Here Comes the Sun: Fashion Goods Retailing under Weather Shocks

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Abstract

The weather has been identified as an important driver of demand and constitutes a major risk for retailers, especially in goods for which usage is affected by weather conditions, such as soft drinks or fashion apparel. Specifically, weather variations change the propensity to visit the point of sales, because travel cost is affected by weather conditions; and they impact differently different product categories, because the reference utility in the mind of the consumer is affected by current weather. We empirically study these two impact dimensions at a large fashion apparel retailer. We find that rain has a large effect on footfall, increasing it in shopping mall stores and decreasing it in street stores, which suggest that it is a first-order factor for channel choice. Temperature has a milder effect on footfall. In contrast, temperature has a large impact on conversion, increasing sales of the "appropriate" categories: summer items are sold more under positive temperature shocks, and winter items less. Finally, although theory suggests that the weather should have a moderating effect on price sensitivity, we find that it is unaffected by the weather.

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1. Introduction

Retailers strive to better understand demand drivers so as to bring to the store the right products at the right time and delight customers with the perfect store experience. Unfortunately, demand can be difficult to predict, especially if products are innovative (Fisher 1997), for instance in fashion apparel. There, Zara and other fast fashion players have developed new operational strategies to better adjust supply to demand (Caro and Martínez-de Albéniz 2015). The fast fashion business model is quite successful at reducing product risk by adjusting production quantities to realized demand.

Despite these improvements, some risks remain difficult to predict and mitigate. One of the most prominent factors of uncertainty is the weather. For example, the Swedish fashion chain H&M attributed a decrease of profits to an unusually warm Winter in 2015 (Armstrong 2016). A similar statement was made later in September 2016: sales had been negatively affected by unusually hot weather (Monaghan 2016). On the other hand, the statement in the second quarter of 2016 blamed cold weather (Reuters 2016). This type of comment is common in the apparel industry: The Gap and Macy's attributed the poor sales trends in July 2016 to unfavorable weather (Derrick 2016); Next stated that demand in the Spring of 2016 was reduced due to cold and damp weather conditions (Farrell and Butler 2016); financial analysts stated that "Britain's erratic weather has really taken its toll on retailers this year, and a warm September was the last thing that the high street needed" (BBC 2016).

While it seems clear that the weather strongly affects customer behavior, it is not obvious in which direction this impacts retailers, and how relevant these weather shocks are. To the very least, this empirical question is a complex one. The literature has indeed studied it before, but does not find strong effects despite the anecdotes described above. This is the case because most of the earlier studies use aggregate data (weekly or monthly, and over regions or countries), so that effects are usually averaged over multiple weather realizations, possibly reducing the estimated impact. Moreover, and perhaps more worrisome, some papers that do have access to disaggregate data only include the weather as one more covariate within a demand model (e.g., Divakar et al. 2005, Kök and Fisher 2007, Eliashberg et al. 2009), but they do not use it to directly inform decisions. This seems to suggest that the weather may have a large influence on demand, but better information about its effect cannot be translated into any value for retailers. This is surprising in the current times, where demand analytics can unlock value by better understanding the impact of different environmental factors, such as queues or sales assistance (Lu et al. 2013, Kesavan et al. 2014, Jain et al. 2016, Musalem et al. 2016).

The objective of this paper is thus to answer the following question: how does weather affect retail performance, in a multi-channel context? To be more precise, we are interested in detailing the impact of different types of variation (temperature and rain) on two key retail variables: footfall (number of visits to a store) and conversion (probability that a customer buys a product). This distinction can help us understand better the mechanisms by which weather changes shopping behaviors. In particular, there is numerous literature in psychology that links weather to moods and behavior. We apply the existing theory to the two processes of interest, i.e., the decisions whether to visit a store and, once inside, whether to purchase. In particular, we focus on the multi-channel aspect and distinguish how the different types of stores respond to weather shocks. Regarding footfall, it predicts that better weather (no rain, higher temperatures) may be favorable to outdoor locations (street stores), but should always be detrimental to indoor locations (shopping

mall stores). Regarding conversion, it predicts that warmer conditions will favor 'summer' products, and hurt 'winter' products. We seek to test these theories by using highly disaggregated data, daily and over a large number of stores in different cities experiencing different weather shocks.

