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Decision Support

Assessing and hedging the cost of unseasonal weather: Case of the apparel sector ☆,☆☆

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ABSTRACT

Retail activities are increasingly exposed to unseasonal weather causing lost sales and profits, as climate change is aggravating climate variability. Although research has provided insights into the role of weather on consumption, little is known about the precise relationship between weather and sales for strategic and financial decision-making. Using apparel as an illustration, for all seasons, we estimate the impact on sales caused by unexpected deviations of daily temperature from seasonal patterns. We apply Seasonal Trend decomposition using Loess to isolate changes in sales volumes. We use a linear regression to find the relationship between temperature and sales anomalies and construct the historical distribution to determine sales-at-risk due to unseasonal weather. We show how to use weather derivatives to offset the potential loss. Our contribution is twofold. We provide a new general method for managers to understand how their performance is weather-related. We lay out a blueprint for tailor-made weather derivatives to mitigate this risk.

1. Introduction

Weather can shift the timing of purchases, generate purchases that would not otherwise occur, or cause a permanent loss of demand (Linden, 1962). In industrialized countries, about 70 percent of firms are exposed to changes in everyday weather in a wide range of economic sectors such as agriculture, tourism, food, beverage, apparel, transportation and construction to name but just a few (Dutton, 2002; Larsen, 2006; Lazo, Lawson, Larsen, & Waidmann, 2011; Starr-McCluer, 2000). In recent years, weather and its potential impact on the economy have turned into a serious concern as climate change is exacerbating naturally occurring climate variability and thus adds to the uncertainty faced by weather-sensitive economic sectors (IPCC, 2014; WMO, 2013).

In the retail sector in particular, there is evidence of the role of the weather on sales and unmet profit targets (Agnew & Thornes, 1995; Bertrand & Sinclair-Desgagné, 2012; Changnon, 1999; Schmidlin, 1993). In its March 2013 statistical bulletin, the UK Office for National Statistics (ONS) blamed unusually cold temperatures for poor sales performance in the non-food retail sector. In August, Next, the UK clothing retailer was caught out by warmer-than-usual conditions which left its stores with a shortage of summer clothes, accounting for several million pounds of lost sales. In Germany, the Textilwirtschaft survey indicated that retailers quoted adverse weather (94 percent) and lower consumer traffic (71 percent) as the most often mentioned reasons for their poor performance. In France, clothing sales were also down in the first half of 2013.

The role of weather on mood (Albert, Rosen, Alexander, & Rosenthal, 1991; Goldstein, 1972; Howarth & Hoffman, 1984; Jorgenson, 1981; Sanders & Brizzolara, 1982) and consumer behavior (Cunningham, 1979; Parsons, 2001; Schneider, Lesko, & Garrett, 1980) has been extensively studied but the impact of actual weather and the value of weather information to business and commercial activities has been largely ignored (see a survey of European corporate treasurers in Bertrand & Sinclair-Desgagné, 2012).

The questions we address in this paper are the following: how much of the demand is weather-driven? How can managers profitably use weather information? How can they protect their firms against weather-related lost sales?

While it is comparatively easy to make assessments of the general relationship between weather factors and production or consumption, or in some cases prices (Cammarota, 1989; Fergus, 1999; Maunder, 1968) the more precise relationships

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required for operational decision-making are difficult to formulate (Maunder, 1973). Many studies have focused on establishing a correlation between actual weather variables and sales (Bahng & Kincade, 2012; Engle, Granger, Rice, & Weiss, 1986; Gagne, 1997; Garcia & Sturzenegger, 2001; Linden, 1959; Marteau, Carle, Fourneaux, Holz, & Moreno, 2004) with a view to determine the level of sales for a given level of temperature or precipitation. On the back of this work, a number of retailers such as Tesco in the UK have been using weather information in an attempt to improve forecast on sales for some years (Choi, Kim, & Kim, 2011; Werdigier, 2009) with mixed success (see the case of Pepsico in Fustier, 2011).

The use of weather forecasts to reduce demand uncertainty is restricted to companies that have the ability to adjust their supply chain within 2 weeks. Météo France, the French official weather service, considers that reliable temperature forecasts in Europe do not extend beyond 10 days, and any attempt to include weather information in demand forecast systems is likely to deteriorate current accuracy levels. Yet, while knowing the relationship between weather and sales is useful, very few businesses can in fact benefit from this work. In the clothing retail sector for instance, lead times range from 3–5 weeks for the most efficient companies (e.g., Inditex in Europe) to 3–5 months for companies sourcing in Asia which supplies 80 percent of the entire apparel sector (Créhalet, Bertrand, & Fortin, 2013).

There are other limitations from previous research work. Many studies have focused on analyzing the impact of severe weather events (e.g., Agnew & Palutikof, 1999; Cachon, Gallino, & Olivares, 2012; Changnon, 1999; Schmidlin, 1993) whereas the weather does not need to be extreme to have serious financial consequences on sales and profits (Berlage, 2013). Also, in the specific case of apparel sales, researchers have analyzed the effect of weather on restricted samples, brands, or type of garments, for a limited period of time and in very restricted geographical areas. As sales strongly depend on ephemeral fashion trends as well as other idiosyncratic causes (Barnes & Lea-Greenwood, 2006; Cachon & Swinney, 2009; McIntyre, Achabal, & Miron, 1993), the results are potentially biased and cannot easily be generalized.

Barsky and Miron (1989) suggest that the seasonal cycle has reasonably fixed attributes (such as the timing of holidays, seasons, factory shutdown periods, auto model production changeover schedules), and therefore the true macroeconomic effect of weather can be calculated by measuring the impact of abnormal weather on normal seasonal business. Building from their work, we model how seasonal sales are affected by unseasonal weather.

To illustrate our case, we focus our analysis on the area of retailing where consumer demand response to a change in weather is most likely to be clear: the apparel sector (Agnew & Palutikof, 1999). The method we present yields stronger statistical weather influence than previous studies. One of the reasons is that we use volume instead of monetary sales. When using monetary figures such as GDP, real or nominal sales, a 1 percent decrease in quantity produced or consumed, even caused by changes in weather conditions, may be offset by a 1 percent rise in price. Therefore, no change in the underlying economic performance can be recorded and potential weather impacts remains undetected. In addition, we analyze monthly data, while most studies use quarterly or annual data, hereby capturing weather impacts that would otherwise have been overlooked using longer time intervals.

We use an additive seasonal decomposition method to analyze sales volume data and isolate unexplained changes in sales from seasonal and trends data. We then applied linear regression to calculate and test the coefficient between a unit-change in temperature and change in sales expressed as a percentage of seasonal normal sales. We calculated what percentage of sales is explained by temperature anomalies by garment type and retail channel. We introduce 30 years of temperature observations to construct sales at risk and estimate potential average and maximum losses caused by unfavorable weather conditions. Finally, we provide an example showing how a retail chain in kids' apparel can hedge its exposure to unseasonal temperatures using a weather derivative and calculate its cost based on burn analysis.

Our study provides a methodology for calculating the cumulative impact over a quarter or a season of unexpected deviations of everyday weather from seasonal patterns. It contributes to a better understanding of weather effects on quarterly sales of retail firms by providing a way to isolate the performance due to weather from true organic performance. With this methodology, managers can now correct past sales data from the effect of the weather and mitigate the impact of the weather on their activity.

The next section reviews the related literature. In Section 3, we describe data and methodology. The model is described in Section 4. We discuss the results in Section 5. Section 6 illustrates how to use weather derivatives to reduce exposure to weather risks and Section 7 discusses managerial implications and concludes.

2. Literature review

The influence of weather on business activities and human behavior has been explored in several fields such as finance and psychology (Cao & Wei, 1998; Chang, Chen, Chou, & Lin, 2008; Goeree & Holt, 1999; Hirschleifer & Shumway, 2003; Howarth & Hoffman, 1984; Jacobsen & Marquering, 2008; Kamstra, Kramer, & Levi, 2003; Pardo & Valor, 2003; Saunders, 1993; Trombley, 1997; Watson, 2000) but little research about weather and retail sales is found in the marketing or management literature (Bahng & Kincade, 2012; Lazo et al., 2011; Parsons, 2001; Starr-McCluer, 2000). Yet, the impact of weather on economic activity has been acknowledged as large and widespread over numerous activity sectors throughout the world (Ellithorpe & Putnam, 2000; Howarth & Hoffman, 1984). In some industries such as agriculture and energy, weather is such a risk factor that it is tracked, documented, and hedged through risk management instruments (Lee & Oren, 2009; Roll, 1984). In the particular sector of retail, weather was cited as early as 1951 (Linden, 1962; Steele, 1951). More recently, Murray, Di Muro, Finn, and Popkowski Leszcyc (2010); Stoltman, Morgan, and Anglin (1999) used weather as one of six factors that affect behavioral reactions while shopping for clothes. Conlin, O'Donoghue, and Vogelsang (2007) found evidence of weather-related projection bias of catalog sales. Fluctuations in monthly retail sales figures are often attributed to unseasonal weather conditions (Murray et al., 2010; Starr-McCluer, 2000) but without providing specific methodological algorithms to replicate or provide tools to measure or hedge against such effect. There is a large body of evidence in the fashion retail industry to suggest that unseasonal weather adds to demand uncertainty (Parsons, 2001, and enclosed references), (Au, Choi, & Yu, 2008), but the identification of causes do not translate into managerially or academically usable instruments to control for it or counter it.

There are several ways in which the weather can affect sales. Consumers can feel uncomfortable going to the stores or be physically prevented from going shopping (Parsons, 2001). This is typically observed in case of snow storms, icy roads or extreme temperature conditions. The impact on consumption is usually short-lived and sales catch up to normal levels after the weather event. The weather can also have psychological effects that change people's shopping behavior: some garments sell better during periods in which certain types of weather prevail (Steele, 1951). Clothing items are, by definition, seasonal and ephemeral which means that the timing of the sale is a strategic issue for retailers (Christopher & Peck, 2004). The ideal climate for clothing retailers seems to be one where the seasons exert themselves early (Bahng & Kincade, 2012; Rowley, 1999). Collections disappear quickly and without price reductions if cold signals are detected early in winter (e.g., October, November) and if days warm up early in spring (e.g., March). In the apparel sector, the seasonal changes measured in terms of the calendar seasons (i.e., Spring, Summer, Fall, Winter) are further complicated by the constant need to introduce more fashion collections throughout the year in an attempt to drive more consumers back to the stores (Caro & de Albéniz, 2009).

The study of the weather's role has led to varying conclusions. Linden (1959) analyzed the effects of rain, sunshine, temperature and snow on the ground during business hours on New York City department stores and found few systematic effects. Swinyard (1993), Babin and Darden (1996), Groenland and Schoormans (1994) focused on the link between consumer mood, behavior and weather. To mitigate the effect of the weather on sales in fashion retail, Caliskan Demirag (2013) studied the effectiveness of weather-conditional rebates applied by numerous retail and manufacturing organizations to promote a variety of products from toys to health and beauty items with cash values incentives when weather conditions are unfavorable. Gao, Chen, and Chao (2011) examined the inventory risk of a joint-decision newsvendor supply chain and suggests a weather derivative hedging policy. Gao et al. used conditional value-at-risk evaluation but did not characterize the causal relationship between temperature and sales, merely assuming it. Chen and Yano (2010) considered a weather-related rebate offered to the retailer by the manufacturer who then hedged himself.

