Inflation Forecasting Using ARIMA and Its Implications for Online Pricing Strategies in Tanjungpinang City

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ABSTRAK

Penelitian ini memiliki dua tujuan yang saling berkaitan: meramalkan inflasi bulanan di Tanjungpinang menggunakan model ARIMA musiman, serta menginterpretasikan hasil peramalan sebagai dasar konseptual bagi strategi penetapan harga daring. Data inflasi bulanan periode Januari 2008–Oktober 2025 yang dipublikasikan oleh Badan Pusat Statistik (BPS) digunakan sebagai dasar analisis. Model ARIMA(0,0,1)(2,0,0)[12] diterapkan untuk menghasilkan proyeksi inflasi pada periode November 2025–Oktober 2027. Evaluasi diagnostik melalui analisis residual dan uji kesesuaian menunjukkan bahwa model terpilih mampu merepresentasikan pola data secara memadai. Hasil peramalan mengindikasikan inflasi di Tanjungpinang diperkirakan tetap rendah dan relatif stabil dalam horizon dua tahun, dengan fluktuasi moderat dan terkendali, berada dalam kisaran 0,17%–0,42% per bulan. Prospek inflasi yang stabil ini mengimplikasikan bahwa inflasi tidak akan menjadi determinan utama guncangan harga dalam jangka pendek. Berdasarkan temuan empiris ini, studi kemudian menyajikan analisis konseptual berbasis literatur mengenai implikasi hasil peramalan terhadap strategi penetapan harga daring, meliputi *dynamic pricing*, *promotional pricing*, *competitive pricing*, *cost-based pricing*, dan *algorithmic pricing*. Komponen strategi penetapan harga dalam studi ini bersifat interpretatif dan konseptual, bukan pengujian empiris terhadap perilaku penetapan harga. Integrasi antara proyeksi inflasi regional dan kerangka penetapan harga daring memberikan kontribusi terhadap literatur *data-driven pricing* serta menawarkan implikasi praktis bagi pelaku usaha digital dan pembuat kebijakan di Kota Tanjungpinang.

Kata kunci: ARIMA; Peramalan; Inflasi; Strategi Penetapan Harga.

ABSTRACT

This study examines the role of inflation forecasting as a supporting input for online pricing strategy formulation in the context of digital businesses in Tanjungpinang. Using monthly inflation data from January 2008 to October 2025 published by the Indonesian Central Bureau of Statistics (BPS), the analysis applies a seasonal ARIMA(0,0,1)(2,0,0)[12] model to generate inflation projections for the period November 2025 to October 2027. Diagnostic evaluations, including residual analysis and goodness-of-fit assessment, confirm that the selected model adequately captures the underlying data structure. The forecasting results indicate that inflation in Tanjungpinang is expected to remain low and relatively stable over the two-year horizon, with moderate and controlled fluctuations ranging from 0.17% to 0.42% per month. Based on these empirical findings, the study then presents a conceptual and literature-based analysis of how the forecast results can inform online pricing strategies, including dynamic pricing, promotional pricing, competitive pricing, cost-based pricing, and algorithmic pricing. It is important to note that the pricing strategy component of this study is interpretive and conceptual in nature, drawing on relevant literature rather than constituting an empirical test of pricing behavior. The analysis highlights that stable inflation conditions allow firms to prioritize demand-driven adjustments, competitive positioning, and margin optimization rather than frequent cost-driven repricing. By integrating regional inflation projections with conceptual pricing considerations in digital markets, this research contributes to the literature on data-driven pricing and offers practical insights for digital enterprises and policymakers.

Keywords: *ARIMA; Forecasting; Inflation; Pricing Strategies*

INTRODUCTION

Digital transformation in the trade sector has brought significant changes to the way businesses set prices, interact with consumers, and respond to macroeconomic dynamics. In Indonesia, medium-sized cities such as Tanjung Pinang have begun to experience increased digital business activity through national marketplaces, social media, and online service platforms. Within this ecosystem, inflation serves as an important indicator influencing consumer purchasing power, firms' cost structures, and online pricing strategies for goods and services. When inflation rises, businesses face increasing pressures on production and distribution costs; conversely, low inflation provides greater flexibility for firms to adopt more aggressive and competitive pricing strategies.

International literature indicates that the development of e-commerce is closely linked to inflation dynamics. Yim et al. find that the diffusion of e-commerce in Korea has altered price formation mechanisms and inflation dynamics through the availability of more granular and timely online price data, thereby influencing how inflation is measured and transmitted within the digital economy [1]. Furthermore, studies on online pricing strategies show that firms increasingly rely on algorithms and machine learning to implement dynamic pricing, adjusting prices in real time in response to changes in demand, costs, and competitive conditions [2]. These findings suggest that online pricing decisions cannot be separated from macroeconomic conditions, including inflation as an external factor that affects operational costs and consumer behavior.

