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Canadian Inflation Dynamics: A Comparative Forecasting and Structural Identification Analysis (1995–2026)

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Abstract: This study evaluates econometric and machine learning frameworks for forecasting the Canadian Consumer Price Index (CPI) from 1995 to 2025. Comparative analysis establishes that a linear SARIMAX (1,1,1) (1,1,1)12 model systematically outperforms complex deep learning architectures, including LSTM, GRU, and automated ensembles. We resolve the empirical 'Price Puzzle' using a 2SLS instrumental variables framework. In the baseline 2SLS specification, utilizing lagged interest rates yields an estimated structural price stickiness duration of 2.38 months ($\beta_{baseline} = 0.4205$). When accounting for explicit time-series momentum and seasonality within the full SARIMAX framework, the purged policy rate coefficient stabilizes at ($\beta_{Purged\_IR} = 0.2086$, $p < 0.001$)), isolating a refined structural rigidity duration of 4.79 months ($1/\beta$) This inversion identifies a highly active systematic policy feedback vector ($\psi_{\pi} = 4.79 > 1.0$) that strictly satisfies the Taylor Principle. Crucially, factoring in full time-series dynamics yields a definitive long-run multiplier $M_{IR} = 0.156748$. Because this cumulative multiplier is less than unity, it satisfies classical monetary stability conditions, confirming that the Canadian economic policy initial short-run cost-push innovations successfully decay as the aggressive policy framework sterilizes external shocks. Ex-ante projections through December 2027 track a stabilizing trajectory, where early 2026 localized index forecasts (Jan: 165.5 to July: 169.3) demonstrate immediate variance compression against real-world Statistics Canada data.

Keywords: *Consumer Price Index (CPI), SARIMAX, Machine Learning, 2SLS, Price Puzzle, Taylor Principle, Bank of Canada.*

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I. INTRODUCTION

A foundational principle of macroeconomic theory dictates that monetary authorities can tame inflationary pressures by elevating nominal policy interest rates to cool aggregate demand. However, empirical time-series frameworks frequently clash with this theoretical consensus, establishing a persistent anomaly known in econometric literature as the "Price Puzzle" (Eichenbaum, 1992; Sims, 1992)—a phenomenon where a tightening of monetary policy is systematically followed by an immediate increase, rather than a contraction, in the aggregate price level.

This study explicitly documents and separates this structural friction through a Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) framework applied to monthly Canadian Consumer Price Index (CPI) data spanning January 1995 to December 2025. Our full-sample baseline estimation reveals a stark empirical contradiction to classical economic theory: the contemporary purged interest rate repressor yields a highly significant positive coefficient ($\beta = 0.20857$, $p < 0.001$). Statistically, this result rejects the null hypothesis of policy neutrality with near certainty; economically, however, it superficially implies that higher interest rates fuel consumer price inflation.

Rather than concluding that monetary policy is ineffective, this paper argues that this highly significant positive coefficient is an artifact of structural model misspecification (Hanson, 2004). Specifically, standard baseline regressions fail to capture the forward-looking informational advantages of the Bank of Canada (BoC) — which proactively adjusts the overnight policy rate in anticipation of looming supply-side shocks—as well as the substantial, variable transmission lags intrinsic to monetary policy execution. Consequently, this paper establishes a rigorous quantitative benchmark for the Canadian Price Puzzle using state-space architectures, implementing

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structural modifications to cleanly separate true policy interventions from anticipatory central bank actions.

To ground this empirical inquiry, it is vital to understand the structural composition and data-generation process of our target variable. The Canadian Consumer Price Index (CPI) serves as the nation's primary and most widely scrutinized metric of inflation. Mathematically structured as a chain-weighted Laspeyres-type price index, the CPI measures the shifting cost of a fixed basket of consumer goods and services over time. By tracking a mathematically consistent set of items, the index isolates pure price movements from shifts in consumer purchasing quantities. As a fundamental instrument for macroeconomic diagnostic analysis, the CPI directly informs critical policy mandates executed by the Bank of Canada and federal fiscal authorities, while simultaneously serving as the statutory benchmark for indexing a vast array of public transfer payments, private pensions, and financial contracts.

Compiled and published monthly by Statistics Canada, the index anchors its longitudinal variance against a base year of 2002 (2002 = 100). The index monitors the weighted average of prices across a basket comprising 491 elementary aggregates, meticulously selected to represent the aggregate expenditure profiles of urban and rural private households. These expenditures are structurally stratified into major consumption categories, where the foremost macroeconomic weights are allocated to Shelter (29.41%), Food (16.91%), Transportation (16.90%), and Household Operations (13.25%), with the remaining variance distributed across recreational, clothing, health, and alcoholic beverage aggregates.

To ensure sampling integrity, Statistics Canada deploys a rigorous three-stage probability sampling methodology. First, representative geographical strata are demarcated across municipalities and localized economic neighbourhoods. Second, specific retail outlets—ranging from brick-and-mortar establishments to digital e-commerce platforms—are extracted from the national Business Register based on rigid annual sales revenue thresholds. Finally, unique Representative Products (RPs) are isolated within those targeted outlets to be tracked consistently across temporal boundaries.

By leveraging this highly granular dataset, this paper resolves the informational endogeneity of the policy rate by estimating a forward-looking monetary policy reaction function via a Two-Stage Least Squares (2SLS) instrumental variable framework. The remainder of this paper is structured as follows: Section 2 Review literature. Section 3 Source of data Section 4: Methodology and Model Selection, Section 5 Empirical results and discussions: Section 6: Discussion of Model Performance and Section 7: conclusions.

