

# Impact of Weather on Retail Sales in Canada: Clothing and Footwear Industry

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## 1. Introduction

Making a profit in retail is more difficult than in any other industry (Gaur et al., 1999). Retailers must avoid costly mistakes i.e., understocking and overstocking. Accurate forecasts of demand and customer footfall will help retailers to improve workforce planning in stores, optimize their prices, and plan their inventory. Retailers' main goal is to provide the right product at the right time to their customers. To achieve this objective, retailers should be able to gauge the demand efficiently. Retail being the last downstream component of the supply chain, any major fluctuations in the demand can disrupt the whole supply chain. Accurate demand forecasting is the basis of many major supply chain functions such as inventory management, material planning, price optimization, etc. Hence, it is important for a resilient supply chain to understand the major factors influencing demand at the retail level.

The weather has been identified as an important driver of demand and constitutes a major risk for retailers. Weather usually has an impact on a consumer's decision-making process, from what they buy to when and where they buy it. These factors have repercussions for merchants and other stakeholders, such as inventory management and staffing (Rose & Dolega, 2020). Furthermore, due to the growing effects of global climate change, there is a great deal of uncertainty about future weather conditions and the implications

for consumption patterns. Especially in the apparel industry weather is believed to have a prominent impact on retail sales (Belkaid et al., 2021). It is difficult to anticipate daily weather in advance, but it has an immediate impact on daily business and sales. Weather such as precipitation (snow and rain) can significantly influence a shopper's decision. It is obscure how consumers will react to weather conditions. The shoppers may choose to consider good weather as a reason for engaging in outdoor activities and thus postpone or forgo purchases. On the other hand, they might consider shopping in clear and sunny weather. During bad weather conditions, retailers often offer low/discounted prices to attract consumers, this might lead to consumer hoarding supplies/bulk buying leading to significant demand fluctuations.

Daily weather conditions, as well as changes in weather conditions, are known to have a significant impact on various economic sectors, affecting up to 35 percent of GDP in developed countries (Parnaudeau & Bertrand, 2018), and can determine a company's success or failure (Ellithorpe & Putnam, 2000). As a result, weather is unquestionably an essential aspect for retailers to consider, especially when projecting sales or planning merchandising seasons. Retailers may face challenges of overstocking or understocking because of varying and unseasonal weather conditions, with consequences such as shelf-space management, wastage, or pricing reductions (Agnew & Thornes, 1995). Some businesses, such as Starbucks and Budweiser, have found success in incorporating weather forecasts into marketing or promotional operations (Bradlow et al., 2017), while others have been known to advertise 'feel-good' items during periods of bad weather (Grewal et al., 2017). It is learned that people in a good mood are more likely to spend more money and reward themselves (Badorf et al., 2020). Extreme weather can have a negative effect on an individual's mood and may have a psychological impact on a shopper's willingness to visit retail stores. It might cause them to shop online or postpone their plan of shopping. Weather being categorized as good or bad depends on a person's perception. Individuals from different socio-demographic backgrounds can perceive weather differently. So, the weather's impact on retail sales is a complex but important topic and needs to be further studied for a better understanding of its business implications.

Weather extremes such as heatwaves, storms, and cold spells cause short-term fluctuations in retail sales. (e.g., Chu, 2018; Inman, 2018). With forecasts of widespread warming and higher fluctuation of other circumstances (Murphy et al., 2010), as well as more frequent weather extremes, it is conceivable that weather will have an even greater impact on the retail industry in the coming years (Herrera et al., 2016; Kantamaneni & Du, 2017). Although it is impossible to forecast what these effects will be, a better knowledge of the current level of influence can assist stakeholders to prepare for future change by informing and preparing them. Even though this is a topic that receives a lot of media attention, there is not much scholarly research on the matter, not just for extreme weather, but for weather in general. As a result, giving solid empirical information that quantifies the impact is seen as unique and valuable by many stakeholders.

## Objective

In this study, we are analyzing the impact of weather factors on retail sales in the major provinces of Canada- Ontario, Quebec, and British Columbia. We are using monthly aggregated weather data to check for its impact on the sales of the clothing and footwear industry. The weather parameters whose impact we are analyzing in our study are snowfall, rainfall, temperature, and wind speed. The goal of using such a combination of weather factors is because these are the predominant weather conditions in Canadian Provinces, and we wanted to thoroughly investigate how these different parameters can combinedly or individually influence retail sales in Canada.

## 2. Literature Review

Steele (1951) was one of the first researchers who analyzed the impact of weather on retail sales. He studied the impact of snowfall, rainfall, temperature, wind speed, and sunshine on the sale of department stores in the period of seven weeks before Easter. According to his study, temperature and sunshine showed a positive impact, whereas rain, wind, and snow showed a negative impact on overall sales. Among the variables analyzed, snow showed the strongest impact on sales at department stores.

