North Carolina Holiday Season Retail Sales Outlook

2026

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Executive Summary

2026 Forecast	Highest Growth
$46.30B	5 Years
+2.30% YoY Growth	Accelerating Recovery
November	**December**
$21.78B	$24.52B
+3.37% YoY	+1.37% YoY

5-Year Trend Analysis (2021–2026): Post-COVID retail recovery is accelerating. After flat growth (2021–2023), momentum increased significantly in 2024 (+0.48%) and 2025 (+1.74%), culminating in 2026's strongest performance—the highest inflation-adjusted growth in the recovery period. This trajectory reflects sustained consumer confidence and normalized market dynamics.

Strategic Implications:

1. Inventory Planning: Strongest growth in 5 years signals strong consumer demand. Retailers should prepare for elevated inventory levels to capture the +2.30% growth opportunity. Stock-outs pose greater risk than overstocking in this environment.

2. Staffing and Operations: Workforce planning should reflect sustained high-traffic retail environment. Labor productivity and customer service capacity will be critical success factors.

3. Market Positioning: Normalized growth (2.30%) following pandemic-era volatility suggests stable, mature market dynamics. Strategic focus should shift from recovery to competitive positioning and market share gains rather than riding overall expansion.

Forecast Confidence: 95% confidence intervals provide decision-makers with reliable planning ranges:

- Total Holiday Sales: $45.05B – $47.76B
- November Range: $21.18B – $22.42B
- December Range: $23.88B – $25.34B

Methodology: Ensemble forecasting (Holt-Winters and Theta Multiplicative) with inflation, calendar, and Box-Cox adjustments. Bootstrap resampling with 95% confidence intervals. NC Department of Revenue retail sales tax data (January 2012 – July 2026).

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1 Introduction

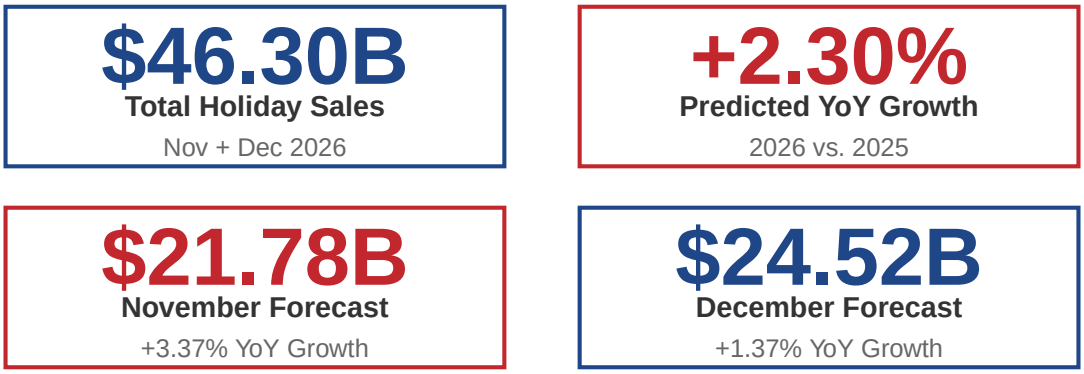
As summer transitions into fall, the retail industry turns its focus to one of the most anticipated and economically impactful times of the year: the holiday season. Beyond back-to-school shopping, this period shapes a broad array of sales patterns and marketing tactics, becoming an essential economic and social event for both families and retailers. For families, it's a time to prepare for gatherings, holiday decor, and gift-giving, while for retailers, it's a make-or-break opportunity for revenue and strategic execution.

Accurate forecasting is crucial for retailers to navigate the holiday rush successfully. By anticipating seasonal shopping trends, they can fine-tune their inventory, pricing, and marketing strategies to meet consumer demand effectively. This preparation helps retailers stock the right products in the correct quantities, minimizing stockouts and overstocking, which directly impacts profitability. Misjudging demand can lead to lost sales or inflated inventory costs, so effective forecasting allows the industry to maximize its performance during this peak season. Additionally, precise forecasting enhances supply chain efficiency, including inventory management and workforce allocation, enabling retailers to better serve their customers and capitalize on the holiday season's unique opportunities.

This report analyzes and predicts retail sales in North Carolina, a key state for consumer spending in the Southeast, for the **2026 holiday season**. It begins by examining historical sales data to identify patterns, trends, and significant features. Understanding these elements not only facilitates a better comprehension of the data but also enhances the accuracy of forecasts. The retail sales data highlights several key characteristics. Notably, there is a distinct upward trend over time, reflecting a consistent increase in sales. However, despite this long-term growth, sales fluctuate from year to year. Additionally, a clear seasonal pattern emerges, with higher sales in December due to the holiday season, followed by sharp declines in January and February as consumer spending decreases after the holidays. Accurate forecasting of this series necessitates consideration of these long-term, yearly, and seasonal trends.

This report employs various industry-standard univariate models to evaluate their forecasting accuracy. By comparing the performance of these models, it aims to identify the most reliable forecasting method. Following this assessment, the report utilizes an ensem-

ble model approach combining Holt-Winters (Multiplicative) and Theta (Multiplicative) models to predict retail sales for the 2026 holiday season, offering valuable insights for retail industry stakeholders and decision-makers.



North Carolina's holiday season retail sales have experienced a gradual recovery trajectory over the past five years (Figure 1), transitioning from post-pandemic stagnation to sustained growth. From 2021 to 2023, the market remained relatively flat, fluctuating between $44.27 billion and $44.46 billion with minimal year-over-year growth—reflecting market normalization following rapid post-COVID expansion. Beginning in 2024, recovery momentum accelerated, with growth climbing from +0.48% to +1.74% in 2025, driven by sustained consumer confidence and accumulated pandemic-era savings.

The 2026 forecast signals a continuation of this growth trajectory. Retail sales are projected to reach $46.30 billion for the holiday season (November–December), reflecting a 2.30% growth compared to $45.26 billion in 2025. This moderation from 2025's +1.74% suggests the retail sector is entering a period of stable, normalized expansion rather than explosive recovery. This progression reflects a maturing market where consumer spending has stabilized at higher sustainable levels, consistent with long-term economic expectations.

Within this overall forecast, November is expected to reach $21.78 billion (+3.37%), while December is projected at $24.52 billion (+1.37%). To understand these forecasts with greater detail, Table 1 provides comprehensive forecasts with 95% confidence intervals: November ranges from $21.18–$22.42 billion, December from $23.88–$25.34 billion, and

the holiday season total from $45.05–$47.76 billion, providing decision-makers with a reliable range for planning purposes.

