A Study on the Effect of Daily Weather on Quarterly Retail Revenues

Susan Sun
University of Toronto
Toronto, Canada
susany.sun@mail.utoronto.ca

Hang Xiang
University of Toronto
Toronto, Canada
hang.xiang@mail.utoronto.ca

Graham Watt
Royal Bank of Canada
Toronto, Canada
graham.watt@rbc.com

Yuri Lawryshyn
University of Toronto
Toronto, Canada
yuri.lawryshyn@utoronto.ca

***Abstract*—This study uses publicly available data to determine the effect of weather on the quarterly revenues of six publicly traded retail companies with physical store locations across Canada. Each of these retailers have between 500-1,500 locations, three of these retailers operate in the grocery and consumer staples retail sectors while the remaining three operate in the hardware, home goods, and furniture retail sectors respectively. The analysis using multi-feature log-linear regression found that precipitation and snow had the most significant impact on quarterly revenues and that retailers in the grocery sector were the least sensitive to changes in weather.**

***Index Terms*—retail, weather, climate, revenue, regression**

I. Introduction

Over the past two decades, abnormal weather events have become increasingly frequent and severe [1]. As a result, it is estimated that the physical risk of climate change at its current rate will cause the global economy to lose 10% of its value by 2050 [2]. A greater understanding of how certain weather features impact the revenues of retail companies and the ability to model the financial impacts of weather fluctuations will help institutions better prepare and mitigate these climate risks.

Existing research around the impact of weather on company financials on a daily frequency has been conducted either from either an investor or consumer perspective. On the investor behaviour side, research has found that equity prices dropped for firms operating in locations that experienced extreme high surface temperature events due to the underpricing of climate risk [3]. This response is anticipated to become more pronounced as more investors begin to recognize the physical risk of climate change on firm operations and financial valuations. On the consumer behavior side, studies have also shown that weather events that depart from seasonal cycles have a significant effect on monthly retail sales [4]. For instance, the early arrival of snow or late departure of summer can induce or prolonged demand of certain seasonal products and influencing consumer spending decisions [5]. While poor weather conditions may deter consumers from leaving their homes to purchase goods, good weather may also entice consumers to spend time outdoors rather than inside a store [6], [7]. Given the nuanced response of consumers to weather, many studies have aimed to measure exactly how these changes in consumer behaviour impact retail sales.

Empirical studies have shown that the complex impact of weather can be observed at the daily sales level with varying magnitude and directionality depending on the store location and sales category [7], [8]. However, most studies focus on retailers that lie within a geographic region with homogeneous weather (i.e., England and Germany [7], [8]) and so not much is known about the net effect for retailers operating in markets such as Canada with more diverse weather climates. Additionally, since many of these daily and monthly fluctuations wash out at the quarterly level, there is little research on how weather events ultimately impact a company's quarterly financial revenues.

This study aims to use only publicly available data to determine the effect of weather on the quarterly revenues of six publicly traded retail companies with physical store locations across Canada. Each of these retailers have between 500-1,500 locations, three of these retailers, Loblaw, Empire, Metro, predominantly operate in the grocery and consumer staples retail sectors while three other retailers, Canadian Tire, Indigo, Leon's, operate in the hardware, home goods, and furniture retail sectors respectively. The key objective is to identify which weather features have the greatest net impact on the quarterly sales of these retailers and then to compare how that impact varies across retailers in different sectors.

The paper is structured as follows. Section II outlines related literature, Section III details the methods used to obtain and clean the required data, Section IV outlines the modelling approaches followed by the results in Section V. Finally, a discussion of the challenges and limitations of this study will be included in the remaining sections.

II. Literature

Significant studies have shown that the impact of weather on daily retail sales can be quantified. A study on the apparel sector specifically found that the response of men, women, and kids apparel sales to the same weather risk, in this case measured by temperature, exhibited different responses [9]. Their approach involved using Seasonal Trend decomposition to isolated changes in sales volumes and linear regression to find a relationship between temperature and sales anomalies [9].

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Other studies have analysed more weather features including temperature, precipitation, humidity, pressure, and how that impacts consumer spending [5], [7]. The first study by Murray found sunlight was the greatest lever for consumer's willingness to buy across four specific products: green tea, orange juice, gym membership, airline ticket, newspaper subscription [5]. The key insight from this study was into the underlying psychology of consumers where they identified that only negative effect influences consumer spending and so while some weather variables such as humidity may have a positive impact on mood, this does not result in any changes in consumer spending [5].