In the particular case of garment and apparel distribution, Bahng and Kincade (2012) provided strong evidence that fluctuation in temperature can affect the sales of seasonal garments on a daily basis. Even though weather anomalies may indeed postpone the sale of garments, there was no attempt to evaluate their potential impact on the entire season. Moreover, their pilot study was limited to the analysis of one brand and 50 bestselling basic and carryover styles targeting women aged 30 to 40, between 1 February 2007 and 29 February 2008. The study was also restricted to two cities. These limitations in samples and location prevent from generalizing the results to all garments and retailers. Rowley (1999) demonstrated what retailers had long suspected, namely, that unseasonal weather substantially affects actual clothing purchases. In addition, weather effects on seasonal retail sales pattern are of course compounded by calendar effects. Easter sales are not equally affected if Easter is in early March or late April (Bahng & Kincade, 2012). Starr-McCluer (2000) estimated that, on the whole, the effect of weather on retail sales in the United States has a small but statistically significant role in explaining monthly retail sales.

The first weather research papers focused on economic output in the United States. The economic data which were analyzed were Gross Domestic Product (GDP) or gross state product data for the 11 non-governmental sectors, principally because the time series were sufficiently long for statistical analysis (Dutton, 2002; Larsen, 2006; Lazo et al., 2011). Using annual data is restrictive however, as it prevents analysts from detecting potential weather signals within a year. In retail, sales are seasonal, which implies that the effect of the weather is not constant throughout the year. The same temperature anomaly is unlikely to have the same impact on sales in January or in July.

In the large domain of the apparel market, the main driver is downstream distribution. Downstream distributors place orders based on seasonal sales forecasts so that upstream manufacturers can supply the consumers with products (Bruce, Daly, & Towers, 2004). The decision is considered months before the actual sale to allow for production, shipment, quality control, advertising and so on to take place. The supply strategy follows two steps: a first order at the beginning of the season and replenishment during the season following updated forecasting through acquired market information (Au et al., 2008). Although functional items (e.g., denim jeans or white T-shirts) can be carried over from one season to the other, fashion items are sold punctually, are rarely replenished and become dated at the end of the season (Barnes & Lea-Greenwood, 2006; Milner & Kouvelis, 2005).

As regards weather variance, retailers can obtain some compensation using the financial weather risk market which offers contracts called weather derivatives. Traditional insurance has offered protection for over a century but weather derivatives are unique as they settle based on values that are keyed to a weather index, rather than to a measure of damage or loss (Dischel, 2002a). The first weather derivative was introduced in 1997 by Enron which sold a temperature-based contract to energy group Koch Industry to protect the company against a potential fall in energy demand due to warmer-than-usual temperatures during the winter season. Enron built a temperature-index to respond to the specific need of the energy sector (e.g., the Degree-Day).

Weather derivatives work like any traditional derivative instrument. The only difference is that the index on which the payout is calculated is a weather index instead of being an exchange rate or a stock price. Most of weather derivatives are options. In addition to over-the-counter (OTC) instruments, standardized contracts based on degree-days were launched on the Chicago Mercantile Exchange (CME) during the summer of 1999 (Davis & Meyer, 2000). New contracts based on snowfall, rain, hurricanes, frost days and so on were introduced later (Considine, 2001; Malinow, 2002; Piszczor, 2012). Other tailor-made indices based on wind and sun-hours were used on the OTC market to hedge renewable energy companies. Some indices combining different weather variables (e.g., sun hours, excess or lack of precipitations, daytime or nighttime heat stress) at different periods were developed over-the-counter to hedge the agriculture risk.

The last available Weather Risk Derivative Survey prepared by PwC for the Weather Risk Management Association (WRMA) in 2011 revealed that the proportion of energy companies represented less than half of the total enquiries about weather risk instruments. Agriculture accounted for 12 percent, construction for 23 percent, transportation for 5 percent and retail for 3 percent. Other sectors including tourism accounted for 11 percent. The volume of transactions grew 18 percent in 2011 to US$12 billion after a peak of US$45 billion in 2006 (PriceWaterhouseCoopers, 2011). It has to be stressed that the survey covers few participants and most of the transactions done between companies and reinsurers such as Swiss Re or Allianz Re remain undisclosed. Similarly, the Climate Corporation, formerly known as Weatherbill (Chen & Yano, 2010), which sells highly customized weather cover to American farmers has not disclosed the total amount of risk the company has underwritten. The US$930 million spent by Monsanto to acquire the Climate Corporation at the end of 2013 serve as an indication that the volume of transactions was significant (Upbin, 2013). Firms that sell weather insurance have targeted retail firms only recently, despite the fact that apparel retail channels are particularly exposed (O'Donnell, 2007).

Retail firms used to depend on other more mundane ways to mitigate the effect of demand uncertainty on their overall profit. The most common is named operational hedging (see Boyabatli & Toktay, 2004, for a comprehensive discussion) which includes choice of product assortment (Devinney & Stewart, 1988), quick response, delayed product differentiation, resource diversification and sharing, and price mark-downs at the end of season. Another way is to hedge against adverse weather with either exchange-traded contracts, through the OTC with customized weather contracts such as those provided by the Climate Corporation or Meteo Protect, or by taking an insurance policy with specialized firms (Caliskan Demirag, 2013; Chen & Yano, 2010; Gao, Caliskan Demirag, & Chen, 2012). In summary, while current academic literature has mostly focused on how to hedge the impact of weather and value weather derivatives, very few papers have discussed how to mathematically establish the relationship between the weather and financial performance. We attempt to address this shortcoming in the present paper.

3. Methodology

We present a methodology applicable to all economic sectors exposed to weather risks. We formalize and test the mathematical

Table 1
Apparel categories and distribution channels from the Institut Français de la Mode database.

Retail garment category	Distribution channel
Ready-to-wear men	Independent stores
Ready-to-wear women	Specialized chains
Small pieces men	Superstores
Small pieces women	Department store
Underwear men	Retail-clothing network
Underwear women	Catalogue
Apparel	Supermarkets

relationship between economic performance (demand or supply) and unseasonal weather in a way which enables managers to gain a greater understanding of their business performance. Statistically significant weather variables can then be used as an index to develop mitigating strategies. The quality and detail of both the weather and sales data are crucial for good modeling as well as evaluating hedging instruments. To illustrate this method, several different retail sectors with acknowledged dependence to weather could have been used (e.g., beverages, ice creams, outdoor entertainment, Bertrand, 2010). We chose to illustrate our method with the apparel sector for two main reasons. The first one is the support of the French Fashion Institute[1] (IFM) and comprehensive sales data made available to us. Earlier research on apparel sales failed to provide seasonal or annual weather impacts, which is one of the gaps we propose to fill with our work. The second reason is simplicity. Weather-sensitivity analyses may involve a combination of several weather variables such as wind, rain, temperature or cloud cover. In the case of apparel sales, temperature is the only variable which needs to be considered as it is the most influential weather parameter (Linden, 1959; Miron, 1986; Starr-McCluer, 2000).

3.1. Apparel and weather data

Researchers from the Economic Observatory of the IFM have been gathering sales figures in volume from a panel of thousands of textile and clothing retailers across France since January 2000. Panel members range from independent multi-brand clothing stores to specialized single brand chain stores and department stores. The data are available by garment type for women, men and children. Sales figures are compiled and analyzed by IFM in a survey (Distribilan[2]) to highlight major trends and changes by product category and distribution channel year-on-year on a monthly basis (see Table 1). Each combination of retail garment category and distribution channel constitutes an IFM index. As these turnover indices are volume-based, they are particularly relevant as a base for testing the impact of weather anomalies, avoiding price variation influence (Barrieu, 2003; Brockett, Wang, & Yang, 2005; Dischel, 2002a).

The choice of weather variables is a key step of the process. We based our analysis on temperature because temperature is the main influential weather variable (Bahng & Kincade, 2012; Bertrand, 2010; Dischel, 2002b). IFM sales figures are produced at national level, whereas weather is a local risk. On a given day at a given time, weather conditions are different in Paris, in Brest (western France), and in Marseille (southern France) (Barrieu, 2003). Therefore, weather variables must be constructed in such a way that they not only are a valid representation of national weather conditions but also capture potential weather signals on economic output. The meteorological data are provided by Meteo Protect which owns certified data from thousands of weather stations worldwide. Since we analyzed variations of national apparel sales, a national weather index was built.

We applied the methodology developed by Météo France and Powernext in 2002 to construct national "economic-climatic" indices. Since retail demand is driven by population and consumer traffic (Parsons, 2001), the national temperature used in our model is the average temperature of regional weather stations weighted by the population of each region (Bertrand, 2010; Quayle & Diaz, 1980).

To facilitate the replication of our work, it is important to detail the calculation process using one example. For each month m of year y, we calculated the national temperature index $T_{m,y}$ as follows:

$$T_{m,y} = \sum_{s=1}^{22} \sum_{d=1}^{l_m} \frac{1}{l_m} \frac{p_s}{p_{\text{total}}} \cdot t^D_{d,s,m,y} \tag{1}$$

where $t^D_{d,s,m,y}$ is the average detrended temperature of day d of year y and month m in the weather station s of the 22 representative cities, l_m is the number of days within the month m, p_v the regional population and finally p_{total} the total population for all regions.

3.2. Time series decomposition

With climate change, observed historical temperatures have evolved over the past decades. Therefore weather time series need to be detrended. We use a simple linear trend calculation for each station and compute the detrended temperature t^D as follows:

$$t^D_{d,s,m,y} = t_{d,s,m,y} - \text{Trend}_{d,s,m,y} + \text{Trend}_{d,s,m,2013} \tag{2}$$

where $t_{d,s,m,y}$ is the average non-detrended temperature of day d of year y and month m in the weather station s.

Since we define weather sensitivity as the exposure to weather anomalies, we calculate weather anomalies as the difference between the observed value and the "normal" value. The normal value is the average observation over 30 years (1983–2012), as defined by the World Meteorological Office. For each month m of year y, the national temperature index anomaly $T'_{m,y}$ is given by the difference between the monthly national temperature index $T_{m,y}$ and the average of the same index over 30 years:

$$T'_{m,y} = T_{m,y} - \frac{1}{30} \sum_{y=1983}^{2012} T_{m,y} \tag{3}$$

Weather sensitivity is about testing how weather anomalies change sales from their expected "normal" level. The first step is to determine "normal" sales. This is done using a Seasonal Trend Decomposition using Loess (STL). This is a filtering method for decomposing a time series Y_t into trend T_t, seasonal S_t and remainder R_t components (see Fig. 1).

$$Y_t = T_t + S_t + R_t \tag{4}$$

The STL method requires the user to specify degrees of variation in the trend and seasonal components of time-series to produce robust estimates that are not distorted by transient outliers. STL has been widely used in several disciplines including environmental science, ecology, epidemiology and public health (Cleveland, Cleveland, McRae, & Terpenning, 1990). In this STL procedure, the time series is assumed to be the sum of the three components. Six parameters determine the degree of smoothing in the trend seasonal components (Cleveland et al., 1990):

- n_p – the number of observations in each seasonal cycle.
- n_i – the number of loess smoothing iterations to update the trend and seasonal components (usually set to equal one or two).
- n_o – the number of robustness iterations. With a value of zero no robustness iteration is applied while values of one or more apply increasing robustness, particularly above 5. This parameter is chosen in combination with n_i.