Figure 1: Holiday Season (Nov-Dec) Retail Sales Trend (2021–2026)



Table 1: Projected NC Retail Sales for the 2026 Holiday Season (November–December)

	2026 Forecast		Year-over-Year	
Month	**Predicted Sales**	**95% Confidence Interval**	**Change from 2025 ($)**	**Change from 2025 (%)**
November	$21.78 billion	$21.18B – $22.42B	**+$0.71 billion**	**+3.37%**
December	$24.52 billion	$23.88B – $25.34B	**+$0.33 billion**	**+1.37%**
Total	**$46.30 billion**	**$45.05B – $47.76B**	**+$1.04 billion**	**+2.30%**

Following this introduction, the report describes the data, its sources, and the adjustments made to prepare it for analysis. It then explores key features and seasonal retail sales trends in greater depth. Next, the report outlines the model training procedure used to identify the best forecasting models. The report concludes by presenting the 2026 holiday season sales forecast and highlighting key takeaways for retail stakeholders.

2 Data Description, Sources, Adjustments, and Features

This report utilizes monthly data on North Carolina taxable sales sourced from the North Carolina Department of Revenue for the period Jan 2012 to Jul 2026. These data are derived from reports and payments submitted by taxpayers and are categorized based on sales and use tax registrations.[1] Table 2 details the retail sectors included in this analysis and their underlying composition.

Preparing time series data is a critical foundation for accurate and meaningful forecasting. This process begins with understanding the structure and nuances of the data, followed by applying a series of transformations designed to improve forecast reliability. The first step involves a calendar adjustment to account for the varying number of days in each month, ensuring that observed differences in sales are not merely artifacts of the calendar. Next, inflation adjustment is applied to express sales in real terms, removing the distortions caused by changing price levels over time. To further stabilize the data and address heteroscedasticity, a Box-Cox transformation is performed.

Once these adjustments are made, various visualization techniques—such as time plots, seasonal subseries plots, and decomposition analysis—are employed to explore trends, seasonality, and irregular patterns. These preprocessing steps not only improve the statistical properties of the series but also enhance the interpretability and performance of forecasting models. Together, they lay the groundwork for producing accurate, actionable forecasts that support informed decision-making.

2.1 Calendar Adjustment

Sales data collected at the monthly frequency can be affected by the varying number of days in each calendar month. For instance, January has 31 days while February has 28 or 29, which can artificially inflate or deflate monthly sales figures even if the underlying daily sales rate remains constant. To correct for this inconsistency, a calendar adjustment was performed by normalizing monthly sales to a constant 30-day month. This adjust-

[1] Additional details of this data, its composition, and tax categories can be found at https://www.ncdor.gov/news/reports-and-statistics/monthly-sales-and-use-tax-statistics.

Table 2: Retail Sector Composition

Retail Sector	Composition
Apparel Group	Boot and shoe stores, clothing stores, clothing and accessory stores, etc.
Automotive Group	Motor vehicle dealers, service stations, garages, automotive supply stores, recappers, and repairers, and manufactured home (mobile home) dealers, etc.
Food Group	Bakeries, grocery stores, meat markets, vending machine operators, restaurants, cafeterias, grills, nightclubs, etc.
Furniture Group	Furniture stores, household appliance dealers and repair services, antique dealers, interior decorators, etc.
General Merchandise Group	Department stores, drugstores, farm implement and supply stores, general stores, hardware stores, jewelry stores, industrial machinery and supply dealers, flea markets, sporting goods stores, toy shops, variety stores, pawn shops, road building equipment and supply dealers, etc.
Lumber & Building Material Group	Sheet metal shops, steel fabricators, building hardware and machine shops, building material dealers, electrical, plumbing, and heating supply dealers, etc.
Unclassified Group	Beauty and barber shops, bookstores, coal and wood dealers, feed stores, florists, funeral homes, photographers, laundries, hospitals, and various other businesses offering a wide range of community services.

ment ensures that observed month-to-month changes in sales are not driven by calendar irregularities, but rather reflect true changes in underlying economic activity. Without this step, months with more days would systematically appear to have higher sales, biasing trend and seasonality analysis.

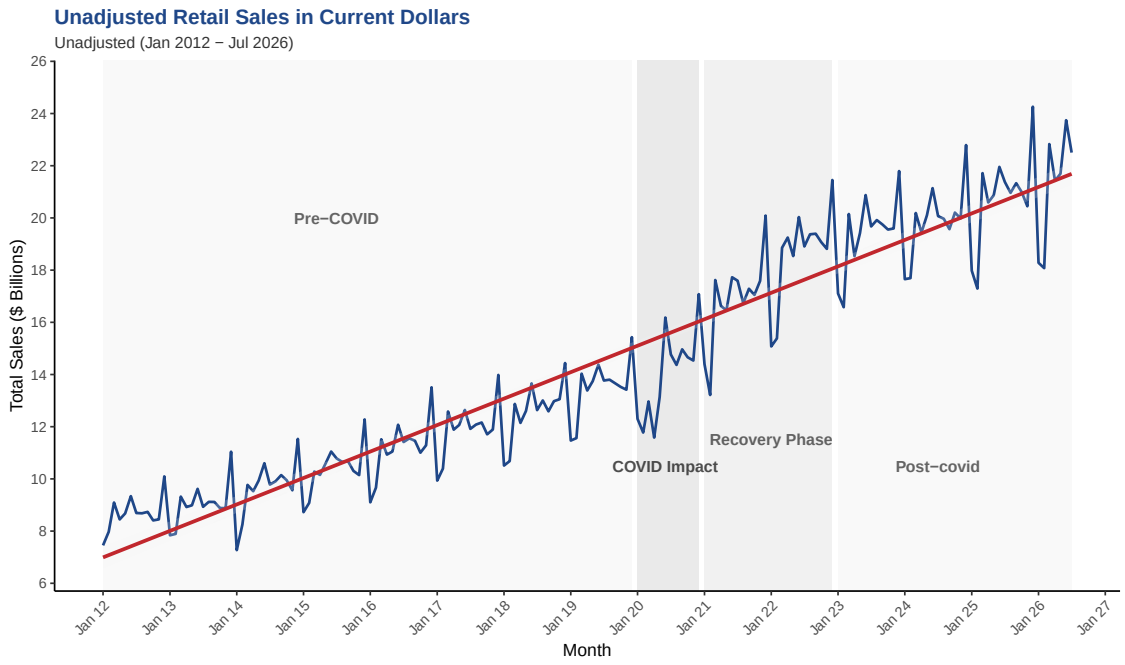
The calendar adjustment improves comparability across months and enhances the reliability of the downstream inflation adjustment and forecasting models. By controlling for time-related distortions, we strengthen the interpretability of the sales data and ensure a cleaner input into time series models.