Several researchers have studied the importance of weather as a critical driver of demand and a major risk factor for retailers, especially where goods sold can be affected by weather conditions, such as fashion apparel (Belkaid et al., 2021). According to Zwebner et al. (2013), people’s product valuations are affected by weather conditions, and people’s opinions of items are more favourable on warm days. According to Bertrand et al. (2015), atypical weather has an impact on apparel sales in the spring and fall, but not in the summer or winter. Steinker et al. (2017) incorporated meteorological data into the largest European online fashion retailer’s sales predictions. They discovered that the amount of sunlight, warmth, and rain have a considerable impact on daily sales, especially during the summer, on weekends, and days with extreme weather. Keles et al. (2018) compared and evaluated two models for estimating the impact of temperature on company profitability. The effect of temperature, rainfall, daylight hours, and relative humidity on shopping centre attendance was investigated by Parsons (2001). Only the colder months of the year were observed, from September to February. The findings demonstrate that temperature and rainfall have a negative impact on tourist numbers, whereas sunshine hours and humidity have negligible effects.

Weather can significantly affect three major shopping decisions among consumers: what to buy, when to buy, and where to buy (Agnew and Thornes, 1995). The way weather can impact these decisions can be boiled down to two main reasons: 1) the physiological difficulties inclement conditions can create, and 2) the psychological effect on consumer’s mood which can be indirectly affected due to changes in weather conditions. This impact of store characteristics on consumers’ mood, satisfaction, and purchasing behavior was researched by Spes et al (1997). Reser and Swim (2011) also came to the same conclusion that bad weather can indirectly affect people by creating a certain degree of anxiety and tension.

## **Psychological Effect**

Weather can affect our mental health in a variety of ways. Rain, for example, causes discomfort (Miranda-Moreno & Lahti, 2013), whereas sunshine has a favourable effect on our mood (Cunningham, 1979; Hirshleifer & Shumway, 2003; Parrott & Sabini, 1990). The main way that weather impacts our bodies is the critical human need to keep our bodies at 37 degrees Celsius by balancing the heat lost to the environment with the heat produced by the body (Fanger, 1973). This equilibrium is influenced by a variety of external factors such as temperature, humidity, air velocity, and pressure, as well as interior factors such as activity level and clothing thermal resistance. When people are out of their comfort zones, they experience tension and discomfort, which has a negative impact on customer behaviour. They will feel more uncomfortable the further they are from the equilibrium point (Humphreys, Nicol, & Raja, 2007). The term “thermal comfort” is used in psychology to describe how weather affects people’s well-being (Humphreys et al., 2007; Nicol & Humphreys, 2002). This approach is pertinent to our topic because choosing clothing and using a store as a thermal environment are two methods for achieving thermal comfort.

Temperature has been discovered to have a unimodal relationship with comfort: extremes of heat or cold are uncomfortable, whereas moderate levels are. For example, Keller et al. (2005) discovered that temperature has an inverted U-shaped relationship with mood. According to Zivin and Neidell (2014), when the temperature is below 25°C, the number of pedestrians on the street increases, and when the temperature is above 25°C, the number of pedestrians on the street drops. The highest temperature for pedestrians in a particular county in California is 27°C, according to Attaset, Schneider, Arnold, and David (2010).

## **Physiological Effect**

There is a lot of research in economics on how people change their leisure activities and the amount of time they spend on them based on the weather. On rainy days, people relocate 30 minutes of leisure time to work on average, according to Connolly (2008), meaning that people exchange leisure and work time based on the weather. Zivin and Neidell (2014) add to the research by demonstrating that better outdoor conditions reduce work hours, and that substitution happens not only between work and leisure, but also between different leisure activities. More data is provided by Izquierdo Sanchez, Elliott, and Simmons (2016), who show that temperature has a significant effect on the substitution of going to the movies versus watching large athletic events, with a favorable trend favoring sports events as the temperature rises. According to

Li (2014), shopping is a leisure activity that should adapt to weather-driven substitution. For example, rain may make shopping less interesting because getting there is more difficult, while other indoor leisure activities become more appealing.

The goal of these studies is to determine the sign and magnitude of weather influences. There are a few exceptions to this rule. First, Steinker, Hoberg, and Thonemann (2017) employ weather to improve online sales demand projections in Germany and adapt staff planning, reducing idle time and expenses. They also discovered that when it rains, online sales increase significantly, implying that shopping online is similar to shopping at a mall and can be used as a substitute for shopping at a street store. Second, Brusset and Bertrand (2018) point out that critical days, or days with temperatures below a certain threshold, are a key driver of sales and that risk hedging methods should be developed accordingly.

