



# What's Ahead for North Carolina Retail Trade: 2024 Holiday Season Predictions and Analysis

NC Retail Merchants Association

P.O. Box 1030, Raleigh, NC 27602

E-mail: [info@ncrma.org](mailto:info@ncrma.org)

Contact: (919) 832-0811

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# 1 Executive Summary

1. This report analyzes North Carolina's monthly sales tax revenue data to identify retail sales patterns and forecast 2024 holiday season sales volume.
2. Historical trends indicate that retail sales reach their highest peak in December.
3. Total retail spending during the 2024 holiday season (November-December) is estimated to be around \$42.24 billion, up from \$42.08 billion in 2023.
4. Projections for the November-December 2024 holiday season suggest a slight overall growth of approximately 0.4 percent compared to last year.
5. November 2024 forecasts anticipate a decline of 1.6 percent compared to November 2023, while December 2024 forecasts predict a 2.2 percent increase from December 2023.
6. These findings provide valuable insights for stakeholders seeking to understand North Carolina's retail sales dynamics during the holiday season.

## 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. Miscalculating 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 for the 2024 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 the best-performing model to predict retail sales for the 2024

holiday season, offering valuable insights for retail industry stakeholders and decision-makers. Projections for the holiday season (November to December 2024) indicate retail sales will reach approximately \$42.24 billion, reflecting a modest growth of \$0.16 billion (0.4 percent) compared to \$42.08 billion in 2023.

- **November 2024:** Expected sales are \$19.62 billion, a decline of \$0.33 billion (-1.6 percent) from \$19.95 billion in November 2023.
- **December 2024:** Projected sales are \$22.62 billion, an increase of \$0.49 billion (2.2 percent) compared to \$22.13 billion in December 2023.

These findings suggest that while total sales volume during the holiday season continues to trend upward, the overall growth rates indicate a deceleration. This shift is likely influenced by changes in consumer behavior and purchasing power amidst recent inflationary pressures.

Table 1: Projected Holiday Season Retail Sales

Month	Predicted Sales	Change from 2023	Growth Rate
<b>November</b>	\$19.62 billion	-\$0.33 billion	-1.6 percent
<b>December</b>	\$22.62 billion	+\$0.49 billion	2.2 percent
<b>Total</b>	<b>\$42.24 billion</b>	<b>+\$0.16 billion</b>	<b>0.4 percent</b>

## 3 Data

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 2024 (latest available month). These data are derived from reports and payments submitted by taxpayers and are categorized based on sales and use tax registrations. A time plot of this data is depicted in Figure 1 below.

To prepare for accurate forecasting, we need to preprocess this data. This involves comprehending the data, examining its features, and making necessary adjustments. The primary objective is to improve forecast accuracy. Initially, inflation adjustments and mathematical transformations are applied to prepare the data for better forecasting. Subsequently, various data visualization techniques, including time plots, seasonal plots, and decomposition analysis, are employed to grasp fundamental data characteristics. These preprocessing steps make the data more suitable for forecasting, enabling more precise predictions for informed decision-making.

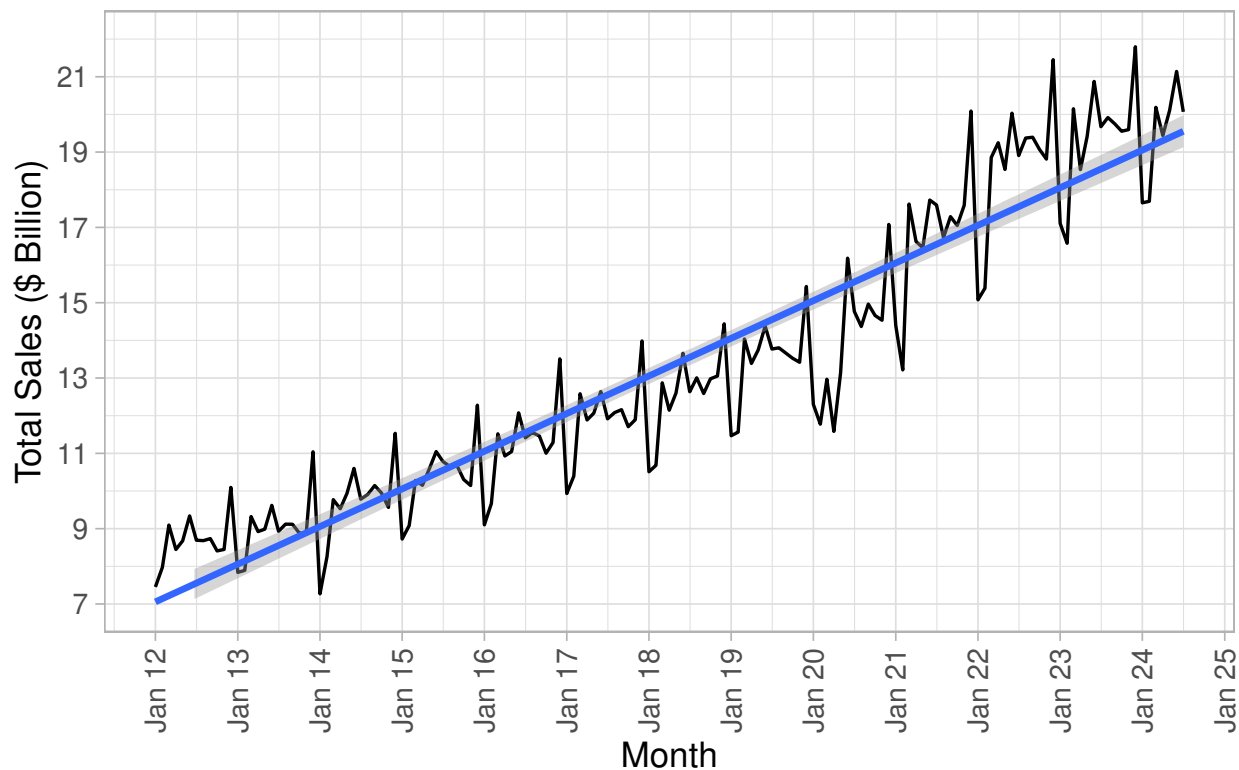
### 3.1 Inflation Adjustment

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, 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.