2.2 Inflation Adjustment

Inflation-adjusting sales data is a critical step for accurate and reliable forecasting. It is important to account for inflation to avoid distorted perceptions of historical sales trends. As inflation erodes the real value of money over time, unadjusted sales figures may overstate sales growth. By applying inflation adjustments using the Consumer Price Index (CPI-U)[2], we gain a clearer and more realistic understanding of the data, enabling us to

[2]U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL

Figure 2: NC Monthly Unadjusted Sales (Jan 2012 - Jul 2026)



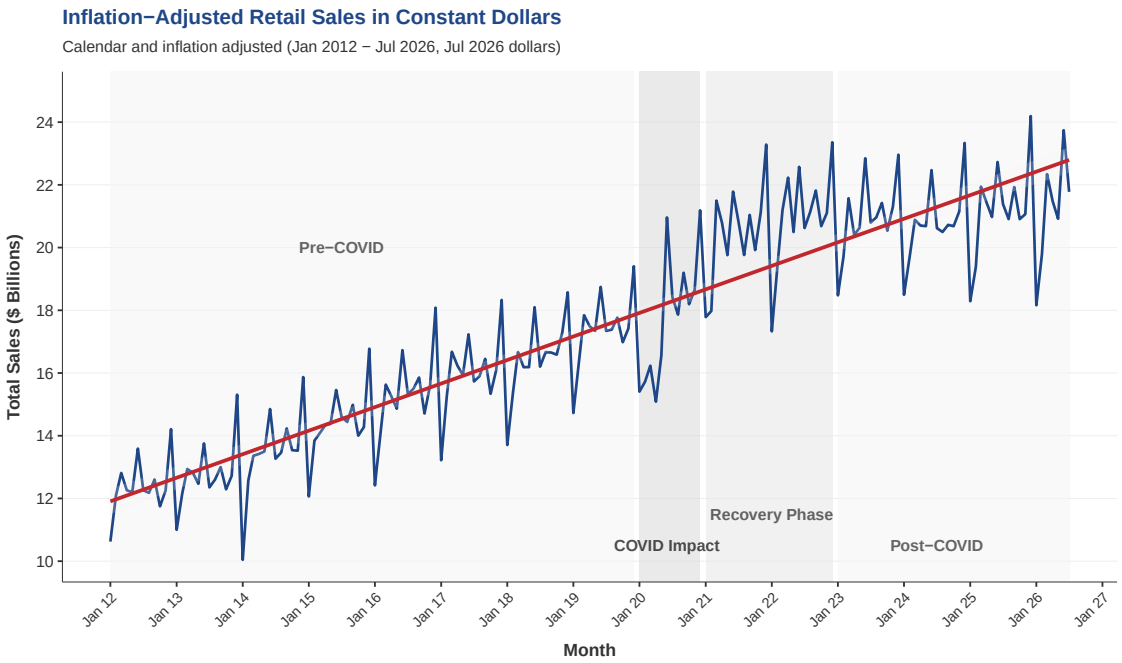
make informed projections. Therefore, this report incorporates inflation-adjusted data into the forecasting models as a fundamental necessity and a best practice. Figure 2 and Figure 3 display unadjusted and inflation-adjusted sales, respectively, with the latter expressed in constant Jul 2026 dollars.

2.3 Mathematical Adjustment

A final adjustment addresses heteroscedasticity within the data. As observed in the inflation-adjusted plot (Figure 3), the magnitude of seasonal fluctuations (the variation in sales) increases as the overall level of sales trends upward. This unequal variance can distort the assumptions of many forecasting models.

To stabilize this variance, we apply a Box-Cox transformation. This mathematical adjustment makes the seasonal variation more uniform across the entire series, simplifying the underlying patterns and improving the reliability of the resulting forecasts. The stabilizing effect of this transformation is clearly visible in the data shown in Figure 4.

Figure 3: Calendar and Inflation Adjusted Monthly Sales (Jan 2012 - Jul 2026)



2.4 Features

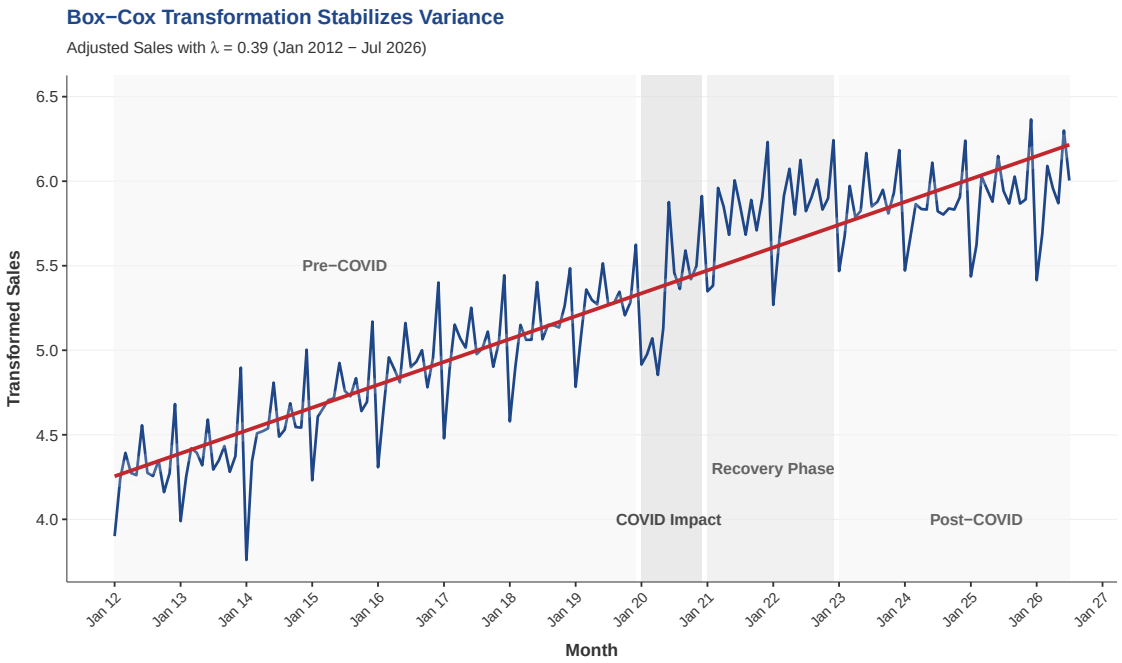
The first thing to do in any data analysis task is to plot the data. Graphs enable many features of the data to be visualized, including patterns, unusual observations, changes over time, and relationships between variables. The features that are seen in plots of the data must then be incorporated, as much as possible, into the forecasting methods to be used.

