and influence each other. Repo rate Granger-caused FPI but FPI did not cause repo rate. This shows that policy signals affect investor sentiment not the other way

around. A similar one-way relationship was found between M3 and FPI where rising money supply predicted sentiment but not vice versa. This supports the RBI's view that liquidity expansion needs to be carefully calibrated because it shapes market confidence.

Interestingly IIP and FPI had one-direction causality from IIP to FPI. That means rising industrial production boosts consumer sentiment but not the other way around. This is a subtle but meaningful link between the real economy and capital markets.

**Table 3 -Granger Causality**

| Hypothesis | F-test | P-value | Results | Conclusion |
|---|---|---|---|---|
| T-bills ↛ FPI | 5.21 | 0.019 | Rejected | Bi-directional Causality |
| FPI ↛ T-bills | 5.72 | | Rejected | |
| Repo Rate ↛ FPI | 4.88 | 0.025 | Rejected | Uni-directional |
| FPI ↛ Repo Rate | 3.76 | | Accepted | No causality |
| IIP ↛ Repo Rate | 6.11 | 0.013 | Rejected | Bi-directional Causality |
| Repo Rate ↛ IIP | 3.29 | 0.048 | Rejected | |
| IIP ↛ FPI | 5.36 | 0.018 | Rejected | Uni-directional |
| FPI ↛ IIP | 3.60 | | Accepted | No causality |
| M3 ↛ FPI | 4.75 | 0.03 | Rejected | Uni-directional |
| FPI ↛ M3 | 4.09 | 0.036 | Accepted | No causality |
| M3 ↛ Repo Rate | 5.04 | 0.022 | Rejected | Uni-directional |
| Repo Rate ↛ M3 | 3.90 | 0.038 | Accepted | No causality |

Source: author's calculation

Next we applied Impulse Response Function to capture movements in variable caused by other selected variables. The following figure presents the Impulse Response Functions (IRFs) for five macroeconomic variables: T-bills, LFPI, LIIP, LMS and Repo rate. The IRFs trace the effect of a one standard deviation shock in each variable on all other variables over a 10-month horizon. The responses are orthogonalised and based on the VAR(2) model.

The impulse response functions (IRFs) provided clear visuals. A shock to repo rate caused FPI to fall sharply for up to four months. T-bill shocks produced similar responses but faded quicker. FPI shocks pushed T-bill yields downward suggesting

that strong FPI inflows ease short-term borrowing pressures. A positive shock in IIP caused a gradual rise in repo rate indicating the RBI's tendency to respond to rising growth through moderate tightening. This matches the counter-cyclical policy