Given the specific nature of the products analysed in that study, it is difficult to conclude whether the same effects would translate into physical retail locations. It is this next paper by Badorf and Hoberg that provided much of the basis for our study into how the impact of weather on retail sales can be quantified. This study used the weather parameters temperature, precipitation, and sunlight to develop a random coefficient model that considers non-linear effects and seasonal differences using different weather parameters [7]. For a major retailer in Germany with 673 stores, they quantified the explanatory power of weather information on daily sales, identified store-specific effects and the influence of specific sales theme [7]. Although our study is unable to analyze each retailer's sales by location and sales theme, we will attempt to draw similar conclusions be comparing the results of retailers with different regional presences and product offerings.

III. Data

We used three key components of temporal and spacial data: the quarterly revenues of retailers, the locations of retail stores, and the daily weather at every location for each retailer. Additionally, it was important that all data sources were publicly available and accessible. Details regarding these datasets and how they were obtained are described in more detail later in this section.

A. Retail Quarterly Revenue Data

The first data source is the quarterly revenue data. For each retailer, 10 years of historical data was obtained for the period of 2009 to 2019 from two primary sources. First, most recent quarterly revenue data were obtained using the Yahoo Finance API. However, this did not contain sufficient historical data and so the remaining data was manually obtained from the Canadian securities regulatory electronic file system, the System from Electronic Document Analysis and Retrieval (SEDAR).

B. Retail Location Data

The next data set that needed to be constructed was all the store locations of each retailer. This is necessary in order to later obtain the historical daily weather of each store. Although the number and location of stores for each retailer is likely to have changed throughout the years, for this study we use the present-day active locations for all periods.

Publicly listed company typically have several retail brands and banners operating under its parent corporation and so a list of all subsidiaries under each retailer was compiled. For instance, as shown in Figure 1, the parent company Metro, operates over 500 storefronts across Ontario and Quebec under the banners: Metro, Food Basics, Super C, etc.

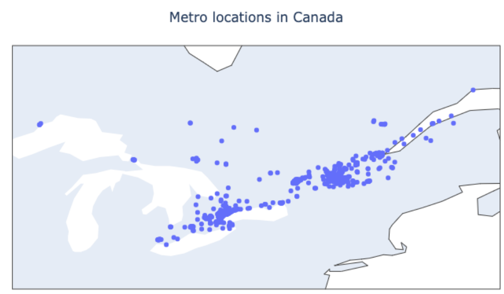

Fig. 1. All Metro store locations in Canada

Next, we compared three publicly location databases against the ground truth to select the best source to programmatically construct our dataset: Open Maps, Enhanced Points of Interest (EPOI), and Google Places API. We selected a single mid-sized retailer, Metro to assess the accuracy of these databases. Ground truth was established by obtaining the number of store locations from Metro's most recent 2020 annual report. Then, the locations of each subsidiary of Metro were searched and tabulated. Table I outlines the comparison between the three datasets and clearly, the Google Places API provided the most accurate results; thus it was selected as the primary source for constructing our retail locations dataset.

TABLE I
Comparison of Metro Locations by Data Source

Data Source	Metro Subsidiaries		
	Metro	*Food Basics*	*Super C*
Actual	326	138	98
Google Places API	320	139	96
EPOI	158	125	76
Overpass API	391	159	103

Using Google Places API, we were able to filter out duplicate searches, locations that were no longer operational, and verify the location type to ensure that the search result was in fact a retailer and not another location with the same or similar name. To comply with Google's API Licencing terms, which states that the data could only be stored for less than 30 days, the store locations were used immediately to obtain the daily weather data, and the longitude and latitudes of those locations were then discarded.

C. Daily Weather Data

Using the longitude and latitudes of the locations, a daily weather dataset was constructed for each location using the Oak Ridge National Laboratory (ORNL) daymet database.

Daymet provides weather variables including daily minimum and maximum temperature, precipitation, vapor pressure, shortwave radiation, snow water equivalent, and day length on a 1 km x 1 km gridded surface over continental North America. An analysis of the correlation between these seven weather features in Figure 2 identified temperature (tmp), precipitation (prcp), snow water equivalent (swe), and short-wave radiation (srad) – which can be interpreted as the amount of sunlight in a day.

