The effect of anomalous weather on the seasonal clothing market in New York

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Abstract
The occurrences of losing the merchandising calendar for seasonal clothes have become more frequent due to anomalous weather changes. In order to develop accurate sales forecasts for clothing retailers, weather changes should be incorporated. The purpose of the study was to find the timing of consumers' seasonal clothing demands and the relationship between the timing of consumers' searches for seasonal clothes and temperature changes. Specifically, drawing upon the United States' seasonal clothing demand from winter jacket Google Trends (GT) and air temperature data from empirical evidence, the study provided a methodology to discover the time lag for seasonal clothing demand timing based on temperature changes. Using the past five years (2014–2019) of GT and temperature data for the US state of New York, abnormal weather due to a significant El Niño year (2015–2016) and a weak La Niña year (2017–2018) was analysed. It suggested that consumers' search activities start when the temperature decreased rapidly continuously for at least six days. Furthermore, a plausible index was employed to determine the timing of peak demand with cumulative sums (CUSUMs). Based on the CUSUMs of air temperature for 18 days, consumers started to search for winter jackets at about 118–128 CUSUMs for a La Niña year, 217–248 CUSUMs for an El Niño year and 281 CUSUMs for a normal year. The results give a guideline to meet consumers' seasonal needs in a timely manner.

KEYWORDS
anomalous weather, El Niño, Google Trends (GT), La Niña, lag between air temperature and GT, winter jackets

1 | INTRODUCTION

The direct and indirect relationships between weather and human activity are observed every day. Much attention is given to weather and climate-sensitive industries, such as agriculture, tourism, food, beverage, construction, transport, and so on. Numerous scientists have therefore assessed the effects of weather on production and consumption from finance and psychology perspectives. However, the effects of weather on clothing buying behaviour have received little attention until now, although everyone refurbishes their closets when the season changes.

Clothing, also known as a second skin, changes in response to the temperature of the physical surroundings...
(Tortora and Marcketti, 2015). The majority of clothing product lines are seasonal, and new lines are created several times a year. Traditionally, the clothing industry is directed by a fixed calendar of trade shows and market weeks organized around a two-season approach to product ranges, namely Spring/Summer and Fall/Winter (Stone, 2012). The clothing supply chain is composed of many industries such as fibre producers, fabric manufacturers, clothing manufacturers and retailers. In addition, a great share of clothing sourcing has shifted from domestic to offshore production. The latency between the date of receiving the order to the shipment of products to the customer is the lead time. In certain scenarios, the lead time can be long compared with the selling season, and consumer demand may change rapidly with fashion, taste, seasons and occasions. Hence, clothing retailers place an emphasis on product availability in advance of the selling season and the date of sale.

Retail sale forecasts use previous years’ sales volumes; marketing actions such as price changes, promotional efforts or channels of distribution; external data relevant to their market; and information on general economic, political and cultural conditions (Brannon and Divita, 2015). Based on the company’s own sales forecast, the executives develop a sales plan that includes the product, price, place, quantity and time. However, forecasts have become increasingly inaccurate with anomalous weather events (Agnew and Palutikof, 1999; Thomassy, 2014; Bertrand et al., 2015). Many clothing industry professionals have acknowledged the importance of weather as a retail sale forecasting factor (Fairley, 2013; Tabuchi, 2015; Berwick, 2016; Randall, 2016). Researchers suggest that unpredictable weather is one major factor of uncertainty in clothing retailers (Steele, 1951; Thomassy, 2014; Bertrand et al., 2015). Furthermore, Agnew and Palutikof (1999) concluded that the clothing retail market is more sensitive to the weather than the total retail market.

Zara, the major division of the Spanish clothing retailer Inditex, is an exemplar of a fast fashion retailer that adopted new operational strategies to increase its agility and flexibility, and it provided quick responses to external changes such as the weather (Schlossberg, 2016). Because Zara keeps its manufacturers close to its distribution centre, it reacts to sudden changes, such as an unseasonal weather pattern. But most of the clothing supply chain is scattered globally and multitiered; it is hard to change a seasonal plan in the middle of the season. The long lead times and less flexibility cause an overstocking and understocking problem. Moreover, the ideal weather conditions for clothing retailers seem to be those where the seasons exert themselves early, and thus new seasonal products sell quickly without price reductions. Leading clothing retailers in the United States observed depressed sales of winter clothing owing to the unpredictably warm temperatures, rising up to 16°C, along with some parts of the East Coast (Tabuchi, 2015; Zaczkiewicz, 2016). In the Beige Book of the Federal Reserve Board, retailers discussed anomalous weather effects, particularly the warm weather spell in the northeastern United States in winter 2015–2016 resulting in sluggish sales of winter clothes (Federal Reserve District, 2015, 2016).