2.4.1 Time Plots

Figure 2 to Figure 4 display the retail data in time plots, showing observations against their respective times. These plots reveal several notable features of the data.

- **Long-Term Growth:** A distinct upward trend is evident, indicating a consistent increase in retail sales over time. Despite fluctuations, there seems to be a general trend of growth in retail sales over the years, indicating a potential overall expansion in the economy or changes in consumer behavior and purchasing power over

Figure 4: Box-Cox Transformation of Inflation Adjusted Sales



time. Following the rapid post-COVID recovery, the trend shows a clear moderation, returning to a more stable growth rate in recent years.

- **Yearly Fluctuations:** There are fluctuations in sales from year to year. Some years, such as 2023, show a general increase in sales compared to previous years, while others, such as 2020, show a dip, possibly due to external factors like economic downturns and Covid-19.

- **Seasonal Trends:** There appears to be a seasonal pattern in the data, with certain months consistently showing higher sales compared to others. For example, December consistently shows the highest sales. This could be attributed to increased spending during the holiday season. However, the post-holiday season in January and February indicates a sharp decline in sales, likely due to reduced consumer spending after the holiday season.

2.4.2 Seasonal Plots

Figure 5 displays a seasonal plot of the data. A seasonal plot presents data against the individual "seasons" during which they were observed, allowing for overlap between the data from each season. This type of plot enhances the visibility of underlying seasonal patterns, which is particularly useful for detecting changes in patterns over time. The sales series exhibits strong seasonality, characterized by a prominent spike each December and a secondary peak in June. Additionally, the data highlights an atypical surge in retail sales in June 2020, likely reflecting post-lockdown pent-up demand.

Figure 5: Seasonal Plot of Adjusted Sales (Jan 2012 - Jul 2026)

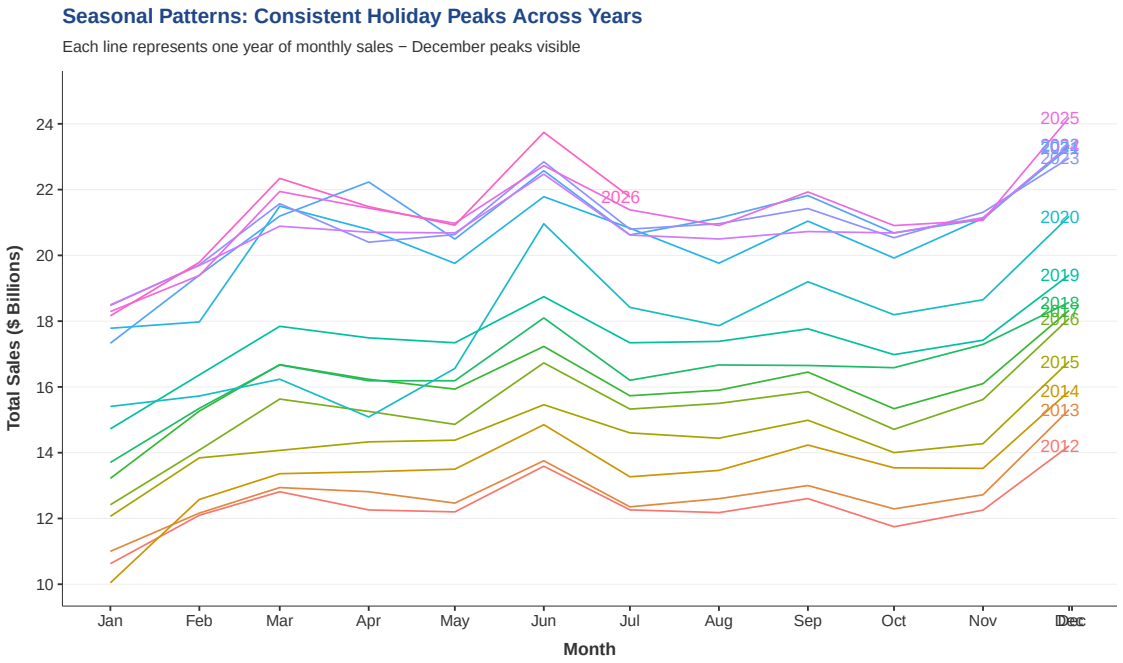
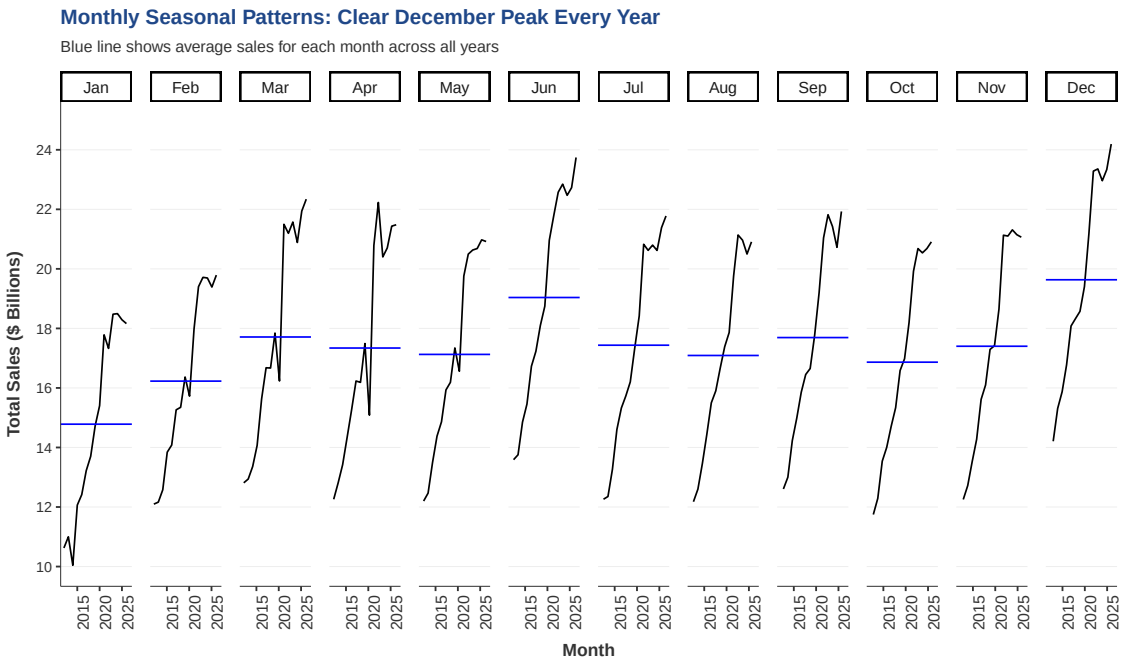


