North Carolina Holiday Season Retail Outlook

2025

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Table of contents

List of Figures

List of Tables

1 Executive Summary

1. This report utilizes North Carolina's monthly sales tax revenue data to examine retail sales patterns and project retail performance for the 2025 holiday season.
2. Historical trends show that retail sales consistently peak in December, reflecting heightened year-end consumer activity.
3. **2025 Poised for Strongest Growth in Four Years:** The 2025 holiday season is projected to be the best-performing season in the 2022-2025 period, signaling a clear rebound from the fluctuating and subdued performance of the previous three years. Both November (projected at **$20.79 billion, a +1.63% increase**) and December (projected at **$23.18 billion, a +2.65% increase**) are forecast to achieve their highest year-over-year growth rates of the period.
4. Overall, total 2025 holiday sales are projected to reach **$43.97 billion**—an increase of $0.93 billion (2.16%) over 2024—indicating a resilient and strengthening retail environment.
5. These findings signal renewed consumer confidence and steady growth, offering valuable insights for inventory management, pricing, and marketing strategies across the state's retail sector.

2 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 2025 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.

During our last holiday season forecast (2024), our projections anticipated a decline of −1.64% in November and growth of 2.21% in December, resulting in a forecasted total seasonal growth of 0.40%.[1] In reality, November 2024 declined by −0.76%, and December grew by +1.64%, producing an actual seasonal growth of approximately 0.49%. This demonstrates that our forecast was remarkably close to the observed outcome, underscoring the accuracy of our 2024 holiday sales projections.

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 the best-performing model to predict retail sales for the 2025 holiday season, offering valuable insights for retail industry stakeholders and decision-makers. Projections for the holiday season (November to December

[1] North Carolina Retail Merchants Association (NCRMA), "Growth Predicted for North Carolina Retailers for 2024 Holiday Season."

2025) indicate retail sales will reach approximately $43.97 billion, reflecting a growth of $0.93 billion (2.16 percent) compared to $43.04 billion in 2024.

- **November 2025**: Expected sales are **$20.79 billion**, an increase of **$0.33 billion** (**1.63 percent**) from **$20.46 billion** in November **2024**.
- **December 2025**: Projected sales are **$23.18 billion**, an increase of **$0.60 billion** (**2.65 percent**) compared to **$22.58 billion** in December **2024**.

These findings suggest a resilient holiday season, with the projected 2.16% total growth marking the **strongest performance in the past four years**. This represents a significant acceleration from the 0.40% growth seen in 2024 and indicates that consumer behavior is stabilizing, even as purchasing power remains a key consideration for shoppers amidst recent inflationary pressures.

Table 1: Projected NC Retail Sales for the 2025 Holiday Season (November–December)

Month	Predicted Sales	Change from 2024	Growth Rate (YoY)
November	$20.79 billion	+$0.33 billion	1.63 percent
December	$23.18 billion	+$0.60 billion	2.65 percent
Total	**$43.97 billion**	**+$0.93 billion**	**2.16 percent**

Following this introduction, the report will describe the data, its sources, and the adjustments made to prepare it for analysis. It will then explore 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. Finally, it concludes with key insights and takeaways for the retail industry.

3 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 January 2012 to July 2025. These data are derived from reports and payments submitted by taxpayers and are categorized based on sales and use tax registrations.[2] A time plot of this data is depicted in Figure 1 below. However, we need to preprocess this data to enhance forecast accuracy.

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.

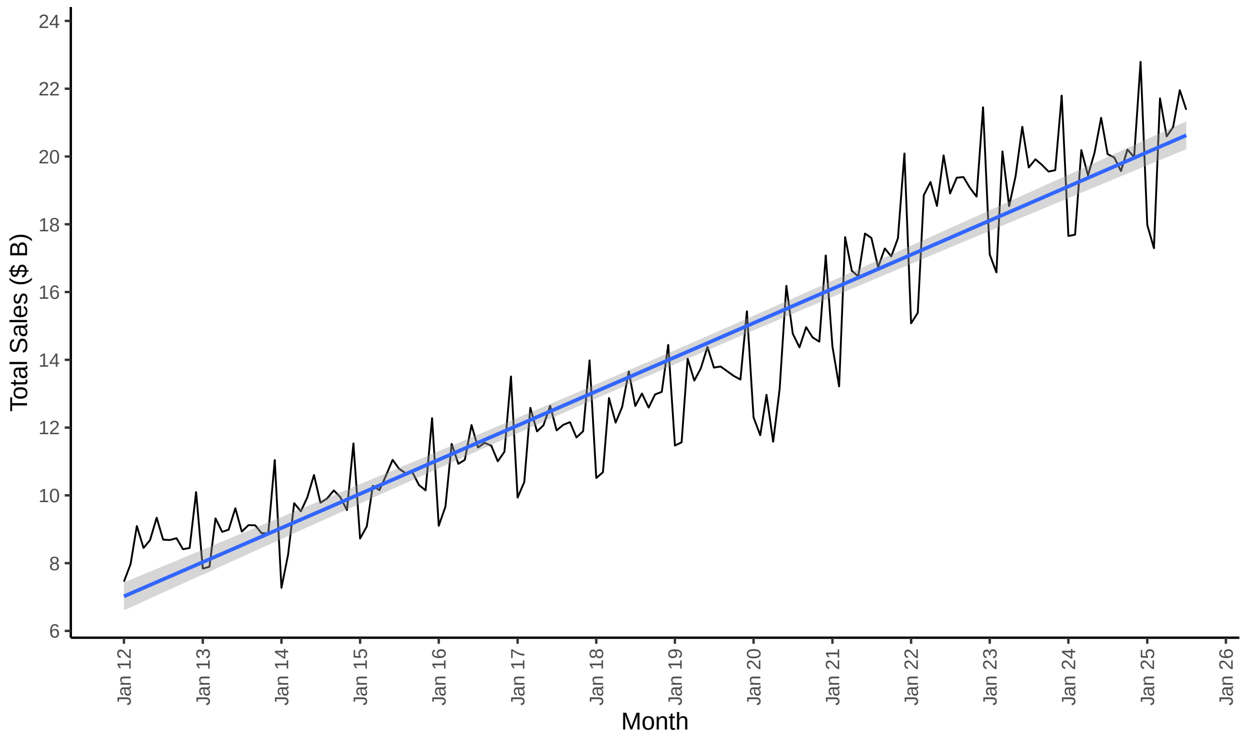
3.1 Calendar Adjustment

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 adjustment 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] 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.