### 3.2 Mathematical Adjustment

Mathematical transformation of data before forecasting is imperative for several reasons. Firstly, it simplifies the time series, making it more amenable to accurate predictions. When historical data is adjusted, it often results in a smoother

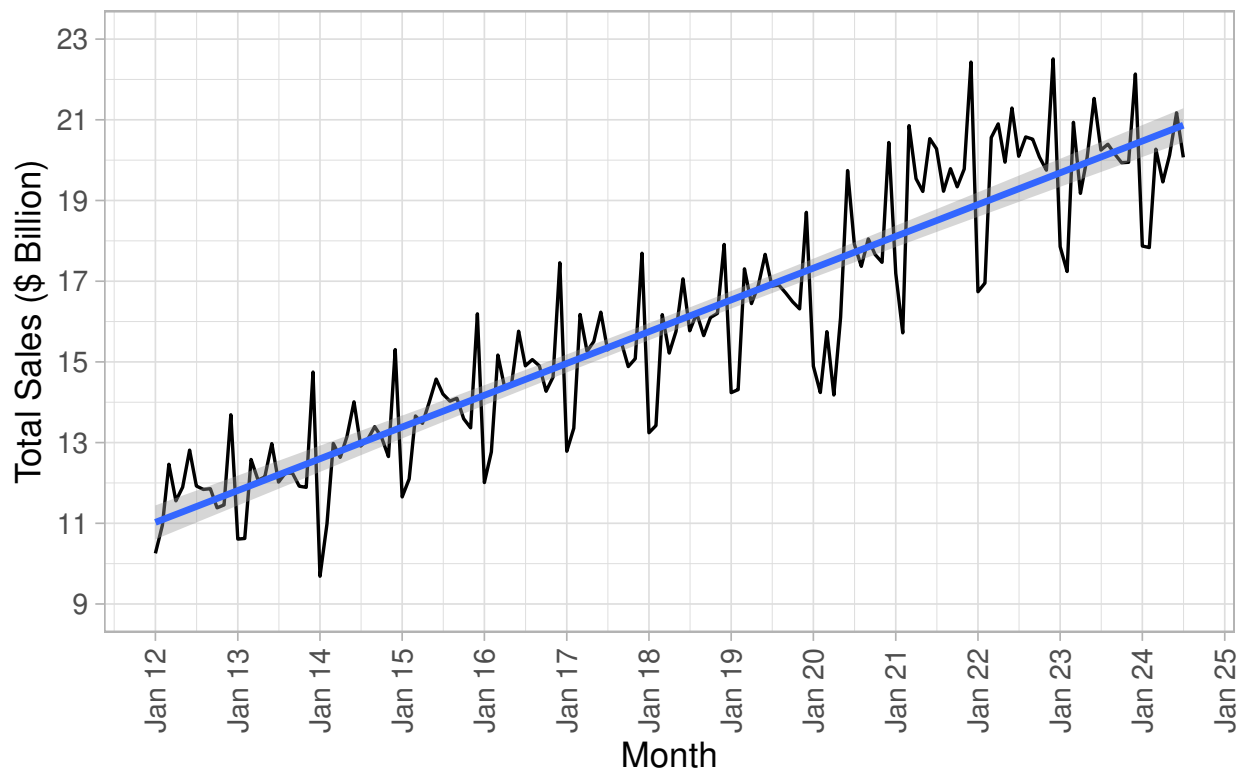
Figure 1: NC Monthly Unadjusted Sales (\$ Billion) (Jan 2012 - July 2024)



and more consistent series. Secondly, if the original data exhibits a level of variation that is proportional to the level of the series, a mathematical transformation becomes invaluable. In the case of our inflation-adjusted data, it is evident that there is a noticeable increase in variation in the later years compared to earlier ones. This discrepancy can lead to inaccurate forecasts if unadjusted. A mathematical transformation can homogenize the variation across the entire series, rendering the forecasting model simpler and more reliable. In essence, this process not only enhances the predictive power of our models but also ensures that forecasts are based on more stable and consistent data. Therefore, we apply a Box-Cox transformation to our data. We can clearly see the improvement in the stability of the series in Figure 3.



Figure 2: Inflation Adjusted Monthly Sales (\$ Billion) (Jan 2012 - July 2024)