Figure 6 presents an alternative seasonal plot format. In this graph, the data for each season are aggregated into separate mini-time plots. Blue horizontal lines mark the means for each month. Analyzing this plot, it becomes evident that, on average, sales tend to peak in December and June. Conversely, the plot illustrates that sales typically dip post-holiday season, indicating lower sales volumes in January and February.

Figure 6: Seasonal Subseries Plot of Adjusted Sales (Jan 2012 - Jul 2026)



2.4.3 Decomposition

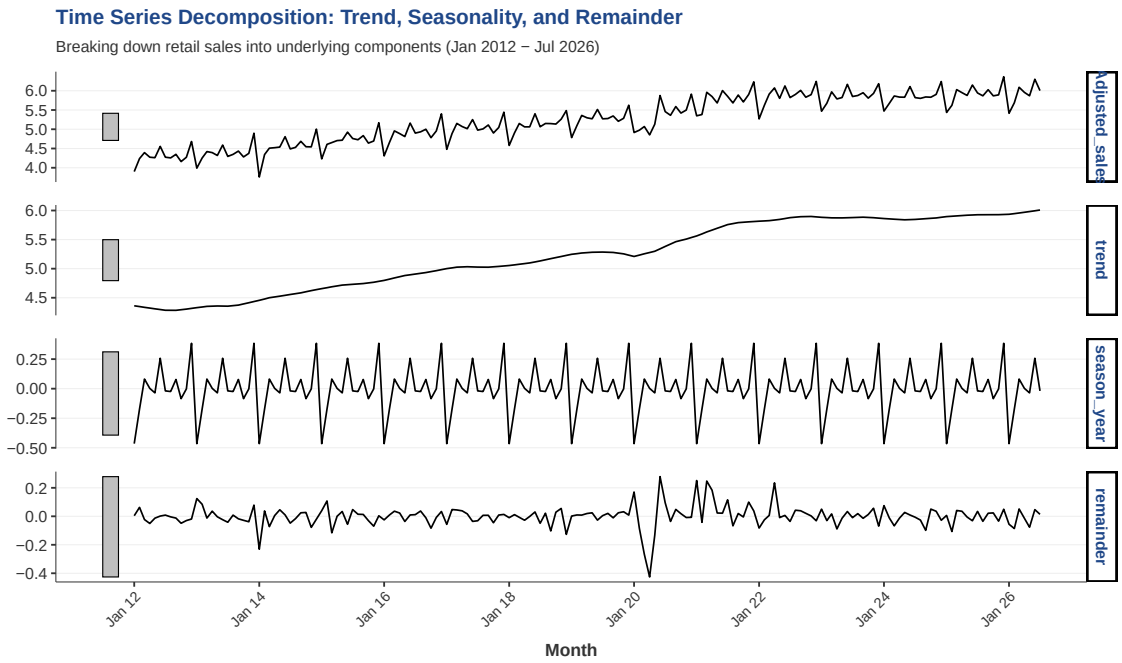
Time series data can manifest diverse patterns, and dissecting it into distinct components, each representing a specific underlying pattern category, is beneficial. Typically, we categorize a time series into three components:

- A trend-cycle component.
- A seasonal component.
- A remainder component (which encompasses any other variations in the time series)

This decomposition enhances comprehension of the time series and improves forecast accuracy. Figure 7 decomposes the retail sales after making inflation and mathematical adjustments to the data. The top panel of this graph displays the adjusted and transformed data. The bottom three panels depict each component separately. We can reconstruct the data shown in the top panel by adding these components together. Once more, the second panel reveals a clear trend. In the third panel, the seasonal component remains

relatively constant over time, indicating a similar pattern between consecutive years and even distant years. The bottom panel illustrates the remainder component, representing what remains after subtracting the seasonal and trend-cycle components from the data.

Figure 7: Decomposition of Inflation Adjusted Transformed Monthly Retail Sales



3 Finding the Optimal Model for the Retail Sales Data

3.1 Train-Test Split

Splitting data into training and test sets is a critical step in developing accurate forecasting models. This division allows us to assess a model's performance on unseen data, which simulates real-world scenarios. By training a model on a subset of the data and testing it on another, we can gauge its ability to forecast beyond the information it was trained on. This practice helps select the most appropriate forecasting model, as it provides an unbiased evaluation of predictive power of a model. Moreover, it guards against overfitting, a common pitfall where a model becomes overly complex and fits the training data too closely, leading to poor performance on new, unseen data. This separation ensures that our model captures underlying patterns without getting bogged down by noise or idiosyncrasies in the training set, ultimately leading to more reliable and robust forecasts.

This report uses data from Jan 2012 to Jul 2025 as the training set. Then, it assesses the prediction accuracy of various forecasting models using a test set spanning Aug 2025 to Jul 2026, which includes the latest available month of data. Finally, it uses the best-performing model to predict retail sales for the holiday season, spanning Nov to Dec 2026.

3.2 Model Training

In this step, this report employs multiple industry-standard forecasting methods on the training set to select the best model. Choosing the appropriate method based on the specific features of the time series data is crucial, as using an unsuitable method can result in inaccurate forecasts. Hence, considering the particular time series features of retail sales data explored above, this report utilizes the following forecasting methods.