Finally, Bertrand and Brusset (2018) investigate the impact of weather on sales and build financial tools to assist managers in reducing financial variance. Aside from these empirical findings, there is also pure theoretical study on how enterprises might utilize pricing methods to respond to weather events (Chen & Yano, 2010; Demirag, 2013). Weather has also been shown to influence crucial long-term decisions such as college choice (Simonsohn, 2009), automobile buying (Busse, Pope, Pope, & Silva-Risso, 2012), and home purchase (Busse, Pope, Pope, & Silva-Risso, 2015).

However, it is unclear how shoppers will react to the weather. The shoppers may opt to use the pleasant weather as an excuse to engage in outdoor activities, deferring or foregoing purchases. They might, on the other hand, consider going shopping when the weather is clear and sunny. Retailers frequently provide low/discounted prices to attract customers during inclement weather, which may result in consumers hoarding supplies/bulk buying, causing major demand changes, or it may cause them to shop online or postpone their shopping plans.

Our research also showed that retail sales are influenced by various economic measures, such as the consumer price index (CPI), disposable income, consumer confidence, and unemployment levels (Allenby et al., 2012; Grimsey, 2018; Tartaglione et al., 2019). Not surprisingly the increase in CPI and unemployment levels will decrease retail sales and increase consumer confidence and disposable income is linked to better retail performance.

Inspired by these past research and studies, we are evaluating the impact of weather on retail sales in Canada (Clothing & Footwear Industry). For our research purpose, we selected weather variables such as snow, temperature, rain, and wind speed as our independent variables. Also, to control retail sales for variables besides the weather, Consumer Price Index (CPI), Disposable income, consumer confidence, and Unemployment rate were included in the model as control variables.

Based on our literature review, this research aims to test the following hypotheses:

- **H1: Retail Sales decrease with an increase in Rainfall**
- **H2: Retail Sales decrease with an increase in Snowfall**
- **H3: Higher wind speed has a negative effect on retail sales**
- **H4: For a given historical temperature, retail sales are negatively influenced by mean temperature**

### 3. Exploratory Data Analysis

#### Methodology

The main goal of our project was to study the impact of weather on consumer retail sales by taking the example of the Clothing and Footwear industry in Canada. We have limited the scope of the analysis by considering only the three biggest provinces in Canada (in-terms of population) and taking them as a proxy to explain the consumer behavior for all of Canada. Also, only data from 2009 to 2019 are considered in

our analysis, because retail sales after 2019 will be significantly affected by covid and this might mask the impact of weather which we wanted to explore in our project.

Monthly aggregated data for the Clothing and Footwear Industry was collected from the website of Statistics Canada, and this was connected to the weather data of the same aggregation level using the API from weatherCAN available in R. Based on previous literature and data availability, we have decided to include only “total\_rain”, “total\_snow”, “mean\_temp”, and “spd\_max\_gust” to study the impact of weather on sales. During data analysis, we decided to add another feature “winter” to augment the impact of total snow. This is because snowfall occurs only during the months of winter, and this may reduce the impact of the weather variable “total\_snow”, thereby diminishing the importance of snowfall in the model predictability.

Models were developed using these weather factors and we controlled for the influence of factors other than our independent variables using a set of control variables. Control variables used in our models, consumer confidence, consumer price index, disposable income, and the unemployment rate were identified based on literature, and they were collected at the required aggregation levels of province and month for 2009 – 2019 from the website of Statistics Canada.

## Univariate Analysis

Figure 1 gives the overall distribution of retail sales over the years from 2009 to 2019. Since the data is right-skewed from the distribution plot, we corrected it using a log transformation before training the linear models. The following histogram plots of original versus transformed sales show how log transformation had helped fix the skewness of our dependent variable.