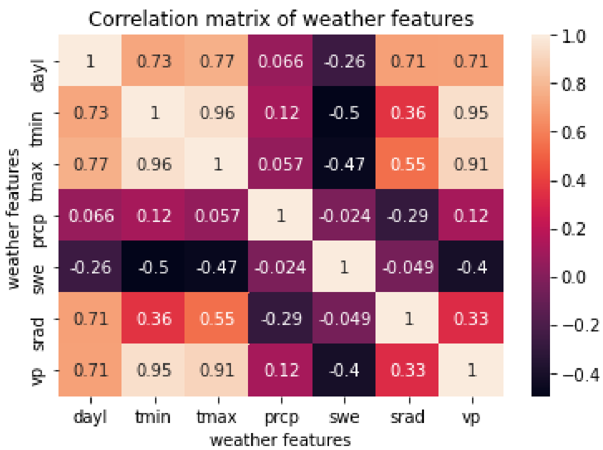

Fig. 2. Correlation of weather parameters

A series of pre-processing steps were used to aggregate the data across all locations in Canada and each fiscal quarter to bring it to the same spatial and temporal dimensions as the quarterly revenues data. First leap year days (February 29) were removed to ensure the same number of days in every-year and then the data was detrended using differencing to remove seasonality trends. Next, the values of each parameter were ranked based on their deviation from the historical distribution of that parameter in the same location and season. As a result, for each location $l = 1, \ldots, L$ and each day $d = 1, \ldots, 28(30, 31)$, month $m = (12, 1, 2), (3, 4, 5), (6, 7, 8), (9, 10, 11)$, and year $y = 2009, \ldots, 2019$, we determined a percentile ranking of its observed temperature $temp_{l,d,m,y}$, precipitation $prcp_{l,d,m,y}$, snow water equivalent $swe_{l,d,m,y}$, short wave radiation $swe_{l,d,m,y}$. Then the tail and head 10% of each parameter were taken to be considered anomalous and one-hot encoded. Weather parameters were intentionally left separate because it is difficult to interpret by intuition exactly which combination of weather parameters are perceived to be a "good" or "bad" day. Instead, this will be left to our model to identify the importance of each weather parameter.

To aggregate the weather features spatially, the one-hot encoded anomalous parameters were averaged across all the locations for each day. The gives an anomalous score - the percentage of locations that experienced anomalous conditions for that specific weather parameter – for each day. Finally, to aggregate the features temporally across each fiscal quarter, the anomalous scores were averaged across all the days in that quarter. It is important to note that some retailers report their year end as October and others as January and so this was taken to account during aggregation for each specific retailer

IV. Model Development

A model using a multi-feature log-linear regression approach was implemented to explore the importance of each weather feature on the impact of quarterly revenues. Quarterly revenues were log transformed to allow the model to interpret the percentage change in revenue more easily quarter over quarter. Only the four weather parameters temperature, precipitation, snow water equivalent, and short-wave radiation were used to reduce multicollinearity. A separate regression model was constructed for each retailer, $r = 1, ..6$, and the equation for the multi-feature regression model with quarters $q = 1, .., 4$ can be expressed as follows:

$$\begin{aligned} ln(quarterlyrevenue_{r,q}) = &\alpha^i + \beta_1^{r,q} * temp_{r,q} \\ &+ \beta_2^{r,q} * prcp_{r,q} \\ &+ \beta_3^{r,q} * swe_{r,q} \\ &+ \beta_4^{r,q} * srad_{r,q} \end{aligned} \tag{1}$$

The detailed coefficients and statistical significance of each parameter will be discussed further in section V results. The purpose of the regression model was to identify whether a feature has a positive or negative impact on a retailer's quarterly revenue.

V. Results

Overall, the R^2 of the models were between 0.15-0.5 with results varying greatly depending on the retailer. While the prediction score was low, the results still indicated that certain weather features did have an impact on the quarterly revenues of retailers. Tables III - VI outlines the coefficient and p-values from the log-linear regression models of each retailer.