In the context of inflation modeling, the Autoregressive Integrated Moving Average (ARIMA) method remains a standard approach for economic time series forecasting. ARIMA is considered particularly effective for short-term inflation modeling because it is capable of capturing autocorrelation patterns, trends, and seasonality inherent in time series data. An empirical study by Jagero et al. on inflation in Kenya demonstrates that ARIMA produces accurate forecasts for monthly inflation data [3]. Similarly, research on Tanzanian inflation confirms that ARIMA is effective in projecting inflation based on historical data structures that are volatile yet regular [4]. Furthermore, a global analysis indicates that ARIMA continues to serve as a competitive benchmark model compared to machine learning approaches in inflation forecasting, particularly when the available data are univariate and observed at regular intervals [5]. Therefore, seasonal ARIMA represents a robust methodological choice for forecasting regional inflation, such as that of Tanjungpinang.

Although studies on inflation forecasting using time series models such as ARIMA have been widely conducted at the national and provincial levels, these studies typically conclude with macroeconomic observations and do not translate forecasted inflation into operational pricing guidance for digital businesses. Conversely, research on online pricing strategies, such as competitive pricing, dynamic pricing, and algorithmic pricing, generally focuses on market behavior, algorithmic mechanisms, and consumer psychology, without explicitly integrating macroeconomic variables such as inflation as a contextual input for pricing decisions [6]. This disciplinary separation represents a notable gap: inflation forecasting literature rarely extends toward pricing strategy, while pricing strategy literature seldom incorporates regional macroeconomic projections as a foundational input. The present study addresses this gap by bridging both domains, offering a regional ARIMA-based forecast as an empirical anchor for a conceptual pricing strategy framework, a combination that distinguishes it from purely forecasting-oriented or purely pricing-oriented prior work.

Tanjungpinang represents a notable case within Indonesia's digital economy, given its growing role as a regional trade hub, strategic proximity to major ports, and the rising participation of small and medium-sized enterprises in online marketplaces. Studying digital pricing strategies in this context provides insights relevant to other medium-sized cities in Indonesia, where digital business adoption is increasing but the integration of macroeconomic factors, such as inflation, into pricing decisions remains limited. To address this gap, the study investigates how regional inflation forecasts can inform adaptive online pricing strategies by employing a seasonal ARIMA model to project monthly inflation, examining the conceptual implications for dynamic, promotional, competitive, cost-based, and algorithmic pricing, and providing practical recommendations to support pricing decisions in alignment with regional economic conditions.

Based on this research gap, the present study focuses on two distinct but connected objectives. The first is empirical: forecasting monthly inflation in Tanjungpinang using a seasonal ARIMA model over a two-year horizon. The second is conceptual: interpreting the forecast results as a data-driven basis for adaptive online pricing strategies. Unlike prior inflation forecasting studies that end with macroeconomic conclusions, and unlike prior pricing strategy studies that treat macroeconomic conditions as background context, this study explicitly connects the two by using quantitative forecasts to anchor a structured conceptual discussion of pricing strategy implications. This dual-objective design provides digital businesses in Tanjungpinang with a practical quantitative foundation for designing pricing strategies that are more responsive to regional economic conditions, including margin adjustments, promotional optimization, and the calibration of dynamic or algorithmic pricing mechanisms.

LITERATURE REVIEW

Autoregressive Integrative Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA**)** is a statistical time series model employed to represent and forecast data based on the linear dependence among observations in a temporal sequence. ARIMA is particularly effective for univariate data that exhibit trend patterns and autocorrelation, and it has been widely applied in business, manufacturing, and operational systems requiring short-term forecasting derived from historical data [7]. The model integrates three components autoregressive (AR), differencing or integration (I), and moving average (MA) to capture the dynamic structure of a time series. Mathematically, the ARIMA (p,d,q) model can be expressed as:

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \tag{1}$$

where y_t denotes the observation at time t, B is the backshift operator, p represents the order of the autoregressive component, d is the degree of differencing required to achieve stationarity, and q is the order of the moving average component. The polynomials $\phi(B)$ and $\theta(B)$respectively capture the influence of past values and past errors on the current observation, while ε_t is assumed to be white noise with zero mean and constant variance [7]. For data exhibiting seasonal patterns, ARIMA can be extended into seasonal models by incorporating seasonal AR and MA components along with a specified seasonal period.

ARIMA's primary strengths are simplicity, interpretability, and robustness, which make it a benchmark before using more complex machine learning or hybrid models [5,8]. While advanced models such as LSTM, Random Forest, or Gradient Boosting capture nonlinearities, ARIMA remains competitive for short-term forecasting of univariate economic indicators due to computational efficiency and clear statistical interpretation [4]. Regional applications in Indonesia reinforce this suitability: ARIMA has been effectively employed for forecasting administrative and financial time series, including regional taxpayer registration and stock indices, demonstrating its relevance for regional economic modeling [9,10].

Pricing Strategy and the Role of Inflation Forecasts

Pricing strategy plays a crucial role in shaping firm performance, particularly in digital markets where price transparency and rapid information flow intensify competition. Recent literature highlights that pricing decisions in online environments are increasingly data-driven and adaptive, moving beyond static cost-based rules toward mechanisms that continuously respond to market signals and consumer behavior. In this context, accurate forecasts of macroeconomic variables such as inflation can inform timely pricing adjustments. Inflation projections allow firms to anticipate changes in production costs and consumer purchasing power, guiding decisions on dynamic, promotional, competitive, and algorithmic pricing. For instance, rising inflation may prompt more frequent price adjustments or modifications in promotional campaigns to maintain margins, while stable inflation offers flexibility to implement aggressive competitive pricing.