We construct two separate reduced-form models for footfall and sales. The two models include temperature and rain as covariates. We control for price variations over time, which are exogenously determined by a central planner, ahead of time and hence independently of actual weather conditions. Finally, in the sales model, we provide one different estimation for every product family. We focus on dresses and coats, which are examples of summer and winter families respectively. The models are estimated using a large dataset provided by a large apparel chain, also used in Boada-Collado and Martínez-de-Albéniz (2019), with daily observations during 2013 and 2014, in 13 cities in 4 European countries, with at least 3 different stores per city.

Our empirical results support all the existing theoretical predictions except that price sensitivity seems to be independent of the weather, while the theory suggests that it should be decreasing in rain and increasing in temperature. While our findings are for the most part consistent with the theory, our study goes one step further by documenting the magnitude of these effects and in particular pinpointing in which step of the shopping process weather variables are most important. Specifically, we find that footfall is most sensitive to rain, and impact is enormous: a day where complete rainy day imply a footfall reduction of 7.5% in street stores and an increase of 5.2% in shopping mall stores; temperature also drives store visits, but with a lesser impact. Conversion on the other hand is affected both by rain and temperature deviations: an increase of 5°C pushes units sales of dresses up by 11%, and those of coats down 9%. Our findings thus contribute to better understanding how weather shocks impact retail operations, and can be used as future building blocks for modelling and optimization. Our work thus contributes to the growing literature on retail operations, shedding light on the role of external stimuli in shaping consumer behavior across channels.

The rest of the paper is organized as follows. §2 describes the relevant literature. We present the basic approach, the data used and formulate the hypotheses in §3. We present the models and estimation results in §4 for footfall and in §5 for sales. We conclude in §6.

2. Literature Review

Our work is related to different streams of literature that we review here. First, we report the theoretical work, mostly from psychology, that links weather stimuli to consumer behavior. Second, we review the empirical studies in operations, marketing and economics fields on the effect of weather on customers.

There are different ways by which weather can affect our physiology and psychology. For example, the presence of rain produces discomfort (Miranda-Moreno and Lahti 2013) and sunshine produces a positive effect on our mood (Hirshleifer and Shumway 2003, Cunningham 1979, Parrott and Sabini 1990). The main process by which weather affects our body is the vital human necessity of maintaining our body at 37°C and balancing the heat lost to the environment and the heat produced by the body (Fanger 1973). This equilibrium depends on several weather variables like temperature, humidity, air velocity or pressure and other internal variables like activity level or thermal resistance of clothing. When this heat balance is lost, it produces physiological and behavioral consequences in order to return to the equilibrium point. For example, at the physiological level, the body can change the heat produced increasing or reducing the cutaneous blood

flow, the sweat secretion and shivering or tensing muscles. People also take actions to maintain this balance such as choosing different environments, adjusting thermal aspects of the environment, e.g., by opening a window, or simply changing clothes (Baker and Standeven 1994, Nikolopoulou et al. 2001). People feel stress and discomfort when they are outside the equilibrium zone, and this usually affects customer behavior. The further they are from the equilibrium point, the more uncomfortable they will feel (Humphreys et al. 2007). In the psychology literature, the concept of *thermal comfort* refers to the effect of weather on people's comfort (Nicol and Humphreys 2002, Humphreys et al. 2007). This process is relevant to our topic as long as the election of clothing and the store as thermal environment are two ways from which people could achieve thermal comfort. People can also feel changes in their emotions. For example, weather variables affect mood (Sanders and Brizzolara 1982) and mood has a strong impact on consumer behavior (Gardner 1985, Gardner and Hill 1988). In general, all results point to a positive relationship between mood and shopping intentions, e.g., mood is positively associated with time spent in the store and the number of products bought (Robert and John 1982, Sherman et al. 1997).