[1] Institut Français de la Mode.
[2] More information can be found on the IFM website.

- n_l – the span of the loess window for each subseries; it is recommended to use the next odd number to n_p.
- n_s – the span of loess window for seasonal extraction. Low values (e.g., from 7 to 10) favor the use of local data while higher figures pool values from the equivalent time of the year across the time-series.
- n_t – the span of the loess window for trend extraction, typically computed as $[1.5n_p/(1 - 1.5n_s^{-1})]$.

The goodness of fit is assessed by using four graphical diagnosis methods: (1) decomposition; (2) trend; (3) seasonal cycle sub-series; and (4) seasonal. Following Cleveland et al. (1990) and Jiang, Liang, Wang, and Xiao (2010), a number of models are constructed using different parameter values and the results are tested against diagnosis plots. The need for data transformation is evaluated using quantile plots of the residuals to ensure that the normal distribution is a good estimate of the actual time-series distribution (Hafen et al., 2009). Additionally, marginal residual plots confirm that there are no residual patterns (Fraccaro, Hyndman, & Veevers, 2000).

Fig. 1 illustrates time series seasonal trend decomposition of apparel sales time series. The original time-series is displayed at the top. The second plot from the top is the seasonal component. It is not constant over time and evolves independently from the overall decreasing trend outlined just below.

Fig. 2 plots the seasonal cycle sub-series of apparel sales. The original time series is decomposed on a monthly basis to highlight the seasonal component for each month.

STL extracts a "global" trend over the entire time-series (2000–2013) and sub-trends for each month (January–December). Not only have "global" sales (the global trend) changed over time, but so have monthly "normal" sales Fig. 2. In 2000, sales peaked in January followed by December and July. In 2013, because of the upward trend in July and downward trend in December, July sales now rank second ahead of December sales.

As already noticed in Fig. 2, taking a value of $n_s = 13$ for the seasonal smoothing parameter allows a cycle evolution consistent with the evolution of apparel sales between 2000 and 2013. Fig. 3 shows the corresponding plots of the seasonal diagnosis for apparel sales. Each of the 12 diagrams presents one cycle-subseries of the detrended data for a month. A line materializes the fitted seasonal component.

Finally, a quantile–quantile plot for the seasonal trend decomposition Fig. 4 confirms the normality of sales anomalies. At the end of the selection process, parameters are set as follows: $n_p = 12$, $n_i = 2$, $n_o = 0$, $n_l = 13$, $n_s = 13$ and $n_t = 100$. As suggested by Cleveland et al. (1990), n_l is equal to the lowest odd integer greater than n_p.

A common assumption in time series analysis is that the data are stationary. Stationary series follow an accurate mathematical definition. For the purpose of this study, we define a series as stationary if mean, variance, and autocorrelation are constant over time. This property means that stationary series are trendless with no seasonal fluctuations. We use the Dickey–Fuller test (Greene, 2011) on all R_t and $T'_{m,y}$ time-series and confirm the hypothesis that all series are stationary.

3.3. Defining weather sensitivity

Weather exposure is the amount of revenues or costs at risk resulting from changes in weather conditions (Brockett et al., 2005). Business managers can execute their plans as long as the weather patterns remain typical. Potential gains or losses arise when weather conditions unexpectedly deviate from their normal values. Meteorologists refer to these deviations as weather "anomalies", used interchangeably in this paper as "unseasonal weather". Because they are unexpected, weather anomalies, or weather surprises (Roll, 1984), can potentially change the economic performance of a firm or a sector. Normal weather conditions are calculated as the average weather over 30 years (Baede, 2001; Dischel, 2002a). The average weather is the climate, and climate variability is the extent to which actual weather differs from climate. An economic sector or a company is

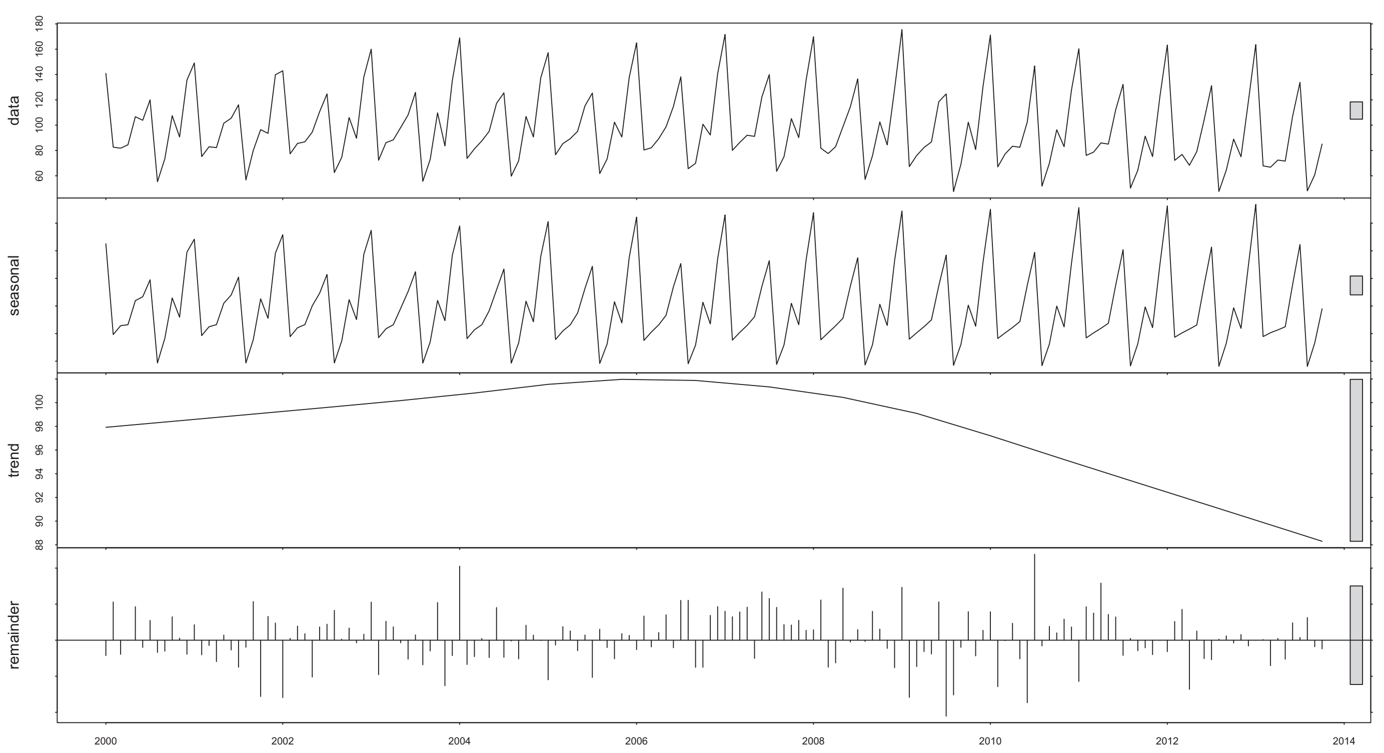

Fig. 1. Seasonal apparel sales decomposition into seasonal, trend and residuals (from top to bottom).

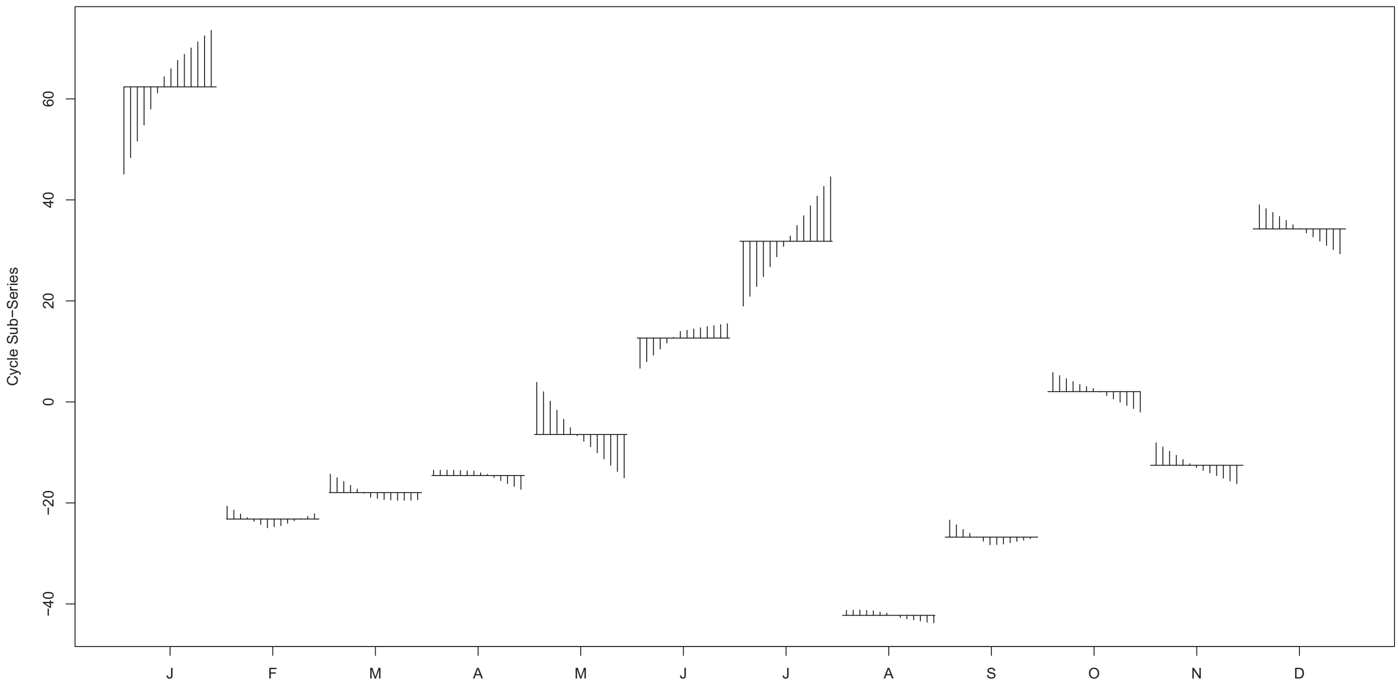

Fig. 2. Seasonal cycle sub-series plot for apparel sales with the seasonal smoothing parameter equal to 13.