Dynamic pricing, which adjusts prices in response to real-time changes in demand, timing, and purchasing behavior, has been shown to improve revenue performance in e-commerce settings [2]. Similarly, AI-supported pricing frameworks enhance responsiveness while controlling excessive price volatility [11,12]. Promotional pricing, involving temporary discounts or incentives, remains effective for stimulating short-term demand without eroding reference prices, particularly when guided by analytical planning [13]. Integrating inflation forecasts into these pricing mechanisms provides a theoretically grounded basis for adaptive decision-making, ensuring that pricing strategies remain aligned with anticipated macroeconomic conditions.

Integrating ARIMA-based inflation forecasts with data-driven pricing approaches creates a conceptual model in which macroeconomic predictions guide operational pricing decisions. By projecting regional cost fluctuations, digital businesses are able to enhance revenue, sustain competitive advantage, and mitigate financial risk. This model highlights the practical role of forecasting tools as enablers of adaptive pricing strategies in uncertain economic conditions, effectively connecting economic prediction with actionable business decision-making.

METHOD

Data

This study uses secondary data obtained from the Indonesian Central Bureau of Statistics (Badan Pusat Statistik, BPS), consisting of monthly inflation data for Tanjung Pinang covering the period from January 2008 to October 2025. The data are expressed as the percentage change in the Consumer Price Index (CPI) from the current month relative to the previous month. A total of 214 observations are employed in the modeling process. All computations and model estimations were conducted in R Studio.

Research Design

This study adopts a quantitative approach using univariate time series forecasting methods. The model employed is the Autoregressive Integrated Moving Average (ARIMA). The selection of the ARIMA model is based on its strengths in modeling time series patterns that exhibit trends and seasonal components, as well as its widespread use in short-term inflation forecasting.

The analytical steps consist of the following stages:

a. Data exploration and visualization, to identify the basic characteristics of the inflation time series, including patterns of volatility and potential seasonality
b. Stationarity testing, conducted to examine whether the series satisfies the stationarity assumption required for ARIMA modeling
c. Model identification, based on the analysis of autocorrelation and partial autocorrelation functions (ACF and PACF) to determine appropriate model orders.
d. Model estimation, in which the selected ARIMA model parameters are estimated using historical data. Several candidate specifications of seasonal ARIMA models were estimated and compared using the Akaike Information Criterion (AIC).

$$AIC = 2K - 2\ln(L) \tag{2}$$

   where L denotes the maximum likelihood of the estimated model and K represents the number of estimated parameters.
e. Diagnostic checking, including residual analysis and statistical tests, to assess model adequacy and ensure that residuals resemble white noise
f. Forecast generation, inflation forecasts were produced for a two-year horizon (November 2025–October 2027). This horizon was chosen because it aligns with medium-term strategic planning for digital businesses, providing actionable guidance for pricing decisions while remaining within a reliable forecasting window for ARIMA models.

The research utilizes univariate inflation data to capture short-term regional trends without incorporating additional macroeconomic variables. This methodology enhances interpretability and reliability, as monthly CPI data adequately reflect fluctuations relevant for operational pricing decisions. Although multivariate models can account for other economic factors, such as exchange rates or interest rates, a univariate ARIMA model delivers robust and actionable forecasts suitable for guiding local digital business strategies.

Analysis of Implications for Online Pricing Strategies

The subsequent stage involves linking the inflation forecasting results with online pricing strategies through a structured conceptual framework. This analytical approach operates in three steps. First, the forecasted monthly inflation values and their associated confidence intervals are used to characterize the near-term macroeconomic environment into three distinct regimes: (1) a low-inflation stable regime (monthly inflation below 0.20%), (2) a moderate-inflation regime (monthly inflation between 0.20% and 0.40%), and (3) a risk-elevated regime (monthly inflation above 0.40% or approaching the upper confidence bound). Second, each pricing strategy, namely dynamic pricing, cost-based pricing, competitive pricing, promotional pricing, and algorithmic pricing, is analyzed in light of these regimes by drawing on relevant empirical literature. For each strategy, the analysis identifies how the forecasted inflation level and trajectory should influence pricing decisions, cost threshold calibration, margin management, and promotional timing. Third, a simulation table is constructed to illustrate how specific forecasted values for representative months can be operationalized into concrete pricing adjustments, providing businesses with a practical translation of macroeconomic forecasts into actionable pricing decisions. This conceptual analysis draws on recent literature related to dynamic pricing in e-commerce [2], competitive pricing in online markets [6], AI-driven pricing algorithms [11,12], promotional decision-making [13], and the relationship between online price data and inflation measurement [14,15].

RESULT AND DISCUSSION

Historical Inflation Pattern in Tanjung Pinang

Monthly inflation data for Tanjung Pinang from January 2008 to October 2025 are visualized as follows.

