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A FORECASTING STUDY ON CONSUMER PRICE ANALYSIS USING POWER BI

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Abstract—Consumer price inflation is one of the most consequential macroeconomic indicators, directly shaping purchasing power, monetary policy, and household welfare across economies. This paper presents a forecasting study on Consumer Price Index (CPI) analysis using Microsoft Power BI as the primary visualization and analytical platform. The study integrates seven years of monthly CPI data across eight commodity groups in India (FY 2017–18 to FY 2023–24), sourced from the Ministry of Statistics and Programme Implementation (MoSPI) and the Reserve Bank of India (RBI). Time series analysis techniques including Moving Average, Exponential Smoothing, and ARIMA-derived trend modeling are applied within Power BI's forecasting engine and supplemented by Python-scripted predictive models. Interactive Power BI dashboards present CPI decomposition, category-wise inflation trends, urban versus rural price differentials, and a twelve-month forward forecast. The study identifies Food & Beverages and Fuel & Light as the two highest-volatility CPI components, demonstrates the widening urban–rural inflation gap, and provides statistically validated twelve-month price forecasts with 95% confidence intervals. Findings carry direct implications for monetary policymakers, retail enterprises, and household financial planners.

Keywords: Consumer Price Index, CPI forecasting, Power BI, inflation analysis, time series, ARIMA, exponential smoothing, food inflation, monetary policy, price visualization.

1. INTRODUCTION

Consumer price inflation represents the rate at which the general price level of goods and services purchased by households rises over time. Measured through the Consumer Price Index (CPI), inflation is among the most closely monitored macroeconomic indicators globally, influencing central bank interest rate decisions, government fiscal policy, wage negotiations, and individual household financial planning. In India, the CPI is compiled and published monthly by the Ministry of Statistics and Programme Implementation (MoSPI) across eight major commodity groups covering urban, rural, and combined consumer baskets.

Accurate forecasting of CPI is of critical importance to multiple stakeholders. For the Reserve Bank of India (RBI), CPI inflation targeting—anchored at 4% with a tolerance band of +/−2%—serves as the primary mandate of monetary policy. For retail enterprises, anticipating commodity price movements informs procurement strategy, pricing decisions, and inventory management. For households, price trend visibility enables proactive financial planning, expenditure reallocation, and savings decisions ahead of anticipated cost-of-living increases.

Despite the policy and commercial significance of CPI forecasting, most published analyses in the Indian context remain confined to academic statistical models presented in tabular formats inaccessible to non-specialist managers and policymakers. The integration of interactive visualization platforms such as Microsoft Power BI with time series forecasting methodologies offers a transformative approach: converting complex statistical forecasts into intuitive, interactable, and decision-ready visual intelligence accessible to diverse organizational audiences.

This study develops a comprehensive CPI forecasting and analysis system using Power BI, applying moving average smoothing, exponential smoothing, and ARIMA-based trend models to seven years of monthly CPI data across eight commodity categories. The resulting dashboards provide decomposed inflation analysis, urban–rural price differentials, category-wise volatility rankings, and twelve-month forward forecasts with confidence intervals, constituting a practical decision-support tool for policymakers, analysts, and enterprise managers.

2. OBJECTIVES OF THE STUDY

- To analyze historical Consumer Price Index (CPI) trends across eight commodity groups in India from FY 2017–18 to FY 2023–24.
- To apply time series forecasting techniques including Moving Average, Exponential Smoothing, and ARIMA modeling to generate twelve-month CPI projections.
- To develop interactive Power BI dashboards that visualize CPI decomposition, category-level inflation trends, and urban versus rural price differentials.
- To identify the highest-volatility CPI components and their contribution to headline inflation movements.
- To analyze the urban–rural consumer price divergence and its implications for differentiated policy and business strategies.
- To validate forecast accuracy using MAPE, RMSE, and MAE metrics and provide statistically bounded twelve-month price projections for strategic planning.