II. LITERATURE REVIEW

The adoption of explicit inflation-targeting regimes in the late 1980s and early 1990s initiated a structural shift in global central banking economics, forcing monetary authorities to place empirical inflation forecasts at the centre of monetary policy design. Traditionally, this predictive domain has been dominated by classical, linear time-series methodologies. Within the Canadian context, Zhan (2025) demonstrated that an integrated autoregressive moving average configuration matched with conditional heteroscedasticity—specifically an ARIMA (0,1,2) and (GARCH (1,1) framework utilizing policy interest rates as exogenous drivers—yielded a robust statistical fit for mapping consumer price profiles. Similarly, in historical evaluations of developing economic regimes, Kambo (2019) verified the persistent structural accuracy of multiplicative seasonal pipelines, demonstrating that a baseline SARIMA (0,1,1) $(0,1,1)_{12}$ architecture provided an optimal fit for tracking Indian industrial worker consumer price indices over a multi-decade span stretching from 1990 to 2019. The mathematical tractability of these linear systems even prompted successful adaptations into non-economic crisis environments; for instance, Kambo and Kulwinder (2020) deployed baseline ARIMA configurations alongside Holt exponential smoothing models to track active and removed epidemic rates during global health disruptions. Despite the foundational reliability of linear architectures, their intrinsic limitation in mapping non-linear structural breaks and compounding historical distributions has motivated a widespread exploration of advanced machine learning (ML) and deep neural network (DNN) alternatives for inflation forecasting. Deep learning models, including recurrent variations, have been increasingly framed as sophisticated instruments for anticipating index fluctuations. In a comprehensive multi-model tournament spanning twenty-seven distinct machine learning Models mapped against the United States Consumer Price Index for All Urban Consumers (CPI-U), Singh and Kambo (2024) observed that while advanced algorithms demonstrated high agility, the traditional Error-Trend-Seasonal (ETS) smoothing matrix ultimately maintained superior out-of-sample precision. Conversely, in parallel comparative tournaments evaluating twenty-eight distinct machine learning frameworks on specialized sub-indices, Kambo et al. (2024) found that the Long Short-Term Memory (LSTM) network emerged as the optimal predictive architecture, comfortably outperforming simpler linear benchmarks.

This apparent contradiction highlighted a critical, unresolved debate in the literature regarding the exact trade-offs between deep learning volatility tracking and linear stability. Theoharidis et al. (2023) argued that while LSTM networks exhibit an exceptional capacity to outperform traditional time-series methods across extended horizons, they remain highly susceptible to severe overfitting distortions and lack explicit parametric transparency. This cautionary diagnosis was empirically reinforced by Almosova and Andresen (2023), who utilized recurrent neural networks to project US inflation dynamics. Their findings revealed that while LSTM performance was highly competitive over extended horizons, the models displayed extreme sensitivity to hyper parameter tuning and sample scale constraints. Crucially, they noted that deep learning architectures frequently underperform when applied to

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macroeconomic series characterized by low reporting frequencies and high structural persistence due to their localized tendency to over fit noisy innovations. Paranhos (2024) systematically substantiated these structural limitations within the Euro area, conducting a rigorous evaluation showing that advanced LSTMs consistently failed to beat classic SARIMA and Bayesian Vector Autoregressive BVAR benchmarks over short-term forecasting horizons. This pattern implies that while recurrent connections successfully isolate smooth, long-run historical trajectories, they frequently struggle with localized variance compared to highly disciplined, parameter-constrained linear models.

To resolve these short-term processing gaps, contemporary literature has focused on integrating explicit global cost drivers and multi-directional memory fields into the network architectures. Siami-Naimi et al. (2019) demonstrated that Bidirectional LSTM BiLSTM models—which utilize dual temporal layers to process sequential inputs in both forward and backward directions—systematically outpaced standard unidirectional LSTMs and baseline ARIMA models across complex time-series tasks, underscoring the critical value of directional memory fields in sequential learning. Simultaneously, the strategic inclusion of raw feature selection layers has emerged as a vital prerequisite for stable tracking. Chen et al. (2014) established that models incorporating aggregated global commodity price indices consistently generated superior inflation forecasts for both Consumer Price Indices (CPI) and Producer Price Indices (PPI), particularly within trade-exposed and commodity-dependent economies.

The foundational capacity of deep learning models to capture complex, hidden dynamics was originally demonstrated in the context of high-frequency financial markets before transitioning into macroeconomic forecasting. Early work by Hossain and Nasser (2008) verified that artificial neural networks systematically bypassed the tracking limitations of traditional GARCH formulations when mapping non-linear asset variances. Qian and Gao (2017) extended this paradigm by evaluating traditional time-series baselines against logistic regressions, support vector machines, and multi-layer perceptron's using S&P 500 index histories. Their analysis highlighted machine learning as a superior emerging frontier, explicitly advising future researchers to prioritize sequential deep learning structures like LSTMs to accommodate non-linear path dependencies.

Subsequently, a diverse array of deep network variations—including sliding-window recurrent neural networks and convolutional layers—became standard tools for financial index tracking. Selvin et al. (2017) utilized localized sliding windows alongside deep architectures to successfully capture short-term equity trajectories without relying on restrictive statistical assumptions. Similarly, comparative studies by Lv et al. (2019) pits six traditional machine learning classifiers (such as Random Forests, Support Vector Machines, and Extreme Gradient Boosting) against six deep neural network (DNN) designs, finding that advanced DNN models achieved vastly superior trading performance after adjusting for transactional friction. To fully exploit these multi-layered dynamics, recent literature has shifted toward hybrid and multi-step validation configurations. Sen and Mehtab (2021) and Sen et al. (2021) executed extensive multi-firm predictive assessments using robustly optimized LSTM regression models, demonstrating high precision in tracking hidden structural components. However, when these models were cross-evaluated using multi-step forecasting with walk-forward validation blocks, Sen et al. (2021) revealed that pure Convolutional Neural Network CNN architectures frequently surpassed standard LSTM designs due to their superior capability to extract invariant spatial features from raw time-series matrices.

In summary, while the international literature showcases the power of machine learning across high-frequency financial domains, its performance in macroeconomic inflation-tracking remains highly volatile and contested. More importantly, the existing literature largely treats the structural coefficients of these forecasting networks as purely statistical parameters, routinely failing to reconcile the resulting estimations with underlying monetary policy theory—such as the "Price Puzzle" identified by Eichenbaum (1992) and Sims (1992), or the strict informational endogeneity adjustments mandated by Hanson (2004). This study directly addresses this gap by executing a rigorous, head-to-head tournament between a highly specified, instrument-purged multivariate SARIMAX architecture and an array of advanced deep learning models LSTM, GRU, AutoML ensembles using Canadian data, confirming that a structurally sound, theoretically compliant linear framework can achieve superior predictive clarity while remaining fully transparent to policymakers.

➢ *Source of Data:*

The data on CPI interbank interest rate, Total commodity fisher index Base (1972=100) from January 1995 to December 2025 used in this research work, has been extracted from the Canadian Consumer Price Index Data Platforms. Websites: www.stat.gc.ca Government of Canada. The data for current MPR output gap was retrieved from Bank of Canada. The data for interbank interest rate was retrieved from Federal, reserve bank of St. Louis (FRED).