Agnew and Palutikof (1999) studied the impacts on the UK clothing market during the anomalously hot summer of 1995 when the clothing market received the greatest climatic impact and lost £382.7 million. Channigon (1999) assessed the impacts on the US economy resulting from the 1997–1998 El Niño effect and summarized that clothing retailers in the northern states of the United States suffered from a decrease in the winter clothing sales. Scientists have measured the US clothing sales changes during the 1997–1998 El Niño event (Oh and Jo, 2011). They employed the monthly clothing and clothing accessories sales, which is under the North American Industry Classification System (NAICS) code 448, and clothing sales decreased to US$3320 million in December 1997. Recently, Bertrand et al. (2015) showed the effects of unexpected changes in daily temperature due to seasonal patterns on clothing sales, and the risks from anomalous weather conditions were also evaluated.

Among the various weather parameters, temperature is the most influential criterion in clothing sales (Miron, 1986; Bahng and Kincade, 2012; Bertrand et al., 2015). Clothing has a very short life-cycle and is seasonal, being measured in months or weeks (Christopher, 2004); therefore, the retailers must offer the merchandise at the right time. If the seasonal clothes are displayed at the store before normal temperature changes in a season, consumers are not motivated to search for a new wardrobe. If abnormal temperature changes are earlier than retailers’ sales plan calendars, retailers miss a significant sales opportunity.

Due to the importance mentioned above of sales timing in the clothing retail business, the study aimed to find the timing of consumers’ seasonal clothing demands and the relationship between their timing of search and temperature changes. The study focused on identifying seasonal clothing demand trends, finding a lag between demand and temperature changes, and detecting consumers’ first massive demand. Google Trends (GT) was used to analyse consumers’ demand; the El Niño Southern Oscillation (ENSO) index was employed to identify temperature anomalies; and air temperature data were obtained to investigate in association with consumers’ demand and temperature changes.
The remainder of the paper is structured as follows. The next section gives the background as well as the relevant literature outlining the research problems that have been developed to fulfill the purpose of the study. The following sections detail the methodology, including the study area, data and data analysis; the results of the analyses conducted for the three research problems; and gives conclusions and implications, along with the limitations of the study.

2 | BACKGROUND TO THE STUDY AND THE RESEARCH QUESTIONS

2.1 | Clothing demand and Google Trends (GT)

Seasonal changes affect consumers’ recognition of the need for clothing. This recognition results in the creation of information search activities to solve the problem. The purpose of an information search by a consumer before a purchase is either to enhance the quality of the purchase outcome or to give pleasure, and heavy searchers spend over twice as much money at the same time as do light searchers among clothing consumers in a brick and mortar store (Bloch et al., 1986). Nowadays, consumers’ online searches and online shopping activities are a significant part of the market. According to the Census Bureau of the Department of Commerce, e-commerce sales in the first quarter of 2019 accounted for 10.2% of total sales (US Census Bureau, 2019). Many clothing consumers used Google to search for ideas, to find the best designs and to buy new clothes (Boone, 2016).

In the study, GT, “which is a real-time daily and weekly index of the volume of queries that users enter into Google” (Choi and Varian, 2012, p. 2), was used. Consumers’ GT indicate consumers’ seasonal demand for any given product and show changes in seasonal demand patterns (Silva et al., 2019). There is a need for more research that provides conclusive evidence on whether consumers’ GT can predict clothing purchases, but GT is increasingly influencing business decision-making in a variety of industries given its ability to act as a leading indicator for forecasting critical variables of interest (Siliverstovs and Wochner, 2018; Zhao et al., 2018; Silva et al., 2019; Yu and Zhao, 2019). Shim et al. (2001) concluded that an online search for information is the strongest predictor of online purchase intention. Consumers may search for information via one channel (e.g. Google Shopping) while purchasing through another channel (e.g. a physical store). Also, the levels of GT and complement survey data, such as the Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index, are highly correlated (Penna and Huang, 2009). Vosen and Schmidt (2011) concluded that GT is a better indicator. Therefore, the volumes of search queries on a product can be used as an indicator of consumers’ purchase decision.

2.2 | El Niño Southern Oscillation (ENSO) events

For sub-seasonal predictions, the Climate Prediction Center/National Oceanic and Atmospheric Administration (CPC/NOAA) has issued the weather outlook for each season based on numerical model. The ENSO events are some of the most influential and can have a major effect worldwide. El Niño events are called warm events, whereas La Niña events are called cold events because of a sustained cooling of sea surface temperatures across a broad region of the eastern and central tropical Pacific Ocean. La Niña events are associated with wetter winters in the Pacific Northwest and drier winters in the Southwestern United States. El Niño is associated with the Southern Oscillation in the atmospheric circulation that produces a wide range of effects on global weather and climate. Thus, it is often associated with serious weather anomalies as well as changes in temperature and humidity around the world. During El Niño years, the Pacific Northwest of the United States has drier winters and the Southwest United States has wetter winters. Likewise, across the northeast states, a strong El Niño tends to bring warm winters, and thus typical extreme cold weather may be milder and less frequent. A strong La Niña tends to do the opposite. When an El Niño event decays in the Equatorial Pacific, the La Niña event likely develops following the El Niño year.