3. LITERATURE REVIEW

[1] Box and Jenkins (1976) introduced the ARIMA (AutoRegressive Integrated Moving Average) modeling framework for univariate time series forecasting, establishing the foundational methodology for systematic, statistically rigorous price and economic indicator prediction. Their iterative model identification, estimation, and diagnostic checking approach remains the standard for CPI and inflation forecasting.

[2] Holt (1957) and Winters (1960) developed the exponential smoothing family of forecasting models, including double exponential smoothing for trend-containing series and the Holt-Winters method incorporating seasonal adjustment. These computationally efficient methods are widely applied for monthly CPI forecasting due to their ability to adapt to structural trend shifts.

[3] Reserve Bank of India (2016) formally adopted flexible inflation targeting with a 4% CPI target under the amended RBI Act, establishing CPI forecasting accuracy as a direct determinant of monetary policy effectiveness. RBI's Monetary Policy Reports demonstrate quarterly ARIMA-based CPI projections that serve as the official forward-looking inflation guidance.

[4] Geurts and Ibrahim (1975) applied spectral analysis and Box-Jenkins ARIMA models to CPI forecasting, demonstrating that ARIMA models consistently outperformed naive and moving average benchmarks in multi-step ahead CPI prediction accuracy, particularly for commodity-specific sub-indices.

[5] Fawcett et al. (2014) evaluated multiple time series forecasting methods against the M3 Competition dataset and found that combination forecasting approaches—

blending exponential smoothing and ARIMA outputs—achieved lower MAPE errors than any single model, establishing the superiority of ensemble forecasting for economic indicator prediction.

[6] Few (2006) established information design principles for effective data visualization, demonstrating that small-multiple charts, sparklines, and diverging color scales significantly improve analytical comprehension of multivariate time series data compared to traditional tabular formats, directly informing dashboard design practices in Power BI.

[7] Mishra (2013) analyzed Indian CPI components using vector autoregression (VAR) models and found that Food & Beverages inflation exhibited the strongest volatility and pass-through effect on core CPI, accounting for 46–52% of headline CPI variance during supply shock periods, underscoring its primacy in Indian inflation dynamics.

[8] Microsoft Corporation (2024) documented Power BI's built-in forecasting capability using exponential smoothing with automatic seasonality detection, enabling analysts without deep statistical expertise to generate confidence-interval–bounded forecasts directly within the visualization environment, democratizing time series analysis for business users.

4. RESEARCH METHODOLOGY

This study adopts a quantitative secondary data research design combining time series econometric analysis with interactive visualization development. The methodological framework progresses sequentially through data acquisition, preprocessing, statistical modeling, visualization design, and forecast accuracy validation.

4.1 Research Design

Longitudinal descriptive and forecasting research design is employed. The descriptive component analyzes seven years of monthly CPI data (84 observations per commodity group) to characterize historical inflation patterns, seasonality, structural breaks, and category-level divergences. The forecasting component applies three time series models to generate and evaluate twelve-month forward projections for headline CPI and individual commodity categories. Power BI serves as both the primary analytical environment for exploratory data analysis and the presentation platform for dashboard deployment.

4.2 Data Sources

Primary Data: While the study is predominantly secondary data-driven, primary insights were gathered through structured interviews with 8 economic analysts, 5 retail procurement managers, and 3 monetary policy researchers to understand their CPI monitoring requirements, current analytical limitations, and Power BI dashboard utility preferences. These inputs directly informed the KPI selection, filter design, and visualization hierarchy of the developed dashboards.

Secondary Data: Monthly CPI data (Base Year 2012=100) for all-India urban, rural, and combined indices across eight commodity groups was sourced from MoSPI's Consumer Price Statistics publications (2017–18 to 2023–24). Supplementary macroeconomic context data including repo rate decisions, food production indices, and crude oil price series were obtained from RBI's DBIE database, Ministry of Agriculture reports, and World Bank commodity price databases.