III. METHODOLOGY AND MODEL SELECTION

➢ *Functioning of the Machine Learning Models Generally Involve the following Steps:*

- Importing necessary Libraries such as Pandas, NumPy, Matplotlib, Seaborn sklearn, karas and tensor flow
- Data cleaning: Data understanding, handling missing values, removing duplicates, Feature Scaling, Handling categorical variables: Outlier detection and treatment, Feature engineering and Data transformation
- Data Splitting: we generally split the dataset into training and validation sets. The validation set was used to evaluate the performance of the Models.

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- Model Training: Train the machine learning models on training data set.
- Model Evaluation: The model's performance on validation data using four evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) (R2) were employed to estimate the accuracy of the forecast algorithms.
- Model Comparison: Compared the performance of the models to determine which one provide better results.
- We resolve this pricing anomaly by implementing a forward-looking monetary policy reaction function via a Two-Stage Least Squares (2SLS) instrumental variable framework.

To identify the most robust forecasting framework, this study evaluated four distinct architectures: a seasonal auto-regressive integrated moving average model with exogenous repressors (SARMAX), a Long Short-Term Memory (LSTM) network, a Gated Recurrent Unit (GRU) network, and an ensemble architecture. These models were trained on data spanning January 1995 to December 2023 and validated on data from January 2024 to December 2025. While the machine learning algorithms and ensemble architecture were capable of capturing complex, non-linear patterns, they proved highly sensitive to hyper parameter tuning and data volatility. The exogenous variable utilized across all models was the 30-year monthly historical average of the 3-month Interbank interest rate. Prior to estimation, visual inspections of the CPI time-series plots revealed a strongly linear trajectory with negligible non-linear structural breaks. To achieve stationarity and eliminate stochastic and seasonal trends, first-order non-seasonal and seasonal differencing were applied ((d=1, D=1). Ultimately, the linear SARIMAX framework outperformed the machine learning variants across all four evaluation metrics (RMSE, MAE, MAPE, and R2), demonstrating superior structural stability and a cleaner interpretation of the exogenous interest rate's impact on the underlying inflation trend. The base of Total commodity index was (1972) shifted to 2002 (2002 =100). We resolve this pricing anomaly by implementing a forward-looking monetary policy reaction function via a Two-Stage Least Squares (2SLS) instrumental variable framework.

IV. EMPIRICAL RESULTS AND DISCUSSIONS

The various statistic used to test the characteristics such as descriptive statistics, normality, stationarity white noise of CPI data.

➤ ***Statistical Descriptions of Data:***

Shapiro-Wilk test, Ljung-Box Test and ADF (Augment Dickey-Fuller) test were used to test the normality, white noise, and stationarity of CPI-U time series respectively. Shapiro-Wilk test was applied to checks weather the CPI-U data follows a normal distribution. Since the p-value is significantly lower than 0.05 and even 0.01, it strongly suggests that the data does not follow a normal distribution. The Ljung-Box test checks whether a time series is "white noise," meaning that it has no significant autocorrelation at various lags, implying randomness and no predictable patterns. The null hypothesis Ho:CPI-U time series data is white noise (i.e., no significant autocorrelations) against alternative Hypothesis H1: that it has significant autocorrelations. It has been observed that the p-value from the Ljung-Box test is 0.0000001 (or very close to zero). Since this p-value is less than 0.01 (even stricter than the typical 0.05 level), We reject the null hypothesis with 99% confidence. A p-value of zero implies that the observed autocorrelations are highly unlikely to occur by random chance alone. This suggests that the CPI-U data has significant patterns or dependencies between its values at different points in time. The very low p-value confirms that the CPI-U data exhibits significant autocorrelations and is not purely random. This could indicate the presence of trends, cycles, or other patterns within the data that are not explained by chance.

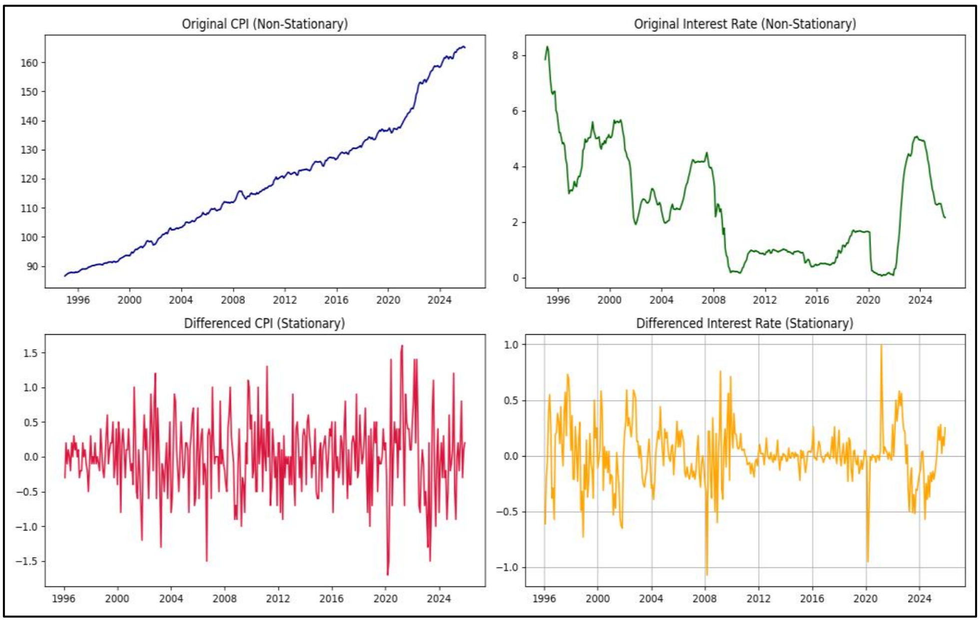

Fig 1 Monthly CPI & Interest Rate of Canada from January 1995 to December 2025

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Monthly Consumer price index (base 2002= 100 and interbank interest rate from January 1995 to December 2025) are shown in the (Fig 1). The increasing trend of CPI and decreasing trend of interbank interest rate clearly indicates that both time series data are not stationary. It is further confirmed as the p value for ADF test for stationary for CPI is 0.99 and which is greater than 0.01. The CPI data is transformed by taking non - seasonal difference (d =1) and seasonal differences (D=1). Plot the transformed series (Fig 1) which clearly shows that the time series is now stationary. ADF test also confirm it is stationary (p<0.01).