Figure 1: NC Monthly Unadjusted Sales (Jan 2012 - Jul 2025)



3.2 Inflation Adjustment

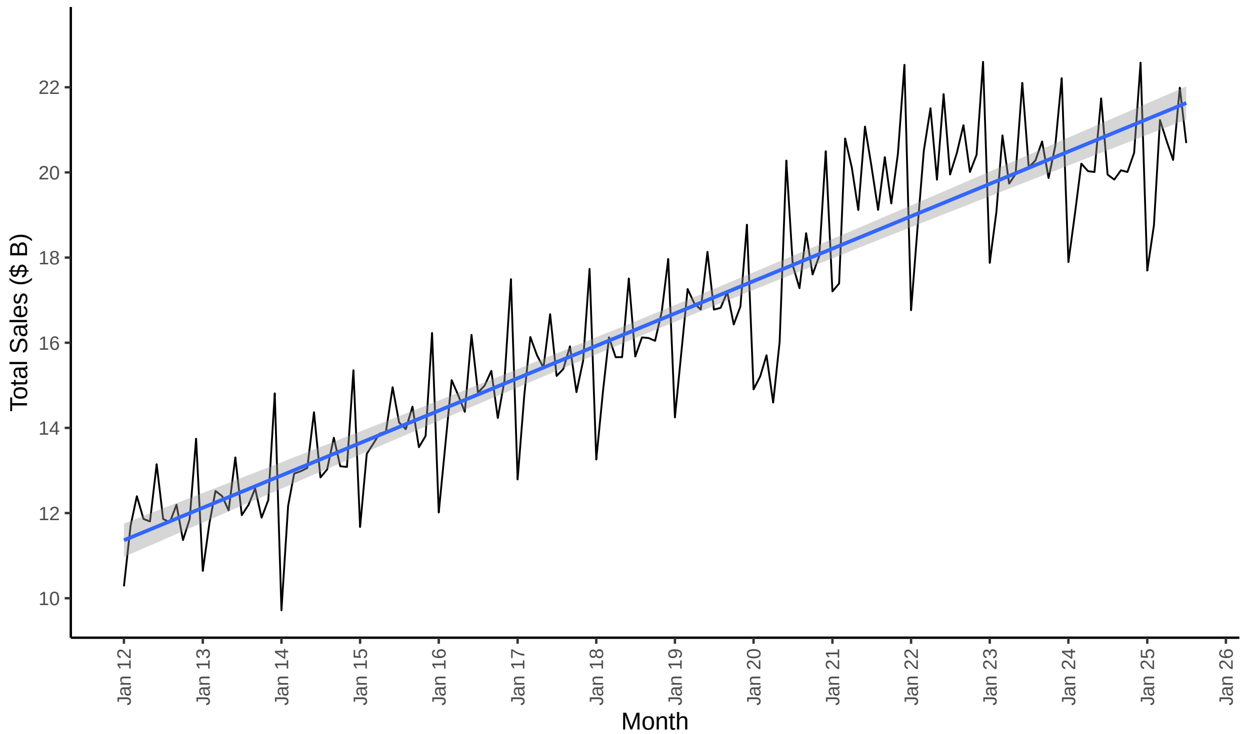
Inflation-adjusting sales data is a critical step for accurate and reliable forecasting. It is important to account for inflation to avoid distorted perceptions of historical sales trends. As inflation erodes the real value of money over time, unadjusted sales figures may overstate sales growth. By applying inflation adjustments using the Consumer Price Index (CPI-U), we gain a clearer and more realistic understanding of the data, enabling us to make informed projections. Therefore, this report incorporates inflation-adjusted data into the forecasting models as a fundamental necessity and a best practice. Figure 2 presents the new inflation-adjusted data, expressed in constant July 2025 dollars.

3.3 Mathematical Adjustment

A final adjustment is necessary to address the issue of heteroscedasticity in the data. As observed in the inflation-adjusted plot (Figure 2), 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.