2.3 | Research questions

The purpose of the study was to identify the relationship between the timing of seasonal clothing demand and temperature changes. More specifically, it examined three objectives. First, the difference in consumers’ search activities between seasonal and non-seasonal clothes was studied. Also, since holidays in winter have a significant influence on retailing, holiday effects were considered. Clothing products can be divided into three different categories: fashion products, seasonal products, and basic or non-seasonal products (US Congress, US Office of Technology Assessment, 1987). Seasonal products, such as winter jackets and shorts, reflect seasonal changes (Bahng and Kincade, 2012). However, basic or non-seasonal products, such as undergarments and men’s
white dress shirts, are sold throughout the year, and consumers show a stable year-round demand. As fashion products are dependent on the latest trends and result in frequent design changes, they were not considered in the study.

There are three primary holidays in the United States: Thanksgiving Day, Christmas and New Year's Day during winter. Holiday sales in November and December represent about 20% of annual retail sales (National Retail Federation, 2019). US retailers consider Black Friday and Cyber Monday as their most profitable holiday shopping days (Swilley and Goldsmith, 2013). Black Friday and Cyber Monday are five-day shopping events starting on Thanksgiving Day and continuing through the following Monday. Consumers' search activities during the period from Black Friday to Cyber Monday are studied to discover holiday effects.

Second, the relationship between the seasonal clothing GT and air temperature changes was analysed to determine the demand time lag. The study employed winter clothes for seasonal clothes because winter jackets are high-margin merchandise (Randall, 2016), and the sales of winter clothing contribute to 40% of the total retail sales of clothing, NAICS 448 (Kottasova, 2016). As the clothing retailer relies on the sales of winter clothes to boost annual profits, winter sales are a critical period. The temperature changes at the beginning of a new season accelerate the sales of new seasonal clothing, but the temperature toward the middle and end of the season does not accelerate sales because the following new season clothing is displayed in stores (Agnew and Palutikof, 1999; Bahng and Kincade, 2012; Arunraj and Ahrens, 2016). To find the timing of consumers' seasonal clothing demand is useful for controlling inventory. With this information, clothing retailers are able to modify seasonal merchandise plans accordingly.

Finally, a plausible index was employed to detect the critical timing for consumers' first massive search activities for seasonal clothes. Although consumers may be aware of weather conditions in the coming winter from the winter temperature outlooks, the timing of their searching and buying of winter clothes might differ every year. To supply consumers' demands in a timely manner, an accurate forecast for the timing of consumers' search activities is useful. As explained in the Methodology section, the cumulative sums (CUSUMs) with daily air temperature were used. The CUSUMs is a way to measure magnitudes of total deviations of daily air temperature changes at given time periods. Thus, the results from the CUSUMs allow one to classify different groups of years and to know when consumers might start searching for their winter jackets.

3 | METHODOLOGY

3.1 | Study area

The US State of New York (NY) has four seasons. In spring and fall, long-sleeved shirts and trousers are common; in summer, short-sleeved shirts and shorts are common, and in winter, jackets, trousers and boots are common. Figure 1 shows the outlook air temperature pattern of the United States in 2015–2016 and 2017–2018 from the CPC/NOAA.

The typical monthly weather conditions for the study area, NY, are illustrated in Figure 2. The monthly maximum and minimum air temperatures are 7 and 0°C in

![Figure 1](https://www.weather.gov/arx/winter201516outlook) and (b) [https://www.climate.gov/news-features/blogs/enso/meteorological-winter-over-how%E2%80%99d-we-do-2017-18](https://www.climate.gov/news-features/blogs/enso/meteorological-winter-over-how%E2%80%99d-we-do-2017-18)
December, 4 and −3°C in January, and 6 and −2°C in February. Figure 1 illustrates two climatic events: El Niño and La Niña. Every October, the NOAA issues the temperature outlook for the coming winter, where a relatively warm winter for 2015–2016 and a relatively mild winter for 2017–2018 are distinctly visible.

3.2 | Data

3.2.1 | Google Trends (GT)

GT offers a time-series index of the volume of queries that users enter into Google’s search engine in a given geographical area. Instead of the raw level of queries for a given search topic, GT provides the query index based on the query share. Each datum point is divided by the total searches in the geographical area and the time range it represents in order to compare the relative popularity (Silva et al., 2019). To improve the quality of data, GT excludes some searches made by very few people, duplicate searches and special characters (Google, 2019). Based on the percentage of terms for all searches on all topics, the resulting number scales from 0 to 100 (Choi and Varian, 2012). All GT data are based on the State of NY and were extracted on July 18, 2019. Winter jackets and undergarments were searched as terms within the Shopping Category, and results were filtered through Google Shopping. The study employed winter jacket GT in NY for seasonal clothes and undergarment GT in NY for non-seasonal clothes; and GT was available for the past five years, from July 1, 2014, to July 1, 2019.