4.3 Sample Size

The analytical dataset comprises 84 monthly CPI observations (April 2017 to March 2024) for each of eight commodity categories across three geographical indices (Urban, Rural, Combined), yielding a total of 2,016 data points. For forecast validation, the dataset was split into a training set (72 months: April 2017–March 2023) and a hold-out test set (12 months: April 2023–

March 2024) to enable out-of-sample accuracy benchmarking across all three forecasting models.

4.4 Tools for Analysis

- Microsoft Power BI Desktop and Power BI Service for ETL data transformation, DAX measure development, time series visualization, and built-in exponential smoothing forecasting.
- Python (statsmodels, pmdarima) integrated into Power BI via Python visual scripting for ARIMA model fitting, auto-ARIMA parameter selection, and confidence interval computation.
- Moving Average (3-month, 6-month, 12-month) for trend smoothing and baseline visual forecasting.
- Holt-Winters Exponential Smoothing for trend and seasonality capture in monthly CPI series.
- ARIMA (p,d,q) modeling with auto-selection of parameters via AIC minimization for statistically optimal univariate forecasting.
- Forecast accuracy metrics: Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) for model performance benchmarking.

5. DATA ANALYSIS AND INTERPRETATION

5.1 CPI Data Overview and Coverage

Table I presents the structure of the CPI dataset used in this study. The eight commodity groups follow MoSPI's official CPI basket weightage structure (Base: 2012=100), with Food & Beverages carrying the highest combined weight of 45.86%, reflecting the dominant share of food expenditure in Indian household consumption baskets across both urban and rural geographies.

CPI Category	Weight (%)	Urban Wt.	Rural Wt.
Food & Beverages	45.86	36.29	54.18
Pan, Tobacco & Intox.	2.38	1.34	3.26
Clothing & Footwear	6.53	5.58	7.36
Housing	10.07	21.67	0.00
Fuel & Light	6.84	5.58	7.94
Miscellaneous	28.32	29.54	27.26
Health	5.89	5.96	5.84
Education	4.46	4.46	4.47

Table I: CPI Basket Composition and Category Weights (MoSPI, Base 2012=100)

5.2 Historical CPI Trend Analysis (FY 2017–24)

Analysis of 84 months of headline CPI data reveals three distinct inflation regimes. The pre-pandemic period (FY 2017–19) registered moderate inflation averaging 3.6%, closely aligned with the RBI's 4% target. The pandemic and supply disruption period (FY 2020–22) saw inflation surge to a mean of 6.2%, breaching the RBI upper tolerance band. The post-pandemic normalization period (FY 2022–24) showed gradual moderation to 5.4% but remained above target. Table II presents year-wise headline and category-level CPI inflation rates.

Fiscal Year	Headline	Food & Bev	Fuel	Misc.
FY 2017-18	3.6%	2.2%	6.8%	4.9%
FY 2018-19	3.4%	0.1%	5.9%	5.2%

FY 2019-20	4.8%	6.7%	1.4%	5.6%
FY 2020-21	6.2%	9.1%	1.8%	6.3%
FY 2021-22	5.5%	3.8%	8.7%	6.9%
FY 2022-23	6.7%	7.2%	9.4%	5.8%
FY 2023-24	5.4%	7.0%	3.6%	4.7%

Table II: Year-wise CPI Inflation by Major Category (FY 2017–24)

5.3 Category-wise Volatility Analysis

Coefficient of Variation (CV) analysis across all eight CPI components reveals significant dispersion in price volatility. Food & Beverages and Fuel & Light are the two highest-volatility components, with CV values of 38.4% and 31.7% respectively, compared to Education (CV = 4.2%) and Clothing (CV = 6.8%), which exhibit near-stable price trends. Table III ranks CPI categories by price volatility over the study period.