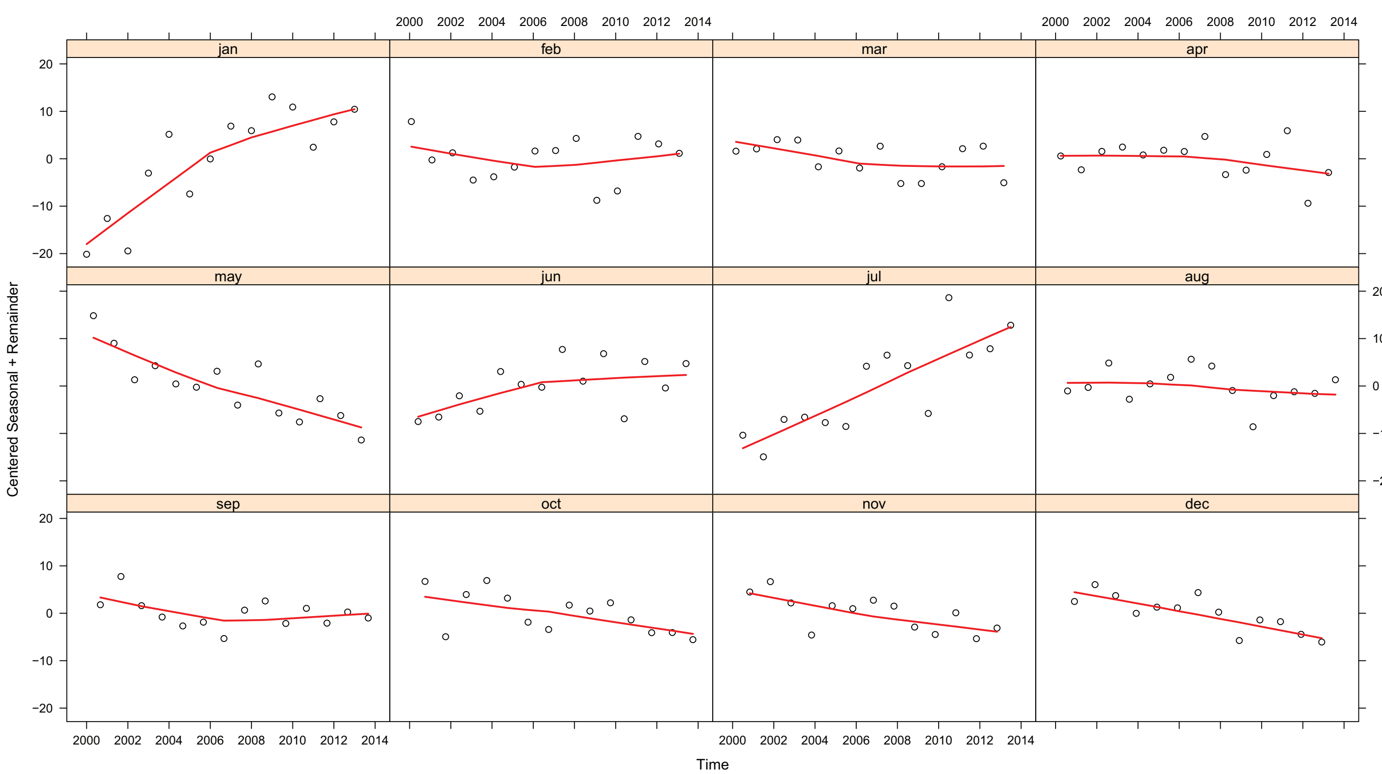

Fig. 3. Seasonal diagnosis plot for apparel sales with the seasonal smoothing parameter equal to 13.

considered weather sensitive if weather anomalies can account for a statistically significant percentage of its variation in business performance: The stronger the relationship, the higher the sensitivity to weather.

4. Model

We want to quantify the impact of 1 degree Celsius anomaly on apparel sales anomalies. Since many times-series exhibit some trend, a 1 degree Celsius anomaly is unlikely to have the same impact on sales in 2000 and in 2013. To circumvent this issue, we used a “relative impact” Z_t defined as:

$$Z_t = \frac{R_t}{T_t + S_t}. \tag{5}$$

Z_t is the relative distance to the “normal” sales index value (seasonal + trend value).

Fig. 5 shows a scatterplot of monthly temperature anomalies against relative apparel sales anomalies in spring. As expected, the

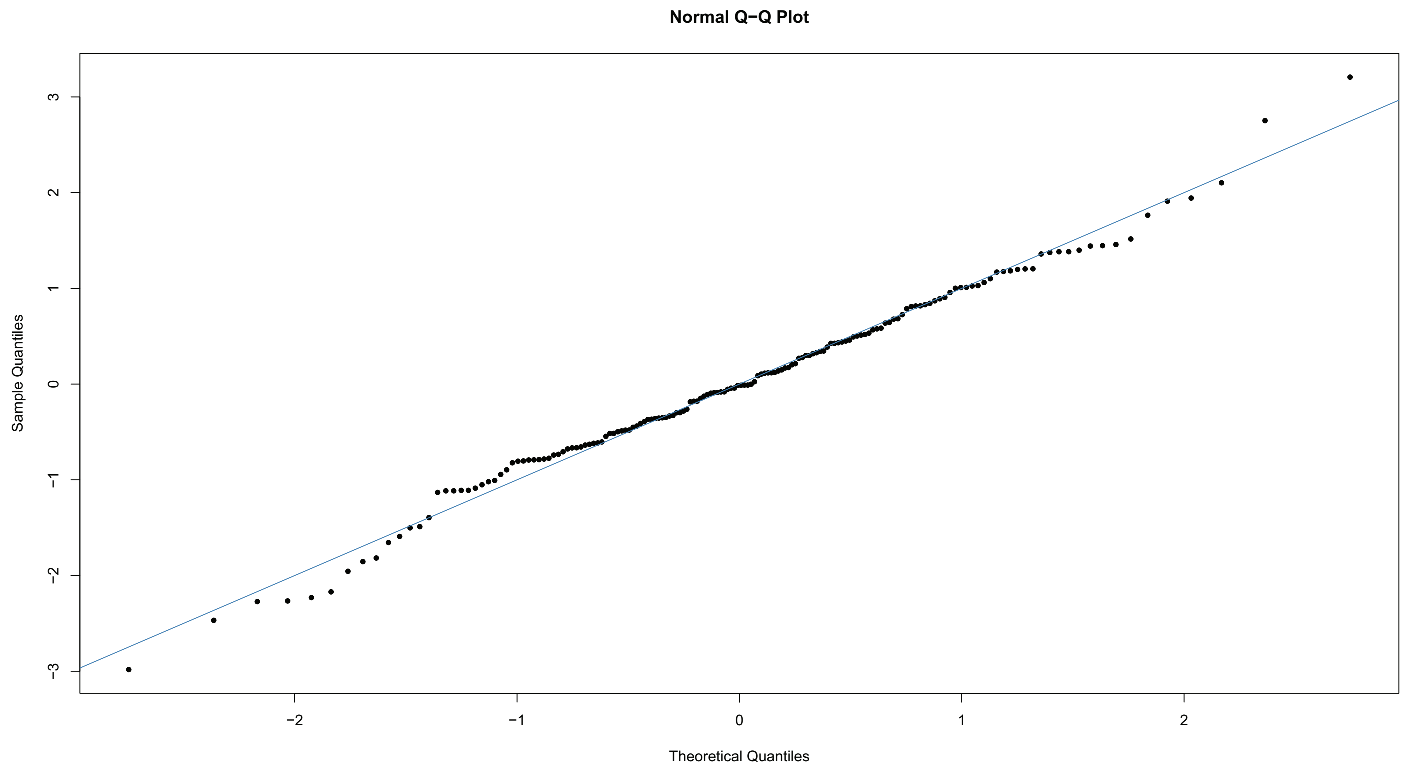

Fig. 4. Quantile–Quantile plot for apparel sales remainder with the seasonal smoothing parameter equal to 13.

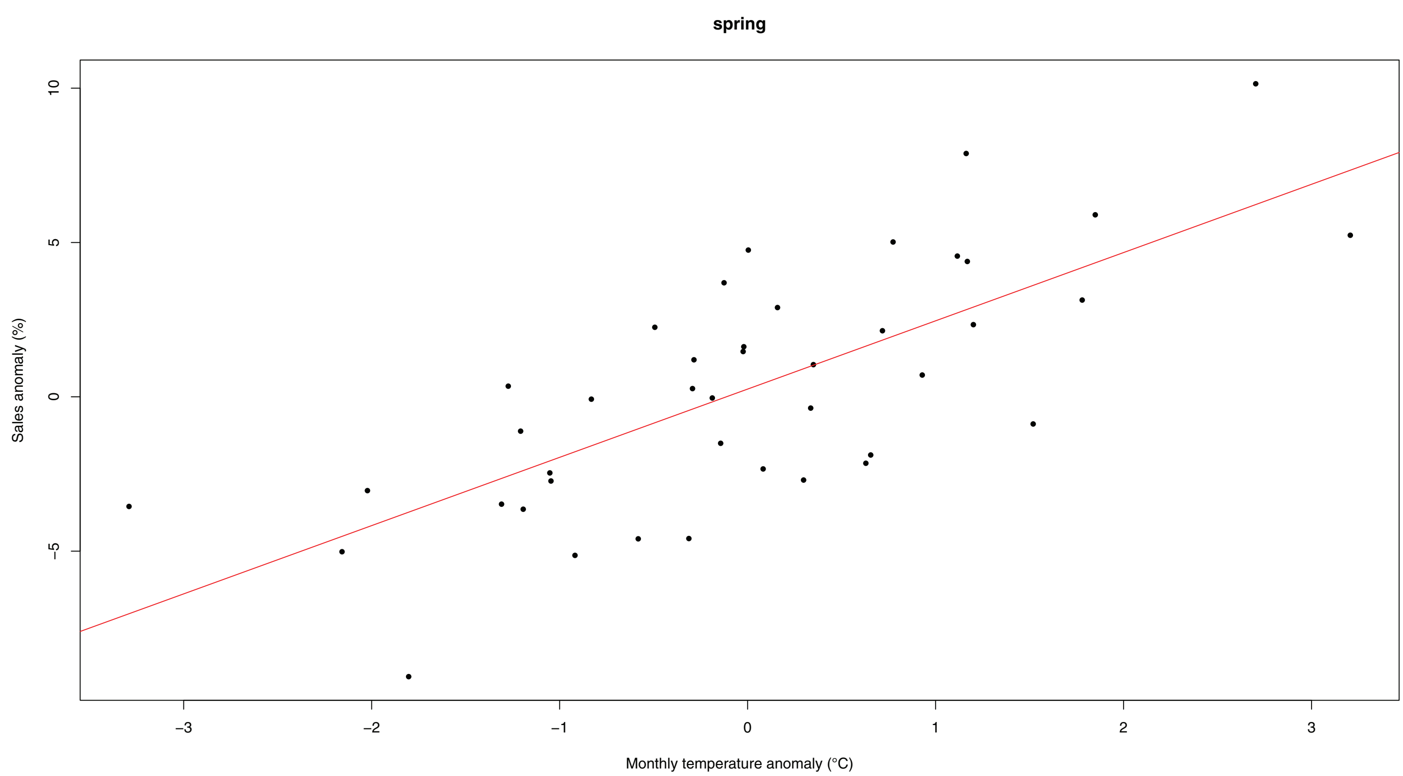

Fig. 5. Scatterplot of apparel sales anomalies against monthly temperature anomalies in spring (black dots) and regression line (red).

upward slope shows that in spring, the warmer the better for apparel sales. We now prove that temperature anomalies are linearly correlated to apparel sales anomalies.