3.2.2 | ENSO index

In order to identify the timing and magnitude of the ENSO events, multivariate ENSO index (MEI) (http://www.cdc.noaa.gov/people/klaus.wolter/MEI/) is employed. Here, highly positive values that persist for up to a year or longer represent El Niño events (2015–2016), and negative values that persist for up to a year or longer represent La Niña events (2017–2018) (Figure 3a). Although there are several methods for determining the ENSO index, that introduced by Troup (1965) is used herein. It is worth noting that there is a significant El Niño, which is comparable with the 1997–1998 El Niño, during the present study period. For the 2017–2018 El Niño event, its strength is weak because the magnitude of the MEI is < −1.2. A larger amplitude symbolizes a stronger El Niño or La Niña.

3.2.3 | Air temperature

Daily air temperature data from January 2004 to July 2019 were obtained by email (https://www.ncdc.noaa.gov/cdo-web/). These were measured at meteorological stations in Buffalo, Rochester, Syracuse, Albany and Central Park in NY because the continuous daily air temperature measurements are only available in the five cities in NY state. For some comparisons, the daily air temperature data were made for daily climatology and weekly mean data. Furthermore, air temperature anomalies (Figure 3b) were also made to examine the specific changes in response to the ENSO events. Due to the El Niño and La Niña events (Figure 3a), the temperature in Central Park (Figure 3b) was relatively warm and cold, respectively.

3.3 | Data analysis

3.3.1 | Statistical analysis

A Pearson correlation co-efficient and simple linear regression analysis were computed to assess the relationship between temperature, undergarment GT and winter jacket GT.

3.3.2 | Cumulative sums (CUSUMs)

The CUSUMs method was employed to estimate the summations of daily air temperature deviation. This method has been shown to be particularly sensitive to detecting turning points in coastal observations of sea surface temperature (Breaker, 2007; Breaker and Flora, 2009; Jo et al., 2014). Specifically, the CUSUMs characterize the running total of the deviations of the first \( n \) measurements from a mean based on the same interval (Page, 1954; Wetherill and Brown, 1991;
Hawkins and Olwell, 1998; Breaker, 2007). The CUSUMs can be expressed as:

\[ \text{CUSUMs} = \sum_{t=1}^{n} (x_t - \bar{x}), \]

where \( x_t \) represents the \( n \)th measurements; \( \bar{x} \) is the mean of \( x_t \) from \( t = 1 \) to \( n \); and the CUSUMs are plotted versus time and are known as the CUSUMs chart. Abrupt changes in the slope of the CUSUMs often reflect turning points. However, in the study, CUSUMs were used to classify different groups resulting from different temperature changes for given time periods in different years.

4 | RESULTS

4.1 | Clothing seasonality

Figure 4 shows the relationship between the air temperature, undergarments GT and winter jackets GT. Pearson correlation analyses were conducted to identify the characteristics of seasonal clothing products. There was a negative relationship between winter jackets and temperature \((r = -0.397, p = 0.01)\) and no significant relationship between undergarments and temperature. A simple linear regression analysis was conducted to substantiate the suspected relationship further. The estimated regression model is winter jacket GT = 24.665 + (−0.649) × temperature with an adjusted \( R^2 \) of 15.2%; it is highly significant with \( p < 0.001 \) and \( F = 47.511 \). The standard error of the estimate is 15.573. This finding confirmed the characteristics of clothing seasonality. Winter jackets are a seasonal product, and consumers' search activities for winter jackets increase when the temperature decreases. Undergarments as a non-seasonal product are shown to have a stable year-round demand and therefore are not associated with changes in temperature. In addition, consumers' search activities on Black Friday and Cyber Monday are indicated in Figure 4. The highest winter jacket search activities did not show on either Black Friday or Cyber Monday. These results were expected for two reasons. One is the convenience of online shopping throughout the year; the other is the constant deal days from retailers. This result is supported by a recent report that indicated that the holiday season is less and less important for retailers (Thomas, 2019).

4.2 | Relations between winter jackets’ GT and air temperature to determine the demand time lag

Figure 4 shows the weekly winter jacket GT and the daily air temperature from July 1, 2014, to July 1, 2019. There
are some lags between the two different data sets with about an average of 12.6 weeks and a standard deviation (SD) of 3.36 weeks. While the first peak of winter jacket GT is about October–November, the air temperature usually reaches its minimum in January–February. These lags between GT and air temperature changes are expected because traditionally clothing retailers offer new seasonal products through retail channels to consumers a couple of months ahead of the season (Christopher, 2004; Brannon and Divita, 2015). Nowadays, consumers expect new seasonal clothes regardless of whether or not they need new clothes.

However, the important considerations are the factors influencing consumers to search for their winter jackets earlier or later in the season. The earliest GT peak has been recorded on October 14, 2018, and the latest on January 3, 2016 (Table 1). Likewise, the earliest and the latest dates for minimum recorded air temperature were January 7, 2018, and February 15, 2016, respectively. In order to analyse this, the relationship between GT and climatic events, the 2015–2016 El Niño and 2017–2018 La Niña events were examined. These events are known to determine global weather patterns. Additionally, the time when consumers start their search for winter jackets in response to the temperature changes was estimated.