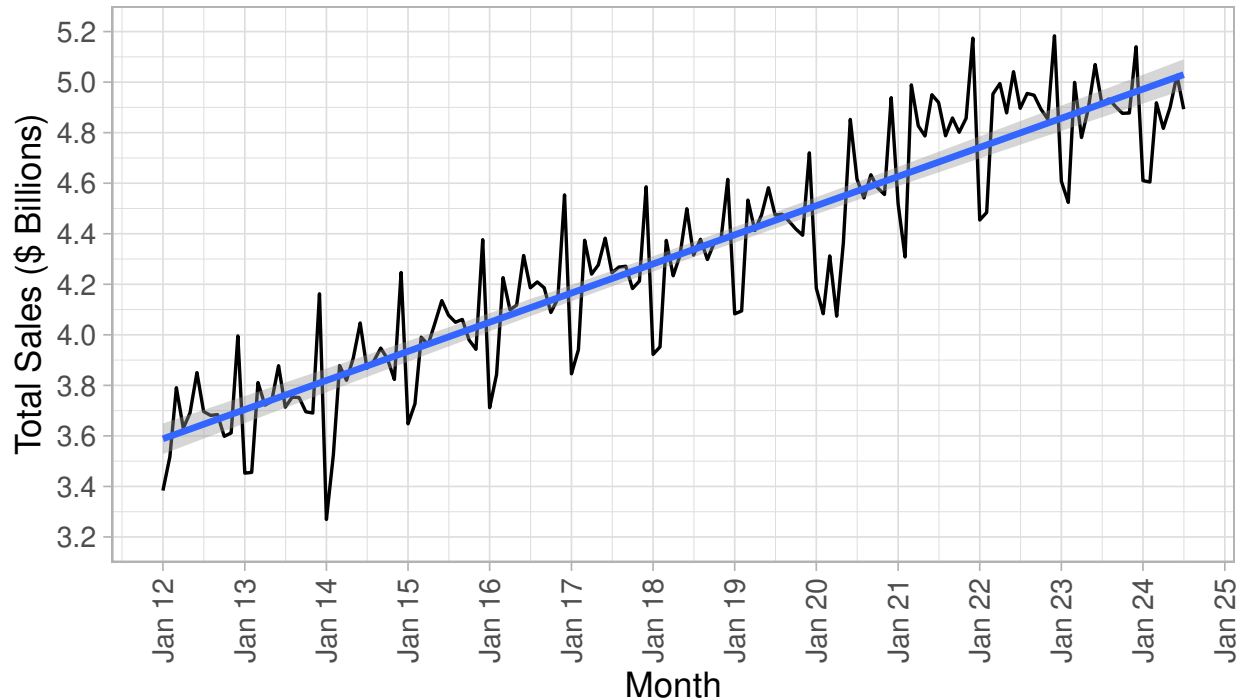
### 3.3 Features

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.

#### 3.3.1 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.

Figure 3: Box-Cox Transformation of Inflation Adjusted Sales

Adjusted Sales with  $\lambda = 0.3$ 

- **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 tends to have higher 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.

### 3.3.2 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 4: Seasonal Plot 1: Retail Trade Sales in North Carolina (Jan 2012 - July 2024)

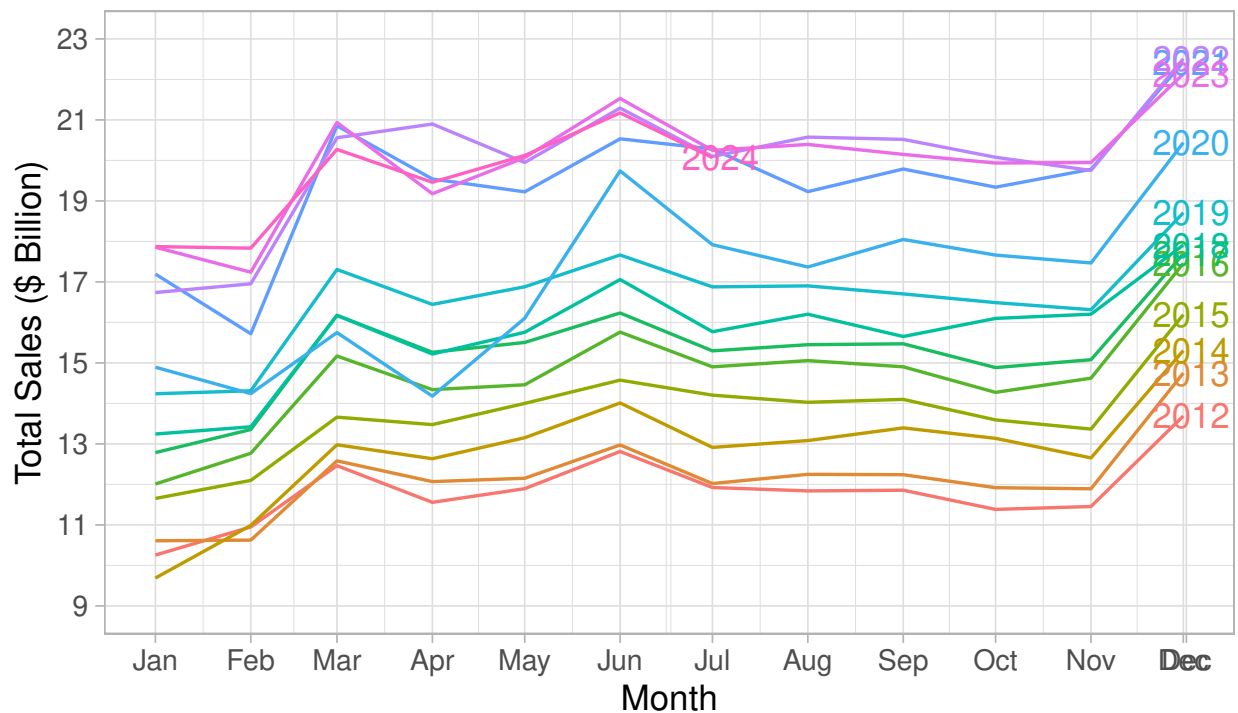
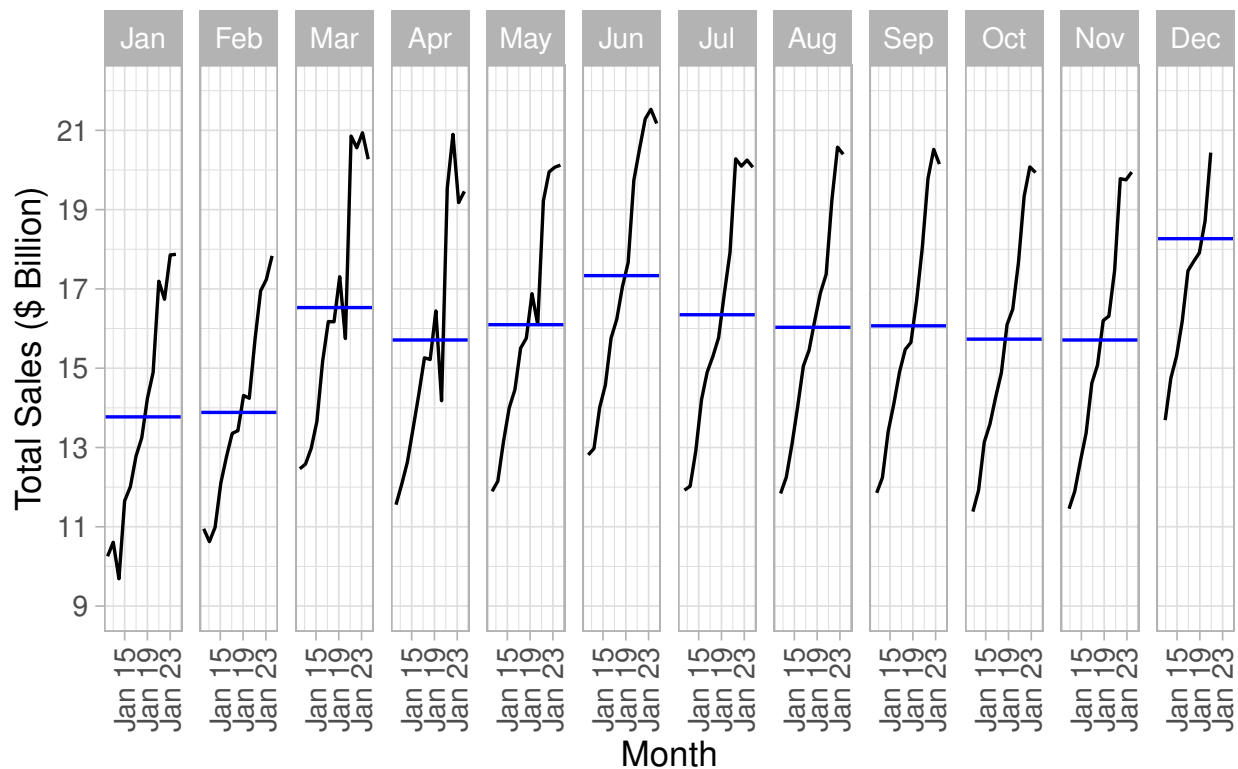