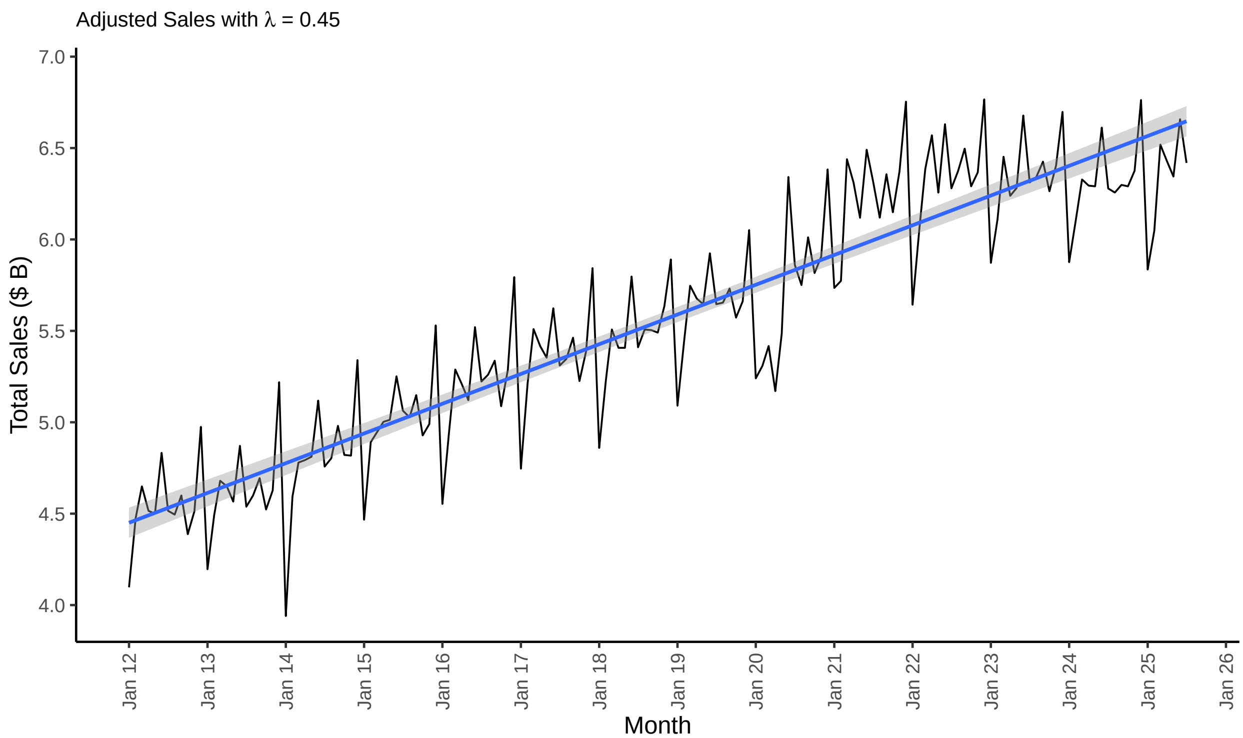
To stabilize this variance, we apply a Box-Cox transformation. This mathematical adjustment makes the seasonal variation more uniform across the entire series, simplifying the underlying

Figure 2: Calendar and Inflation Adjusted Monthly Sales (Jan 2012 - Jul 2025)



patterns and improving the reliability of the resulting forecasts. The stabilizing effect of this transformation is clearly visible in the data shown in Figure 3.

Figure 3: Box-Cox Transformation of Inflation Adjusted Sales



3.4 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.

3.4.1 Time Plots

Figure 1 to Figure 3 display the retail data in time plots, showing observations against their respective times. These plots reveal several notable features of the data.

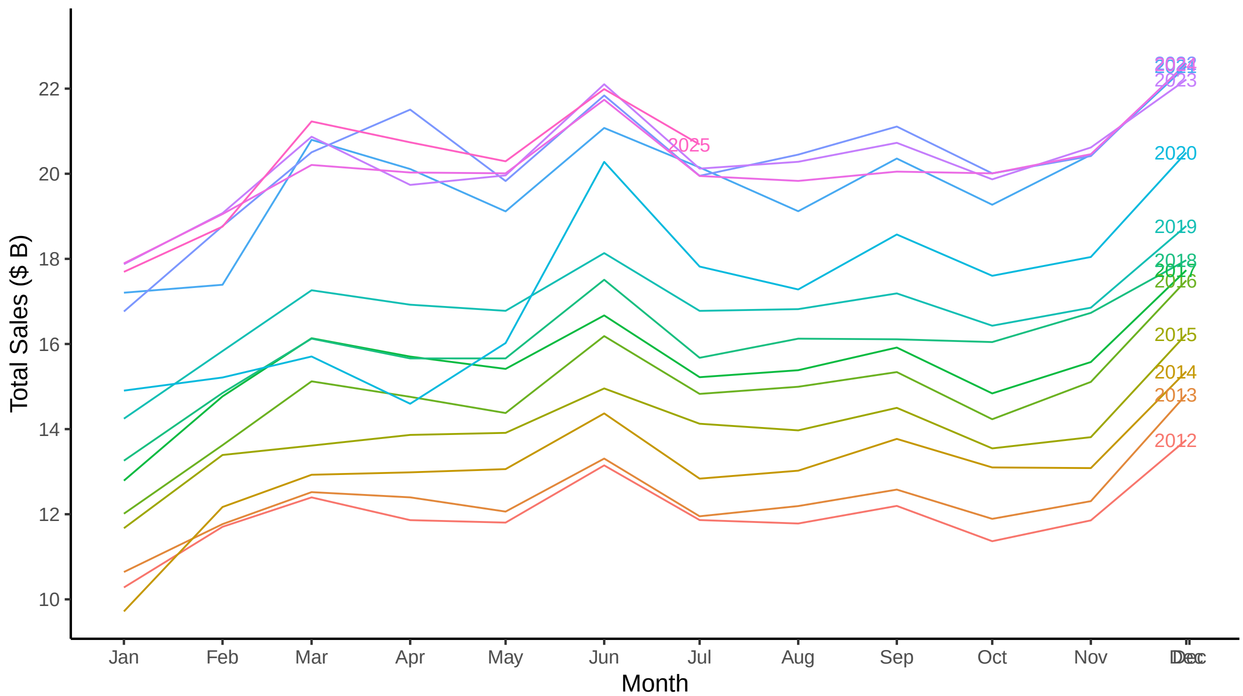
- **Long-Term Growth:** A distinct upward trend is evident, indicating a consistent increase in retail sales over time. Despite fluctuations, there seems to be a general trend of growth in retail sales over the years, indicating a potential overall expansion in the economy or changes in consumer behavior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

3.4.2 Seasonal Plots

Figure 4 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. Examining this plot, a notable observation is the significant spike in sales consistently occurring in December each year. Additionally, the plot highlights an unusually high number of sales in June 2020.