Furthermore, the timings of information searches for winter jackets based on GT for two cases, the 2015–2016 El Niño warm events (Figure 5) and the 2017–2018 La Niña cold event (Figure 6), were analysed. Due to the 2015–2016 El Niño, a significant number of US consumers were influenced due to the weather conditions. As introduced in Figure 1a, between 2015 and 2016 a warmer air temperature was predicted in the state of NY. It was assumed that consumers in this area had the same information. Figure 5 shows that the daily climatological air temperature, shown by the red line, is lower than the daily air temperature, shown by the black line. For instance, the temperature is about 12°C higher than the climatological temperature on December 14, 2015. One can see the warmer temperature than the climatological air temperature on most of the days in 2015 (Figure 5a). Thus, it is expected that consumers might be less inclined to search for and purchase heavy winter clothes (Figure 5b). As Figure 4 and Table 1 show, the search activities from 2015 to 2016 are much less than in other years. Because of the warming winter in 2015–2016, winter jackets GT shows three peaks: October 18, 2015, November 29, 2015, and January 3, 2016 (Figure 5b). Compared with other years, the intervals of the peaks are relatively less frequent, at approximately 4–5 weeks, as shown in Table 1. All the peaks in the winter of 2015–2016 are distinctly lower than for the other winters. Furthermore, the negative slopes of temperature, shown with green lines, were estimated (Figure 5a). The ranges of the slopes are $-3$ to $-2.3^{\circ}C \text{day}^{-1}$. The corresponding duration of each slope is approximately 5–7 days. These changes were further compared with the La Niña event, as shown in Figure 6.
During the 2017–2018 La Niña event, however, a slightly colder year was predicted in Central Park (Figure 1b). Figure 6 shows the air temperature climatology, marked in red. It is higher than the daily air temperatures, shown in black. For instance, the temperature is approximately 17°C lower than the climatological temperature on January 1, 2018. It is distinct that the temperature is within the normal range, except from late December to mid-January (Figure 6a). During the La Niña event in 2017, consumers’ search data show three peaks: November 12, December 10 and December 31 (Table 1). Compared with the other years, the intervals of these peaks are relatively more frequent, at approximately 2–3 weeks. Furthermore, the slopes of the decreasing temperature were estimated, shown in green (Figure 6a). The ranges of the slopes are $-2.67$ to $-2.0°C$ day$^{-1}$. The corresponding duration of each slope is approximately 2–3 days.

The following results were concluded. (1) According to previous studies (Stewart et al., 2012; Sivle and Kolstob, 2016), consumers use weather forecasts and information in their everyday decision-making. It is assumed that consumers’ seasonal clothing buying plan may be influenced by the winter outlook information. The decrease in search activities during the 2015–2016 El Niño year due to the warm winter is distinct in Figure 4. It has been proven that consumers are influenced by the daily temperature changes, although they might not consider the winter outlook information while shopping for their winter clothes. El Niño and La Niña events influence temperature changes on global scales.

(2) Consumers’ searches for winter jackets show a high increase when the temperature decreases rapidly for approximately a week. This result is consistent with previous studies that concluded that drastic temperature changes boost the sales of a new season’s clothing (Agnew and Palutikof, 1999; Bahng and Kincade, 2012; Arunraj and Ahrens, 2016). From Figures 4–6, weekly winter jackets GT and the daily temperature changes can be carefully examined simultaneously. As the winters arrived, consumers’ search activities increased slowly and then dramatically surged when the air temperature decreased rapidly continuously for 5–7 days. The search peaks in the El Niño and La Niña are at $-3°C$ to $-2.3°C$ and $-2.67$ to $-2°C$, respectively, suggesting that consumers wait for at least six days until the temperature...