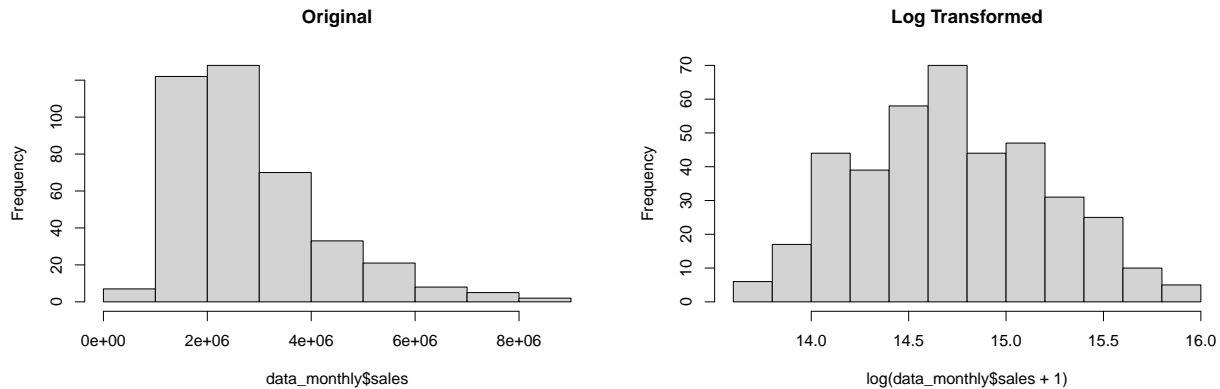


Figure 1: Histogram of Retail Sale

## Multivariate Analysis

The independent variables considered in our analysis were all numerical and there was no need to dummy encode variables in the study. The first step in our multivariate analysis was to calculate the Pearson correlation values between the numerical variables. This gives us the linear relationship between the variables. This is critical for our analysis because we are using linear predictive models and one of the basic assumptions of model validity is that the predictors should be independent to each other. The following correlation table and Figure 2 highlights the linear relationships that exist between the variables in our data. Apart from using correlation plots, we have also added a second level of protection against multicollinearity by validating the models using Variance Inflation Factor (VIF).

Table 1: Correlation Matrix

|                     | sales  | max_temp | mean_temp | min_temp | spd_max_gust | total_precip | total_rain | total_snow | cpi_index | disposable_income | unemployment_rate | consumer_confidence |
|---------------------|--------|----------|-----------|----------|--------------|--------------|------------|------------|-----------|-------------------|-------------------|---------------------|
| sales               | 1.000  | -0.002   | 0.006     | 0.057    | -0.210       | -0.348       | -0.397     | -0.134     | -0.413    | 0.868             | -0.265            | 0.043               |
| max_temp            | -0.002 | 1.000    | 0.906     | 0.858    | -0.194       | -0.068       | 0.127      | -0.774     | 0.175     | -0.042            | -0.200            | -0.020              |
| mean_temp           | 0.006  | 0.906    | 1.000     | 0.944    | -0.148       | 0.038        | 0.239      | -0.821     | 0.180     | -0.063            | -0.180            | -0.015              |
| min_temp            | 0.057  | 0.858    | 0.944     | 1.000    | -0.190       | -0.071       | 0.111      | -0.793     | 0.102     | 0.005             | -0.191            | 0.046               |
| spd_max_gust        | -0.210 | -0.194   | -0.148    | -0.190   | 1.000        | 0.457        | 0.407      | 0.253      | 0.408     | -0.312            | -0.235            | 0.163               |
| total_precip        | -0.348 | -0.068   | 0.038     | -0.071   | 0.457        | 1.000        | 0.955      | 0.136      | 0.440     | -0.474            | -0.195            | 0.111               |
| total_rain          | -0.397 | 0.127    | 0.239     | 0.111    | 0.407        | 0.955        | 1.000      | -0.116     | 0.532     | -0.525            | -0.203            | 0.029               |
| total_snow          | -0.134 | -0.774   | -0.821    | -0.793   | 0.253        | 0.136        | -0.116     | 1.000      | -0.142    | -0.115            | 0.184             | 0.055               |
| cpi_index           | -0.413 | 0.175    | 0.180     | 0.102    | 0.408        | 0.440        | 0.532      | -0.142     | 1.000     | -0.508            | -0.486            | 0.171               |
| disposable_income   | 0.868  | -0.042   | -0.063    | 0.005    | -0.312       | -0.474       | -0.525     | -0.115     | -0.508    | 1.000             | -0.120            | -0.027              |
| unemployment_rate   | -0.265 | -0.200   | -0.180    | -0.191   | -0.235       | -0.195       | -0.203     | 0.184      | -0.486    | -0.120            | 1.000             | -0.520              |
| consumer_confidence | 0.043  | -0.020   | -0.015    | 0.046    | 0.163        | 0.111        | 0.029      | 0.055      | 0.171     | -0.027            | -0.520            | 1.000               |