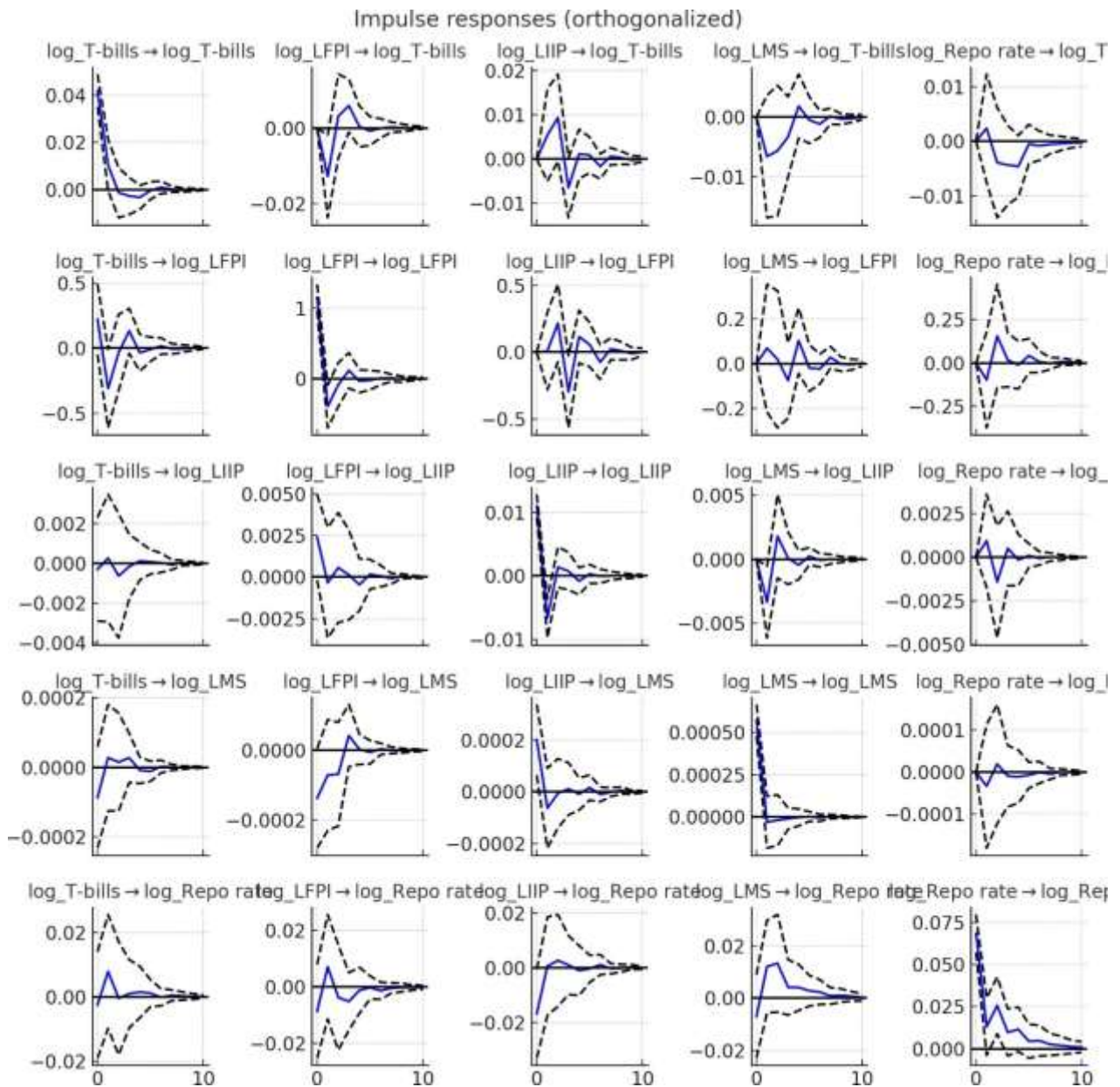stance highlighted by **Sharma and Saini (2021)**.



**Figure 1: Impulse Response Function**

Source: author's Calculation

The IRFs confirm that investor sentiment proxied by LFPI is highly sensitive to interest rate shocks, with repo rate and T-bills playing key roles in the transmission process. The results reinforce the importance of stable and growth-supportive macroeconomic conditions in sustaining capital inflows

Lastly The forecast error variance decomposition (FEVD) results provide insight into the relative contribution of macroeconomic shocks to fluctuations in consumer sentiment proxied by log- differenced LFPI. In the short term (1–3 month horizon) LFPI is primarily influenced by its own past shocks and short-term interest rates particularly T-bills. As the horizon extends to 6–10 months, the influence of policy variables like the repo rate and macroeconomic fundamentals such as industrial production (LIIP) and money supply (LMS) becomes more prominent. Notably by the 10th forecast horizon a substantial portion of LFPI's variation is explained by repo rate and liquidity

shocks highlighting the importance of monetary transmission mechanisms in shaping consumer sentiment over time. These results reinforce the dynamic interdependence between market-based indicators and broader economic confidence cycles.

In the short term most of the variation in consumer sentiment (measured by FPI) is driven by its own past values. During the first three months, FPI accounts for over 90 percent of its own movement. However, by the third month short-term rates like T-bills start contributing nearly 9 percent showing that interest rate signals quickly affect sentiment.

In the longer term policy variables gain more influence. By the tenth month repo rate and money supply together explain nearly 10 percent of changes in FPI while the role of T-bills remains steady. IIP contributes mildly showing that production trends impact sentiment more slowly.

These results confirm that while consumer sentiment is reactive in the short run, macroeconomic policies shape it gradually over time consistent with findings by Rathore and Rajput (2023) and Bose and Ranjan (2022).