Figure 5 presents an alternative seasonal plot format. In this graph, the data for each season are aggregated into separate mini-time plots. Blue horizontal lines

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 5: Seasonal Plot 2: Retail Trade Sales in North Carolina (Jan 2012 - July 2024)



### 3.3.3 Decomposition

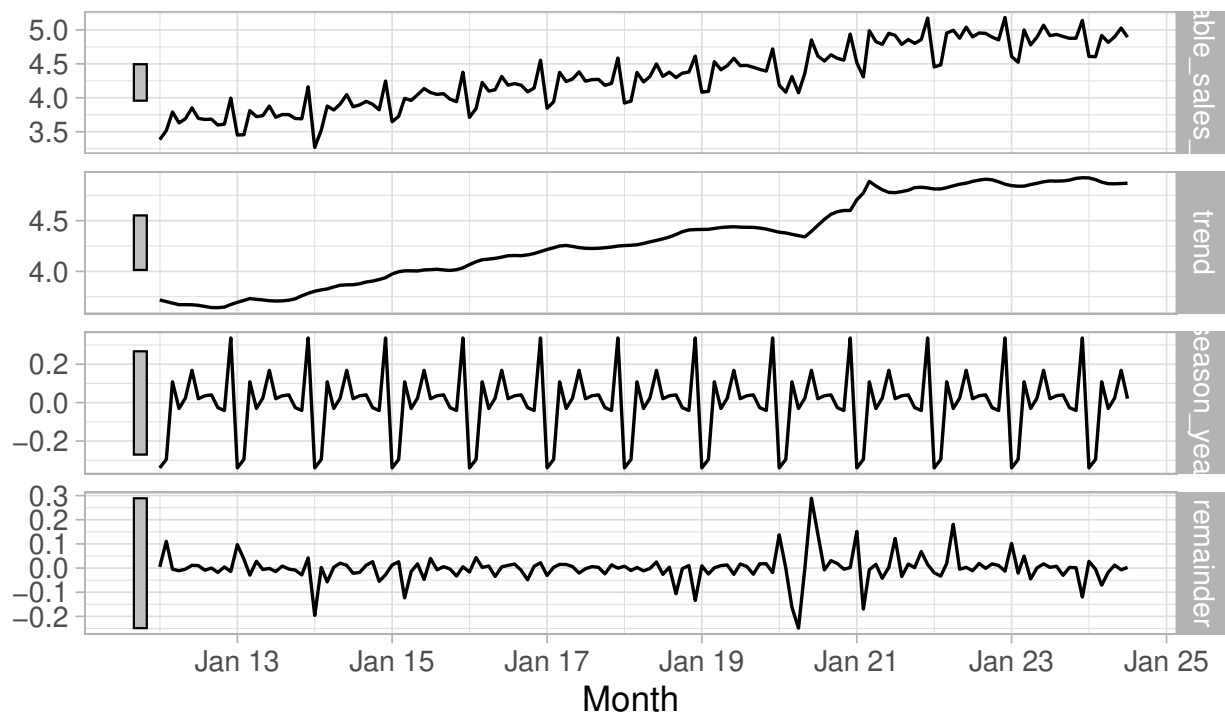
Time series data can manifest diverse patterns, and dissecting it into distinct components, each representing a specific underlying pattern category, is beneficial. Typically, we categorize a time series into three components:

- 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 6: Decomposition of Inflation Adjusted Transformed Monthly Retail Sales



## 4 Forecasting Holiday Season Retail Sales

### 4.1 Training vs. Test Sets

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 2023 as a training set. It then assesses the prediction accuracy of various forecasting models using a test set spanning from August 2023 to July 2024, the latest available data month. Finally, it employs the best-performing forecasting model to predict retail sales for the months spanning November 2024 to February 2025.

### 4.2 Fitting the Forecasting Methods on the Training Set

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 (Ad, A)
- Holt-Winters' with Additive Damped Trend and Multiplicative Seasonality (Ad, M)
- Innovations State Space Models
- Prophet Model with Additive Seasonality
- Prophet Model with Multiplicative Seasonality
- SARIMA (Seasonal AutoRegressive Integrated Moving Average Model)
- Simple Exponential Smoothing
- 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 Testing Out of Sample Forecast Accuracy

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 2 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. Based on out-of-sample accuracy measures, the Seasonal Naive method shows the highest performance, followed by the Holt-Winters method with a damped trend and additive seasonality. The Theta method, which also uses additive seasonality, ranks third.