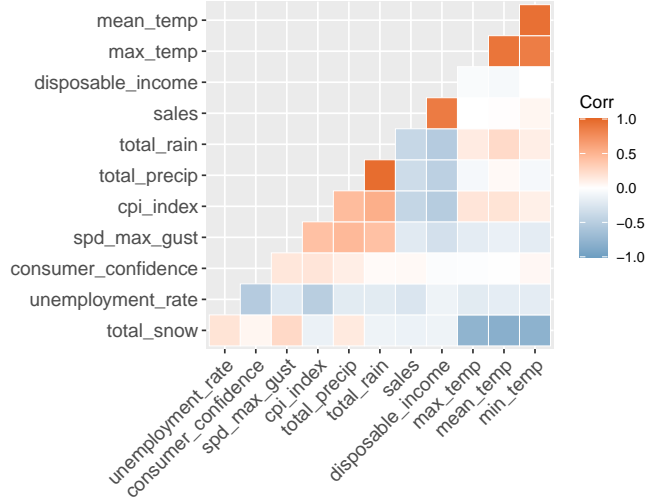


Figure 2: Correlation Heatmap

From the boxplots (Figure 3) of sales by provinces, we can see that there is a significant difference between the sales distribution across the regions. Retail sales from clothing and footwear is maximum in Ontario, followed by Quebec, and then British Columbia. But we are not adding province as a predictor in our models because we found that it has a strong multicollinear effects on the other predictors, and this suppresses their coefficients and predictive importance.

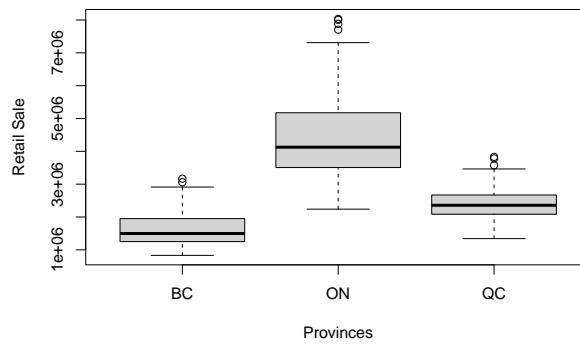


Figure 3: Boxplot of sales by province

The following scatterplots (Figure 4) are indicative of the effects of weather on sales which we wanted to study in the research. Retail sales have a negatively trending relation with total snow, total rain, and max gust, thus providing a preliminary backup to our hypothesis. Retail sales do not seem to be affected by the mean temperature of the region, which is different from the literature and thereby negates our fourth hypothesis.