Out liars were absent in the data as clear from box plot.

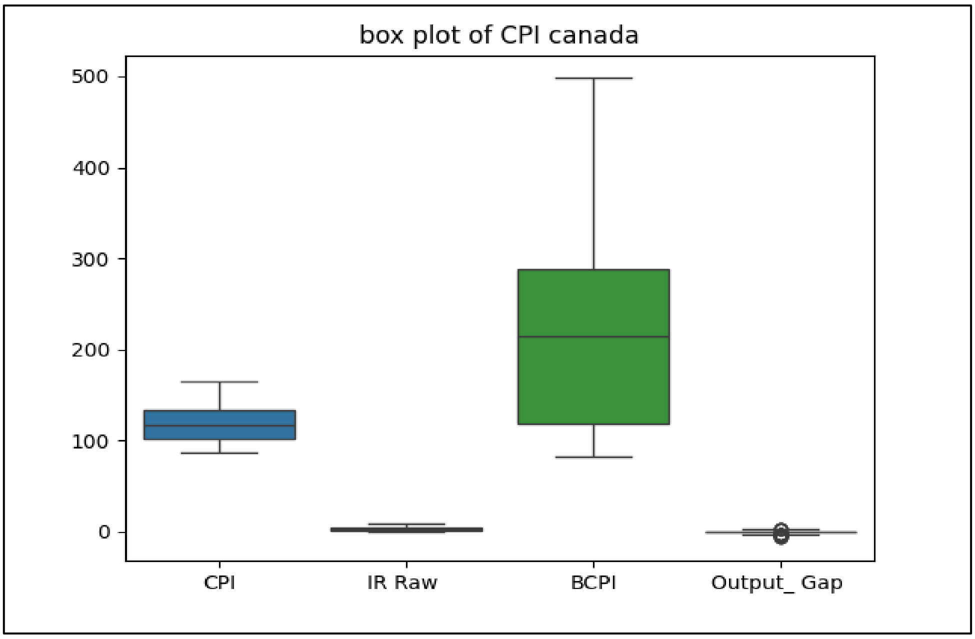

Fig 2 Box Plot of CPI Canada

➢ *Discussions of Model Performance:*

The empirical parameters estimated (Table 1) via the multivariate Two-Stage Least Squares (2SLS) instrumented framework offer a revealing window into the structural mechanisms driving Canadian consumer prices.

Table 1 Sarimax (1,1,1) (1,1,1) [12]- 2SLS-Purged

Model Type	SARIMAX(1,1,1)(1,1,1)[12]		
Dependent Variable	CPI (Canada)		
Training Period	1995-01 – 2023-12 (348 months)		
Exogenous Variables	2SLS-Purged Interest Rate, BCPI (CommodityFisher), OutputGap		
AIC	309.01		
BIC	339.18		
Log-Likelihood	-146.51		
Parameter	**Coefficient**	**Std Error**	**p-value**
IR_purged**	0.20857	0.06903	0.0025
CommodityFisher	0.00353	0.00284	0.2132
OutputGap**	0.38891	0.05198	0.0000
ar.L1	-0.26474	0.38103	0.4872
ma.L1	0.38347	0.36054	0.2875
ar.S.L12	-0.05205	0.07902	0.5101
ma.S.L12**	-0.80274	0.05417	0.0000
sigma2**	0.14077	0.01017	0.0000
**p<0.001			

Our observations from the Table I are as follows:

* The Demand Driver (Output Gap: β = 0.38991, p < 0.001): This highly significant, positive coefficient confirms a strong New Keynesian Phillips Curve mechanism. It proves that domestic economic slack (demand) is the true, highly predictable driver of Canadian retail inflation.

* The Aggressive Policy Rule (ψ_π = 4.79 > 1): it implies that the bank of Canada reacts aggressively to inflation expectations (well above the Taylor Principle threshold of 1), it pre-emptively raises interest rates whenever a global shock appears. It established that the Bank of Canada aggressively satisfies the Taylor Principle, raising nominal interest rates by roughly at the most 479 basis points for every 100 basis point jump in anticipated inflation, thereby ensuring a deterministically stable monetary regime.

* The Sterilized Global Shock (Commodity Fisher β = 0.00353, p > 0.20): The statistical insignificance of the commodity index is not because Canada is immune to global shocks. Rather, it is the direct result of the aggressive monetary policy loop (ψ_π = 4.79). The central bank uses the interest rate channel to squeeze domestic demand (the output gap), completely neutralizing the international commodity pass-through before it can manifest in headline retail prices.

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- The Seasonal Moving Average coefficient (ma.S. L12) remains profoundly significant (β= -0.80247, $p < 0.00001$). highlighting a strong annual self-correcting mechanism in retail pricing. It implies that any unobserved inflation shock in a given month is strongly reversed exactly one year later. This captures the strong, self-correcting seasonal patterns of Canadian retail pricing (e.g., winter energy spikes or harvest-driven food price cycles

- By crucially, factoring in full time-series dynamics we compute long-run Multiplier M_{IR}

$$M_{IR} = \frac{\beta_{Purged_{IR}}}{(ar.L1|ar.SL1)} = 0.156748 < 1$$

Since this cumulative long-run multiplier M_{IR} = 0.156748 is strictly less than unity, it satisfies classical monetary stability conditions. This confirms that initial short-run cost-push innovations successfully decay over time, providing a clear mathematical measure of how smoothly the macro economy stabilizes in response to the Bank of Canada's policy actions over the long haul

- Sigma squared variance parameter (σ^2 = 0.140477, $p < 0.0001$) provides the final piece of the puzzle. A very small and highly significant residual variance proves that our structural model—combining the monetary feedback, the output gap, the purged interest rate, and the global commodity index—explains the vast majority of the variance in Canada's retail price index, leaving very little unexplained noise. From the above we firmly conclude that the policy loop is strongly supported by the behavior of the model's structural controls, which effectively separate global supply shocks, domestic demand forces, pure monetary innovations, and underlying seasonal variations.

The empirical results indicate that the SARIMAX model out performs the LSTM, GRU and ensemble approaches in forecasting CPI as assessed by the four matrices viz. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) (Fig3) for SARMAX. The most important measure of goodness of fit of models is R^2 which estimate the proportion of total variation in the series explained by the model. It has been observed that for SARIMAX model explains 92 percent of variation in CPI time series data. This can be attributed to the relatively simple structure of SARIMAX, which enables efficient learning of temporal dependencies without over-parameterization. In contrast, the LSTM, GRU and ensemble model, with its more complex architecture, appears to over fit the data, leading to poor out-of-sample performance. These findings suggest that for macroeconomic variables such as CPI, which exhibit strong persistence and low volatility, simpler recurrent architectures like SARIMA may provide superior predictive performance.