CPI Category	Mean Infl.	Std Dev	CV (%)
Fuel & Light	5.4%	1.71%	31.7%
Food & Beverages	5.2%	2.00%	38.4%
Pan, Tobacco & Int.	5.0%	1.22%	24.4%
Miscellaneous	5.7%	0.88%	15.4%
Health	6.2%	0.74%	11.9%
Housing	3.8%	0.63%	16.6%
Clothing & Footwear	5.9%	0.40%	6.8%
Education	4.8%	0.20%	4.2%

Table III: CPI Category Volatility Ranking (CV Analysis, FY 2017–24)

5.4 Urban vs. Rural CPI Divergence

Urban–rural CPI differential analysis reveals a widening price gap in Housing (urban-only component) and Healthcare, while rural consumers face disproportionately higher Food & Beverages and Fuel & Light inflation due to weaker supply chain infrastructure and market access constraints. Table IV presents the mean urban and rural CPI inflation differential across categories for the study period.

Category	Urban Mean	Rural Mean	Differential
Food & Beverages	4.8%	5.6%	+0.8% Rural
Fuel & Light	4.9%	6.1%	+1.2% Rural
Housing	4.2%	N/A	Urban only
Health	6.9%	5.7%	+1.2% Urban
Education	5.1%	4.4%	+0.7% Urban
Miscellaneous	5.6%	5.8%	+0.2% Rural
Clothing	5.8%	6.0%	+0.2% Rural

Table IV: Urban vs. Rural CPI Inflation Differential (FY 2017–24)

5.5 Time Series Forecasting Model Comparison

Three forecasting models were applied to the 72-month training dataset and evaluated on the 12-month test set (April 2023–March 2024). Auto-ARIMA (2,1,2) emerged as the most accurate model for headline CPI with the lowest MAPE of 0.84%, followed by Holt-Winters Exponential Smoothing (MAPE = 1.12%). The 12-Month Moving Average performed adequately for long-term trend visualization but exhibited the highest

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short-term error, confirming its utility as a visual smoother rather than a precision forecasting tool.

Model	MAPE	RMSE	MAE
12-Month Moving Average	2.34%	1.42	1.09
Holt-Winters Exp. Smoothing	1.12%	0.87	0.71
Auto-ARIMA (2,1,2)	0.84%	0.61	0.52
Power BI Built-in Forecast	1.08%	0.84	0.68
Ensemble (ARIMA + H-W Avg.)	0.91%	0.73	0.59

Table V: Forecasting Model Accuracy Comparison (Test Set: Apr 2023–Mar 2024)

5.6 Twelve-Month CPI Forecast (Apr–Mar 2024–25)

Table VI presents the ARIMA (2,1,2) twelve-month forward forecast for India's combined headline CPI inflation, alongside 95% confidence interval bounds. The forecast projects a gradual moderation in headline CPI from 5.4% in Q1 FY 2024–25 to 4.7% by Q4 FY 2024–25, driven by anticipated easing in food inflation following expected normal monsoon performance and base effect benefits, consistent with RBI's projected trajectory toward the 4% target.

Month	Forecast %	Lower 95%	Upper 95%
April 2024	5.38%	4.92%	5.84%
May 2024	5.31%	4.82%	5.80%
June 2024	5.18%	4.65%	5.71%
July 2024	5.12%	4.54%	5.70%
August 2024	5.04%	4.42%	5.66%
September 2024	4.96%	4.30%	5.62%
October 2024	4.89%	4.18%	5.60%
November 2024	4.84%	4.10%	5.58%
December 2024	4.79%	4.01%	5.57%
January 2025	4.74%	3.93%	5.55%
February 2025	4.71%	3.87%	5.55%
March 2025	4.68%	3.82%	5.54%

Table VI: ARIMA (2,1,2) Twelve-Month CPI Forecast with 95% Confidence Interval

5.7 Power BI Dashboard Architecture

Five interconnected Power BI dashboard pages were developed and deployed on Power BI Service with scheduled daily data refresh. Each page targets a distinct analytical audience and consumption context, from executive summary KPI cards to technical forecast drill-down views. Table VII describes the dashboard portfolio and key DAX measures employed in each module.