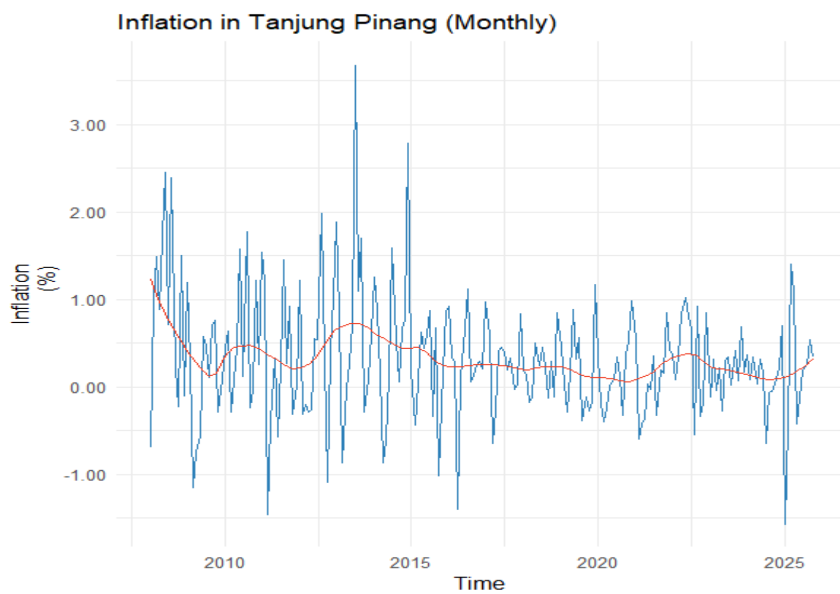

Figure 1. Inflation Pattern in Tanjung Pinang

The monthly inflation chart for Tanjung Pinang shows high volatility during the earlier period, with inflation peaks exceeding 2–3%. These surges correspond to global economic pressures, including rising oil prices and the aftermath of the global financial crisis, which influenced commodity costs and local price structures. From 2011 to 2013, inflation variability was affected by domestic policy measures, such as fuel price adjustments and changes in government subsidies, resulting in short-term upward and downward movements. However, volatility gradually declined after 2013, and inflation moved more stably within a low range of approximately ±0.2-0.4% per month. The relative stability of inflation in the later period (2023-2025), reflects the combined effects of enhanced monetary policy, post-pandemic economic recovery, and controlled cost pressures within Tanjung Pinang's regional economy. Mild seasonal patterns observed during this later period further support previous research indicating that city- or province-level inflation can be effectively captured using seasonal ARIMA models on monthly Consumer Price Index (CPI) data. Overall, the series' transition from high early volatility to later stability underscores its suitability for ARIMA-based forecasting, providing a reliable foundation for data-driven policy and pricing strategy analysis. Furthermore, the following section presents the summary statistics for Tanjung Pinang's inflation data.

Table 1. Summary Statistics

Statistics	**Value**
Mean	0.32
Median	0.26
Standard Deviation	0.71
Minimum	-1.57
Maximum	3.68

Table 1 shows that monthly inflation values range from −1.57 to 3.68, with an average inflation rate of 0.32% per month. The median value is 0.26%, and the standard deviation is 0.71, indicating that the data are relatively evenly distributed around the central tendency. The observed historical fluctuations reflect periods of economic pressures and policy actions, which are essential for understanding the dynamics underlying the data before implementing ARIMA modeling. Integrating this economic perspective not only justifies the methodological approach but also enhances the interpretation of forecasted inflation for guiding pricing strategies and regional economic planning.