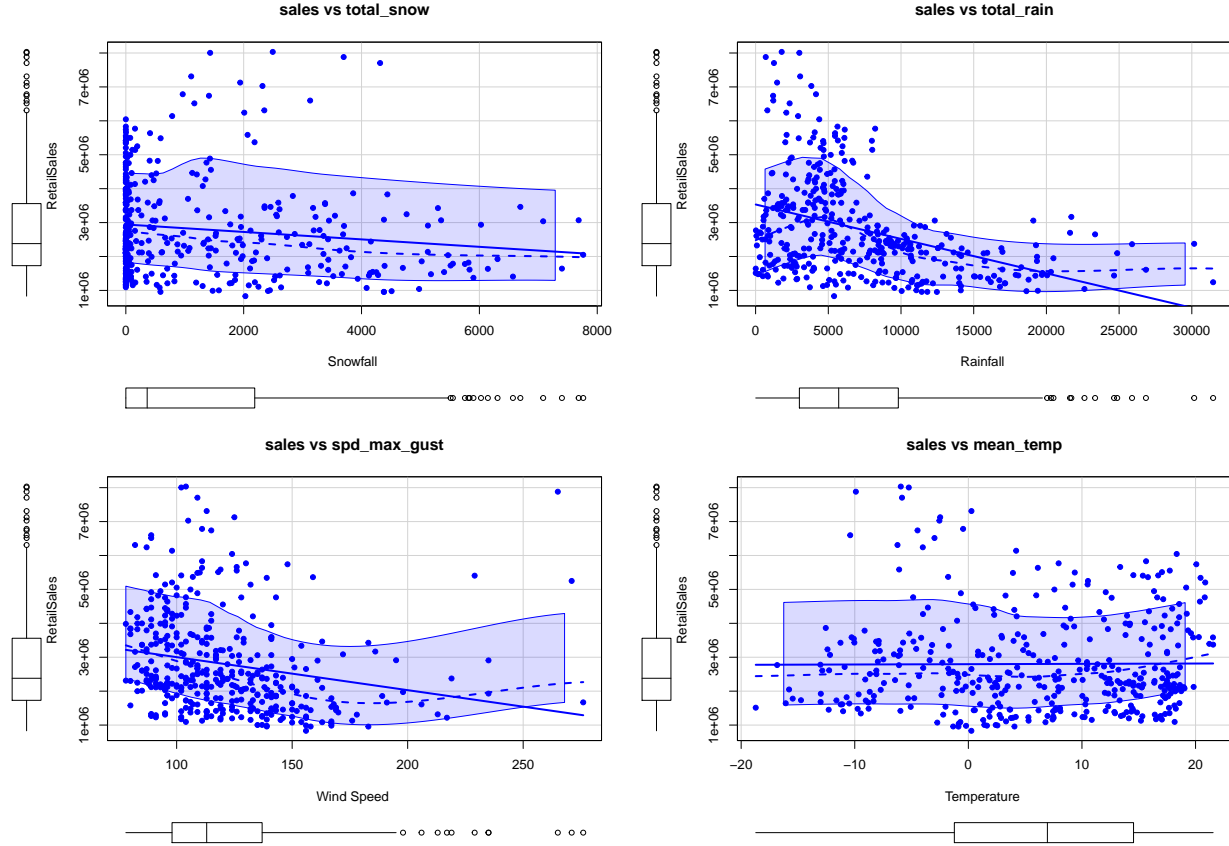


Figure 4: Scatterplots of Sales vs Weather

The scatterplots also indicated the presence of outliers which was confirmed using the summary table below. Also, since the input variables are of different scales, we have decided to scale the variables using z-score transformations and trim outliers that have a z-value of more than 3. The resulting nulls were imputed using KNN imputation. KNN looks at the values of the nearest neighbors to the null values and imputes them with their averages.

Table 2: Descriptive Statistics

| Statistic           | Mean          | St. Dev.      | Min       | Pctl(25)  | Pctl(75)    | Max        |
|---------------------|---------------|---------------|-----------|-----------|-------------|------------|
| sales               | 2,801,184.000 | 1,437,481.000 | 831,155   | 1,731,315 | 3,552,433.0 | 8,032,570  |
| max_temp            | 26.509        | 8.855         | 1.000     | 18.675    | 34.000      | 45.500     |
| mean_temp           | 5.929         | 9.746         | -18.716   | -1.184    | 14.536      | 21.548     |
| min_temp            | -21.894       | 15.926        | -56       | -37.5     | -6          | 2          |
| spd_max_gust        | 120.755       | 31.002        | 78        | 98        | 137         | 276        |
| total_precip        | 13,656.510    | 7,721.778     | 2,422.100 | 8,480.950 | 16,590.700  | 46,705.900 |
| total_rain          | 7,219.686     | 5,625.045     | 8.900     | 3,011.200 | 9,804.750   | 31,466.400 |
| total_snow          | 1,299.713     | 1,760.732     | 0.000     | 0.375     | 2,186.500   | 7,762.300  |
| cpi_index           | 94.680        | 6.287         | 81.200    | 90.000    | 99.425      | 112.300    |
| disposable_income   | 261,759.500   | 117,635.100   | 120,292   | 171,454   | 374,962     | 498,688    |
| unemployment_rate   | 5.889         | 1.162         | 3.200     | 5.000     | 6.625       | 8.800      |
| consumer_confidence | 104.705       | 23.470        | 57.567    | 90.169    | 115.719     | 172.681    |

## 4. Models

To examine the relationship between weather and retail sales, we have used linear regression models. We developed the models based on a distinct set of control variables. For explaining the weather effect on sales, 4 multiple regression models were developed by adding the control variables one each at a time along with the remaining independent variables. Since the control variables are significantly correlated to each other based on the correlation table, adding them together will naturally enhance the R-squared values. But it made it exceedingly difficult to study the impact of our weather variables in predicting sales. Therefore, we have taken this approach of using 4 separate models to validate our hypothesis. The data is standardized so that the coefficients in result tables are interpretable.

In the various models developed, we analyzed the variability caused by independent variables: snow, rain, wind speed, and temperature. We also considered the interaction effects of the binary variable (winter) with snow, rain, and wind. In model 1 we have used consumer confidence as the control variable, whereas the cpi index is the additional control variable in model 2. Both control variables are significant in their respective models. Disposable income in model 3 is positively related to retail sales and has high significance. The unemployment rate is highly significant, but it has a negative relation to retail sales. If the disposable income and consumer confidence of people in the province increases, then it has a positive impact on retail sales performance. On the other hand, if the unemployment rate and consumer price index in a province increase then the retail sales will decrease. It can also be observed that the interaction variables is not significant in any of the models.