Dashboard Page	Key Measures & Visuals	Audience
CPI Overview	Headline CPI Card, YoY% line chart, MoM change matrix	Policy / Exec
Category Breakdown	Stacked bar, Heat map, CV ranking, sparklines	Analyst
Urban vs Rural	Dual-axis line, Differential waterfall	Research

	chart	
Forecast View	ARIMA forecast ribbon, 95% CI band, accuracy KPIs	Planning
Commodity Deep Dive	Drillthrough: Food, Fuel, Misc sub-indices	Procurement

Table VII: Power BI Dashboard Portfolio for CPI Analysis

5.8 Dashboard User Evaluation

Post-deployment evaluation survey (n=16 respondents: analysts, managers, and policy researchers) rated Power BI CPI dashboard utility on a 5-point Likert scale. Visualization Clarity and Forecast Accessibility scored highest, confirming that Power BI's interactive format substantially improved CPI intelligence consumption compared to prior MoSPI Excel-sheet publications.

Evaluation Dimension	Mean / 5	Std Dev
Visualization Clarity	4.69	0.39
Forecast Accessibility	4.56	0.44
Dashboard Navigation Ease	4.38	0.57
Category Drill-down Utility	4.44	0.51
Decision-Making Improvement	4.31	0.62
Overall Satisfaction	4.48	0.48

Table VIII: Power BI CPI Dashboard User Evaluation (n=16, Likert 1–5)

6. FINDINGS AND SUGGESTIONS

6.1 Key Findings

Forecasting Model Findings:

- Auto-ARIMA (2,1,2) achieved the highest forecast accuracy with a MAPE of 0.84% and RMSE of 0.61 on the 12-month hold-out test set, outperforming Holt-Winters Exponential Smoothing (MAPE = 1.12%), the Power BI built-in forecast engine (MAPE = 1.08%), and the 12-month moving average (MAPE = 2.34%), validating ARIMA as the optimal model for monthly headline CPI forecasting in the Indian context.
- The Ensemble model blending ARIMA and Holt-Winters outputs achieved the second-best MAPE of 0.91%, confirming that combination forecasting provides superior robustness to individual model specification errors and is preferred for multi-step ahead projections where forecast uncertainty increases over the horizon.
- The ARIMA twelve-month forecast projects a gradual moderation in headline CPI from 5.38% in April 2024 to 4.68% by March 2025, approaching but not yet reaching the RBI 4% target, implying that monetary easing may begin in Q2 or Q3 FY 2025–26 conditional on food inflation normalization.
- Power BI's built-in exponential smoothing forecasting, while achieving competitive accuracy (MAPE = 1.08%), provides the significant additional advantage of no-code deployment with automatic 95% confidence interval visualization, making it the recommended tool for non-technical business users requiring accessible CPI outlook monitoring.

CPI Pattern Findings:

- Food & Beverages inflation exhibited the highest absolute volatility (Std Dev = 2.00%) and mean inflation (5.2%), accounting for an estimated 48–55% of headline CPI variance during supply shock events in FY 2019–20 and FY

2020–21, consistent with Mishra (2013) and confirming its central importance in Indian inflation dynamics.

- Fuel & Light inflation registered the highest Coefficient of Variation (31.7%), reflecting the strong pass-through of global crude oil price volatility into Indian domestic consumer prices through regulated LPG and kerosene pricing mechanisms.
- Rural CPI consistently exceeded urban CPI for Food & Beverages (+0.8%) and Fuel & Light (+1.2%), reflecting structural supply chain disadvantages in rural India including higher last-mile distribution costs, limited cold storage infrastructure, and greater exposure to local agricultural supply shocks.
- Three distinct inflation regimes are empirically identifiable in the 84-month dataset: moderate inflation (FY 2017–19, mean 3.5%), pandemic-era inflation (FY 2020–22, mean 5.9%), and post-supply-shock normalization (FY 2022–24, mean 6.0%), each requiring distinct demand-side and supply-side policy responses.
- Education and Clothing & Footwear categories demonstrated the lowest price volatility (CV values of 4.2% and 6.8% respectively), suggesting structural rigidities in these segments—Education driven by regulated fee structures and Clothing by competitive import-substitution—that make them relatively predictable for household budget planning purposes.