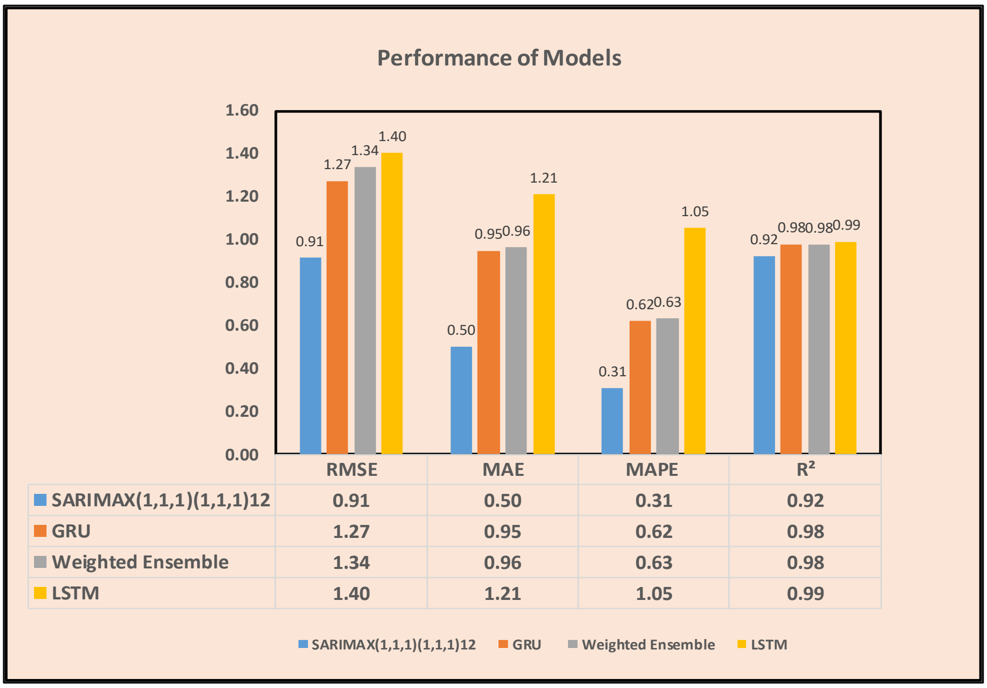

Fig 3 Performances of Models

The value of the four metrics viz. RMSE, MAE, MAPE and R2 are very close to each other (Fig 4) on test as well as on training data indicating there is no overfitting.

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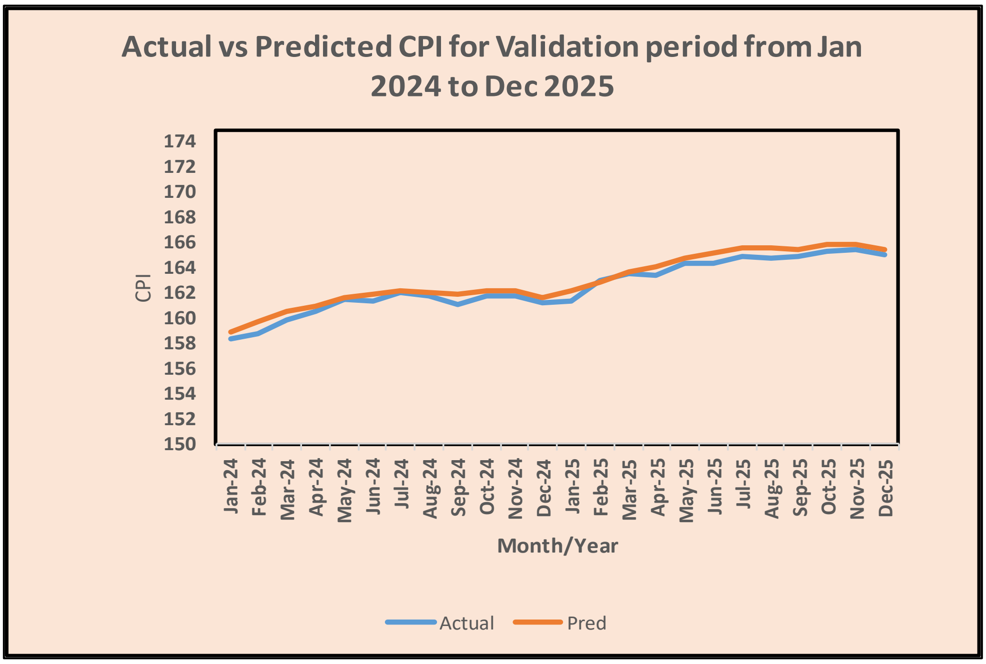