Figure 7: Out of Sample Forecast Accuracy Comparison

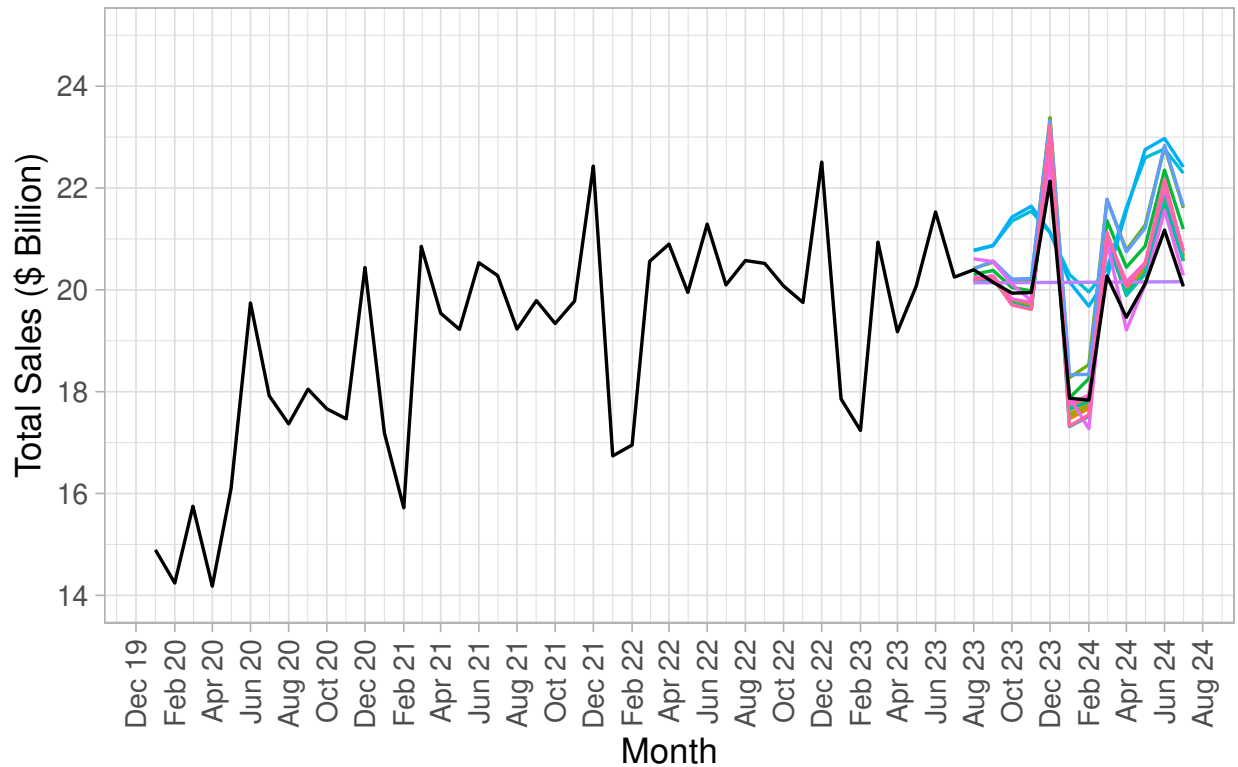




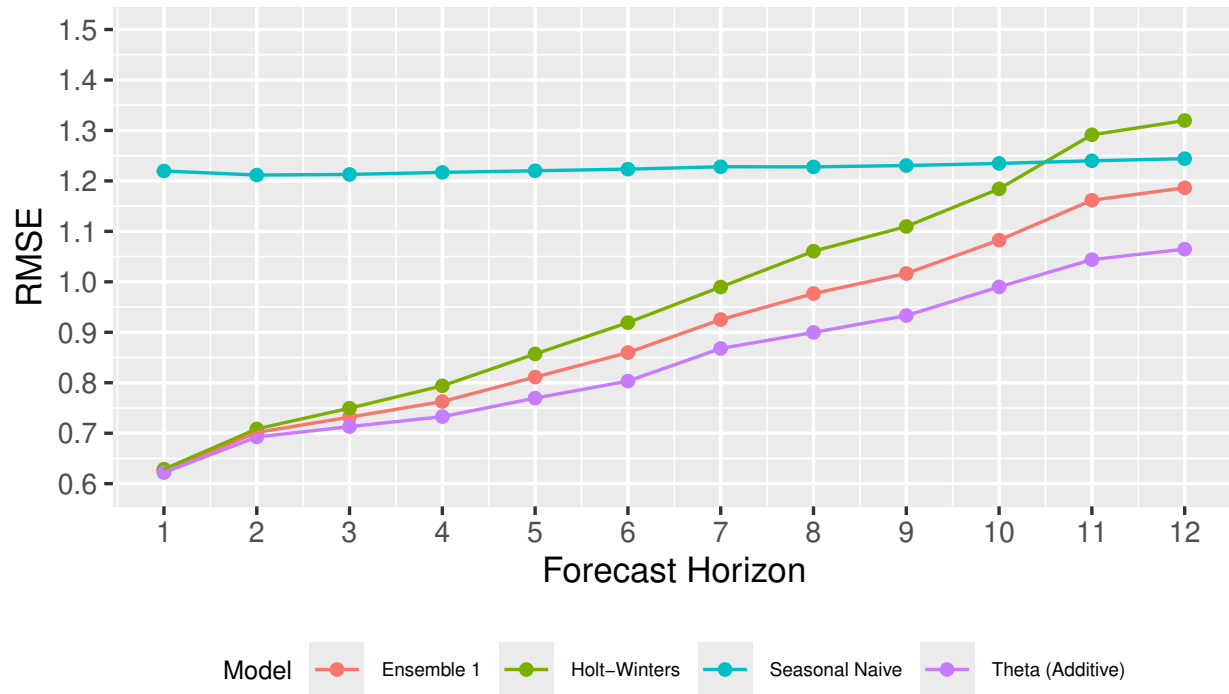
Table 2: Out of Sample Forecast Accuracy Comparison