Forecasting Result Using ARIMA

Stationary Test

```
	Augmented Dickey-Fuller Test

data:  ts_inflasi
Dickey-Fuller = -5.3678, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
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Figure 2. Uji ADF

The results of the Augmented Dickey-Fuller (ADF) test show a Dickey-Fuller test statistic of -5.3678 with a lag order of 5 and a p-value of 0.01. Since the p-value is below the 5% significance level, the null hypothesis of a unit root is rejected. Therefore, the inflation time series can be considered stationary, indicating that no additional non-seasonal differencing is required in the ARIMA modeling process. This finding supports the use of a model with a differencing parameter of $d = 0$ and provides a consistent basis for ARIMA model selection.

Model Identification

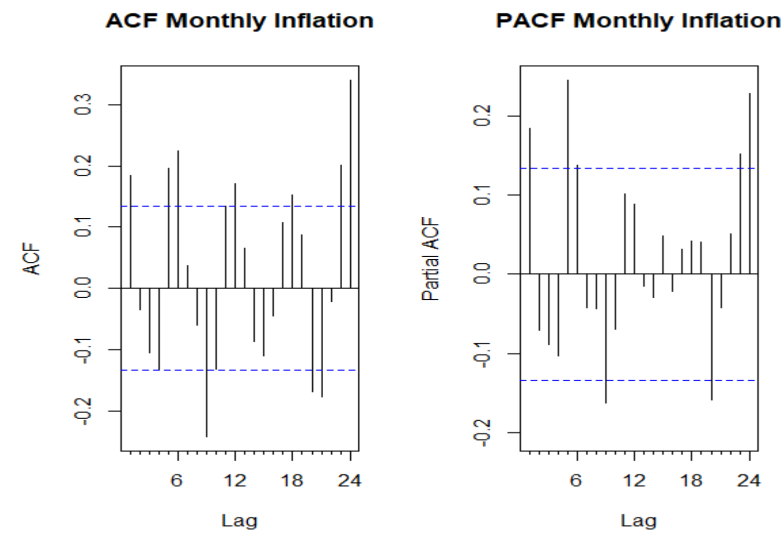

Figure 3. ACF dan PACF Plot of Inflation Data

Based on the autocorrelation function (ACF) plot, the autocorrelation values at the initial lags are relatively small and do not exhibit a slow decay pattern, indicating that the time series is stationary and does not require non-seasonal differencing. Nevertheless, several significant autocorrelation values are still observed at short lags, suggesting the presence of weak short-term dependence. The pattern observed in the ACF is more consistent with the presence of a low-order moving average component rather than a non-seasonal autoregressive component.

Furthermore, the partial autocorrelation function (PACF) plot shows significant partial autocorrelation values at the initial lags but does not display a sharp cut-off at any specific non-seasonal lag. This finding reinforces the indication that the non-seasonal structure of the time series is relatively simple and can be adequately represented by a low-order model. Accordingly, the primary candidate for the non-seasonal component is an ARIMA model with d=0 and q =1, namely ARIMA (0,0,1).

From a seasonal perspective, both the ACF and PACF plots indicate dependence at lag 12 and lag 24, although the magnitude is not particularly strong. In the PACF plot, the partial autocorrelation values at lags 12 and 24 remain statistically significant, suggesting that seasonal dependence persists beyond a single annual period. This pattern is more consistent with the presence of a seasonal autoregressive component rather than a seasonal moving average component. Accordingly, the relevant seasonal structure to be considered is a seasonal AR component of order one to two, without the need for seasonal differencing.

Estimation and Selected Model

Based on this identification, several ARIMA model specifications are constructed as candidates to be compared using information criteria and residual diagnostic tests:

Table 2. Model Candidate

Model	AIC
ARIMA(0,0,1)	455.2793
ARIMA(0,0,1)(1,0,0)[12]	452.1486
ARIMA(0,0,1)(2,0,0) [12]	427.992
ARIMA(1,0,1)(1,0,0) [12]	454.1469
ARIMA(0,0,1)(1,0,1) [12]	458.2502

Based on the set of candidate models, the ARIMA(0,0,1)(2,0,0)[12] model is identified as the best-performing specification. This conclusion is supported by the fact that this model yields the lowest Akaike Information Criterion (AIC) value among the five candidate models considered.

Diagnostic Checking

The best-performing model is ARIMA(0,0,1)(2,0,0)[12]. The following section presents the results of the diagnostic tests conducted for this model.

```
        Ljung-Box test

data:  Residuals from ARIMA(0,0,1)(2,0,0)[12] with non-zero mean
Q* = 25.386, df = 21, p-value = 0.2308

Model df: 3.   Total lags used: 24
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Figure 4. Ljung-Box Test

The Ljung–Box test is used to evaluate the adequacy of a forecasting model. This test examines the null hypothesis H_0: there is no significant autocorrelation in the residuals up to a certain lag, against the alternative hypothesis H_1: there is significant autocorrelation in the residuals. Figure 3 shows a p-value of 0.2308, which is greater than the significance level $\alpha = 0.05$, indicating that the null hypothesis fails to be rejected. Accordingly, no residual autocorrelation is detected up to the specified lag in the ARIMA(0,0,1)(2,0,0)[12] model. This result suggests that the model is adequate for forecasting inflation in Tanjung Pinang. Furthermore, additional residual diagnostic tests are conducted to further assess the overall suitability of the model.