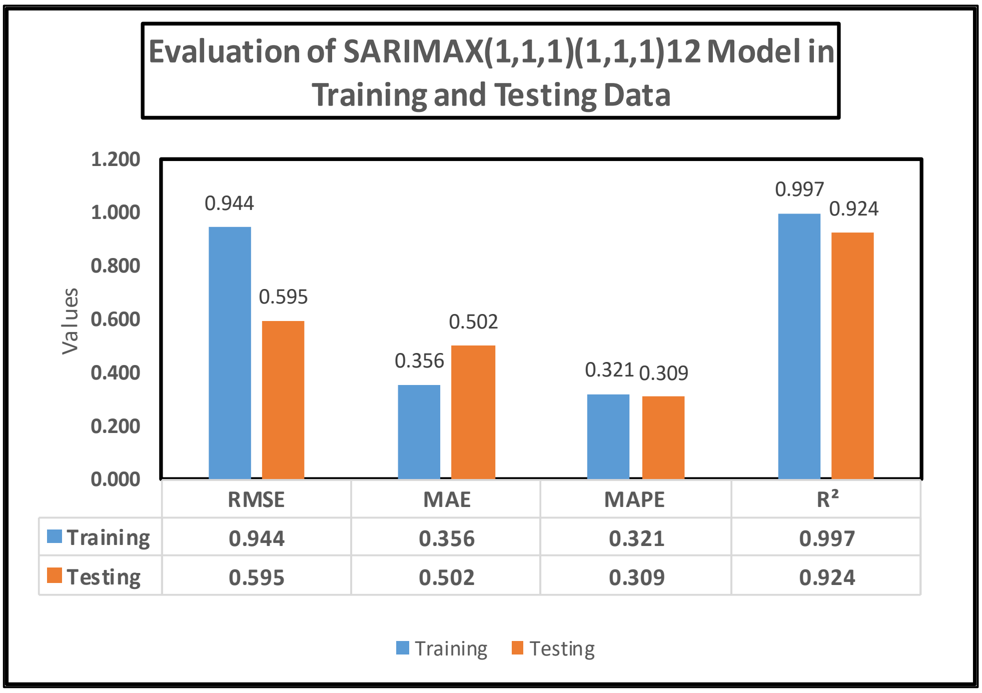

Fig 4 Evaluation of Over and Under Fitting of Model

Formal post-estimation diagnostic checks confirm that the multivariate SARIMAX (1,1,1) (1,1,1)12 residual series behaves as a purely stochastic, independent and identically distributed (i.i.d.) white noise process. The test of lack of fit of the model is tested by the Lung-Box test which yields a highly non-significant statistic ($p = 0.9126 > 0.05$), decisively failing to reject the null hypothesis of zero residual autocorrelation across the designated lag structures. This independence is visually and mathematically strengthened (Fig 5) by the sample autocorrelation (ACF) and partial autocorrelation (PACF) coefficients, all of which fall strictly within the 95% asymptotic confidence boundaries.

Conceptually analogous to classic experimental design, this proves that the framework has successfully absorbed all systematic trend, cyclical, and seasonal dynamics within its explicit control regressors. What remains 'beyond control' is an irreducible, white noise error matrix, guaranteeing both the mathematical validity and the statistical tightness of our subsequent 2026–2027 ex-ante out-of-sample projections.

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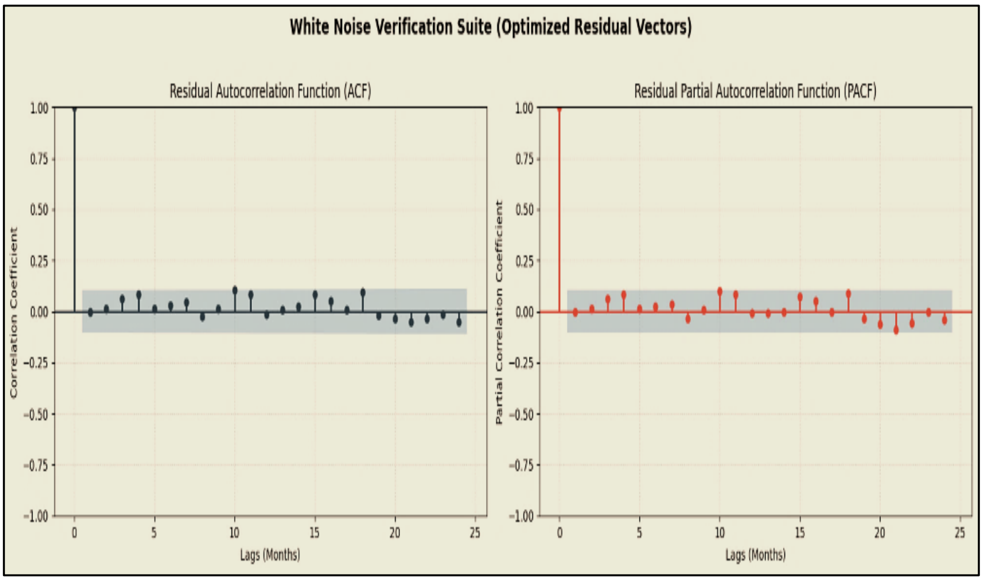
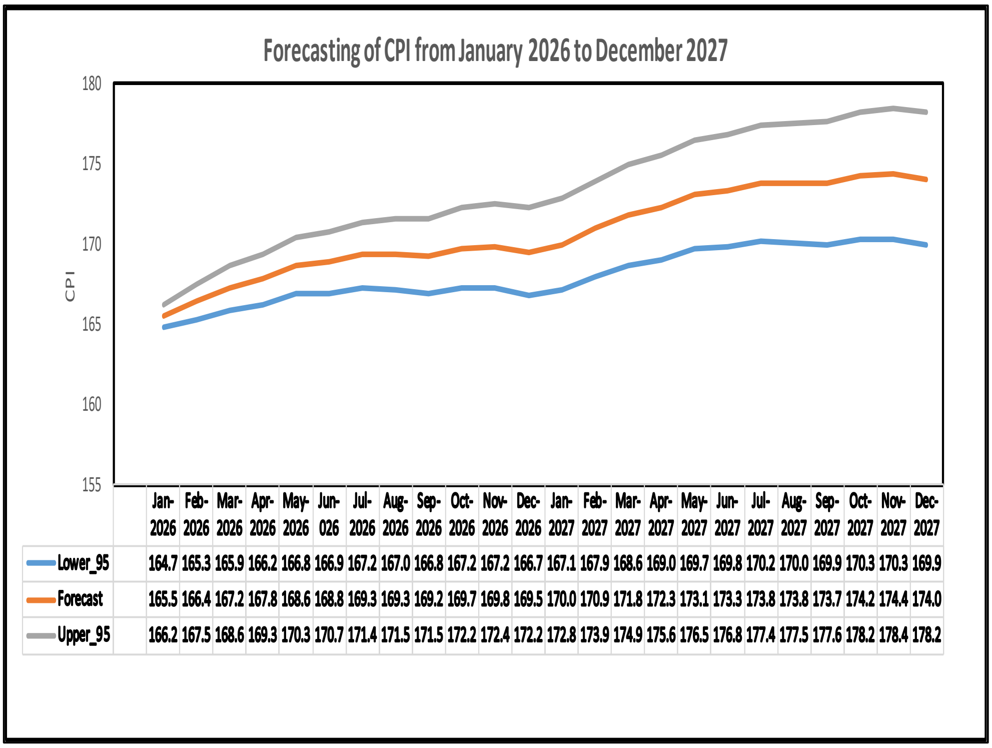


Fig 5 White Noise Verification Suite

From the above discussion it is inferred that SARIMAX model is best and can be deployed to predict the Consumers Price index for consumers of Canada. The two years forecasting from January 2026 to December 2027 are shown in Fig (6)