For each season, each product category, and each distribution channel we construct one linear model to quantify the impact of monthly temperature anomalies on the monthly apparel sales anomalies. We assume that within a season, the relative impact of 1 degree Celsius for each month of the same season is the same. The linear regression model is as follows:

$$Z_{m,y} = a + bT'_{m,y} + \epsilon, \tag{6}$$

where $Z_{m,y}$ represents the relative apparel sales anomaly of the month m and the year y, T' the absolute temperature anomaly in the same

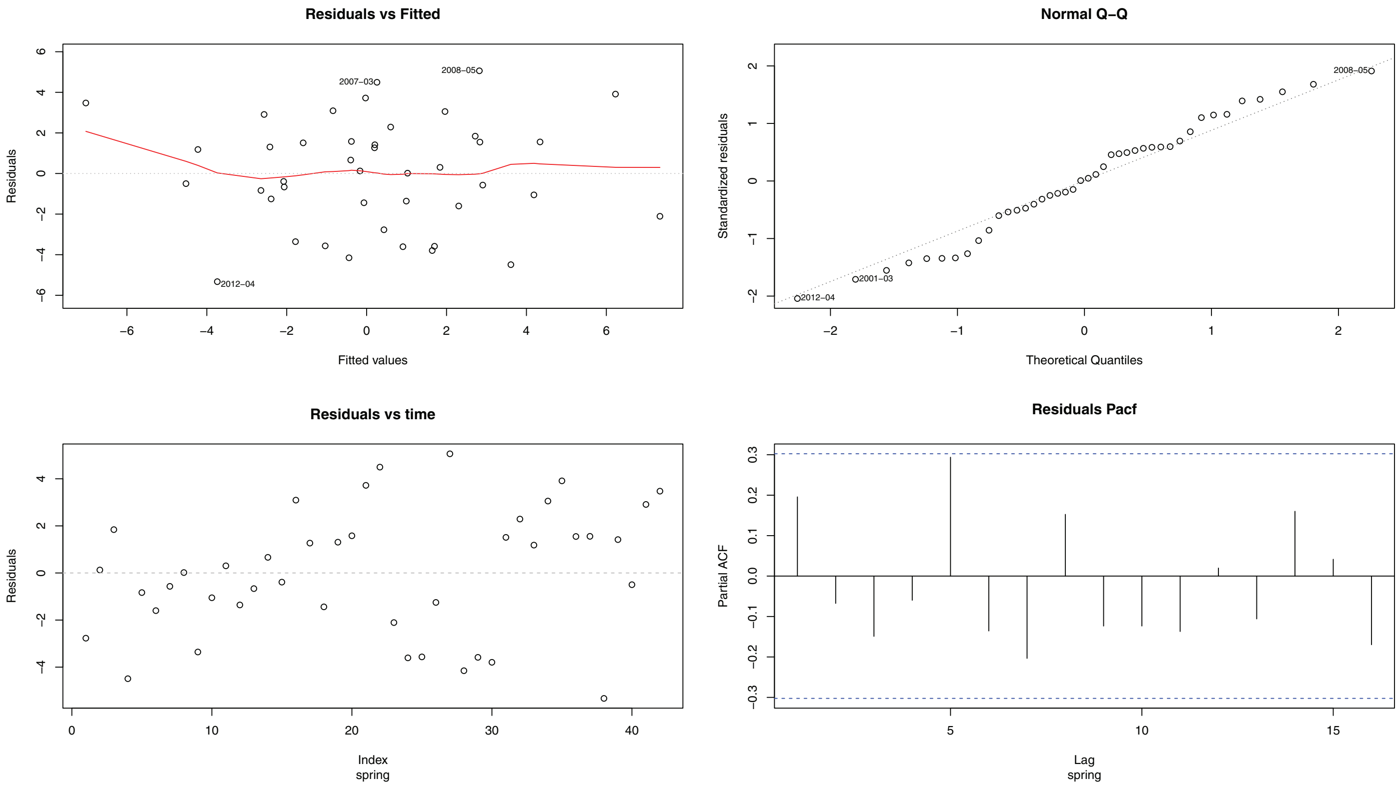

Fig. 6. Example of linear regression diagnosis plots used for spring apparel sales analysis validation.

Table 2
Example of significance test for parameter *b* for spring apparel sales – all channels.

	Estimate	Std. error	*t*-value	*p*-value	R^2
b	2.2118	0.3265	6.774	3.87e−08	0.5227

period, *a* and *b* parameters to be estimated, and ϵ a centered normally distributed variable.

We built 63 different models. We analyzed sales of clothes for three broad categories (ready-to-wear, small garments and underwear) for men and women in seven different retail channels (independent stores, department stores, catalog, superstores, supermarkets, retail clothing networks and specialized chains). We did the same for kids' clothes in the seven distribution channels. Finally, we examined total sales for the overall apparel sector (all distribution channels, all categories).

Fig. 6 provides an illustration in the case of apparel sales for the spring season. Residuals versus fitted values, normal quantile–quantile, residuals versus time and partial autocorrelation function of residuals plot are represented. The residuals versus fitted values plot ensures that the relationship between the dependent and the explanatory variable is linear, and that no significant bias exists. The Normal Q–Q plot ensures the normality of residuals of the regression if they are aligned along the diagonal. The different quantiles lay around the $y = x$ gray dotted line. The residuals versus time index plot confirms homoscedasticity (the variance of the errors does not change over time). Finally, the absence of significant serial correlation in the partial autocorrelation function (PACF) residuals plot validates the independence of the errors.

We then construct each model and test its validity. Table 2 presents the regression model parameters for spring apparel sales anomalies The estimated coefficient *b*, associated standard error, *t*-statistic and corresponding (two-sided) *p*-value are computed. Table 2 shows that the null hypothesis for parameter *b* can be rejected at the 1 percent level (*p*-value is <0.01). Thus, sales increase with warmer-than-normal temperatures at the rate of approximately 2.21 percent per degree Celsius. The adjusted *R*-squared of the regression is equal to 0.5227 which means that temperature anomalies explain 52 percent of spring apparel sales variability.

For each model, we validated the linear regression hypothesis. All calculations are available from the authors upon request.

4.1. Quantifying supply side effects

We use sales data aggregated over a country, a distribution channel or a garment category so as to overcome any particular action or influence at micro-economic level. However, a cause of change in demand could arguably be related to managerial action deployed to adapt to weather forecasts and their expected impact on sales. As previously mentioned, firms like Tesco or Pepsico will adjust their assortment, their workforce, their promotions in an attempt to take advantage or counteract the effects of expected weather. In apparel retail, Zara managers in France rotate product assortment depending on weather forecasts thanks to short lead times. Consequently, we cannot discard the possibility that the weather and managers could both be influencing the demand for apparel at macro-economic level.

The weather can either boost or dampen sales. This is illustrated by Fig. 5 which plots the linear effect of unseasonal weather on sales anomalies. Managerial action, however, will always try to boost sales. If managerial action has an influence, it should counter the negative impact of unseasonal weather and enhance its boosting influence. This means that when above normal temperatures boost sales, managerial action should boost even more. Conversely, when temperatures are below normal, managerial action should reduce the dampening effect. If managerial action has a moderating effect on weather impact, we ought to witness different slopes in the regression line between

Table 3
Temperature sensitivity per distribution channel.

	Spring		Summer		Fall		Winter	
	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2
Independent stores	2.08***	0.34	−1.14**	0.09	−1.84***	0.32	-	-
Department stores	1.49***	0.16	−1.49*	0.06	−1.52***	0.25	-	-
Superstores	2.66***	0.31	-	-	−3.51***	0.58	-	-
Catalogue	-	-	−1.77**	0.1	−1.61***	0.15	-	-
Supermarkets	2.51***	0.52	-	-	−2.03***	0.48	-	-
Retail networks	3.26***	0.4	−1.15**	0.07	−2.59***	0.45	-	-
Specialized stores	2.41***	0.48	-	-	−1.75***	0.39	-	-
Apparel - all channels	2.21***	0.52	-	-	−1.88***	0.58	-	-

*** Significant at the 1 percent level ($p < 0.01$).
** Significant at the 5 percent level ($p < 0.05$).
* Significant at the 10 percent level ($p < 0.1$).
- not significant.

above zero and below zero observations on both axes. Positive unseasonal and weather-related managerial action effects should cumulate while negative unseasonal weather effects should be attenuated by weather-related managerial action. Taking our cue from Fig. 5, there should be a kink at zero on the monthly temperature anomaly axis: the above-zero temperature anomalies should generate higher sales and therefore a higher slope than the displayed regression line. Below-zero temperature anomalies should also generate higher sales but this time represented by a lower slope than the displayed regression line.

So as to measure potential managerial action impact, we have separated the data for each of the 63 series between positive and negative monthly temperature anomalies and performed linear regression analyses on each. We thus established two estimates for the regression coefficient b (see (6)): b^+ as the regression factor for positive temperature anomalies and b^- as the regression factor for negative temperature anomalies.

If managerial action has an impact, it should positively affect sales for all four seasons. To test this hypothesis, we made a two-tailed significance test on the difference between b and b^+ on one side and b and b^- on the other side. For the apparel sector as a whole, no statistical difference exists except for the fall season where the hypothesis of a significant difference can be accepted for b^-. This would imply that, in the fall and in the fall only, managers have a positive influence in enhancing sales when temperature anomalies are below normal. The hypothesis is rejected in all other cases, including when, in the fall, temperatures are above normal. This result begs the question as to why would managerial action be manifested only in one season in the year. We discard this result as being a false positive and conclude that, as was intuitively expected, weather-related managerial action does not influence sales volume at the aggregate level of garment type or distribution channel.

As a further test of potential impact of managerial action to counterbalance that of temperature, we have modeled the contribution of both price and temperature on the sales volume. For all 63 time series, we computed the multi-linear regression between price and temperature as independent variables and sales volume as dependent one. On balance, the difference between this new model and the one with temperature only is almost negligible (see Tables B.11 and B.12 in Appendix B). This is interpreted as meaning that the price is not a variable used by managers to counter the negative influence of temperature on sales.