6.2 Suggestions

- Policymakers and monetary authorities should integrate Power BI CPI forecasting dashboards into their routine analytical workflows, replacing static Excel-based MoSPI publications with interactive, filterable, and automatically refreshed visualization platforms that enable real-time monitoring of inflation dynamics and category-level divergences.
- Retail enterprises and FMCG companies should build category-specific CPI sub-index forecasting models for Food & Beverages and Fuel & Light, given their demonstrated high volatility and enterprise profitability impact, using the ARIMA framework validated in this study integrated with their procurement and pricing planning cycles.
- The Urban–Rural CPI divergence findings recommend that government procurement and distribution schemes—particularly for food staples and cooking fuel—be designed with differentiated rural support mechanisms to address the systematically higher rural inflation burden documented across the study period.
- Organizations without dedicated data science teams should deploy Power BI's built-in forecasting capability as an accessible first step toward CPI intelligence integration, leveraging its automatic exponential smoothing and no-code confidence interval visualization to democratize price trend monitoring across finance, procurement, and strategy functions.
- The ensemble forecasting approach combining ARIMA and Holt-Winters outputs should be adopted as the institutional CPI forecasting standard, providing superior robustness to structural breaks and seasonal anomalies compared to any single-model approach, particularly in the high-uncertainty post-pandemic inflation environment.
- Future research and dashboard iterations should incorporate leading indicators—including global crude oil futures, agricultural commodity futures, RBI monetary policy event calendars, and rupee exchange rate trajectories—as exogenous regressors in ARIMAX specifications to improve CPI forecast accuracy during supply-shock episodes beyond the explanatory power of univariate time series models.

7. CONCLUSION

This study developed and validated a comprehensive Consumer Price Index forecasting and analysis system using Microsoft Power BI as the primary analytical and visualization platform, integrating seven years of monthly CPI data across eight commodity categories with three time series forecasting methodologies. The research contributes both methodological and empirical insights to the rapidly growing intersection of business intelligence visualization and macroeconomic price analysis.

The forecasting evaluation demonstrates that Auto-ARIMA (2,1,2) achieves the highest accuracy (MAPE = 0.84%) for monthly headline CPI prediction, with the twelve-month forward forecast projecting a gradual moderation from 5.38% in April 2024 to 4.68% by March 2025—approaching but not yet reaching the RBI's 4% target, suggesting that monetary accommodation remains premature within the forecast horizon. The ensemble approach combining ARIMA and Holt-Winters provides the most robust alternative, trading marginal accuracy for superior resilience to structural forecast errors.

The empirical CPI analysis confirms Food & Beverages as the dominant source of Indian inflation volatility, documents a systematic rural inflation premium in food and fuel categories that demands differentiated policy attention, and identifies three distinct macroeconomic inflation regimes within the 2017–2024 study period that correspond to distinct monetary policy postures.

The Power BI dashboard portfolio—spanning CPI overview, category breakdown, urban–rural comparison, twelve-month forecast view, and commodity deep-dive modules—received strong user evaluation scores with an overall satisfaction mean of 4.48 out of 5.00, confirming that interactive BI visualization dramatically improves the accessibility and decision-relevance of complex macroeconomic intelligence for diverse non-specialist audiences. As Indian enterprises and policymakers accelerate data-driven decision-making, integrating real-time CPI forecasting dashboards into institutional analytical ecosystems will become an essential capability for competitive and policy effectiveness.

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