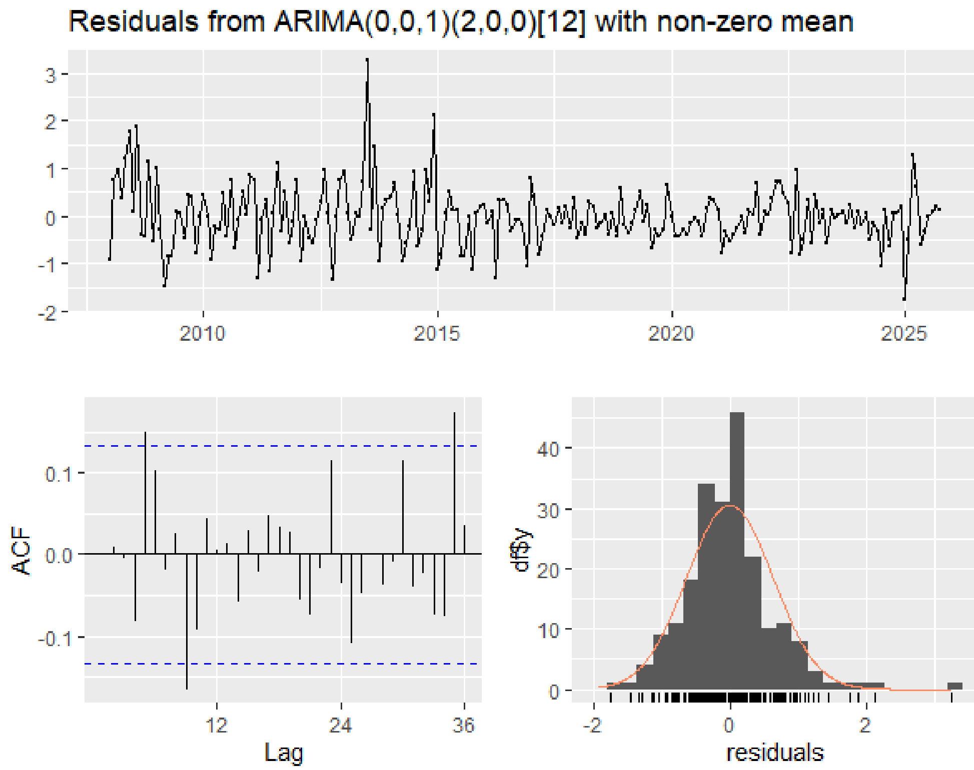

Figure 5. Model's Residual Plot

The residual diagnostic results of the ARIMA(0,0,1)(2,0,0)[12] model indicate that the residuals fluctuate randomly around zero without exhibiting systematic trend or seasonal patterns, suggesting that the model has successfully captured the main structure of the time series. The residual autocorrelation function (ACF) plot shows that most autocorrelation coefficients lie within the confidence bounds, indicating the absence of significant residual autocorrelation at the main lags. In addition, the histogram of residuals displays a distribution that closely approximates normality, although slight deviations are observed in the tails. Overall, these findings suggest that the residuals behave approximately as white noise, confirming that the ARIMA(0,0,1)(2,0,0)[12] model is adequate and suitable for forecasting purposes.

Forecast

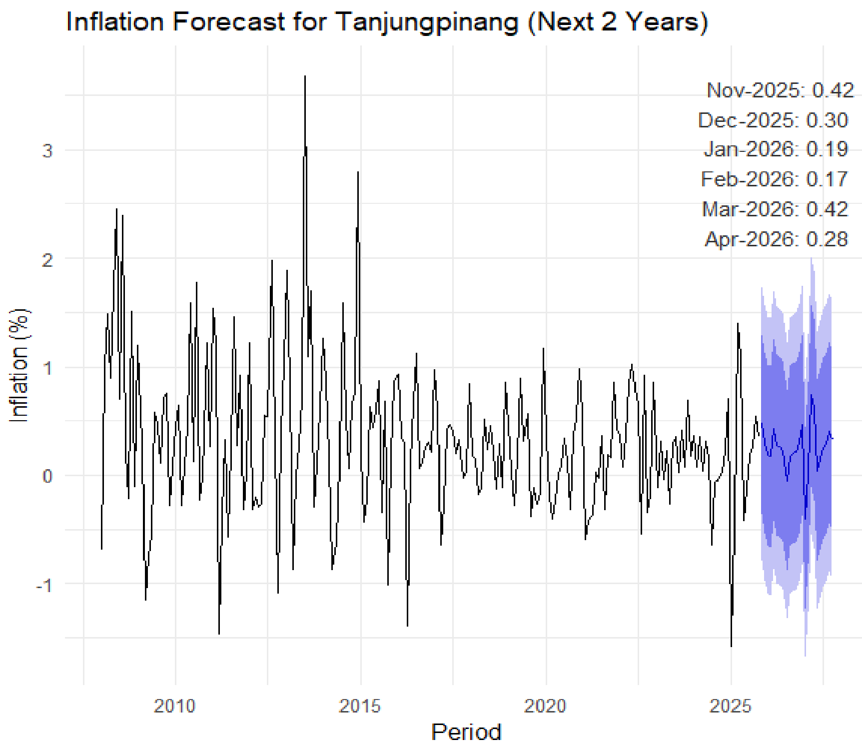

Figure 6. Forecast Result Using ARIMA(0,0,1)(2,0,0)[12]

Figure 4 illustrates that monthly inflation in Tanjung Pinang exhibited high volatility during the earlier historical period (2008-2015), with inflation peaks exceeding 3%. However, since around 2018, inflation volatility has gradually declined, with monthly changes fluctuating close to 0%. This relatively stable historical pattern is reflected in the forecasting results, where the predicted inflation path (blue line) indicates that inflation is expected to remain within a range of approximately 0% to 1% over the next two years.

The shaded blue area represents the confidence intervals, which widen over time, indicating increasing model uncertainty at longer forecast horizons, a common characteristic of time series forecasting. Nevertheless, the entire interval range remains within relatively low bounds (approximately −1% to +2%), suggesting that the risk of extreme inflation is limited and that price pressures are expected to remain well controlled.