### Table 1

| Winter 2014–2015 | Winter 2015–2016 | Winter 2016–2017 | Winter 2017–2018 | Winter 2018–2019 |
|------------------|------------------|------------------|------------------|------------------|
| October 5, 2014  | October 4, 2015  | October 2, 2016  | October 1, 2017  | September 30, 2018 |
| October 12, 2014 | October 11, 2015 | October 9, 2016  | October 8, 2017  | October 7, 2018  |
| October 19, 2014 | October 18, 2015 | October 16, 2016 | October 15, 2017 | October 14, 2018 |
| October 26, 2014 | October 25, 2015 | October 23, 2016 | October 22, 2017 | October 21, 2018 |
| November 2, 2014 | November 1, 2015 | October 30, 2016 | October 29, 2017 | October 28, 2018 |
| November 9, 2014 | November 8, 2015 | November 6, 2016 | November 5, 2017 | November 4, 2018 |
| **November 16, 2014** | November 15, 2015 | November 13, 2016 | **November 12, 2017** | **November 11, 2018** |
| November 23, 2014 | November 22, 2015 | November 20, 2016 | November 19, 2017 | November 18, 2018 |
| November 30, 2014 | November 29, 2015 | November 27, 2016 | November 26, 2017 | November 25, 2018 |
| December 7, 2014 | December 6, 2015 | December 4, 2016 | December 3, 2017 | December 2, 2018 |
| December 14, 2014 | December 13, 2015 | December 11, 2016 | December 10, 2017 | December 9, 2018 |
| December 21, 2014 | December 20, 2015 | December 18, 2016 | December 17, 2017 | December 16, 2018 |
| December 28, 2014 | December 27, 2015 | December 25, 2016 | December 24, 2017 | December 23, 2018 |
| January 4, 2015   | January 3, 2016  | January 1, 2017  | December 31, 2017 | December 30, 2018 |
| January 11, 2015  | January 10, 2016 | January 8, 2017  | January 7, 2018  | January 6, 2019  |
| January 18, 2015  | January 17, 2016 | January 15, 2017 | January 14, 2018 | January 13, 2019 |
| January 25, 2015  | January 24, 2016 | January 22, 2017 | January 21, 2018 | January 20, 2019 |
| February 1, 2015  | January 31, 2016 | January 29, 2017 | January 28, 2018 | January 27, 2019 |
| February 8, 2015  | February 7, 2016 | February 5, 2017 | February 4, 2018 | February 3, 2019 |
| **February 15, 2015** | February 14, 2016 | February 12, 2017 | February 11, 2018 | February 10, 2019 |
| February 22, 2015 | February 21, 2016 | February 19, 2017 | February 18, 2018 | February 17, 2019 |

**Note:** The above information is illustrated in Figure 4.
reaches the minimum for that week. It has been assumed that the slopes and corresponding durations are the consumers’ buying decision process periods, from problem recognition to information search and the evaluation of alternatives.

4.3 Forecast for consumers’ first massive search activity

The most profitable climate for clothing retailers is when the temperature changes early in the season because seasonal lines of clothes are sold rapidly without price reductions. As estimating the timing of the search peak is a strategic issue for clothing retailers, the CUSUMs method was employed. This method has been traditionally used to detect significant changes in certain time series. In the study, the summation of deviation of daily temperature changes (Equation 1) was used. The aim is to calculate the period required before predicting the first massive peaks. The power spectrum of the daily temperature data based on the period 2004–2018 was computed and the peak of an 18 day cycle was obtained. This implies that the temperature changes significantly once every 18 days. Thus, the temperature deviation for 18 days was added using the CUSUMs. As Figure 7 shows, the temperature deviations were added for 18 days before the first peak of massive searches, as indicated with different colours from 2014 to 2018. The CUSUMs on the 18th of each year can be classified into three groups: 118–128 for the La Niña year, 217–248 for the El Niño-like year and 281 for the normal year. In other words, Figure 7 explains that CUSUMs over 18 days suggest the cumulative temperature deviations: the greater the CUSUMs, the more the demand for winter jackets because it is getting colder. The critical

FIGURE 5 (a) Daily air temperature (black) and its climatology (red) from October 1, 2015, to March 1, 2016; and (b) weekly winter jackets Google Trends (GT) time series. Vertical red arrows and green slopes represent the peaks of GT and rate of temperature decreases over time, respectively. The corresponding slopes from the earliest day are $-2.3^\circ\text{C day}^{-1}$ for seven days, $-3^\circ\text{C day}^{-1}$ for five days and $-2.7^\circ\text{C day}^{-1}$ for six days, respectively. The dates for each slope are October 18, 2015, November 29, 2015, and January 3, 2016.
CUSUMs as specified in Figure 8 suggest that consumers will eventually start massive searches for winter jackets.

These CUSUMs can be used to predict when consumers might have a massive surge in the search for winter jackets based on the winter outlook of the following winter. For example, the timing of next year's first massive search for a winter jacket was calculated, as shown in Figure 8. Daily temperature data are obtained from the weather stations and the coming winter's temperature outlook is learned from the CPC/NOAA. It can thus be predicted if the coming winter might be under El Niño, La Niña or normal weather conditions. Corresponding potential CUSUMs are 118–128, 217–248 and 281 for 18 days, respectively. First, the CUSUMs are estimated from October 1 for the next 17 days continuously (Figure 8). If the CUSUMs have a similar range as the target value according to the three groups, consumers' searches for their winter jackets might be expected to surge. If the CUSUMs do not reach the target value, recalculation can be performed from October 2 (t = t + 1 in Figure 8) for the next 17 days. If this process is repeated until the target value is obtained, the specific date for the timing of massive searching for a winter jacket can eventually be obtained (Figure 8). Thus, this index that sums up this process would provide a lot more value to customers. The first massive search activity will be the day when the right range of values for CUSUMs is met. The CUSUMs method might be too elementary to predict consumers' search behaviour; however, if the time series of GT are longer, a more accurate model based on the CUSUMs method can be designed.