Model	RMSE	MAPE	MASE	RMSSE
Seasonal Naive	0.354	1.465	0.322	0.293
Holt-Winters (Ad, A)*	0.396	1.656	0.369	0.328
Ensemble 1	0.445	1.913	0.424	0.369
Ensemble 2	0.448	1.831	0.409	0.371
Ensemble 3	0.459	1.921	0.428	0.380
Ensemble 4	0.487	2.029	0.451	0.404
Theta (Additive)*	0.507	2.026	0.453	0.420
Holt-Winters (Ad, M)*	0.507	2.176	0.480	0.420
Theta (Multiplicative)	0.611	2.594	0.575	0.506
State Space Model	0.730	2.833	0.631	0.605
SARIMA	1.024	4.241	0.939	0.849
Dynamic Regression	1.034	4.287	0.948	0.857
Simple Exponential Smoothing	1.161	3.967	0.842	0.963
Prophet (Additive)	1.706	7.777	1.671	1.415
Prophet (Multiplicative)	1.719	7.773	1.676	1.425

As a final test, this report examines the cross-validation of the top models by evaluating their ability to forecast sales one to twelve months into the future. Cross-validation is a more sophisticated approach than using simple training/test sets. In this procedure, there are multiple test sets, each consisting of a single observation. The corresponding training set includes only observations that occurred before the observation formed the test set, ensuring that no future observations are used to construct the forecast. The forecast accuracy is computed by averaging the errors over all test sets.

Figure 8 below evaluates the forecasting performance of these models for one- to twelve-month-ahead forecasts. The plot shows that the forecast error increases as the forecast horizon extends, which is expected. It can be seen that the Seasonal Naive method fails this test by producing the largest errors. In contrast, the Theta method with additive seasonality performs very well, maintaining the lowest error across all forecast horizons. Therefore, this test reveals the superiority of the Theta method in forecasting this time series.

Figure 8: Cross-Validation of the Top Models



#### 4.4 Residual Diagnostic of the Best Forecast Method

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 (Table 3). This test returns a relatively large p-value, 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