Figure 5 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 4: Seasonal Plot of Adjusted Sales (Jan 2012 - Jul 2025)



3.4.3 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 6 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 5: Seasonal Subseries Plot of Adjusted Sales (Jan 2012 - Jul 2025)

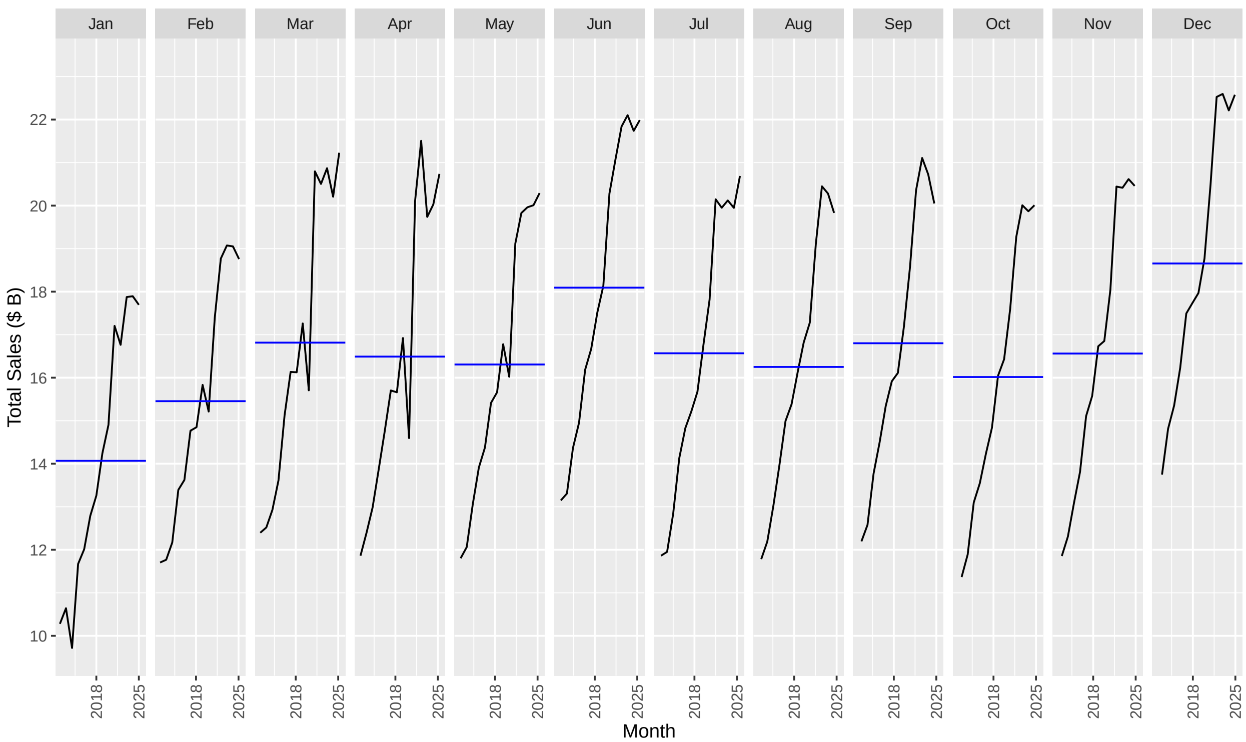


Figure 6: Decomposition of Inflation Adjusted Transformed Monthly Retail Sales

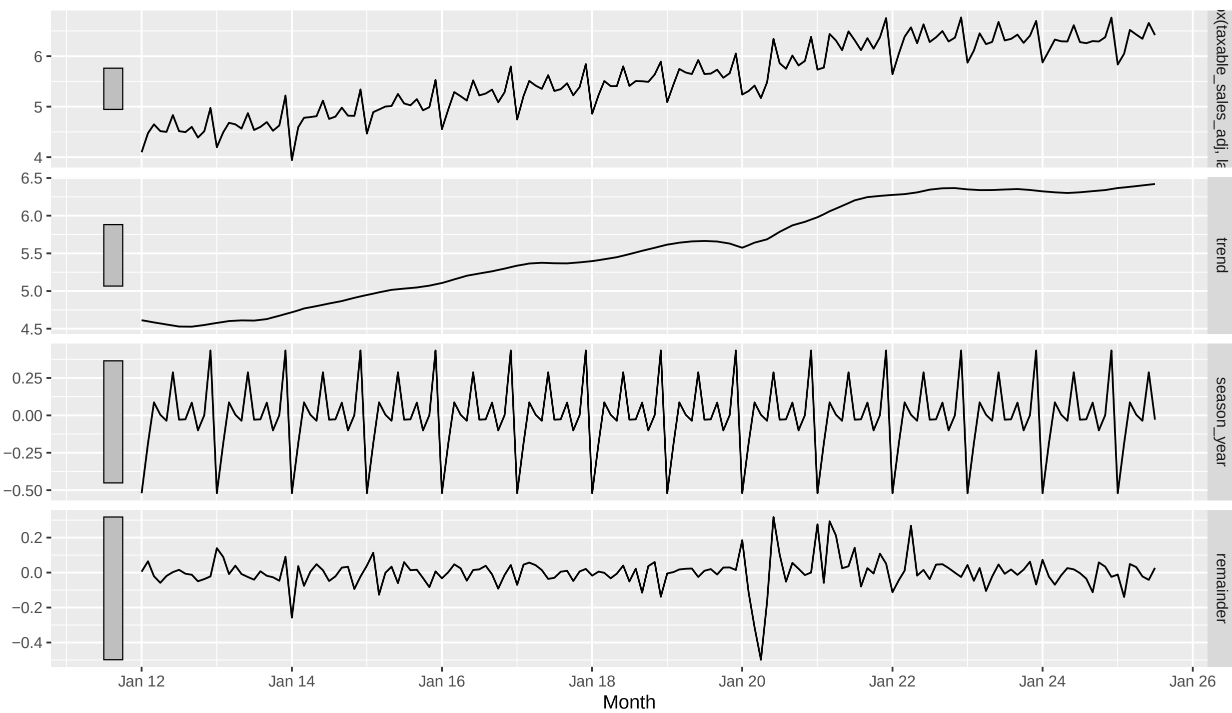


Table 2: Retail Sector Composition

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 stores, 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.