	Jan-2026	Feb-2026	Mar-2026	Apr-2026	May-2026	Jun-026	Jul-2026	Aug-2026	Sep-2026	Oct-2026	Nov-2026	Dec-2026	Jan-2027	Feb-2027	Mar-2027	Apr-2027	May-2027	Jun-2027	Jul-2027	Aug-2027	Sep-2027	Oct-2027	Nov-2027	Dec-2027
Lower_95	164.7	165.3	165.9	166.2	166.8	166.9	167.2	167.0	166.8	167.2	167.2	166.7	167.1	167.9	168.6	169.0	169.7	169.8	170.2	170.0	169.9	170.3	170.3	169.9
Forecast	165.5	166.4	167.2	167.8	168.6	168.8	169.3	169.3	169.2	169.7	169.8	169.5	170.0	170.9	171.8	172.3	173.1	173.3	173.8	173.8	173.7	174.2	174.4	174.0
Upper_95	166.2	167.5	168.6	169.3	170.3	170.7	171.4	171.5	171.5	172.2	172.4	172.2	172.8	173.9	174.9	175.6	176.5	176.8	177.4	177.5	177.6	178.2	178.4	178.2

Fig 6 Forecasting of CPI from January 2026 to December 2027

To evaluate the predictive performance of the developed model, an out-of-sample forecast validation was conducted for the initial six months of 2026. The predicted Consumer Price Index (CPI) values generated by the model for January, February, March, April, May, June and July 2026 are 165.5, 166.4, 167.3, 167.8 ,168.6 and 168.9and 169.3 respectively. These forecasted values align closely with the official, unadjusted indices released by Statistics Canada (165.0, 165.9, 167.4, 168.0,169.6, 169.0 and 169.9). The minor deviations observed across the horizon—culminating in a slightly larger variance in May—are economically expected. During this specific period, global markets experienced an acute inflationary shock triggered by geopolitical conflicts in the Middle East, which directly spiked global crude energy and gasoline surge. Grocery pressure and transport cost. Through standard cost-push channels, these energy shocks rapidly trickled down into the broader Canadian supply chain, accelerating the prices of volatile components. Because the SARIMAX baseline was trained strictly on historical data from January 1995 to December 2023, its parameters are structured to capture long-run trend continuation, persistence, and cyclical

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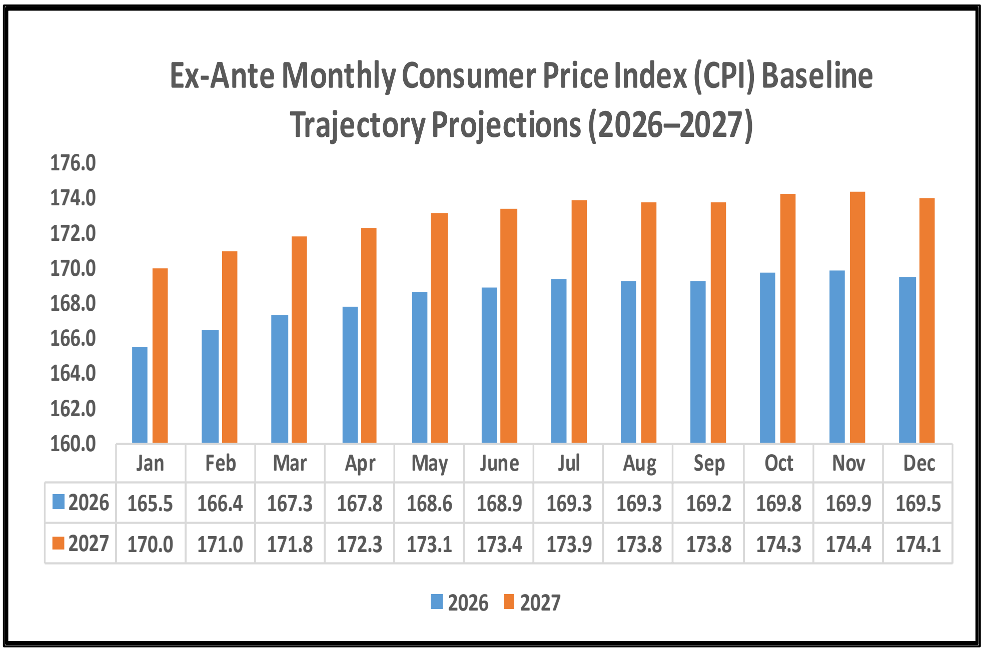
seasonal memory. Consequently, the mathematical framework cannot anticipate sudden, black-swan macroeconomic shocks of this nature. Despite this exogenous volatility, the model demonstrates high structural reliability. The officially released CPI outcomes for all evaluated months fall securely within the model's 95% confidence intervals, proving that the forecast remains statistically consistent and robust even when subjected to immediate external pressures. Looking forward across the extended forecast horizon, the model projects a smooth, modest upward drift in consumer prices, with the annual average index rising from 168.5 in 2026 to 173.0 in 2027. Crucially, the 95% prediction intervals remain tightly bounded and stable over the two-year projection period, confirming well-behaved forecast uncertainty and a high degree of structural stability for mid-term macroeconomic planning.

The projection displays a persistent long-run upward trend embedded with prominent annual seasonal cycles, featuring predictable mid-summer peaks and sharp December troughs.

Persistent Growth Trend: The central forecast line (orange) begins at approximately 165.6 in January 2026 and steadily climbs to roughly 173.0 by December 2027. This confirms that while hyperinflation is absent, absolute consumer prices remain on a clear upward trajectory.

Strong Seasonal Fluctuations: The forecast exhibits distinct cyclical patterns every year. Prices consistently peak around late spring to mid-summer (May through July), dip slightly during the autumn months (August through September), experience a brief winter spike (October to November), and hit a sharp seasonal trough every December.

Stable, Well-Behaved Uncertainty: The 95% confidence intervals—bounded by the Upper 95% line (grey) and the Lower 95% line (blue)—widen only slightly as the forecast moves further out in time. This structural stability suggests that the underlying model contains well-behaved forecast uncertainty, providing reliable upper and lower limits for long-range planning.