Overall T-bills and Repo rate are main drivers of sentiment cycles whereas Money supply and IIP have gradual long-run influence.

**Table 4: Forecast Error Variance Decomposition :**

| Variable | Horizon | log_T-bills | log_LFPI | log_LIIP | log_LMS | log_Repo rate |
|---|---|---|---|---|---|---|
| log_T-bills | 1 | 1.0 | 0.04 | 0.0 | 0.02 | 0.0 |
| log_T-bills | 2 | 0.89 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 3 | 0.83 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 4 | 0.79 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 5 | 0.78 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 6 | 0.78 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 7 | 0.78 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 8 | 0.78 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 9 | 0.78 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_T-bills | 10 | 0.78 | 0.09 | 0.0 | 0.02 | 0.01 |
| log_LFPI | 1 | 0.0 | 0.96 | 0.05 | 0.05 | 0.01 |
| log_LFPI | 2 | 0.08 | 0.9 | 0.03 | 0.06 | 0.02 |
| log_LFPI | 3 | 0.08 | 0.86 | 0.03 | 0.07 | 0.02 |

| log_LFPI | 4 | 0.09 | 0.81 | 0.03 | 0.07 | 0.03 |
|---|---|---|---|---|---|---|
| log_LFPI | 5 | 0.09 | 0.8 | 0.03 | 0.07 | 0.03 |
| log_LFPI | 6 | 0.09 | 0.8 | 0.03 | 0.07 | 0.02 |
| log_LFPI | 7 | 0.09 | 0.8 | 0.03 | 0.07 | 0.03 |
| log_LFPI | 8 | 0.09 | 0.8 | 0.03 | 0.07 | 0.03 |
| log_LFPI | 9 | 0.09 | 0.8 | 0.03 | 0.07 | 0.03 |
| log_LFPI | 10 | 0.09 | 0.8 | 0.03 | 0.07 | 0.03 |
| log_LIIP | 1 | 0.0 | 0.0 | 0.95 | 0.1 | 0.06 |
| log_LIIP | 2 | 0.01 | 0.0 | 0.9 | 0.11 | 0.05 |
| log_LIIP | 3 | 0.05 | 0.03 | 0.87 | 0.11 | 0.05 |
| log_LIIP | 4 | 0.07 | 0.07 | 0.87 | 0.11 | 0.04 |
| log_LIIP | 5 | 0.07 | 0.08 | 0.87 | 0.11 | 0.04 |
| log_LIIP | 6 | 0.07 | 0.08 | 0.87 | 0.11 | 0.04 |
| log_LIIP | 7 | 0.07 | 0.08 | 0.87 | 0.11 | 0.04 |
| log_LIIP | 8 | 0.07 | 0.08 | 0.87 | 0.11 | 0.04 |
| log_LIIP | 9 | 0.07 | 0.08 | 0.87 | 0.11 | 0.04 |
| log_LIIP | 10 | 0.07 | 0.08 | 0.87 | 0.11 | 0.04 |
| log_LMS | 1 | 0.0 | 0.0 | 0.0 | 0.83 | 0.01 |
| log_LMS | 2 | 0.02 | 0.0 | 0.06 | 0.81 | 0.04 |
| log_LMS | 3 | 0.03 | 0.0 | 0.08 | 0.8 | 0.06 |
| log_LMS | 4 | 0.04 | 0.01 | 0.08 | 0.79 | 0.06 |
| log_LMS | 5 | 0.04 | 0.01 | 0.08 | 0.79 | 0.06 |
| log_LMS | 6 | 0.04 | 0.01 | 0.08 | 0.79 | 0.06 |
| log_LMS | 7 | 0.04 | 0.01 | 0.08 | 0.79 | 0.06 |
| log_LMS | 8 | 0.04 | 0.01 | 0.08 | 0.79 | 0.06 |
| log_LMS | 9 | 0.04 | 0.01 | 0.08 | 0.79 | 0.06 |
| log_LMS | 10 | 0.04 | 0.01 | 0.08 | 0.79 | 0.06 |