4 Finding the Optimal Model for the Retail Sales Data

4.1 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 January 2012 to July 2024 as the training set. Then, it assesses the prediction accuracy of various forecasting models using a test set spanning August 2024 to July 2025, which includes the latest available month of data. Finally, it uses the best-performing model to predict retail sales for the holiday season, spanning November to December 2025.

4.2 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
- 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. 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.

4.3 Out-of-Sample Forecast Evaluation

Figure 7 presents the forecast accuracy comparison across all the models. Clearly, most of the models are able to capture the patterns in the original series (black line). Similarly, Table 3 presents several out-of-sample forecasting accuracy results across all models. The accuracy measures in this table include Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error (MASE), and Root Mean Squared Scaled Error (RMSSE). This table also includes four ensembled models, calculated using all possible combinations of the top models indicated by an asterisk (*). A good forecast method produces the lowest out-of-sample error.

Table 3 shows that the Theta (Additive) model achieves the lowest RMSE of 0.33. This is followed closely by several ensemble models (Ensemble 3, Ensemble 4, and Ensemble 1), which all posted an RMSE of 0.34. The top individual models, marked by an asterisk, are the Theta (Additive) (0.33), Theta (Multiplicative) (0.37), and the State Space Model (0.39). It is noteworthy that the best individual model outperformed all ensemble combinations, suggesting that the Theta (Additive) model is the most robust for this dataset.

Models such as Prophet (Additive) and Holt-Winters (Additive) show competitive performance. In contrast, Seasonal Naive, SARIMA, Neural Network, and Dynamic Regression all produce substantially higher errors, making them less suitable for this dataset.

Figure 7: Out of Sample Forecast Accuracy Comparison

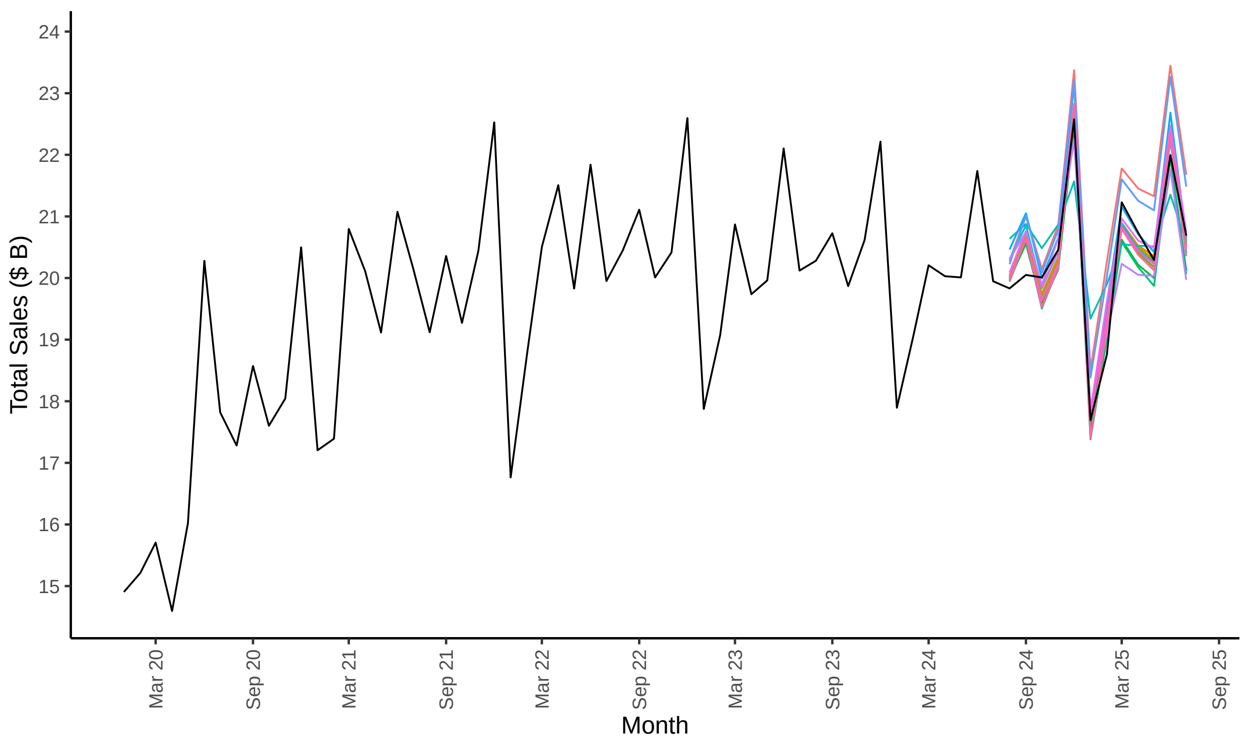


Table 3: Out of Sample Forecast Accuracy Comparison

Model	RMSE	MAPE	MASE	RMSSE
Theta (Additive)*	0.33	1.35	0.31	0.28
Ensemble 3	0.34	1.38	0.32	0.29
Ensemble 4	0.34	1.51	0.35	0.29
Ensemble 1	0.34	1.35	0.31	0.29
Ensemble 2	0.35	1.42	0.33	0.30
Theta (Multiplicative)*	0.37	1.71	0.40	0.31
State Space Model*	0.39	1.45	0.34	0.33
Holt-Winters (Additive)	0.40	1.70	0.40	0.34
Prophet (Additive)	0.40	1.58	0.36	0.34
Holt-Winters (Multiplicative)	0.42	1.79	0.41	0.36
Prophet (Multiplicative)	0.50	1.76	0.41	0.42
Seasonal Naive	0.51	2.13	0.50	0.43
SARIMA	0.76	3.34	0.78	0.65
Neural Network	0.80	3.43	0.78	0.68
Dynamic Regression	0.91	4.04	0.94	0.77