- Benchmark: Seasonal Naive
- Dynamic Regression Model
- Dynamic Regression (Fourier)

- Holt-Winters' with Additive Damped Trend and Additive Seasonality
- Holt-Winters' with Additive Damped Trend and Multiplicative Seasonality
- Innovations State Space Models
- Neural Network Model
- Prophet Model Additive Seasonality
- Prophet Model Multiplicative Seasonality
- SARIMA (Seasonal AutoRegressive Integrated Moving Average Model)
- Theta Method with Additive Seasonality
- Theta Method with Multiplicative Seasonality

Moreover, employing multiple forecasting methods on the same time series and averaging the resulting forecasts is highly effective in improving out-of-sample forecast accuracy. This method, proposed by Bates and Granger in 1969, has consistently shown enhanced forecast accuracy. Numerous studies have confirmed that combining forecasts, even through simple averaging, consistently leads to better forecasting performance.[3] Therefore, this report also evaluates the test set accuracy of all possible combinations of the top three models to determine if forecast accuracy could be improved by averaging these models.

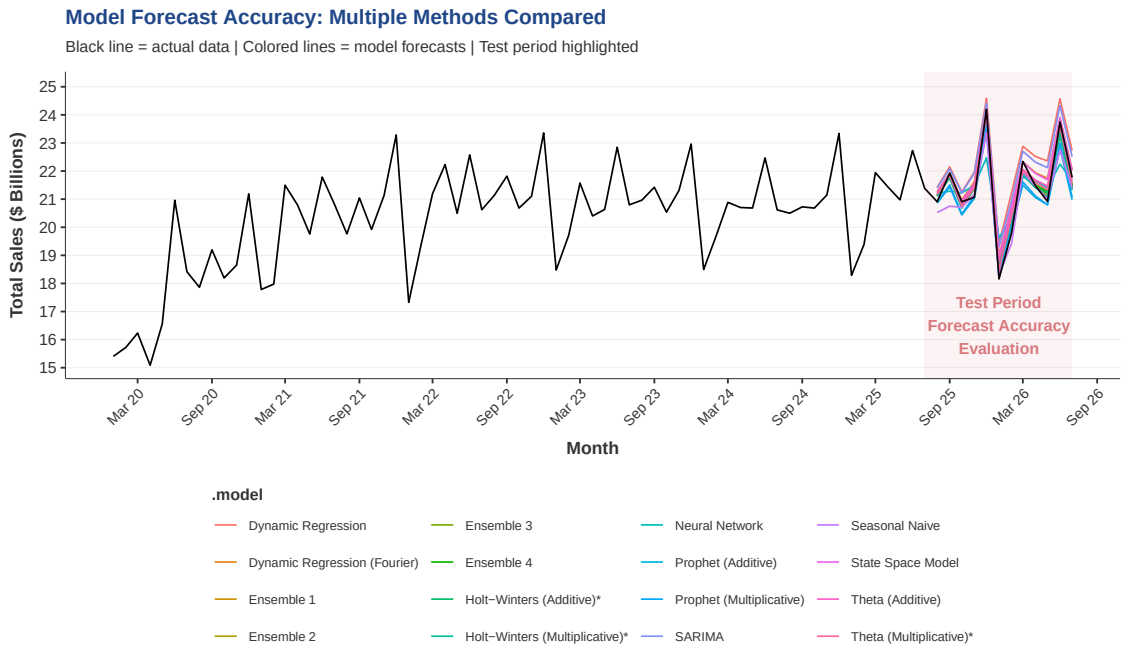
3.3 Out-of-Sample Forecast Evaluation

Figure 8 compares the predictions of each method against the test set (black line). Although all models capture the series' overall trajectory, their tracking precision varies. To formally compare performance, we evaluate each model using standard forecast accuracy metrics.

Table 3 presents comprehensive forecasting accuracy results across all candidate models. The accuracy measures include Root Mean Squared Error (RMSE), Mean Absolute

[3] Bates, J. M., & Granger, C. W. (1969). The combination of forecasts. Journal of the Operational Research Society, 20(4), 451-468.

Figure 8: Out of Sample Forecast Accuracy Comparison



Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE). A good forecast method produces the lowest out-of-sample error across these metrics.

Ensemble 2—the simple average of Holt-Winters (Multiplicative) and Theta (Multiplicative)—achieves the lowest RMSE of 0.278, with MAPE of 29.1% and MASE of 0.235. This is followed closely by Theta (Multiplicative) and Holt-Winters (Multiplicative) models.

Notably, the ensemble approach outperforms both individual component models, demonstrating the value of combining forecasting methods. This result aligns with the Bates and Granger (1969) principle that averaging multiple forecasts consistently improves accuracy by leveraging the strengths of different methodological approaches while reducing model-specific errors.

Models such as Prophet (Additive/Multiplicative), Holt-Winters (Additive), and Theta (Additive) show competitive but higher error rates. In contrast, Seasonal Naive, SARIMA, Neural Network, and Dynamic Regression all produce substantially higher errors (RMSE > 0.50), making them less suitable for this dataset.

Table 3: Out of Sample Forecast Accuracy Comparison

Model	RMSE	MAE	MAPE	MASE
Ensemble 2	**0.278**	**1.200**	**0.292**	**0.236**
Theta (Multiplicative)*	0.290	1.167	0.279	0.246
Ensemble 3	0.303	1.304	0.318	0.257
Holt-Winters (Multiplicative)*	0.304	1.298	0.322	0.257
Ensemble 4	0.314	1.338	0.324	0.266
Ensemble 1	0.328	1.422	0.350	0.278
Holt-Winters (Additive)*	0.361	1.558	0.381	0.306
Theta (Additive)	0.383	1.501	0.357	0.325
Prophet (Multiplicative)	0.453	1.613	0.415	0.383
State Space Model	0.471	1.745	0.411	0.399
Dynamic Regression (Fourier)	0.501	1.847	0.434	0.425
Prophet (Additive)	0.543	2.008	0.514	0.460
Seasonal Naive	0.555	1.903	0.487	0.470
SARIMA	0.758	3.218	0.773	0.642
Neural Network	0.866	3.183	0.792	0.733
Dynamic Regression	0.915	3.930	0.950	0.775

3.4 Residual Diagnostics of the Best Model

The "residuals" in a time series model are the differences between the actual observations and the corresponding forecasted values after fitting the model.

Residual = Actual value − Forecast value

A good forecasting method should produce residuals with specific characteristics: they should be uncorrelated and have a mean of zero. If there are correlations between these residuals, it indicates untapped information that should have been used to enhance forecast accuracy. Similarly, if the residuals have a mean different from zero, the forecasts are biased. If either property is not met, modifying the forecasting method can lead to improved forecasts.