Table 3: Regression Table

|                                | <i>Dependent variable:</i> |                   |                   |                   |
|--------------------------------|----------------------------|-------------------|-------------------|-------------------|
|                                | sales                      |                   |                   |                   |
|                                | (1)                        | (2)               | (3)               | (4)               |
| consumer_confidence            | 0.095*** (0.019)           |                   |                   |                   |
| cpi_index                      |                            | -0.159*** (0.024) |                   |                   |
| disposable_income              |                            |                   | 0.424*** (0.010)  |                   |
| unemployment_rate              |                            |                   |                   | -0.146*** (0.019) |
| total_snow                     | -0.191*** (0.044)          | -0.196*** (0.043) | -0.044** (0.020)  | -0.155*** (0.043) |
| total_rain                     | -0.225*** (0.030)          | -0.200*** (0.030) | -0.015 (0.015)    | -0.228*** (0.029) |
| mean_temp                      | -0.051 (0.037)             | -0.038 (0.036)    | 0.045*** (0.017)  | -0.055 (0.036)    |
| spd_max_gust                   | -0.105*** (0.030)          | -0.014 (0.031)    | -0.015 (0.014)    | -0.133*** (0.029) |
| winter                         | 0.693*** (0.125)           | 0.613*** (0.123)  | 0.500*** (0.056)  | 0.572*** (0.121)  |
| I(mean_temp^2)                 | -0.044* (0.024)            | -0.084*** (0.025) | -0.049*** (0.011) | -0.025 (0.024)    |
| total_rain:winter              | 0.062 (0.067)              | 0.073 (0.066)     | -0.034 (0.030)    | 0.048 (0.065)     |
| total_snow:winter              | 0.030 (0.105)              | 0.043 (0.103)     | 0.087* (0.047)    | 0.051 (0.101)     |
| spd_max_gust:winter            | -0.098 (0.095)             | -0.068 (0.093)    | 0.002 (0.043)     | -0.053 (0.091)    |
| Constant                       | 14.692*** (0.031)          | 14.744*** (0.032) | 14.722*** (0.014) | 14.679*** (0.030) |
| Observations                   | 396                        | 396               | 396               | 396               |
| R <sup>2</sup>                 | 0.441                      | 0.465             | 0.887             | 0.482             |
| Adjusted R <sup>2</sup>        | 0.426                      | 0.451             | 0.884             | 0.468             |
| Residual Std. Error (df = 385) | 0.369                      | 0.361             | 0.166             | 0.355             |
| F Statistic (df = 10; 385)     | 30.340***                  | 33.416***         | 302.359***        | 35.791***         |

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

## 5. Results and implications

From the regression table, we can see that model 3 has the highest adjusted R<sup>2</sup> value. However, the independent variables of snow and wind are not significant in this model based on the p-value scores from t-tests. From the correlation table, we observed that disposable income is significantly correlated (0.8) to retail sales, which diminishes the impact of weather on retail prediction as most of the variability is explained by this one variable. Disposable income is also correlated with the weather factors, leading to possibilities of multicollinearity in the 3rd model. Hence, we decided to take model 4 as the best performing model, with an adjusted R<sup>2</sup> value equal to 0.482.

$$\widehat{\text{sales}} = 14.68 - 0.15(\text{unemployment\_rate}) - 0.16(\text{total\_snow}) - 0.23(\text{total\_rain}) - 0.06(\text{mean\_temp}) - 0.13(\text{spd\_max\_gust}) + 0.57(\text{winter}) - 0.02(\text{mean\_temp}^2) + 0.05(\text{total\_rain} \times \text{winter}) + 0.05(\text{total\_snow} \times \text{winter}) - 0.05(\text{spd\_max\_gust} \times \text{winter}) \quad (1)$$

Robustness checks were then performed on the final regression model to validate the impact of weather on consumer behavior and retail performance obtained from the model output. The final model conforms to all the assumptions of linear regression, and it passed the validity tests of 1. Linearity, 2. Nearly Normal Residuals, and 3. Constant Variability (Homoskedasticity). (Figure 5)

Linearity assumption was verified from the Residual vs Fitted line plots; the fitted line from the model equation closely aligns with the x-axis. Normality assumption was verified from the Q-Q plot of residuals and its corresponding distribution plot. Homoskedasticity assumption was also proven from the Residual vs Fitted line plots as the data points are centered around the x-axis with constant variability.

Contrary to previous literature, from our analysis, we found out that temperature does not play a significant role in predicting retail sales. Thus rejecting our hypothesis about temperature. However, we have found that other weather variables such as wind, snow, and rain can be strong predictors of retail sales. This is not

surprising as rain, snow, and wind create substantial changes in consumer comfort while temperature whose impact depends on the amount of deviation from base temperature level has a negligible impact (Belkaid et. al 2021).

Our research was focused on offline retail sales across all kinds of stores. Street-side stores have a prominent presence in the clothing and footwear industry. But consumers might prefer mall stores during harsh weather and may consider shopping at street stores during pleasant weather conditions. Hence, the impact of weather can be significantly different from the street stores to retail mall stores, this can be explored further in future studies. Moreover, we have not considered the shift of consumer shopping interest to online stores in periods of bad weather whose impact on retail sales can be incredibly significant.

We tried to cover most of the weather parameters in our research, but a few of the parameters like sunlight and humidity, whose impact on retail sales is believed to be significant in past studies are out of the scope of our research.