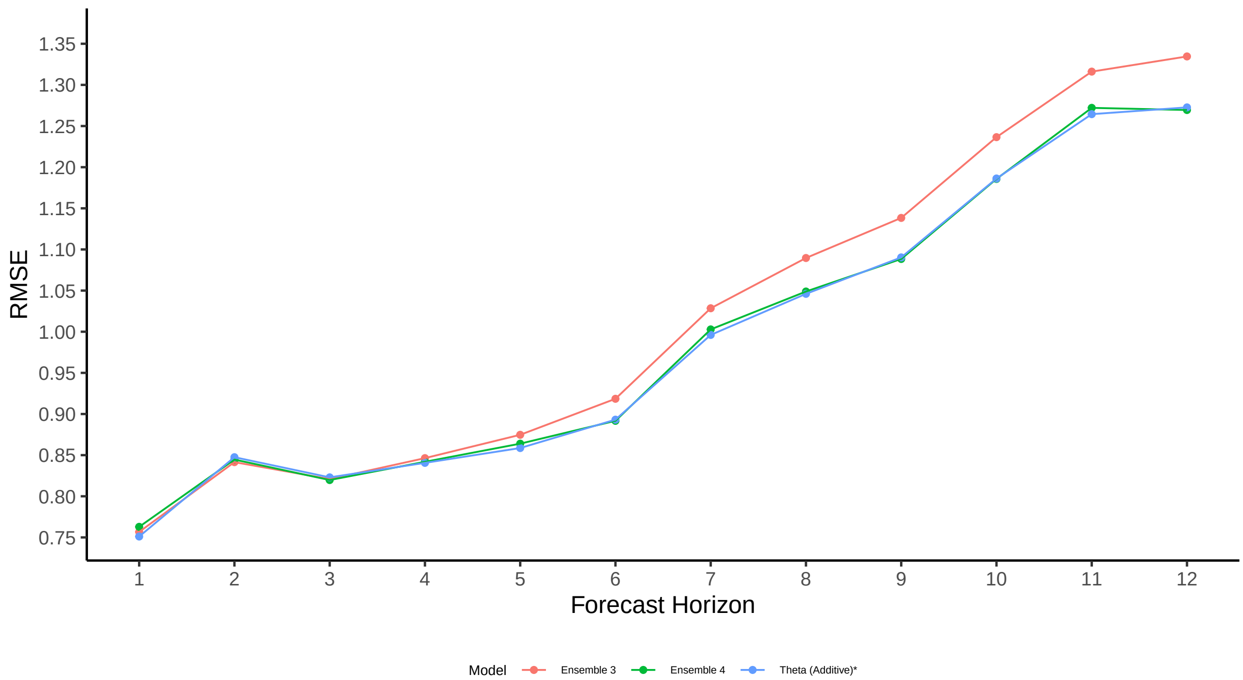
As a final evaluation, this report uses rolling-origin cross-validation to assess the forecasting performance of the top models over horizons ranging from one to twelve months ahead. Unlike a single train/test split, this method creates multiple test sets where each test observation occurs strictly after its corresponding training data. This setup provides a more realistic and robust measure of forecasting accuracy by averaging errors across all test sets.

Figure 8 displays the cross-validation results. Forecast errors naturally increase as the forecast horizon extends. The Ensemble 3 model—an average of State Space Model, Theta (Additive), and Theta (Multiplicative)—consistently shows the largest errors, indicating weaker predictive performance. In contrast, the Theta (Additive) method achieves the lowest errors across all horizons, demonstrating its reliability and strength in multi-step forecasting. The Ensemble 4 method—an average of Theta (Additive) and Theta (Multiplicative)—does not outperform the Theta (Additive) method but performs very close to it.

This cross-validation result reinforces our findings from the 12-month out-of-sample test (Table 3), where the Theta (Additive) model also showed the lowest error. The rolling-origin validation, which better captures the challenges of real-world, sequential forecasting, confirms the superior and consistent performance of the Theta (Additive) method.

Taking both out-of-sample and cross-validation results into account, this report selects the Theta (Additive) method as the preferred forecasting approach due to its consistent accuracy, robustness, and suitability for predicting our data.

Figure 8: Cross-Validation of the Top Models



4.4 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 Theta method. 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 0.94, 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 Theta method effectively captures the information in the data and is likely to produce accurate forecasts.