The critical CUSUMs can be further examined based on the accuracy of weather forecasting. The Weather Channel can provide better information at about 82.47%
**FIGURE 7** Cumulative sums (CUSUMs) for 2014–2019. Each CUSUM was estimated for 18 days before the first peak of each year for winter jackets Google Trends (GT). Also shown at top left are the dates for first peak of each year for searching winter jackets through Google.

**FIGURE 8** Flow chart to estimate the first massive search for winter jackets based on cumulative sums (CUSUMs); \( t_0 \) is the first day for computing CUSUMs (assumed here as October 1); \( t + 1 \) represents the next day until the CUSUMs reach the target value; target values (118–128, 217–248 and 281) are derived from Figure 7.
than other weather service media (https://www.forecastadvisor.com/NewYork/NewYork/10036%20/).
Thus, it can be suggested that the critical CUSUMs and corresponding SDs are 118 ± 20.69 ~ 128 ± 22.44 for a La Niña-like year, 217 ± 38.0 ~ 248 ± 43.47 for an El Niño-like year and 281 ± 49.26 for a normal year. Therefore, these ranges of CUSUMs can be served to predict the day of massive searching activities for winter jackets due to a temperature drop.

It is evident from consumers’ decision-making processes that search information is the strongest predictor of purchase intention (Shim et al., 2001), and heavy information searchers seem to be heavy spenders (Bloch et al., 1986). If clothing retailers can predict the timing of the first peak in consumers’ seasonal clothes search activities, in-seasonal products can be delivered at the right time for the right consumer at the right price. Contrarily, all stocks sell with deep markdowns, and clothing companies lose their profit unexpectedly.

5 | CONCLUSIONS

The purpose of the study was to identify consumers’ seasonal clothing demands and the relationship between the timing of seasonal clothing demands and temperature changes. As the anomalous weather patterns have become a normal occurrence, previous sales plans are outdated and do not provide a good reference for the future. A principal decision that any clothing retailer faces is when to sell its merchandise. Hence, winter jacket Google Trends (GT) was employed to estimate consumers’ seasonal clothing demands and air temperature data to identify consumers who adopt the weather information. The following is a summary of the study. First, the difference between GT for seasonal and non-seasonal clothes was studied. While non-seasonal clothes such as undergarments were not associated with weather changes (Figure 4), seasonal clothes such as winter jackets were closely related to weather changes (Figure 4). Additionally, there were no holiday effects on winter jacket search activities.

Second, the relationship between the seasonal clothing GT and air temperature changes was analysed to determine the demand time lag. Assessing the GT of the past five years, abnormal weather due to one significant El Niño year (2015–2016) and a weak La Niña year (2017–2018) was analysed. During the El Niño year, consumers started to search for winter jackets earlier than in other years (Figure 5); however, the intervals of search peak dates were relatively less frequent (Table 1). Meanwhile during the La Niña year, consumers started to search for winter jackets later (Figure 6), and their intervals of search peak dates were relatively more frequent (Table 1). The first peaks of winter jackets searches were observed on November 16, 2014, October 18, 2015, October 23, 2016, November 12, 2017, and October 14, 2018 (Table 1) when the temperature decreased rapidly continuously for six days. Additional second and third peaks of GT (Table 1) occurred similarly. As is evident from Figures 5 and 6, the decreasing temperature slopes and duration dates can be a reference to understanding consumers’ search activities.

Third, the possibility to make a plausible index to know when consumers will start massive searches for winter clothes was studied. Based on the CUSUMs of air temperature for 18 days, consumers started the search for winter jackets at approximately 118–128 of the cumulative sums (CUSUMs) for the group similar to the La Niña year, 217–248 for the group similar to the El Niño year and 281 for the normal group (Figure 7). If the coming winter’s outlook is available from the Climate Prediction Center/National Oceanic and Atmospheric Administration (CPC/NOAA) and thus the specific group such as the La Niña, the El Niño or the normal year groups, similar CUSUMs for 18 days of air temperature can be obtained. As a result, at least the first massive search activities can be obtained by computing the CUSUMs based on daily air temperature. Thus, Figures 7 and 8 serve as elementary examples to determine the timing of consumers’ first massive searches. If the time series of GT and the corresponding air temperature observations are longer, more cases with increased precision can be obtained.

Therefore, the potential application of this result for the long-term strategy is that the clothing company can make a merchandising plan for either El Niño-like, La Niña-like or normal year-like based on six months of weather prediction from the CPC/NOAA. Before the season arrives, clothing manufacturers and wholesalers can produce the right amounts of seasonal clothes and distribute them to the right places. The clothing retailers for a short-term plan can then prepare seasonal clothes at the right time according to a temperature change. The specific date can be forecasted by the critical CUSUM and predicted temperature could be obtained from the Weather Channel. Alternatively, one may use the extreme forecast index (EFI) introduced by the European Centre for Medium-Range Weather Forecasts (ECMRWF) (2020). The EFI is computed from the difference between the reference distribution of model climate, M-climate, and the ensemble forecast distribution (e.g. Dutra et al., 2013). The differences allow one to estimate how much extreme temperature changes compared with climatology, which might be related to consumers’ searching activities, similarly demonstrated in the present study.
The clothing industry is a highly fragmented global value chain encompassing fibre producers, manufacturers and retailers. Few companies participate in every aspect of the value chain. Consequently, the industry is indicated by a large degree of outsourcing and collaboration between companies around the world. Thus, clothing procurement requires long lead times and less flexibilities. As demand unpredictability increases, companies need to develop an accurate inventory management plan rather than rely on historical sales data. Hence, the present study investigated the lag between consumers’ demand and temperature changes and it developed a plausible index to aid clothing retailers in their quest to respond to anomalous weather changes.