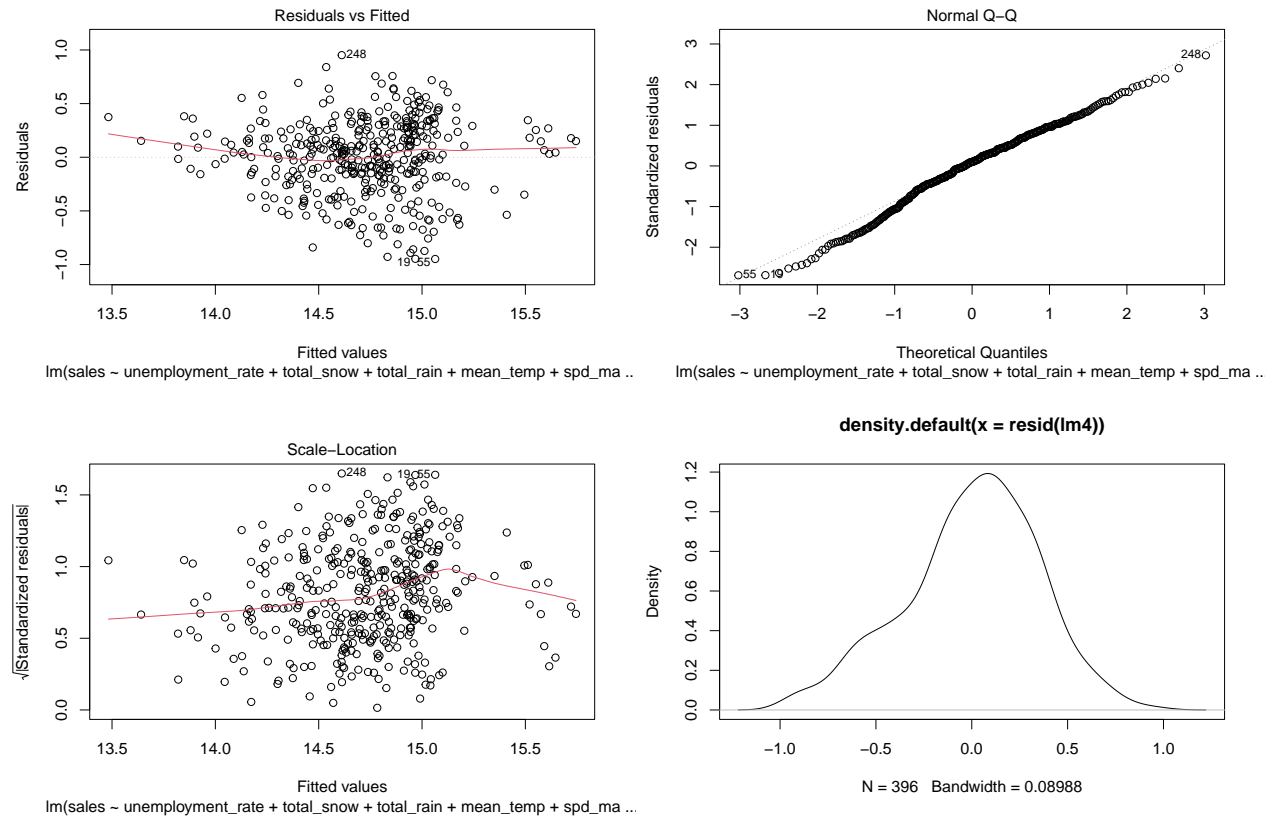


Figure 5: Model Validation

## 6. Conclusion

In this paper, we empirically studied the effect of rainfall, snowfall, temperature, and gust on the sales of the Clothing and Footwear industry in Canada. We conducted the study at a monthly level and considered the sales of Ontario, Quebec, and British Columbia to be a proxy for sales across Canada. We were able to establish a clear relationship between weather effects and sales which was in line with the literature on physiology and psychology. Harsh weather, in general, has an overall negative effect on sales. This may be due to both its physiological limitations and psychological implications. Since the weather information

was collected at an aggregated level, we were not able to capture the impact of sudden onsets of inclement weather; for example, snowstorms, freezing rain, etc. Also, we are not considering sales at different retail channels. Since most retail stores have adopted or are adopting omnichannel strategies, it will be especially important to study the exact impact weather has on these individual channels.

In conclusion, we were able to validate three of our hypotheses regarding weather and retail sales. Temperature does not seem to have any impact on fashion retail sales in Canada, as opposed to previous literature which suggested otherwise. Our research is novel because none of the researchers have studied the effect of weather on retail sales in Canada before, but they have all admitted that the impact of weather is regional and can change depending on the population. We hope that this study can inspire new research in this field because it has immense potential to improve the existing demand forecasting models, and other complementary functions in the supply chain which can significantly alter an organization's bottom line.

## 7. References

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