Figure 9: Residual Diagnostics of the Top Model

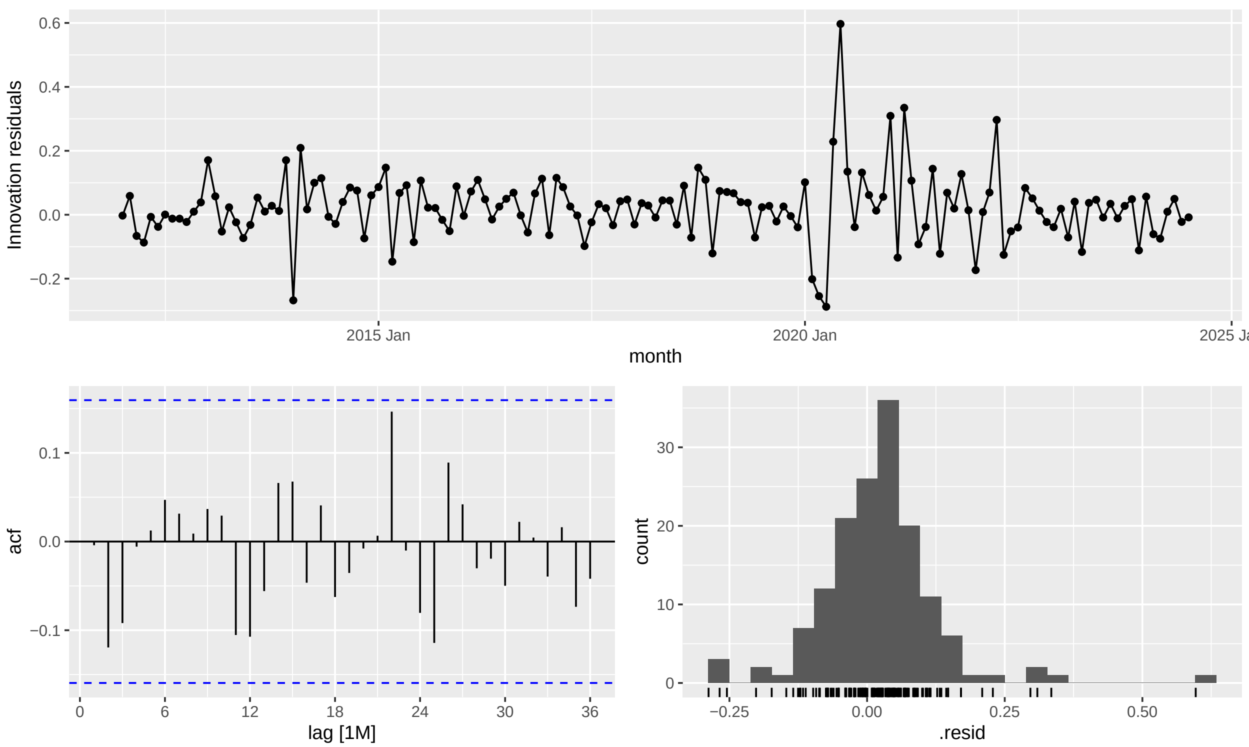


Table 4: The Ljung-Box Test for the Residuals

Ljung-Box Stat	Ljung-Box p-value
23.64	0.94

5 2025 Holiday Season Retail Sales Forecast

As a final step in forecasting, this report uses the Theta method with additive seasonality applied to data from January 2012 through July 2025 (the most recent available month) to predict retail sales for the six-month period from August 2025 to January 2026. The forecast results are shown in Figure 10, while Table 5 highlights projected retail sales for the 2025 holiday season.

Figure 10: Holiday Season Adjusted Sales Forecast

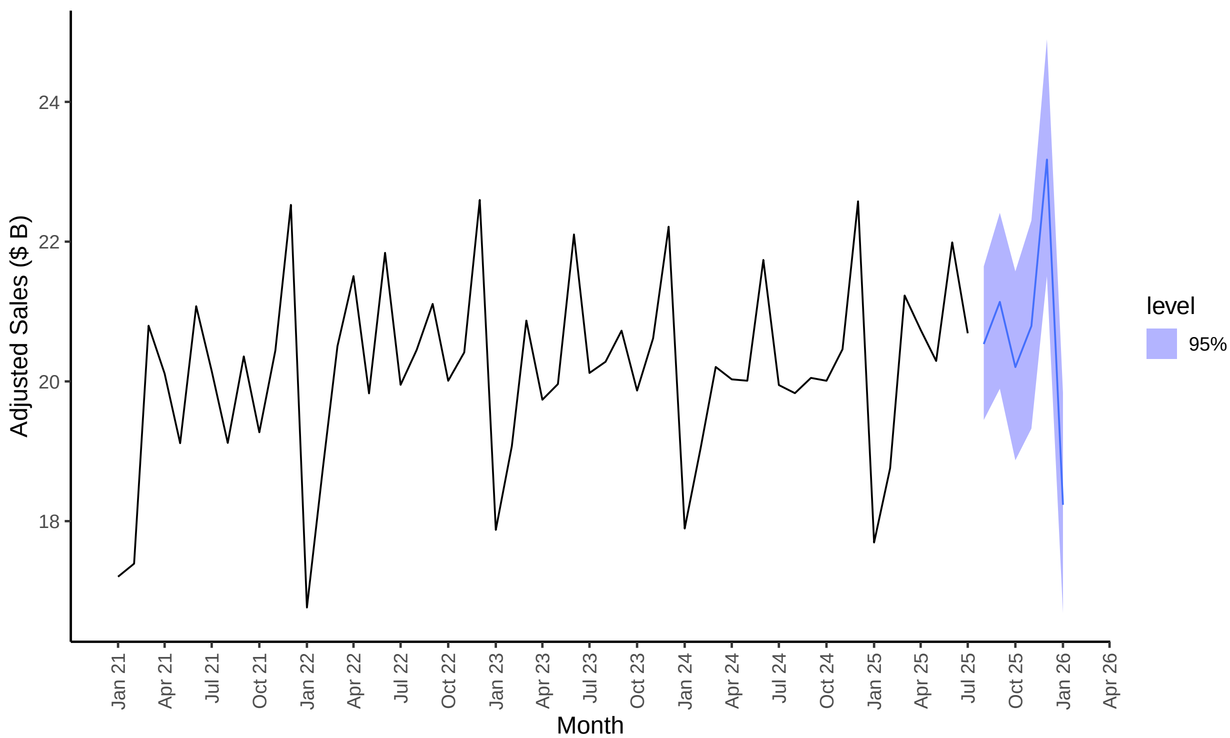


Table 5 compares the 2025 holiday season retail sales forecasts with previous years' inflation-adjusted sales, showing both year-over-year (YoY) and month-over-month (MoM) changes. When we compare the 2025 season with the same period in 2024, several key takeaways stand out:

- **November:** Retail sales in November 2025 are projected to reach **$20.79 billion**, an increase of **$0.33 billion (1.63%)** from $20.46 billion in November 2024. The 95% confidence range for this forecast is $19.33–$22.30 billion, meaning actual sales are very likely to fall within this range.
- **December:** For December 2025, projected sales are **$23.18 billion**, up **$0.60 billion (2.65%)** from $22.58 billion in December 2024. The 95% confidence range for December is $21.51–$24.90 billion.