The behavioral evidence comes mainly from experimental and field work. However, there is also literature based on data analysis that provide evidence of particular impact of weather on different fields like economics, marketing and operations, but the number of works is more limited.

In economics, there is an important stream of work that explores how people change their leisure activities and the time dedicated for leisure according to weather. Connolly (2008) finds that on rainy days, 30 minutes of leisure time are transferred to work on average, which implies that people substitute leisure and work time according to the weather. Zivin and Neidell (2014) provide more evidence that better conditions outdoors reduce the hours at work, and show that substitution is not only occurring between work and leisure, but also across different leisure activities. More evidence is provided by Izquierdo Sanchez et al. (2016) who show significant effect of temperature on substitution between visiting the cinema and viewing large sports events, in a positive direction for sports events as temperature rises. Li (2014) describes shopping as a leisure activity that should also be subject to weather-driven substitution. In particular, rain can make the shopping place less attractive because it becomes harder to get there in favor of other indoor leisure activities. It is shown that rain affects negatively all outdoor leisure activities, while temperature has different effects depending on the location of the store. This complements earlier work by Parsons (2001) who finds a significant relationship between temperature and rain with the number of people in a shopping center in New Zealand. In studies of customer behavior regarding consumption, the earliest study that we can report was Steele (1951), but not much more was done until the 2000s. Murray et al. (2010) focuses on the effect of sunlight on one independent store specialized in tea and finds a significant positive relationship between amount of sunlight and consumption of tea. Closer to our application in apparel retailing, Bahng and Kincade (2012) shows that fluctuations in temperature impact sales of seasonal garments (branded women's business wear). Bertrand et al. (2015) also show that fluctuations in temperature have an important and significant influence on apparel sales. Badorf and Hoberg (2016) provide a similar study to ours focusing on daily sales over different stores in Germany. They show that weather effects may be non-monotonic, and that reaction to weather depends on the store location, as we also find. These works focus on establishing the sign and magnitude of weather effects, but do not use these additional information to make better decisions. The exception is Steinker et al. (2017), who uses the weather to improve demand forecasts of online sales in Germany and to adjust workforce planning, which saves idle times and excess costs. Interestingly, they find that online sales strongly increase with rain, which suggests

that shopping online resembles shopping at the mall and is a substitute to shopping at a street store.

Our paper has three main differences with the literature: it uses disaggregated data at a large scale (daily, store level), which has only been used before in Bahng and Kincade (2012), Badorf and Hoberg (2016) and Steinker et al. (2017), while other papers with daily data only consider effects in a single location (Parsons 2001, Murray et al. 2010); it separates effects on store footfall and conversion, which allows us to support our findings with existing theory; and it provides a recommendation on how to make weather effects useful to retailers, through weather-contingent pricing.

3. Context, Data and Expected Behaviors

3.1 Shopping process

Shopping is a complex process that has been studied for years in the field of consumer behavior in marketing. In particular, different types of products entail different shopping behaviors. Hirschman and Holbrook (1982) differentiate hedonic products from the utilitarian ones, defining the first ones as those related with emotional experiences of the consumer. In this paper, we focus on fashion apparel retailing which is a typical example of a hedonic product in marketing research (see p. 95 in Hirschman and Holbrook 1982). The consumption of this kind of products is very related to an emotional experience while shopping and hence customers normally decide whether to buy once they are in the store, as opposed to bringing a shopping list to the store. As a result, the contextual environment at the moment of purchase plays a major role (Salkin 2005).

In this context, to generate a retail sale, a customer (female in this paper) goes through two main decisions, described in Figure 1. First, she decides to travel to a store, which involves a trade-off between that choice and other alternatives, such as staying at home or other leisure activities. This step should be influenced by factors that drive the cost, time or convenience of the different alternatives, such as the weather which is our focus here. Of course, there might be other drivers such as transportation or parking congestion. Second, once in the store, the customer decides whether to purchase a product in a certain category, or leave empty-handed. This second step is driven by store variables, such as assortment variety or promotions, but may also be impacted by the weather. Although within a store, there may not be a direct experience of outside weather, customers use outside weather as a reference point and adapt their in-store behavior to that benchmark. We detail below the theory behind these adaptation processes.