5. Discussion of results

5.1. Weather-sensitivity of the French apparel sector

Our results on the apparel sector show that unseasonal temperature has an important and statistically significant influence on apparel sales in spring and fall (Table 3). Regression coefficients are significant at the 1 percent level. Temperature anomalies explain 52 percent of variance in sales in spring and 58 percent in fall. As expected, in spring, sales increase with warmer-than-normal temperatures at the rate of 2.21 percent per degree Celsius. In fall, sales increase with colder-than-normal temperatures at the rate of 1.88 percent per degree Celsius. In summer and winter, apparel sales are not exposed to weather anomalies. This is consistent with Marteau et al. (2004) who found that the most significant correlation factors between clothing and temperature were observed in March, April, and May on one side, and in September, October, and November, on the other. In all distribution channels, a positive temperature anomaly has a positive impact on sales in spring and a negative impact on sales in fall (see Table 3). In France, sales are restricted to two periods per year whose dates are set by the local authorities. One is in early January and the other is in early July. As can be seen in Fig. 2, sales for both January and July have increased over the 13 years of the sample as more consumers strategically postpone their season's purchases to these particular periods, and retailers adapt their offerings accordingly. This combination of behaviors may explain the lack of correlation between temperature and sales anomalies. One would have to observe sales over a longer period so that the consumption pattern may have the time to settle.

However, the temperature does not affect all distribution channels uniformly. In spring, temperature anomalies explain between 16 percent (department stores) and 52 percent (supermarkets) of sales anomalies and coefficients range from 1.49 percent per degree Celsius (department stores) to 3.26 percent per degree Celsius (retail clothing networks). In fall, the temperature explains from 25 percent (department stores) to 58 percent (superstores) of sales anomalies, excluding catalog sales, and coefficients range from 1.52 percent per degree Celsius (department stores) to 3.51 percent per degree Celsius (superstores). All coefficients are significant at the 1 percent level. For some distribution channels (independent stores, department stores, and catalog sales), there is a small level of temperature-sensitivity in summer. The temperature, however, does not account for more than 10 percent of sales anomalies. The absence of correlation for catalog sales in spring is intuitively obvious: people who order from catalogs are typically at home, hence relatively immune from the temperature outside. In summer and fall, the relationship might be due to the fact that nice weather entices consumers to abandon their catalogs.

When we analyze the results by market segment, sales are always positively affected by warmer-than-usual temperatures in spring and negatively affected in fall. Again, all models are significant at the 1 percent level (Table 4). The women's ready-to-wear business is not significantly exposed to temperature in summer and winter. Men's ready-to-wear sales are marginally exposed in summer but the coefficient is only significant at the 10 percent level. In the ready-to-wear segment, an increase of 1 degree Celsius generates 2.54 percent

Table 4
Temperature sensitivity per garment type.

	Spring		Summer		Fall		Winter	
	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2
Men Ready to Wear	1.47***	0.33	−0.92*	0.04	−2.3***	0.57	–	–
Men Small Garments	2.28***	0.37	–	–	−2.02***	0.44	–	–
Men Underwear	1.15***	0.25	–	–	−1.24***	0.3	−0.71**	0.07
Women Ready to Wear	2.54***	0.45	–	–	−1.54***	0.31	–	–
Women Small Garments	2.44***	0.45	–	–	−1.62***	0.33	–	–
Women Underwear	1.18***	0.2	–	–	−1***	0.22	–	–
Kids	3.07***	0.48	−2.06***	0.23	−3.15***	0.56	–	–

*** Significant at the 1 percent level ($p < 0.01$).
** Significant at the 5 percent level ($p < 0.05$).
* Significant at the 10 percent level ($p < 0.1$).
– not significant.

(women) and 1.47 percent (men) of additional sales and destroys 1.54 percent (women) and 2.3 percent (men) in fall. In comparison, the small garment segment is slightly more reactive to temperature: an increase of 1 degree Celsius generates 2.44 percent (women) and 2.28 percent (men) of additional sales and destroys 1.62 percent (women) and 2.02 percent (men) in fall. Of all segments, the one for kids' clothing is the most exposed to changes in temperature conditions. Sales change by 3.07 percent per degree Celsius in spring and −3.15 percent per degree Celsius in fall. Kids' clothing is also the only segment which displays a significant exposure to temperature at the 1 percent level in summer (−2.06 percent per degree Celsius and 23 percent).

More tables presenting ready-to-wear, small garments and underwear results can be found in Appendix A (Tables A.8–A.10).

The example above shows that unseasonal temperatures cannot be related to sales anomalies in summer or in winter. In previous papers such as Starr-McCluer (2000), the model presented related monthly sales intertemporally: if a month's nominal sales are affected by bad weather, the demand is carried over to the following month. The reverse happens when the temperature for that month is hotter than normal. If the model does indeed show some catch-up over 3 months, the method used does not discriminate between the seasons. A distinction is introduced between abnormally cold and abnormally hot weather, where abnormal is the difference between observed temperature and a fixed, all-year-round arbitrary value of 65 degree Fahrenheit. When the model is extended to cover data over quarters, the coefficients are not significant and explained variance close to zero.

In Choi et al. (2011), the difference between normal and observed temperatures is again used and compared to absolute sales volumes. Inter-temporality is observed between weekly sales to capture memory and regret effects. Using temperature as an exogenous random variable, two sales forecasting models that apply to winter and summer are drawn. Those contribute to a modified predictive newsvendor model. The use of temperature as a random variable (instead of demand) evidently does not do justice to the potentially important effect of unseasonal weather as exemplified in our model. The difference made by taking temperature into account occurred only when using two seasons of one year and one type of garment (T-shirt).

If that were true in our own model, since we have aggregated sales per quarter, we might expect lost sales in February, say, to be recovered in March, thus nullifying the weather's impact over the full three months. Clearly, this is not the case (or, alternately, it could mean that sales vary even more wildly within a quarter). Such results do not provide insight into why sales increase or decrease. We contend that the present method allows for precise and complete information about the impact of temperature on sales. Taking temperature as a proxy for the weather, the detrended, unseasonalized, temperature-corrected sales data can be read as cleaned for weather, seasonal and trend factors. The remaining information in those sales numbers can only be explained by the actions of management, the market or competition. With our model, managers can now clearly tailor their marketing, commercial, supply campaigns to suit the true conditions of consumer demand and competitors' actions.

Table 5
Minimum, maximum, and standard deviation of weather anomalies' impact since 2000.

Channel	Min (percent)	Max (percent)	Std. dev. (percent)
Independent stores	−6.6	6.9	2.0
Department stores	−4.6	5.1	1.4
Superstores	−8.1	9.6	2.9
Catalog sales	−7.0	4.5	1.7
Supermarkets	−8.2	8.1	2.1
Retail clothing networks	−10.6	10.6	2.7
Specialized stores	−7.7	8.0	1.9
Apparel – all channels	−7.0	7.3	1.9

Bahng and Kincade (2012) draw conclusions by linking increased absolute levels of winter sales by garment type and a substantial absolute fall of temperature. The authors suggest using weather reports to moderate retailers' assortment plans. No indication is provided to account for the difference between horizons for both (2 months for an assortment planning versus 2 weeks at most for weather forecasts). Even if the data had enabled the authors to extend their model to cover apparel retail sales, the fact that the authors look for a relationship between absolute levels of sales and temperatures will not produce statistically relevant results because of the amount of data around the mean that hide the importance of unseasonal sales and weather. A similar effect is at work in our own summer data.

No other studies in the last 15 years have been identified which aim to evaluate the impact of the weather on retail sales as such.

5.2. Historical impact of the weather on apparel sales since 2000

Once the relationships between temperature anomalies and sales anomalies have been defined, we calculate the impact of the weather on apparel sales by introducing historical temperatures into the models developed in Section 3.2. Since 2000, the impact of the temperature on apparel sales has remained within a range of −7.0 percent to +7.3 percent of monthly sales with a standard deviation of 1.9 percent (Table 5). In the Kids segment, the impact of temperature ranges from −9.8 percent to +10.1 percent of monthly sales with a standard deviation of 3.2 percent. In the ready-to-wear business, temperature had bigger minimum and maximum impacts on women's clothes compared to men's clothes (respectively −8.2 percent to +8.3 percent compared to −5.0 percent to +6.3 percent and a standard deviation of respectively. 1.8 percent versus 1.9 percent).

Table 6
Monthly weather impact (percent of sales).

Year–Month	Apparel	Men	Women	Kids
2013–01	0.0	0.0	0.0	0.0
2013–02	0.0	0.0	0.0	0.0
2013–03	−3.2	−1.8	−4.7	−4.8
Q1	−1.1	−0.6	−1.4	−1.9
2013–04	−1.9	−1.3	−2.1	−2.6
2013–05	−5.2	−3.9	−7.0	−8.2
2013–06	0.0	0.0	0.0	5.3
Q2	−2.8	−1.9	−3.7	−1.9
2013–07	0.0	0.0	0.0	−4.2
2013–08	0.0	0.0	0.0	0.4
2013–09	−0.1	−0.2	−0.1	−0.3
Q3	−0.1	0.0	0.0	−1.7

Table 7
Impact of the weather on French apparel sales between 2000 and 2013.

	Apparel sales (index)	Weather	Impact (percent)	Sales excluding weather
2000	1183	2.9	0.2	1180
2001	1179	4.9	0.4	1174
2002	1194	1.5	0.1	1192
2003	1196	9.9	0.8	1186
2004	1216	−4.5	−0.4	1220
2005	1210	−2.6	−0.2	1213
2006	1238	−11.7	−0.9	1249
2007	1253	14.9	1.2	1238
2008	1210	6.2	0.5	1204
2009	1162	0.5	0.0	1161
2010	1160	1.2	0.1	1158
2011	1135	5.0	0.4	1130
2012	1090	2.0	0.2	1088
2013*	877	−12.0	−1.4	889

* Provisional data.

Apparel sales in volume in France have been declining every year since 2007 (see the trend chart in Fig. 1). Professionals are under the impression that the weather explains a large share of this poor performance. We performed a statistical analysis to verify this impression using two time scales: a monthly and an annual one. Let us start with monthly data analysis before turning to evaluating annual data. In 2013, as discussed in Section 1 of this paper, the recorded temperature is indeed correlated with lower sales in March (−3.2 percent), April (−1.9 percent), May (−5.2 percent) and to a lesser degree in October (−1.6 percent). In the Kids and Women segments, the drop in sales was more important: respectively −4.8 percent and −4.7 percent in March, −2.6 percent and −2.1 percent in April, and −7.0 percent and −3.9 percent in May.

However, when looking in Table 6 at the impact of temperature on a quarterly or annual level, the compensating effects from one month to another and from one quarter to another (Starr-McCluer, 2000) iron out such dips. On the same note, on an annual basis between 2000 and 2013 (see Table 7), the effect of temperature on an annual basis has remained within a tight range of −1.4 percent (2013) and +1.2 percent (2007) since 2000. Between 2007 and 2012, the contribution of temperature was always positive. Two conclusions can be drawn: either the steady sales decline cannot be attributed to temperature, and overall sales would have been even lower had it not been for the temperature, or lost sales from one month are not completely recovered in the following ones. In the particular case of fashion items, the second explanation may appear more accurate.