Figure 9 produces residual diagnostic tests for the chooses ensemble model. On average, the mean of the residuals is close to zero, indicating that, on average, our model forecasts the actual values fairly accurately. A time plot of the residuals shows that their variation remains relatively constant over the historical data, except for one outlier. Therefore, the residual variance can be treated as constant. The autocorrelation function (ACF) graph shows no significant correlation in the residuals. However, the histogram suggests that

the residuals may not follow a normal distribution, as the right tail appears somewhat long even when the outlier is ignored. This implies that while the forecasts from this method are likely to be quite accurate, the prediction intervals, which assume a normal distribution, may be unreliable. To check for autocorrelation further, we can use the Ljung-Box test. This test returns a p-value of **0.74**, which is large, indicating that the residuals are not significantly different from a white noise series. This suggests that the method captures all the available information when producing forecasts.

Overall, these residual diagnostics suggest that the Ensemble 2—the simple average of Holt-Winters (Multiplicative) and Theta (Multiplicative) effectively captures the information in the data and is likely to produce accurate forecasts.

Figure 9: Residual Diagnostics of the Top Model

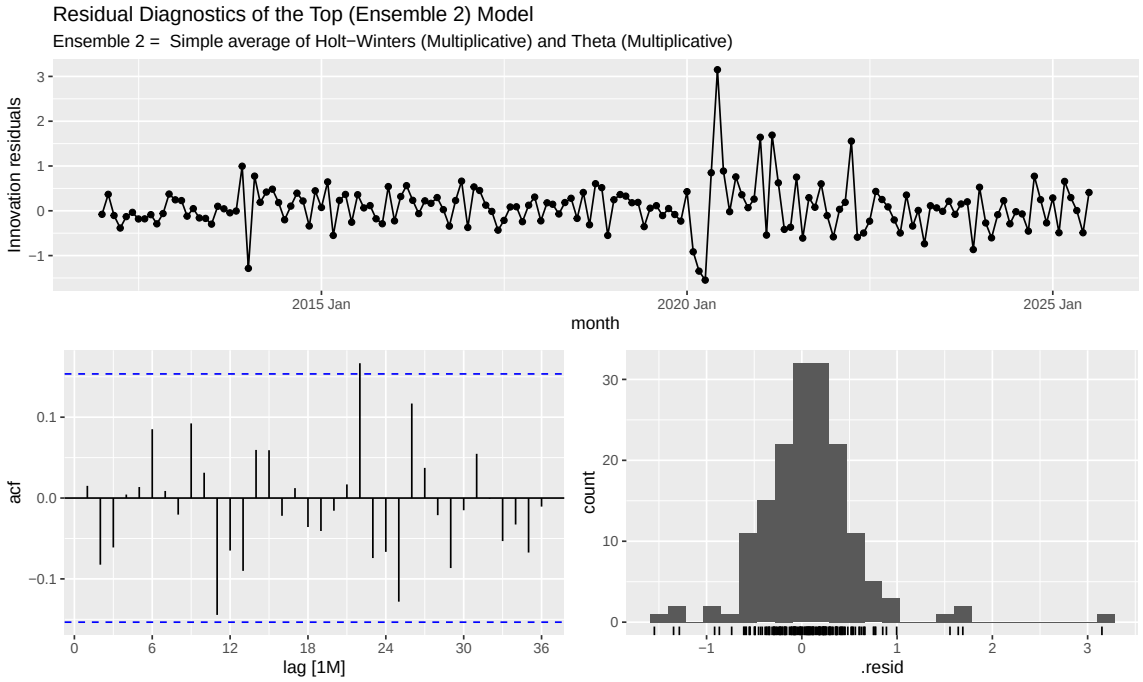


Table 4: The Ljung-Box Test for the Residuals

Ljung-Box Stat	Ljung-Box p-value
30.182	**0.741**

4 2026 Holiday Season Retail Sales Forecast

As a final step in forecasting, this report employs an ensemble modeling approach combining Holt-Winters (Multiplicative) and Theta (Multiplicative) methods, applied to data from Jan 2012 through Jul 2026 (the most recent available month) to predict retail sales for the six-month period from Aug 2026 to Jan 2027. This ensemble methodology leverages bootstrap sampling with 1000 simulations to provide robust 95% confidence intervals to capture model uncertainty. The forecast results are shown in Figure 10.

When we compare the 2026 season with the same period in 2025, several key takeaways stand out:

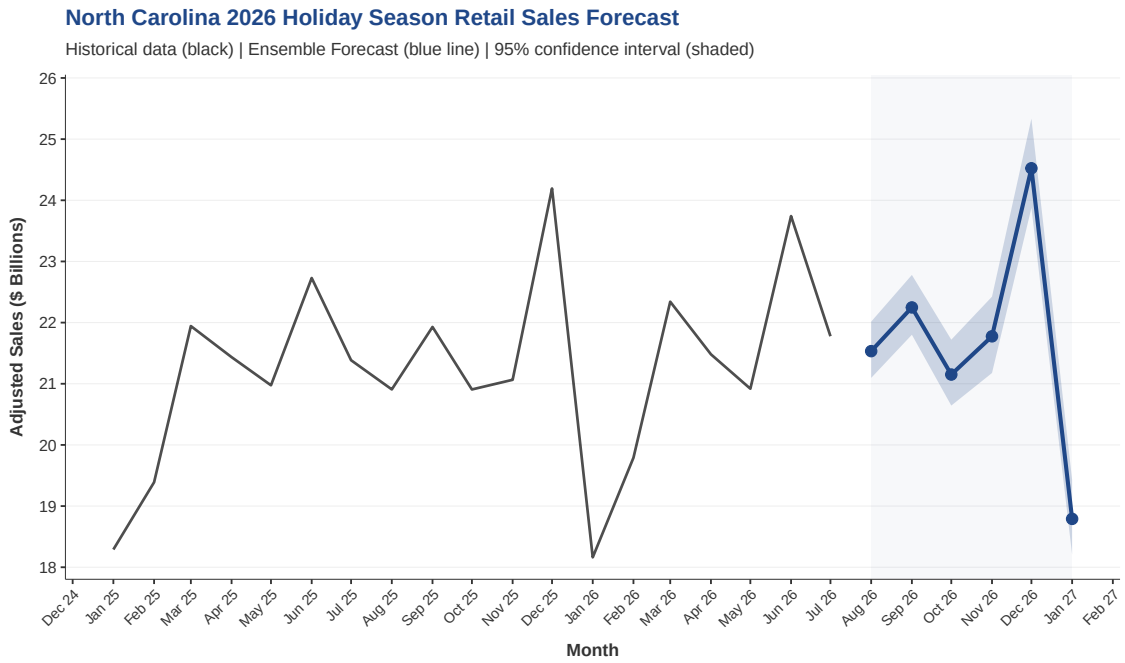
November: Retail sales in November 2026 are projected to reach $21.78 billion, an increase of $0.71 billion (3.37%) from $21.06 billion in November 2025. The 95% confidence range for this forecast is $21.18–$22.42 billion, meaning actual sales are very likely to fall within this range.