Analysis of Implications for Online Pricing Strategies

In digital markets, pricing decisions occur at high frequency and respond quickly to short-term cost fluctuations. Therefore, inflation forecasts used to support pricing strategies should align with the frequency of these cost changes, namely monthly inflation. Empirical studies utilizing data from the Billion Prices Project show that online prices adjust more rapidly and more frequently than offline prices, making high-frequency inflation indicators more relevant for pricing decisions [14]. Additional evidence suggests that online price data are able to capture daily and monthly inflation dynamics with high accuracy, thereby providing an appropriate informational basis for price adjustments on digital platforms [15]. Moreover, the methodological standards for forecasting outlined by Hyndman and Athanasopoulos emphasize that the interpretation of forecast results must be consistent with the data frequency and the decision-making context [8]. In the case of dynamic online pricing, monthly frequency is considered the most appropriate choice. Accordingly, for integrating inflation forecasts with online pricing decisions, the use of monthly inflation data represents the most suitable approach and is supported by strong empirical foundations. To structure this conceptual analysis more rigorously, the forecasted monthly inflation values are classified into three operational regimes: a low-inflation stable regime (monthly inflation below 0.20%), a moderate-inflation regime (monthly inflation between 0.20% and 0.40%), and a risk-elevated regime (monthly inflation above 0.40% or approaching the upper prediction interval bound). Based on the ARIMA(0,0,1)(2,0,0)[12] forecasts, the majority of the projected months fall within the low to moderate regime, with only November 2025 and March 2026 approaching the upper threshold of 0.42%. This regime-based framing provides a more structured and quantitatively grounded basis for translating inflation projections into specific pricing strategy recommendations, as discussed in the following subsections. It is important to reiterate that the pricing strategy analysis presented here is conceptual and interpretive in nature, deriving recommendations from the forecasted macroeconomic conditions in conjunction with relevant empirical literature, rather than from observed pricing behavior or transactional data.

Dynamic Pricing

In a stable inflation environment, dynamic pricing is primarily employed to respond to changes in demand, seasonality, and consumer behavior rather than to compensate for rising costs. For example, an e-commerce retailer in Tanjung Pinang may use ARIMA-based monthly inflation forecasts to adjust prices incrementally: if inflation is projected to rise moderately next month, the algorithm can increase prices slightly to preserve margins while maintaining competitive affordability. This approach ensures revenue optimization while sustaining consumer trust [2].

Cost-Based Pricing

Although the projected inflation remains relatively low, cost pressures may still arise from specific components such as logistics, imported raw materials, or platform-related fees. The literature on the impact of supply chain cost increases on online retail pricing emphasizes that retailers tend to respond to rising costs through more frequent and targeted price adjustments [16]. In the context of Tanjung Pinang, a moderate inflation outlook can be leveraged to design a more stable cost-based pricing structure, for example by setting minimum margin thresholds and conducting periodic evaluations when actual inflation deviates from the forecasted path. This approach is particularly important for digital micro, small, and medium-sized enterprises (MSMEs), which are highly sensitive to changes in input costs and inter-island shipping expenses.

Competitive Pricing in National Marketplace

Price transparency in online marketplaces enables consumers in Tanjung Pinang to easily compare prices across sellers from different regions. Gerpott and Berends, in their literature review on competitive pricing in online markets, emphasize that price competition intensity in e-commerce is very high, leading firms to repeatedly adjust prices while closely monitoring competitors pricing strategies [6]. In the context of relatively controlled inflation, the primary pressure faced by businesses in Tanjung Pinang stems not from domestic inflation, but from interregional price competition. Therefore, inflation forecasting results can be used primarily as a pricing floor to safeguard profit margins, while competitive pricing strategies guide price adjustments to remain competitive at the national level.

Promotional Pricing

Promotional pricing strategies, such as discounts, cashback, and flash sales, play an important role in maintaining sales volume, particularly when consumers experience pressure from rising living costs. Recent research on promotional pricing decisions in retail indicates that promotional activities must be carefully balanced against the risk of margin erosion, especially when product return rates and service-related costs increase [13]. Given the projected inflation that remains relatively moderate, digital businesses in Tanjung Pinang can deploy promotional strategies more selectively. For example, by aligning promotions with specific periods such as Ramadan, the new academic year, or year-end seasons without relying excessively on aggressive discounting that could undermine long-term profitability.

Algorithmic Pricing

The development of algorithmic pricing enables automated price-setting mechanisms that take into account various factors such as competitors' prices, inventory levels, and demand responses. Learning-based pricing algorithms can generate new pricing patterns in online markets, including the risk of algorithmic collusion if not properly monitored [11]. In the context of Tanjung Pinang, relatively stable inflation can be incorporated as an additional input in AI-based pricing systems to establish upper and lower bounds for price adjustments within each period. This approach helps prevent excessively aggressive pricing during temporary cost shocks while maintaining price consistency for local consumers.

In summary, the ARIMA-based monthly inflation forecasts for Tanjungpinang provide a quantitatively grounded macroeconomic context for conceptually evaluating online pricing strategies. By classifying forecasted inflation into operational regimes and mapping each regime to specific pricing strategy implications, the analysis offers a more structured approach to translating macroeconomic projections into pricing guidance. Dynamic pricing can be incrementally adjusted according to projected inflation regimes, maintaining margins while responding to demand and seasonal trends. Cost-based pricing can incorporate inflation projections to periodically recalibrate base prices for logistics, raw materials, and platform fees, ensuring minimum margin thresholds are preserved. Promotional pricing can leverage forecasted inflation to time discounts and campaigns strategically, aligning with periods of expected consumer activity without eroding profitability. Competitive pricing can use the stable inflation baseline as a floor constraint, allowing businesses to focus their price adjustments on interregional competitiveness rather than cost absorption. Algorithmic pricing can incorporate forecasted inflation as a bounding parameter to prevent excessive price volatility. The pricing strategy adjustments demonstrated through the simulation table in this section are illustrative and scenario-based; their empirical validity in actual e-commerce settings would require further testing using real transaction data. Overall, integrating forecasted inflation into these mechanisms represents a data-informed conceptual model for digital businesses seeking to balance competitiveness, revenue optimization, and financial stability under regional macroeconomic conditions.