When we analyze sales on a yearly basis, removing the contribution of the temperature offers a different perspective on sales outputs. In 2007, for instance, sales were up 1.25 percent from 2006. Excluding temperature effect, they were actually down 0.72 percent. This was due to the combination of a negative temperature impact of −0.8 percent in 2006 and a positive impact of +1.2 percent in 2007. In most countries, retail sales are published on a monthly basis. Analysts and business managers focus on the monthly change year-on-year to evaluate performance. A year-on-year increase in sales is positive news. In the absence of other information, analysts and managers assume that something has been done right to grow the business and shareholders' value. If, however, sales are not corrected for meteorological effects, there is a risk of misinterpretation (Fig. 7). Since 2000, the average discrepancy between year-on-year actual change in sales and change in sales excluding weather impact was, in terms of absolute difference, 3.1 percent on average and as high as 12 percent. The standard deviation of monthly change in sales falls from 5.7 percent to 3.9 percent when the temperature impact has been removed.

5.3. Sales at risk

"Sales at Risk", like Value at Risk (VaR) in finance, is a statistical measure of possible losses for a retailer due to the volatility of the weather. The concept of VaR stems from the fact that volatility in foreign exchange, interest rates, and commodity prices increased substantially in the late 1990s (Linsmaier & Pearson, 2000). Using a historical simulation, we illustrate the statistical procedure using apparel monthly sales. The approach involves using historical changes in temperatures to construct a distribution of potential future profits and losses resulting from weather anomalies. We use 30 years of historical data in keeping with the evaluation method of the World Meteorological Organization. Using the definition of VaR (Duffie & Pan, 1997), Sales at Risk is the loss that is expected to be exceeded with a probability of $x = 5$ percent. For apparel sales, Sales at Risk is 2.9 percent with a 95 percent confidence level Fig. 8. In other words, 95 percent of the time, the loss caused by weather should not exceed 2.9 percent of sales.

6. Hedging unseasonal weather: a numerical illustration

The increase in climate variability has a growing impact on sales and therefore cash-flows of clothing firms. It increasingly leads finance executives to look for ways of limiting the financial impact of unfavorable weather conditions through the use of weather derivatives for which the payout is precisely conditioned by the occurrence of unfavorable weather. The weather-sensitivity analysis provides the weather parameters (index) that have an impact on sales and the relationship between the index and sales.

The holder of a weather derivative can buy protection against a rise (call) or against a fall (put) of the index from a given level called a strike. The holder pays a premium up-front and is paid if the end-value of the index is below (put) or above (call) the strike. A weather derivative contract is usually defined by five elements: (1) the hedging period (days to months); (2) the geographical area and corresponding weather station(s); (3) the payout formula which can be a fixed amount per critical day (e.g. rainy, snowy, icy, etc.) or an amount proportional to the value of the index (e.g. $1000 per degree Celsius or by millimeter of rain, etc.); (4) the strike (the value of the index which triggers the payout); and (5) the maximum payout. At the end of the contract period, the final value of the index is determined from weather observations collected at the stations. It is often referred to as the "weather report". If the final value of the index is such that the strike is triggered, the payout is calculated using the final value of the index and the funds are automatically wired to the holder of the contract. Weather derivatives differ from weather insurance which requires proof of loss and usually includes additional conditions specifying when the insurer is liable.

In traditional finance, it is always possible to create a portfolio with an asset to replicate the behavior and the value of any derivative instrument based on this underlying asset. The market is said to be complete. With the weather however, it is not possible to do so since

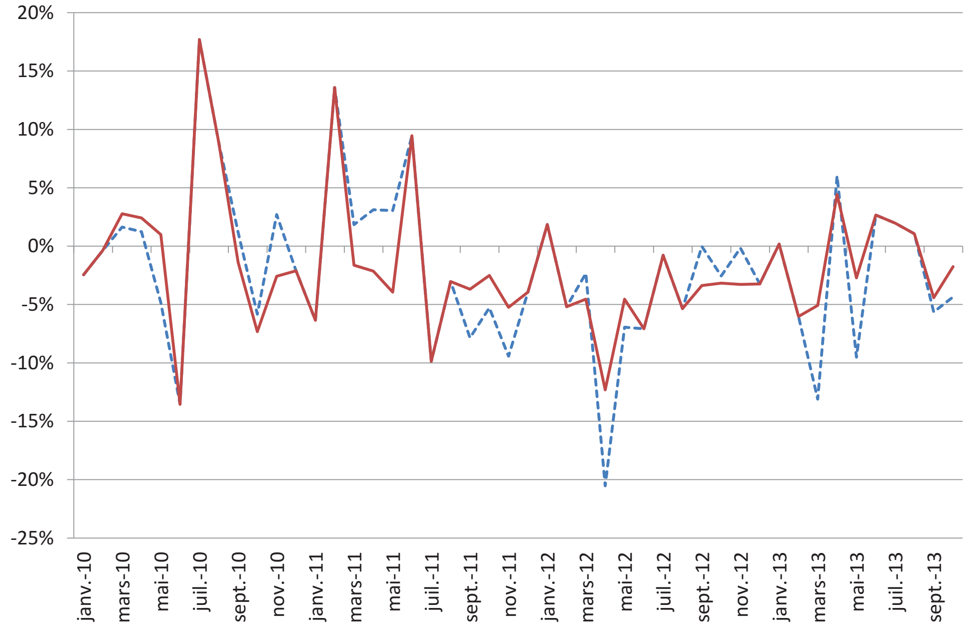

Fig. 7. Change in apparel sales YoY (dotted line: actual; plain line: excluding weather impact).

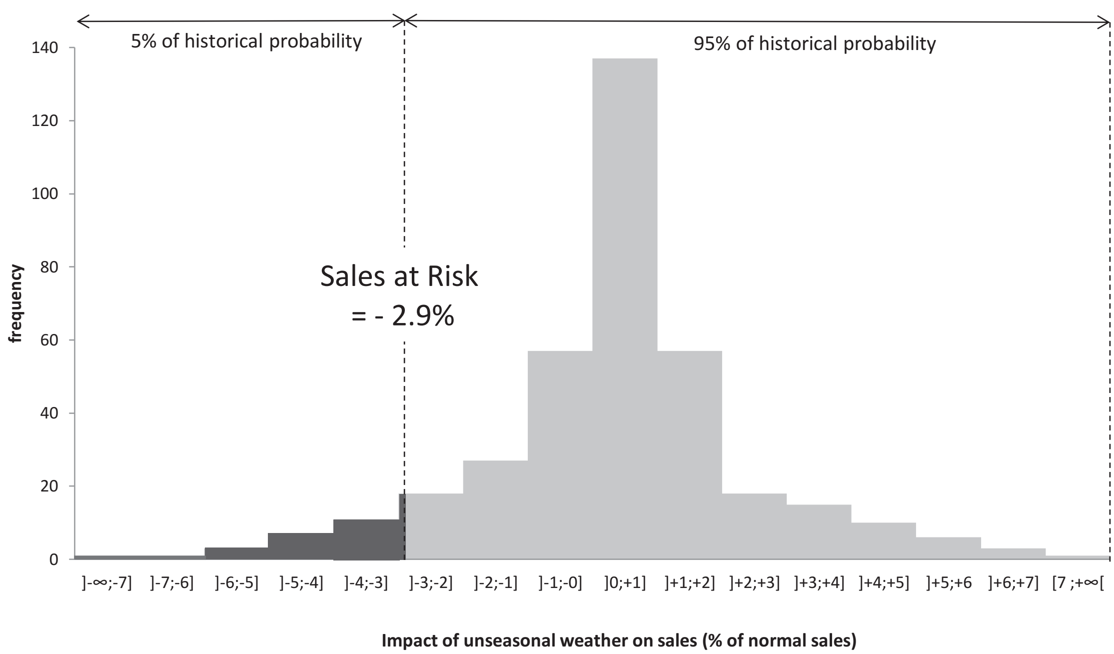

Fig. 8. Histogram of monthly profits and losses on apparel sales.

temperatures or wind speeds cannot be bought or sold or borrowed or even stored in a portfolio (Davis, 1998, 2001). Weather markets are incomplete. As a result, classical derivative valuation methods, such as Black & Scholes or Cox, Ross and Rubinstein cannot be applied (Cao, 2000; Dischel, 1998; Geman, 1999; Geman & Leonardi, 2005; Moreno, 2000; Young & Zariphopoulou, 2002). There are four categories of alternative valuation methods (Brockett et al., 2005, and enclosed references): actuarial, replication of the underlying weather index using weather swaps (Jewson & Zervos, 2005) or energy derivatives (Geman, 1999), equilibrium models (Richards, Manfredo, & Sanders, 2004) and utility functions. In practice, in weather markets, the theoretical value of a derivative is generally evaluated against the expected value of the underlying weather index and related payout at the date of expiry of the derivative discounted back at the risk-free rate. The determination of the expected value of the weather index relies on the construction of a mathematical distribution based on historical weather observations. The distribution is then used to calculate the historical payout and its standard deviation (Jewson & Zervos, 2005). This method is called *Burn Analysis*.

To illustrate how this is done, let us assume that the finance director of a firm which sells Kids' clothes in France through specialized stores is looking to hedge some of its exposure to the weather during the spring season.

We assume that the finance director accepts to retain a risk equal to one standard deviation but wants to be hedged if the loss caused by weather exceeds €270,000 (the strike). This loss corresponds to an average temperature during the period of 10.98461 degree Celsius. The maximum desired payout is the difference between the worst loss over 30 years (€722,067 or 9.50921 degree Celsius) and the strike. For each year, the payout is equal to Min(0; strike – sales anomaly). The hedging structure would have paid 4 times over the last 30 years: €136,906 (1984), €52,267 (1986), €33,934 (2010) and €452,067 (2013). The burn analysis or the expected payout is the average payout of the structure: €21,780. The volatility (standard deviation) is €84,120. The price of the derivative is the expected payout + the cost of capital + a risk premium (Marteau et al., 2004). The ultimate risk taker is usually a reinsurance company which is required to deposit in an escrow account an amount equal to the maximum payout during the life of the derivative. Assuming a required rate of return for the funds of 10 percent, the cost of capital is 3/12 ∗ €452,067 ∗ 10 percent = €11,302. Finally, the risk premium is equal to 25 percent of the volatility (€84,120 times 0.25 = €21,030). As a result the total cost of the derivative instrument is the burn + the cost of capital + the risk premium = €21,780 + €11,302 + €21,030 = €54,112. The finance director can therefore buy a hedging contract (a put on a temperature index) at the price €54,112 to limit the exposure to weather. The contract has the following characteristics: (1) the hedging period: 1st March 2014 to 31st May 2014; (2) geographical area and corresponding weather station(s): France; (3) payout formula: €30.50/0.0001 degree Celsius; (4) Strike = average temperature > 10.9846 degree Celsius and (5) the maximum payout: €452,067 (9.5092 degree Celsius).

7. Conclusion

We distinguish scientific contributions from managerial ones.