December: For December 2026, projected sales are $24.52 billion, up $0.33 billion (1.37%) from $24.19 billion in December 2025. The 95% confidence range for December is $23.88–$25.34 billion.

Holiday Season (November–December): Altogether, total holiday sales in 2026 are expected to reach $46.30 billion, an increase of $1.04 billion from $45.26 billion in 2025—a 2.30% total seasonal growth. The 95% confidence range for the holiday total is $45.05–$47.76 billion.



Figure 10: Holiday Season Adjusted Sales Forecast

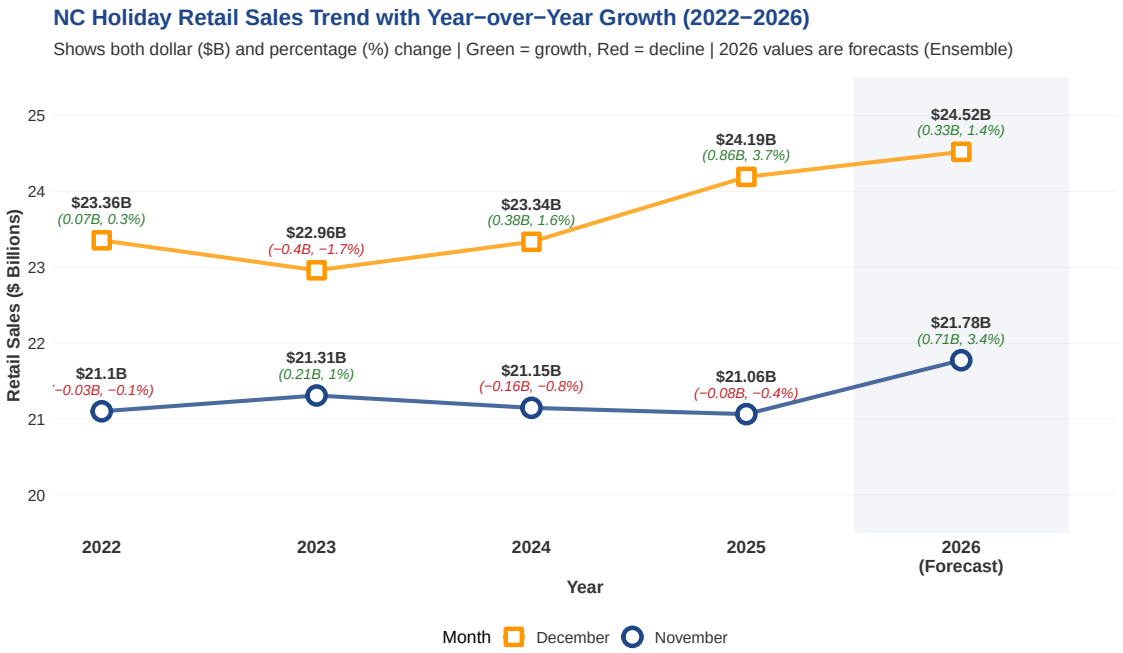


This 2.30% gain reflects the sustained consumer momentum documented in Figure 1, confirming that retail spending remains resilient and stable as the 2026 holiday season approaches. The forecast aligns with the broader market normalization trajectory, signaling continued steady growth in line with long-term economic expectations.

Retail Planning Priorities. The +2.30% growth projection represents the strongest inflation-adjusted growth in five years, signaling robust consumer demand. Inventory levels should align with this opportunity, with particular emphasis on elevated stock to prevent stockouts, prioritizing high-margin holiday categories, and timing procurement to align with November's stronger momentum (+3.37%). November's sustained peak traffic (+3.37% year-over-year) requires workforce planning for continuous high-volume retail operations rather than single-day peaks, supported by training and scheduling to maximize customer service quality. Normalized growth (2.30%) following pandemic-era volatility supports strategic positioning over recovery-mode discounting, allowing retailers to optimize margins with confidence in pricing power and focus on market share gains.

Success depends on aligning stock levels with confidence intervals ($45.05B–$47.76B), staffing for November's stronger momentum relative to December, leveraging omnichannel growth opportunities, tracking performance weekly, and recognizing that overall growth masks sector-specific variations. The 2026 holiday season outlook presents a favorable environment for growth characterized by sustained consumer confidence, manageable volatility within clear planning boundaries, and strategic stability supporting margin-focused strategies. Retailers who align their inventory, staffing, and promotional strategies with these projections—while remaining vigilant to local and sector-specific variations—are well-positioned to capitalize on this strong period.

Figure 11: Holiday Season (Nov-Dec) Retail Sales YoY Change (2022–2026)



5 Summary

The success of retailers during the holiday season depends on precise forecasting to adapt inventory, pricing, and marketing strategies. This report focuses on retail sales projections in North Carolina for the 2026 holiday season (November–December).

The analysis begins with historical data to identify growth patterns. Results confirm that the holiday season consistently represents the largest annual seasonal peak in retail sales, with December demonstrating particularly strong performance. While sales have grown steadily over time, year-to-year fluctuations are common. After strong growth in 2025, both November and December sales are projected to continue rising in 2026, signaling sustained consumer momentum and economic stability.

Overall, these projections suggest continued strength in retail sales for the 2026 holiday season, totaling approximately **$46.30 billion**, up **$1.04 billion or 2.30%** from $45.26 billion in 2025. This growth highlights the importance of carefully aligned retail strategies to accommodate fluctuating demand and capitalize on sustained consumer spending momentum. The 95% confidence interval for this forecast ($45.05–$47.76 billion) reflects the uncertainty inherent in forecasting while providing decision-makers with a plausible range for planning purposes.

The forecasts are based on aggregated sales tax data across various retail sectors and regions, using an ensemble methodology combining Holt-Winters (Multiplicative) and Theta (Multiplicative) models with bootstrap sampling. While they provide a strong indication of overall holiday sales trends, local variations and sector-specific patterns may differ from these projections.