This simulation table illustrating how forecasted monthly inflation can guide practical pricing adjustments in an e-commerce setting for Tanjung Pinang. The table shows example scenarios for dynamic pricing, cost-based pricing, and promotional pricing based on forecasted inflation.

Table 3. Example of Operational Pricing Adjustments Based on Forecasted Monthly Inflation in Tanjung Pinang

Month	Forecasted Inflation (%)	Dynamic Pricing Adjustment	Cost-Based Pricing Adjustment	Promotional Pricing Example
Nov 2025	0.42	Increase product prices by 0.42% to maintain margins	Adjust base costs for logistics and raw materials by 0.42%	Minor cashback or flash promotion to stimulate demand without eroding margins
Dec 2025	0.3	Incremental price increase of 0.30% for high-demand items	Reassess minimum margin thresholds; apply 0.30% price floor	Year-end seasonal discount, keeping margin reduction within 0.3%
Jan 2026	0.19	Small dynamic adjustment of 0.19% to reflect seasonal demand	Minor cost-based price adjustment	Promotional bundle for New Year with controlled discounting
Feb 2026	0.17	Incremental adjustment of 0.17% on trending products	Update platform fees allocation for minor cost increase	Flash sale with limited duration to preserve margin
Mar 2026	0.42	Dynamic adjustment of 0.42% for high-demand items	Recalculate shipping and input costs for 0.42% inflation	Targeted promotional campaign for key customer segments
Apr 2026	0.28	Gradual price increase of 0.28% on stable-selling items	Periodic review of cost-based prices; minor upward adjustment	Selective promotions aligned with seasonal demand patterns

The ARIMA-based monthly inflation forecasts for Tanjung Pinang provide a practical basis for guiding online pricing strategies. Dynamic pricing can be adjusted incrementally according to projected inflation, maintaining margins while responding to demand and seasonal trends. Cost-based pricing can incorporate inflation projections to adjust base prices for logistics, raw materials, and platform fees, ensuring minimum margin thresholds are preserved. Promotional pricing can leverage forecasted inflation to time discounts and campaigns strategically, aligning with periods of expected consumer activity without eroding profitability. Overall, integrating forecasted inflation into these mechanisms allows digital businesses to implement data-driven, market-responsive pricing strategies that balance competitiveness, revenue optimization, and financial stability.

CONCLUSION

This study pursues two interrelated objectives: forecasting monthly inflation in Tanjungpinang using a seasonal ARIMA model, and conceptually interpreting the forecast results as a basis for adaptive online pricing strategies. On the forecasting side, the ARIMA(0,0,1)(2,0,0)[12] model, estimated from historical BPS data spanning January 2008 to October 2025, projects that inflation over the two-year horizon (November 2025–October 2027) will remain at a low to moderate level, averaging approximately 0.25% per month, slightly below the historical average of 0.32%. The prediction intervals suggest the possibility of mild deflation as well as moderate inflation; however, they do not indicate a risk of extreme inflation within the analyzed forecast horizon. These empirical findings represent the primary contribution of the study, providing a validated quantitative projection of regional price dynamics.

Based on these forecasting results, the study offers a conceptual interpretation of pricing strategy implications for digital businesses in Tanjungpinang. It should be emphasized that this pricing strategy discussion is literature-based and interpretive in nature, and does not constitute an empirical test of pricing behavior or business outcomes. Within this conceptual scope, the analysis suggests that a stable, low-inflation environment provides digital businesses with greater flexibility to prioritize demand-driven and competitive pricing adjustments over cost-driven repricing. Dynamic and algorithmic pricing mechanisms may be calibrated to respond incrementally to demand fluctuations and seasonal patterns, cost-based pricing can establish stable margin thresholds with periodic recalibration, and promotional strategies can be timed to align with periods of anticipated consumer activity without the pressure of high cost inflation.

The study contributes to the intersection of regional inflation forecasting and digital pricing literature by demonstrating how a validated ARIMA-based regional forecast can serve as a structured input for conceptual pricing strategy analysis, thereby bridging macroeconomic analysis and e-commerce strategy. The novelty lies in the explicit disciplinary bridging: unlike prior forecasting studies that limit their scope to macroeconomic conclusions, and unlike prior pricing strategy studies that treat macroeconomic conditions as background context, this work provides a formal analytical link between the two. The pricing strategy recommendations should, however, be understood as conceptual propositions rather than empirically validated findings, and their practical application would benefit from further empirical testing using actual transaction data. Future research is encouraged to validate these pricing frameworks using real e-commerce transaction records from Tanjungpinang or comparable cities, extend the forecasting approach using multivariate models that incorporate additional cost drivers such as exchange rates and logistics costs, and explore hybrid forecasting techniques to further enhance precision and applicability in dynamic digital environments.

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