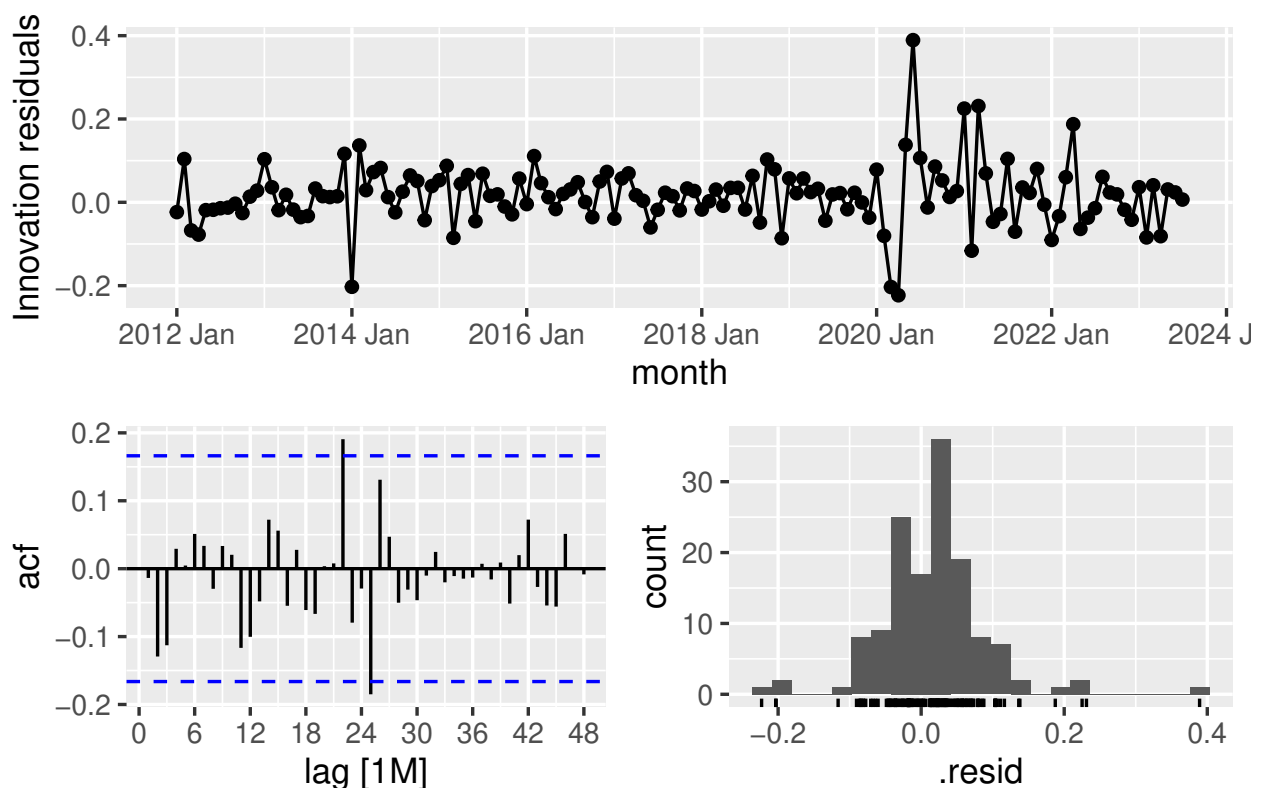


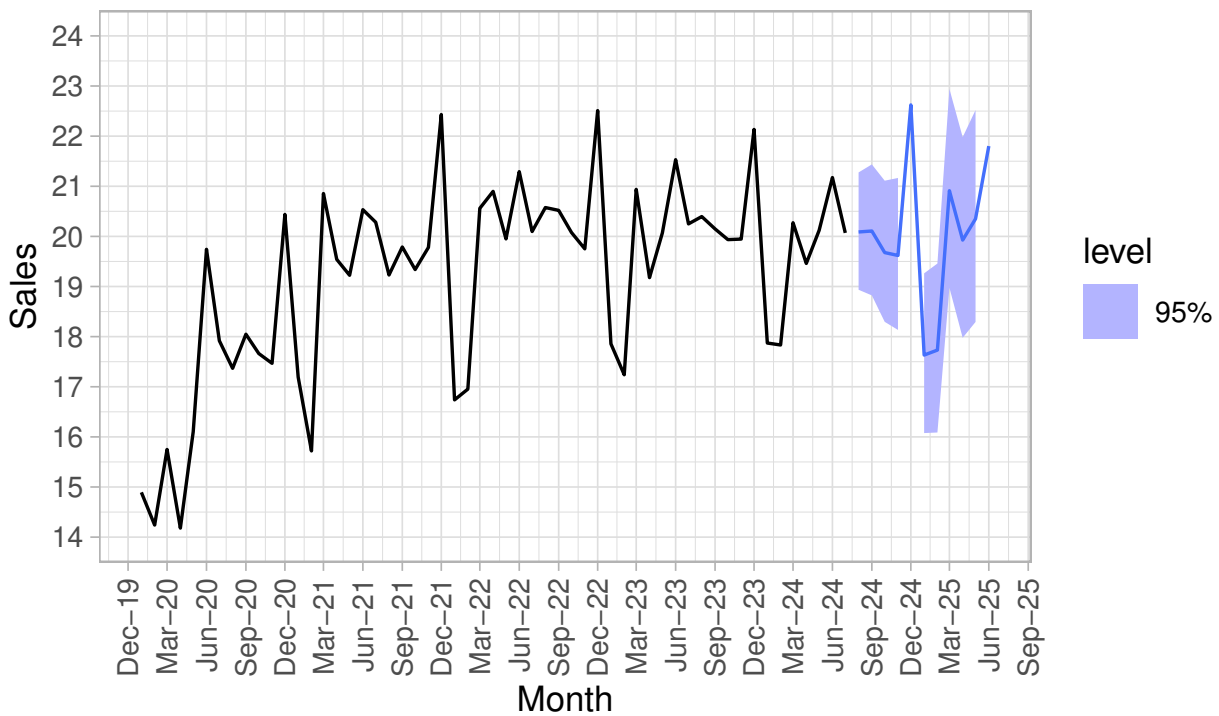
Table 3: The Ljung-Box Test for the Residuals

Ljung-Box Stat	Ljung-Box p-value
30.39	0.732

### 4.5 Forecasts

As a final step in forecasting, this report employs the Theta method with additive seasonality on the data from January 2012 to July 2024 (the latest available data month) to predict retail sales for the next seven months, spanning August 2024 to February 2024. The forecasted values are presented in Figure 10.

Figure 10: Retail Sales Forecasts (August 2024-February 2025)



Similarly, Table 4 presents retail sales predictions for November 2024 to February 2025, comparing the predicted values with inflation-adjusted values from the same months in previous years.

The predictions indicate mixed results for the holiday and post-holiday seasons. For the holiday season (November–December), total sales are projected to reach approximately \$42.24 billion, marking an average positive monthly increase compared to the same season in the previous year.

- **November 2024:** Sales are predicted to be \$19.62 billion, which represents a decrease of \$0.33 billion, or a -1.6 percent growth rate compared to November 2023.
- **December 2024:** Sales are expected to reach \$22.62 billion, showing an increase of \$0.49 billion, or a 2.2 percent growth rate, over December 2023.
- **Holiday Season 2024 (November–December):** Total sales are expected to reach \$42.24 billion, up from \$42.08 billion last year, marking a modest increase of \$0.16 billion, or 0.4 percent.

Overall, these predictions suggest a stable, albeit modest, growth in sales volume during the 2024 holiday season compared to the previous year.

Table 4: Retail Sales Forecasts for Nov 2024 - Feb 2025

Month	Predicted Sales	Change (\$Billion)	Growth (%)
2024 Nov	19.62	-0.33	-1.64
2024 Dec	22.62	0.49	2.21
2025 Jan	17.63	-0.24	-1.34
2025 Feb	17.73	-0.10	-0.57

To further understand these forecasts, Figure 11 provides a month-by-month comparison of holiday season sales predictions with inflation-adjusted retail sales from 2020 to 2024. The data show generally positive growth in holiday retail sales over the past several years, although growth rates have fluctuated and recently decelerated.