7.1. Scientific contribution

Unseasonal weather conditions affect demand and supply of many companies operating in a wide range of economic sectors. As stressed by the World Meteorological Organization in its Annual Climate Statement 2012, climate change is aggravating naturally occurring climate variability and is becoming an additional source of uncertainty for climate-sensitive sectors. The main contributions of this paper are twofold. First, the contribution of this paper is in elaborating a new method to isolate the contribution of unseasonal temperatures from sales performance. The discussion is moved from testing how temperature is correlated to sales as presented in the literature (see Bahng & Kincade, 2012; Caliskan Demirag, 2013; Caro & de Albéniz, 2009, to name but the latest) to evaluating how *unseasonal* weather explains sales *anomalies*. Second, we show how to evaluate sales at risk and open new avenues for weather risk transfer through financial products or risk mitigation through product-mix diversification. Our method can be extended to various other areas of scientific interest using other weather databases to understand patterns of human activity.

Using the apparel sector as an example, we have answered the three questions set out in Section 1. Having isolated the impact of temperature on sales for men, women and kids' clothes in a variety of distribution channels, managers can use the cleaned data to understand better the impact of supply side effects and the consequences of their managerial actions on sales. We demonstrate that seasons do not have the same sales exposition to temperature anomalies. We show that the response of men, women and kids apparel sales to the same weather risk are different. We also show that different distribution channels exhibit different responses to the same risk.

In this paper, we dealt with one weather variable only (temperature). The exposure to precipitation, sun hours and wind could be tested using exactly the same methodology. In this case, Partial Least Squares regression would be used instead of linear regression to overcome potential multi-colinearities between weather variables (Bertrand, 2010). When several weather variables are identified they can be combined as one single weather-index and used to structure a weather derivative in the same way as shown in Section 6.

As climate variability rises, we expect growing interest from academia in weather risk management to be applied in management research fields such as marketing, supply chain, and finance management. Similar research effort should be performed on various other economic sectors in other regions of the world, drawing world-wide weather-sensitivity maps, and evaluating the potential effects.

7.2. Managerial implications

An increase in unseasonal weather patterns leads to higher swings in year-on-year revenues and earnings. Over the years, managers have learnt to manage the seasonality of their business. The relationship between seasonal weather and demand or supply levels is not an issue. Unseasonal weather, however, can be disruptive. Managers require better understanding of unseasonal weather effects on the performance of their organization.

CEOs, CFOs, sales and marketing managers can take appropriate strategic operating and financial actions to mitigate the risk, and more importantly to increase the resilience of their organizations in a changing climate environment.

For the apparel economic sector, we calculate the sensitivity to weather of each product category, for each distribution channel, for men, women and children. As a result, we show how to remove the impact of temperature on the historical apparel sector performance to display the true organic performance. We show how to specifically identify periods of the year which exhibit the highest exposure to changes in temperature conditions. A retail firm can use the weather impact per season in its channel and or garment type to correct its sales data from weather effects. And finally, we provide the evaluation of "sales at risk", the first step towards effective weather risk management.

The fact that the weather has an impact on apparel sales is not news to retailers. For the first time however, our findings formalize the relationship between temperature as a proxy for the weather and apparel sales, and provide retailers with valuable information about both their *performance* excluding weather effect as well as their *exposure* to weather risk. Once the exposure to weather is well defined and understood, managers can consider financial hedging using weather derivatives.

This new approach delivers far more insightful inferences into the causes of under- or over-performance of an organization's management and can be put to profit in many different ways. Marketing managers can now correct their past sales data not only of seasonal factors but also of *unseasonal* weather. A sales manager can clean sales data from weather related distortions to reward the sales force appropriately. Removing the impact of weather on historical sales also allows for better forecasting when past sales figures are used to forecast future sales, thanks to the greater fit of known controllable variables as shown in Thomassey (2010) or in Ni and Fan (2011). With better information, supply chain managers can streamline inventory or redirect logistics or procurement earlier as well as analyze ex post those decisions. *Mutatis mutandis*, this result also applies to revenue managers in hotels, leisure parks, or airlines.

Additionally, a firm can adapt its product mix or geographical mix to reduce the overall exposure to unwelcome weather effects. Financial analysts can use weather sensitivity to adapt their guidance on a listed company or calculate weather-related value at risk to include in their rating system. Risk managers can pinpoint and hedge the risks stemming from supplies as well as sales and reduce the volatility of results and therefore the cost of funding.

Appendix A. Statistical correlations between apparel sales and unseasonal temperature

Table A.8
Small garments weather sensitivity per distribution channel.

	Spring		Summer		Fall		Winter	
	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2
Men – independent stores	2.58***	0.21	−1.32*	0.07	−2.52***	0.27	–	–
Women – independent stores	1.18*	0.05	−1.76**	0.08	−1.39**	0.11	–	–
Men – department stores	1.96***	0.18	–	–	−1.29***	0.18	–	–
Women – department stores	1.9***	0.15	−1.37*	0.05	−1.54***	0.16	–	–
Men – superstores	3.82***	0.52	–	–	−4.09***	0.65	–	–
Women – superstores	4.18***	0.37	–	–	−3.21***	0.34	–	–
Men – catalog	1.73**	0.07	−2.25**	0.09	−1.89*	0.05	–	–
Women – catalog	–	–	−2.07**	0.09	−1.33*	0.07	–	–
Men – supermarkets	4.22***	0.36	–	–	−2.2***	0.23	–	–
Women – supermarkets	4.23***	0.35	–	–	−1.78**	0.08	–	–
Men – clothing retail networks	3.31***	0.34	–	–	−3.21***	0.48	–	–
Women – clothing retail networks	3.93***	0.39	–	–	−2.16***	0.21	–	–
Men – specialized chains	1.68***	0.16	–	–	−1.84***	0.21	–	–
Women – specialized chains	2.83***	0.40	–	–	−1.8***	0.28	–	–

*** Significant at the 1 percent level ($p < 0.01$).
** Significant at the 5 percent level ($p < 0.05$).
* Significant at the 10 percent level ($p < 0.1$).
– not significant.

Table A.9
Ready-To-Wear (RTW) weather sensitivity per distribution channel.

	Spring		Summer		Fall		Winter	
	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2
Men – independent stores	1.72***	0.25	−1.2**	0.07	−2.57***	0.32	–	–
Women – independent stores	1.18*	0.05	−1.76**	0.08	−1.39**	0.11	–	–
Kids – independent stores	–	–	−2.19***	0.25	−1.58**	0.08	–	–
Men – department stores	1.57***	0.16	−1.5*	0.05	−1.98***	0.29	–	–
Women – department stores	1.9***	0.15	−1.37*	0.05	−1.54***	0.16	–	–
Kids – department stores	1.4*	0.06	−2.62***	0.18	−2.79***	0.35	–	–
Men – catalog	–	–	–	–	–	–	–	–
Women – catalog	–	–	−2.07**	0.09	−1.33*	0.07	–	–
Kids – catalog	–	–	−3.32***	0.17	−2.63***	0.18	–	–
Men – supermarkets	1.36*	0.06	–	–	−1.4*	0.05	–	–
Women – supermarkets	4.23***	0.35	–	–	−1.78**	0.08	–	–
Kids – supermarkets	3.18***	0.35	−0.97*	0.04	−2.65***	0.44	–	–
Men – retail clothing network	1.73**	0.08	−1.42**	0.11	−3.13***	0.45	–	–
Women – retail clothing network	3.93***	0.39	–	–	−2.16***	0.21	–	–
Kids – retail clothing network	3.66***	0.37	−1.99***	0.19	−4.12***	0.54	–	–
Men – specialized chains	1.32***	0.15	–	–	−2.39***	0.44	–	–
Women – specialized chains	2.83***	0.4	–	–	−1.8***	0.28	–	–
Kids – specialized chains	3.05***	0.39	−2.38***	0.17	−3.45***	0.48	–	–

*** Significant at the 1 percent level ($p < 0.01$).
** Significant at the 5 percent level ($p < 0.05$).
* Significant at the 10 percent level ($p < 0.1$).
– not significant.

Table A.10
Underwear weather sensitivity per distribution channel.

	Spring		Summer		Fall		Winter	
	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2
Men – independent stores	2.02**	0.09	–	–	−1.83**	0.08	–	–
Women – independent stores	2.75***	0.26	–	–	–	–	–	–
Men – department stores	–	–	–	–	–	–	–	–
Women – department stores	1.09**	0.07	–	–	−0.88***	0.12	–	–
Men – superstores	3.8***	0.53	–	–	−3.81***	0.59	–	–
Women – superstores	1.16**	0.07	−0.79**	0.07	−2.84***	0.51	–	–
Men – catalog	–	–	–	–	–	–	–	–
Women – catalog	–	–	–	–	–	–	–	–
Men – supermarkets	0.89**	0.1	–	–	−1.05***	0.12	–	–
Women – supermarkets	–	–	–	–	−1.78***	0.31	0.91**	0.12
Men – clothing retail networks	–	–	–	–	–	–	–	–
Women – clothing retail networks	1.95***	0.26	–	–	−1.14*	0.05	–	–
Men – specialized chains	1.21**	0.09	–	–	−2.61***	0.43	−1.69***	0.14
Women – specialized chains	1.16**	0.07	–	–	–	–	–	–

*** Significant at the 1 percent level ($p < 0.01$).
** Significant at the 5 percent level ($p < 0.05$).
* Significant at the 10 percent level ($p < 0.1$).
– not significant.

Appendix B. Supply side impact on sales volume

Table B.11
Difference between weather sensitivity (w) and weather and price sensitivity ($w + p$) for each season and channel, when $w - (w + p) < 0$, the price increases the impact of temperature. The difference in R^2 reflects the difference in explaining power. On the bottom line is the average for all channels per season.

	Spring		Summer		Fall		Winter	
	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2	Percent per degree Celsius	R^2
Independent stores	0.09	0.02	−0.03	0.02	0	0	0	0
Department stores	0.18	−0.03	−0.15	−0.02	−0.01	0	0	0
Superstores	−0.2	−0.21	0.96	−0.26	0.12	−0	0	0
Catalog sales	0	0	−0.09	0.03	0.02	−0	0	0
Supermarkets	0.24	−0.04	0	0	−0.11	−0	−0.62	−0.44
Retail clothing networks	0.24	−0.01	1.11	−0.05	−0.03	0	0	0
Specialized stores	0.11	0.02	0	0	0	0	0	0
Apparel – all channels	0.15	−0.01	0	0	−0.01	0	0	0
Average	0.10		0.26		0.00		−0.09	

Table B.12
Difference between weather sensitivity (w) and weather and price sensitivity ($w + p$): for each season and garment type, when $w - (w + p) < 0$, the price increases the impact of temperature. The difference in R^2 reflects the difference in explaining power. On the bottom line is the average for all channels per season.

	Spring		Summer		Fall		Winter	
Men ready to wear	0.08	0	−0.92	0.04	−0.01	0	0	0
Men small garments	−0.2	0.18	1.26	−0.05	0.43	0.2	0	0
Men underwear	−0.7	0.1	0	0	0.02	0.1	−0.71	0.07
Women ready to wear	−1	−0.13	0	0	2.43	−0	0	0
Women small garments	0.62	0.39	2.22	−0.07	0.48	0.2	0	0
Women underwear	−2.8	−0.17	0	0	1.15	0	0	0
Kids	−0.1	0.17	−2.06	0.23	0.06	0.1	0	0
Average	−0.59		0.07		0.65		−0.10	

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