- **Holiday Season (November–December):** Altogether, total holiday sales in 2025 are expected to reach **$43.97 billion**, an increase of **$0.93 billion** from **$43.04 billion** in 2024 — a **2.16% total seasonal growth**.

This 2.16% gain marks a clear improvement over the 0.40% growth recorded in 2024, suggesting that consumer spending is picking up strength as the 2025 holiday season approaches.

Table 5: Retail Sales Forecasts for the 2025 Holiday Season

Month	Forecast ($B)	Forecast Range (95%)	YoY Growth (%)	MoM Growth (%)
2025 Nov	20.79	19.33 - 22.30	1.63	2.91
2025 Dec	23.18	21.51 - 24.90	2.65	11.46
2026 Jan	18.23	16.68 - 19.84	3.05	-21.32

Holiday Season Year-over-Year Growth Comparison (2022 - 2025)

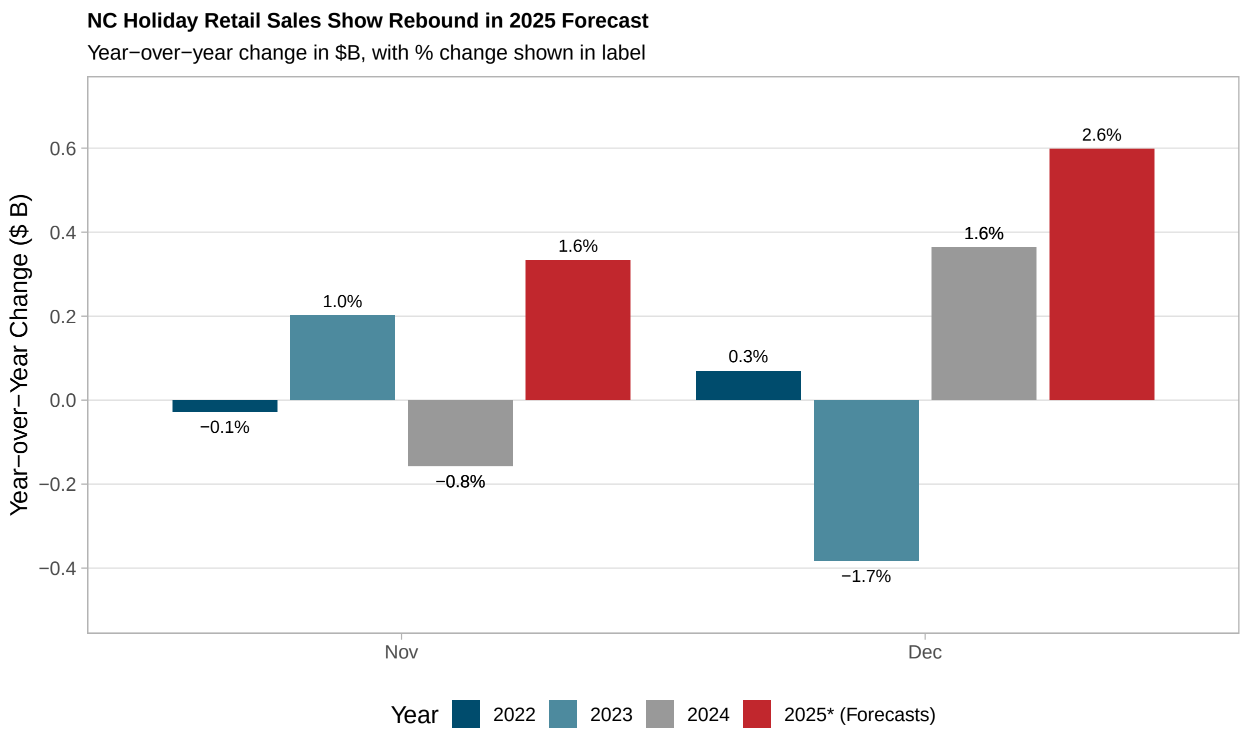
To further understand these forecasts, Figure 11 provides a detailed month-by-month comparison of projected 2025 holiday sales with inflation-adjusted figures from 2022 to 2024. The data reveal a modestly positive trend for the 2025 season, marking an improvement after several years of fluctuating but generally subdued growth.

- In November 2025, retail sales are projected to grow by 1.63% to $20.79 billion, marking a rebound from −0.76% in November 2024 ($20.46 billion). In contrast, earlier years showed modest movement, with +0.99% in 2023 and −0.14% in 2022, indicating that 2025 represents a return to steady seasonal growth.

  In December 2025, sales are expected to rise by 2.65% to $23.18 billion, a stronger gain compared to +1.64% in 2024 ($22.58 billion). This follows more muted changes in previous years—−1.69% in 2023 and +0.31% in 2022—highlighting a more robust finish to the 2025 holiday season.

- Overall, 2025 holiday sales are projected to total $43.97 billion—up $0.93 billion (2.16%) from 2024—signaling renewed consumer confidence and stronger seasonal demand.

Figure 11: Holiday Season (Nov-Dec) Retail Sales YoY Change (2022–2025)



6 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 2025 holiday season (November–December).

The analysis begins with historical data to identify growth patterns. Results confirm that the holiday season consistently represents the annual peak in retail activity. While sales have grown steadily over time, year-to-year fluctuations are common. After modest declines in 2022 and 2024, both November and December sales are projected to rise again in 2025, signaling renewed consumer momentum and steady economic recovery.

Overall, these projections suggest a clear rebound in retail sales for the 2025 holiday season, totaling approximately $43.97 billion, up $0.93 billion or 2.16% from $43.04 billion in 2024. This growth highlights the importance of carefully aligned retail strategies to accommodate fluctuating demand and capitalize on renewed consumer spending momentum.

The forecasts are based on aggregated sales tax data across various retail sectors and regions. While they provide a strong indication of overall holiday sales trends, local variations and sector-specific patterns may differ from these projections.