TABLE II
R^2 VALUES FOR VARIOUS RETAILERS

	Metro	*Loblaw*	*Empire*	*Can. Tire*	*Leon's*	*Indigo*
R^2	0.152	0.153	0.146	0.384	0.147	0.488

TABLE III
COEFFICIENTS OF LINEAR REGRESSION MODEL – METRO

Parameter	**Metro**		
	coefficient	***t value***	***p value***
Constant	0.8713	3.258	0.003
Temperature	-0.0030	-0.617	0.542
Precipitation	0.0171	1.846	0.074
Snow Water Equivalent	-0.0015	-0.687	0.497
Short Wave Radiation	0.0046	0.461	0.648

TABLE IV
COEFFICIENTS OF LINEAR REGRESSION MODEL - LOBLAW

Parameter	Loblaw		
	coefficient	***t value***	***p value***
Constant	2.8173	6.338	0.000
Temperature	-0.0056	-0.744	0.463
Precipitation	-0.0063	-0.416	0.680
Snow Water Equivalent	-2.451	-1.963	0.019
Short Wave Radiation	-0.294	-1.938	0.771

TABLE V
COEFFICIENTS OF LINEAR REGRESSION MODEL - EMPIRE

Parameter	Empire		
	coefficient	***t value***	***p value***
Constant	1.6270	16.054	0.000
Temperature	0.0097	1.028	0.311
Precipitation	0.0182	1.246	0.221
Snow Water Equivalent	-1.747	-1.963	0.090
Short Wave Radiation	-0.507	-1.938	0.616

TABLE VI
COEFFICIENTS OF LINEAR REGRESSION MODEL – CANADIAN TIRE

Parameter	Canadian Tire		
	coefficient	***t value***	***p value***
Constant	1.4266	4.359	0.000
Temperature	-0.0035	-0.657	0.516
Precipitation	0.0257	2.328	0.026
Snow Water Equivalent	-0.0077	-3.097	0.004
Short Wave Radiation	-0.0306	-3.124	0.004

TABLE VII
COEFFICIENTS OF LINEAR REGRESSION MODEL – LEON'S

Parameter	Leon's		
	coefficient	***t value***	***p value***
Constant	0.4369	0.387	0. 701
Temperature	-0.0201	-1.078	0. 289
Precipitation	0.0230	0.613	0.544
Snow Water Equivalent	0.00	-1.905	0.065
Short Wave Radiation	-0.0426	-1.220	0.231

TABLE VIII
COEFFICIENTS OF LINEAR REGRESSION MODEL – INDIGO

Parameter	Indigo		
	coefficient	***t value***	***p value***
Constant	-1.7958	-3.850	0. 000
Temperature	0.0209	2.699	0. 011
Precipitation	0.0455	3.054	0.004
Snow Water Equivalent	-0.0022	-0.701	0.488
Short Wave Radiation	-0.0781	-5.688	0.000

VI. DISCUSSION

Grocery and furniture retailers were the least affected by weather, with all four retailers low R^2 values of around 0.15 and low weather parameter coefficient magnitudes. This is likely because for consumer staples goods, consumer purchasing behaviour is relatively invariable. Similarly, furniture purchases are generally larger purchases that require preemptive planning on behalf of consumers.

For the two retailers in the hardware and home goods retail sectors, we see much more variation in terms of the magnitude, directionality, and importance of features. Canadian Tire showed the strongest sensitivity to snow, sunlight, and precipitation which is interesting given the highly seasonal nature of many of its products (e.g. snow shovels, lawn mowers, etc). Indigo was the only retailer that had the temperature parameter as one of its most significant features. This is perhaps due to the fact that the home goods are considered more leisure rather than necessary purchases and are thus more perceptible to consumer mood.

Some of the key limitations around the models is that given the weather data is down sampled from a daily to a quarterly frequency and is then aggregated across a large geographic area, it loses some sensitivity to local fluctuations in weather. Additionally since we the present day store lotions as a proxy for the historical distribution of store locations this model is unable to capture changes in the climate risk landscape for a retailer over time as it expands or withdraws from certain regions. Adding a temporal dimension to the retail location data set would enable a more nuanced analysis of these climate risks.

VII. CONCLUSION

It is clear that quarterly revenues of retailers across a variety of industries are affected by weather. The magnitude and directionality varies significantly across retail sectors with grocery and consumer staple chains experiencing the least impact and hardware and home goods retailers that experience more seasonality experiencing the most impact. The next steps would be to improve the prediction of these models, incorporate more historical data, and apply the models to more retailers to identify commonalities amongst retailers within the same sector.

ACKNOWLEDGMENT

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