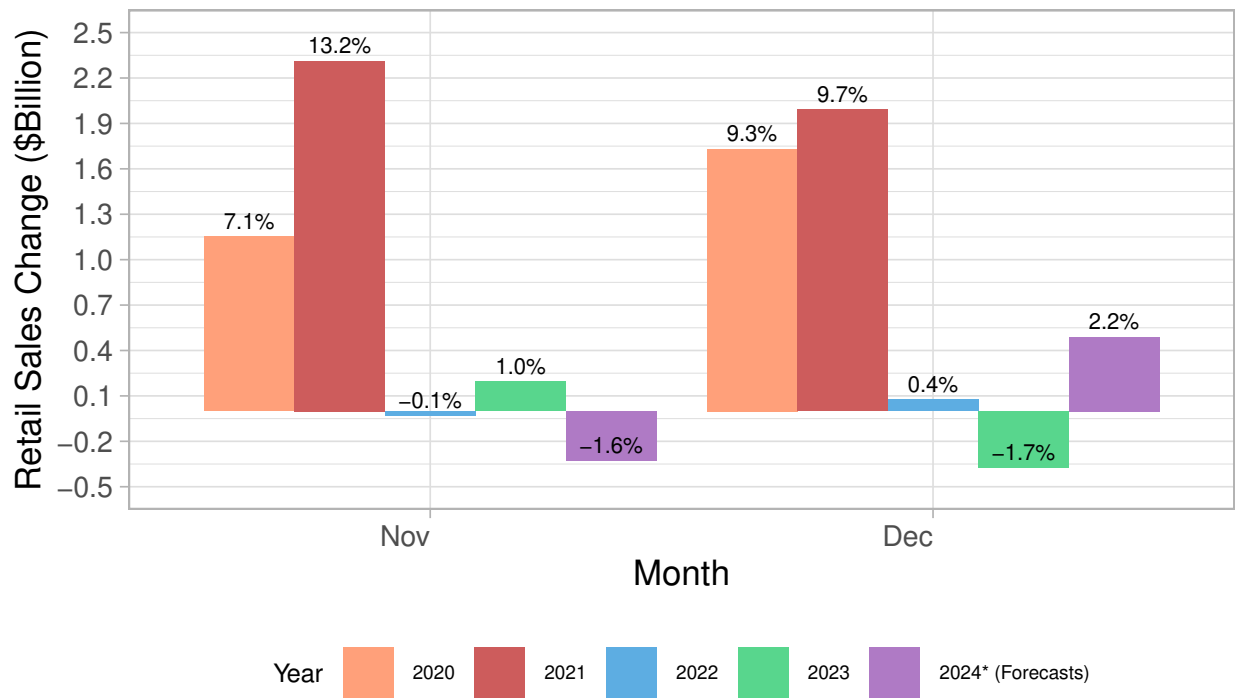
- **For November:** Projected retail sales for November 2024 are expected to reach \$19.62 billion, down from \$19.95 billion in November 2023. Historical growth rates for November have varied significantly, starting at 7.1% in 2020, sharply increasing to 13.2% in 2021, then dropping to -0.1% in 2022, and rising to 1.0% in 2023. For 2024, a projected decline of -1.6% is anticipated.
- **For December:** For December 2024, projected retail sales are expected to be \$22.62 billion, up from \$22.13 billion in December 2023. The growth

rates for December have also fluctuated, beginning at 9.3% in 2020, slightly increasing to 9.7% in 2021, declining to 0.4% in 2022, and experiencing a decrease of -1.7% in 2023. December 2024 is forecasted to see a moderate recovery with a growth rate of 2.2%.

- **Holiday Season (November–December):** For the holiday season, total sales are projected to reach \$42.25 billion, reflecting a change of \$0.16 billion from the same period last year and a growth rate of 0.40%, suggesting a gradual improvement in spending patterns. In comparison, holiday season sales in 2021 increased by \$4.31 billion or 11.36% from 2020, indicating strong consumer spending. In 2022, sales slightly increased by \$0.05 billion with a growth rate of 0.12% compared to the same period in 2021, suggesting stabilization after the previous year's growth. However, in 2023, total sales declined by \$0.18 billion, indicating a decline of 0.43% from 2022, reflecting challenges in consumer spending amid economic uncertainties.

While retail sales volume during the holiday season shows a slight increase, the slower growth rates indicate a decelerating pace. This trend may reflect a cooling in consumer spending, likely influenced by sustained high inflation impacting purchasing power in recent years.

Figure 11: Holiday Season (Nov-Dec) Retail Sales Change (2020–2024)





## 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 2024 holiday season (November–December).

The analysis begins with historical data insights to identify growth patterns. Historical data shows that the holiday season is the largest peak for retail sales, reflecting substantial year-end spending. Retail sales tend to experience consistent growth over time, although rates fluctuate annually.

Predicted sales for the 2024 holiday season (November–December) show a slight increase from the previous year, totaling around \$42.24 billion. November sales are anticipated to decline slightly by -1.6 percent from November 2023, while December 2024 is expected to recover with a moderate growth of 2.2 percent over December 2023.

Overall, these projections suggest stable but modest growth in retail sales during the holiday season, highlighting the importance of carefully aligned retail strategies to accommodate fluctuating demand amidst recent economic challenges.

The forecasts are based on sales tax data from various retail sectors across all regions but may not capture specific geographic variations or sector-specific sales patterns. Some geographic areas and sectors may experience growth trends that differ from those projected in these aggregated values.

For example, areas affected by Hurricane Helene may experience significant differences in retail trade sales compared to statewide growth rates, depending on the storm's impacts. The economic effects of Helene on state sales could vary based on the characteristics of the retail sector and specifics of the affected areas. The overall impact of Helene could be negative, positive, or neutral, depending on the factors outlined below:

- **Negative Impact:** Sales may decline due to business closures, which would reduce income for employees and limit their spending capacity, potentially creating a cascading effect on the local economy.

- **Positive Impact:** Recovery efforts may increase spending, as funds allocated for rebuilding boost income for local businesses and employees, leading to a positive ripple effect in retail purchases across the local economy.
- **Neutral Impact:** Effective recovery efforts and stable consumer confidence could offset lost income. If these conditions are met, Helene's effect on the local economy and holiday retail sales may be neutral, with spending patterns largely unaffected.

Therefore, it is important to consider these limitations when using these forecasts for decision-making purposes.

Table 5: Retail Sector Composition

<b>Retail Sector</b>	<b>Composition</b>
<b>Apparel Group</b>	Boot and shoe stores, clothing stores, clothing and accessory stores, etc.
<b>Automotive Group</b>	Motor vehicle dealers, service stations, garages, automotive supply stores, recappers, and repairers, and manufactured home (mobile home) dealers, etc.
<b>Food Group</b>	Bakeries, grocery stores, meat markets, vending machine operators, restaurants, cafeterias, grills, nightclubs, etc.
<b>Furniture Group</b>	Furniture stores, household appliance dealers and repair services, antique dealers, interior decorators, etc.
<b>General Merchandise Group</b>	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.
<b>Lumber &amp; Building Material Group</b>	Sheet metal shops, steel fabricators, building hardware and machine stores, building material dealers, electrical, plumbing, and heating supply dealers, etc.
<b>Unclassified Group</b>	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.