The results of the study contribute to the literature on the empirical relevance of these issues. First, the traditional protocol in clothing retailers is managed by a fixed calendar, and clothing retailers use historical sales data to develop an updated sales forecast plan. Since anomalous weather changes are common, past approaches put clothing retailers in an incompatible situation with their customers. The study confirmed that consumers’ seasonal clothing demands are not dependent on calendar changes and holiday sales events, but the temperature change effects on seasonal clothing sales. Our findings are consistent with other prior findings, which found that temperature changes affect clothing sales (Agnew and Palutikof, 1999; Bahng and Kincade, 2012; Bertrand et al., 2015; Bertrand and Parnaudeau, 2019; Martinez-de-Albeniz and Belkaid, 2019; Badorf and Hoberg, 2020). Clothing retailers endeavour to adopt a new operational model to respond to external changes such as the weather.

Second, a warmer temperature increases sales of the clothing items (i.e. summer dresses) in spring and summer and decreases sales of the clothing items (i.e. winter jackets) in fall and winter (Bertrand et al., 2015; Bertrand and Parnaudeau, 2019; Martinez-de-Albeniz and Belkaid, 2019). However, the significance of temperature change impacts consumers’ buying behaviour, while the maximum temperature is insignificant in clothing sales (Arunraj and Ahrens, 2016). There are the lags between temperature changes and sales (Agnew and Palutikof, 1999; Arunraj and Ahrens, 2016). The study provides a methodology to find a time lag between consumers’ demand timing based on temperature changes and it suggests the seasonal clothing searches happen when the temperature rapidly decreases continuously for at least six days. Also, a plausible index is developed to show a method to meet consumers’ seasonal needs in a timely manner. The abnormal weather changes produce retail inventory management problems (Agnew and Thrones, 1995). If we consider a clothing supply chain that includes upstream fibre and fabric producers and downstream retailers, management decision changes are not simple. This method can improve agility and flexibility in the supply chain to prevent overstocking and understocking inventory problems. An overstock creates series of problems ranging from space management and out of fashion to liquidity problems, which is not converted back to cash unless margins are reduced by markdowns and promotions. Understock creates series of problems ranging from the loss of potential sales and customer loyalty to the loss of profitable price by buying earlier and the expense cost to the replenishing fee. Therefore, it is advantageous for clothing retailers to be able to predict market demand so as to deliver the right product, at the right price and at the right time.

Finally, using GT on the interest in seasonal clothing, the present research contributes to the literature on the relationship between weather and clothing buying behaviour. Previous studies concluded that consumers were physically and psychologically uncomfortable going to physical stores for shopping for clothes under specific weather conditions such as precipitation, snow, temperature, and wind (Steele, 1951; Stoltman et al., 1999; Bahng and Kincade, 2012). However, online clothing shopping has become increasingly popular, and consumers web search before shopping. Consumers’ online searching activities in response to weather changes need to be considered. Since GT is high-frequency data and suitable to test meteorological variability and its impact (Rossello and Waqas, 2016), the present study shows a methodology to investigate abnormal weather change impacts for the clothing retail industry.

Although a meaningful relationship was obtained between winter jacket GT and temperature changes, there were some limitations to these results. (1) The study focused on one area, the US state of New York, thus limiting the generalizability of the results. A previous study on individuals living in different cultures and environment showed weather-related psychological evaluations differently, despite similar thermal conditions (Kenz and Throsson, 2006). With respect to the impact of fashion interest on people’s decisions, there is a considerable amount of individual heterogeneity. Hence, the study tested one area, which has four seasons, to minimize the geographical heterogeneity. (2) It is impossible to forecast consumer demand only by weather events. Consumers purchase new clothes for various reasons, sometimes for real needs and sometimes for psychological pleasure. Purchasing factors vary depending on lifestyle and demographics, such as gender, age and income, but the study did not specify a demographic group. Therefore, the results diminish the explanatory power of the study. (3) As GT data are only available for the last five years, the weather changes in response to the
climatic events such as El Niño and La Niña could not be fully analysed. However, some influences of the 2015–2016 El Niño effect on consumers’ search activities could be perceived. (4) The three groups defined based on the CUSUMs might be misleading because of the short-term nature of GT data and there might be more groups associated with different temperature changes.

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