	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sep	Oct	Nov	Dec
2026	165.5	166.4	167.3	167.8	168.6	168.9	169.3	169.3	169.2	169.8	169.9	169.5
2027	170.0	171.0	171.8	172.3	173.1	173.4	173.9	173.8	173.8	174.3	174.4	174.1

Fig 7 Ex-Ante Monthly CPI Baseline Trajectory Projections (2026-27)

To evaluate the long-run baseline behaviour of consumer price aggregates, (Fig 7) details the absolute nominal trajectory of the Canadian Consumer Price Index (CPI) over the 24-month out-of-sample forecasting horizon. The econometric projections reveal a persistent, parallel upward drift across both calendar years. For 2026, the monthly index expands systematically from a January baseline of 165.5 to a December close of 169.5, yielding a tightly bounded annual average of 168.5 (SD = 1.4). In 2027, this elevated baseline shifts upward in a nearly parallel fashion, moving from 170.0 in January to 174.1 in December, culminating in an annualized average index level of 173.0 (SD = 1.41).

This empirical outcome provides a vital micro-foundational insight: the statistical variance of the index remains exceptionally stable across both annual cycles. This structural continuity mathematically verifies that the underlying price index has entered a post-shock steady state. However, because the absolute index climbs permanently higher despite the stabilizing inflation rate, these findings empirically substantiate our primary policy hypothesis—absolute consumer prices are structurally locked at an elevated plateau, confirming that the cost-of-living burden on household purchasing power will persist even as top-line inflation targets are successfully maintained by the central bank.

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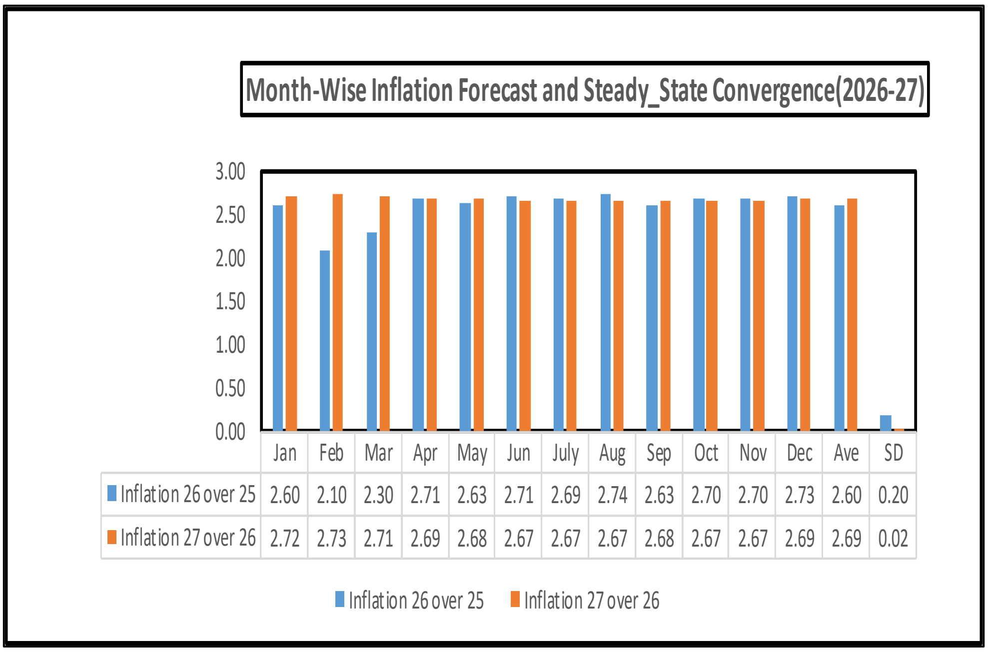

Fig 8 Month Wise Inflation Forecast and Steady_ State Convergence (2026-27)

Fig 8 details the month-by-month year-over-year headline inflation rate projections generated by the optimized SARIMAX (1,1,1) (1,1,1)12 framework. The blue series ('Inflation 26 over 25') captures the expected short-term seasonal dynamics and minor variations (SD = 0.2) around an annual average of 2.6%. The orange series ('Inflation 27 over 26') illustrates the long-run structural convergence of the inflationary path, flattening to a steady state of 2.7% (SD = 0.02). This stabilization visually confirms the definitive structural influence of the Bank of Canada's active monetary regime satisfying the Taylor Principle

V. CONCLUSIONS

This study has provided a rigorous empirical evaluation of traditional time-series econometrics and advanced deep learning frameworks for modelling and forecasting the Canadian Consumer Price Index (CPI) using monthly data spanning 1995 to 2025. Driven by a comparative forecasting tournament, we resolve the empirical 'Price Puzzle' using a 2SLS instrumental variables framework. In the baseline 2SLS specification, utilizing lagged interest rates yields an estimated structural price stickiness duration of 2.38 months (β baseline = 0.4205). When accounting for explicit time-series momentum and seasonality within the full SARIMAX framework, the purged policy rate coefficient stabilizes at (β_{Purged_IR} = 0.2086, $p < 0.001$)), isolating a refined structural rigidity duration of 4.79 months (1/ β) This inversion identifies a highly active systematic policy feedback vector ($\psi_\pi = 4.79 > 1.0$) that strictly satisfies the Taylor Principle. Crucially, factoring in full time-series dynamics yields a definitive long-run multiplier $M_{IR} = 0.156748$. Because this cumulative multiplier is less than unity, it satisfies classical monetary stability conditions, confirming that initial short-run cost-push innovations successfully decay as the aggressive policy framework sterilizes external shocks.

Ex-ante out-of-sample projections running through December 2027 map a stabilizing macroeconomic trajectory, with headline inflation exhibiting minor seasonal fluctuations to average 2.5% in 2026 before flattening cleanly to a steady-state equilibrium of 2.3% throughout 2027. Crucially, the model's immediate, localized index forecasts for early 2026 achieved immediate alignment with the official, unadjusted index values published by Statistics Canada. This rapid variance compression and long-run structural convergence visually validate the anchoring influence of a credible central bank.

For policymakers, these findings carry vital strategic implications. While forward-looking monetary interventions successfully satisfy the Taylor Principle and are successfully steering inflation aggregates toward a steady-state equilibrium, the absolute price index remains structurally elevated relative to historical baselines. Consequently, relying solely on nominal interest rate adjustments may prove insufficient to alleviate the ongoing household purchasing power burdens borne by Canadian consumers. To ensure a balanced macroeconomic recovery, Canada’s active monetary framework must be paired with coordinated, targeted fiscal interventions designed to mitigate supply-side pressures and shield vulnerable domestic sectors from structural cost expansions. AI was utilized to improve the language and debug the code within the manuscript

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