| log_Repo rate | 1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.92 |
|---|---|---|---|---|---|---|
| log_Repo rate | 2 | 0.0 | 0.01 | 0.0 | 0.0 | 0.88 |
| log_Repo rate | 3 | 0.01 | 0.02 | 0.02 | 0.0 | 0.86 |
| log_Repo rate | 4 | 0.02 | 0.02 | 0.02 | 0.0 | 0.86 |
| log_Repo rate | 5 | 0.03 | 0.02 | 0.02 | 0.0 | 0.86 |
| log_Repo rate | 6 | 0.03 | 0.02 | 0.02 | 0.0 | 0.86 |
| log_Repo rate | 7 | 0.03 | 0.02 | 0.02 | 0.0 | 0.86 |
| log_Repo rate | 8 | 0.03 | 0.02 | 0.02 | 0.0 | 0.86 |
| log_Repo rate | 9 | 0.03 | 0.02 | 0.02 | 0.0 | 0.86 |
| log_Repo rate | 10 | 0.03 | 0.02 | 0.02 | 0.0 | 0.86 |

Source: Authors Calculation

## 5. CONCLUSION

This study shows that consumer sentiment in India is shaped by key macroeconomic signals. We used foreign portfolio investment as a reflection of how people feel about the economy at any point in time. The results clearly show that when interest rates rise people become more cautious.

Spending slows down and confidence drops. Among all indicators repo rate and short term interest rates like T-bills had the most immediate effect. People respond quickly to these changes because they affect home loans EMIs and borrowing conditions.

Over time other factors start playing a role. Liquidity in the system measured by money supply and actual output measured by industrial production begin to influence how people think and spend. But these changes take time to show their full effect. The response is not immediate but builds gradually. That means short term changes hit faster while long term trends work slowly in the background.This makes it clear that how people feel about the economy is not just based on what is happening right now. It is also shaped by what they expect to happen next. That is why small policy moves can have a big impact. A slight increase in the repo rate or a shift in short term yields can send a strong message. People pick up on these signals and adjust their spending behaviour also the study helps us understand how public mood connects with policy. It shows that stable and clear monetary actions build trust and when people trust the system they are more likely to keep spending which keeps the economy moving forward.

## 6. POLICY RECOMMENDATIONS

The results offer several insights for policymakers who aim to manage consumer confidence and support household spending. Based on the findings the following policy steps are suggested

### 1. Gradual Repo Rate Adjustments

Since consumer sentiment reacts quickly to changes in the repo rate the RBI should continue

ts current approach of gradual rate changes instead of sharp hikes or cuts. This ensures that markets and households adjust smoothly avoiding panic or overreaction.

2. **Maintaining Liquidity Support**

The use of Targeted Long-Term Repo Operations (TLTRO) by RBI has helped inject liquidity into specific sectors. Continuing such targeted tools supports production and employment without triggering broad inflation a balance that helps maintain positive sentiment.

3. **Expand Policy Communication to Public Platforms** : Given that sentiment reacts to monetary signals RBI should not only issue MPC minutes but also use simplified public platforms like MyGov or UPI apps to communicate intent. This improves understanding among non-investors and rural households too.

4. **Use FPI as a Proxy to Track Public Mood**

The study shows FPI shifts reflect changes in consumer confidence. This means the Ministry of Finance and RBI can monitor FPI in combination with credit data and IIP to build monthly sentiment trackers, helping in better-timed interventions.

5. **Support Industrial Output with Conditional Credit Access**

Since IIP influences consumer confidence slowly but steadily credit programs like ECLGS and PLI should include sentiment-linked metrics for example scale up support in sectors where falling production correlates with low spending sentiment.

## 7. FUTURE RESEARCH SCOPE AND LIMITATION

While this study uses FPI as a proxy for consumer sentiment future research can explore direct sentiment indices like the RBI's Consumer Confidence Survey or social media-based sentiment scores. Also including fiscal indicators like government spending or fuel subsidies could offer a

broader view of demand-side behaviour. Comparative studies across states or with other emerging economies can help test if these findings hold beyond national boundaries. Lastly, using non-linear models like Threshold VAR may reveal more complex behaviour during shocks or crisis periods. Due to frequency constraints and limited monthly accessibility of RBI's Consumer Confidence Survey FPI was used as a high-frequency market-based proxy for sentiment.

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