Our focus in this study is to identify the impact of different weather variables on the customer decisions with respect to visits and purchases. Specifically, we consider two quantitative variables affected by the weather: we use the count of people N_{st} that enter store s on a given day t, which we call *store footfall*, and the number of units U_{stj} sold within a certain category j sold in store s that day t.

3.2 Data description

We obtained a large data set from a large apparel retailer with revenues of several hundred millions of euros. This data has been used in the past by Boada-Collado and Martínez-de-Albéniz (2019). We focused on 98 stores located in four different European countries, grouped in 13 different cities

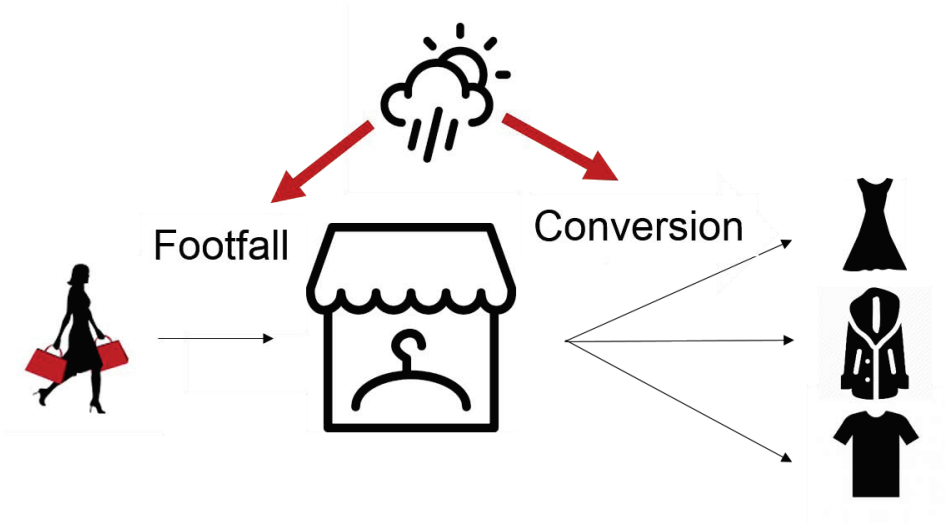

Figure 1: Diagram of the shopping process: store visit and purchase.

that have at least 3 different stores each. We also have information about location: whether it is on the street (41 of them) or within a shopping center (57). We describe next the different variables used in our empirical study.

Footfall. Store footfall data provides the total number of visitors for each store and day. As illustration, Figure 2 shows the daily footfall for two months in four different stores, for two different markets and location types. We observe that seasonality is qualitatively similar in all the curves, e.g., there are peaks on Saturdays (on most Sundays, the stores are closed). However the magnitude of seasonality patterns is different between stores on the street and in a shopping mall, and the same is true across different markets. For these reasons, we will include location type - city specific seasonality covariates, as discussed later.

Category sales. We obtained product-level transaction data (products are defined by different model and color, but may contain multiple sizes). We considered unit sales per product and aggregated them into families, as defined by the retailer. Family classifies the type of garment: dress, t-shirt, coat, pullover, skirt, trousers and shirt. In our study, we define the category as the product family. Table 1 shows some descriptive statistics of the categories. Note that in the table and our subsequent analysis, we focus on two different periods: March 1 to June 30 and September 1 to December 31. The objective of this selection is to remove periods of clearance sales in the four countries under consideration, when shopping patterns may be different from the more stable parts of the Spring-Summer and Fall-Winter seasons.

Since we are working with the number of units sold per category, we need to control for possible occasional discounts. Note that discounts are generally endogenous, because they are decided based on the retailer's forecast of demand. This might also be the case with our data, but our focus is on the effect of the weather, so to obtain unbiased estimates we only need to ensure that the discount levels are independent of the weather. In our context, discounts were managed centrally: we had access to the weekly merchandizing plans, which were prepared one week ahead of time, and in

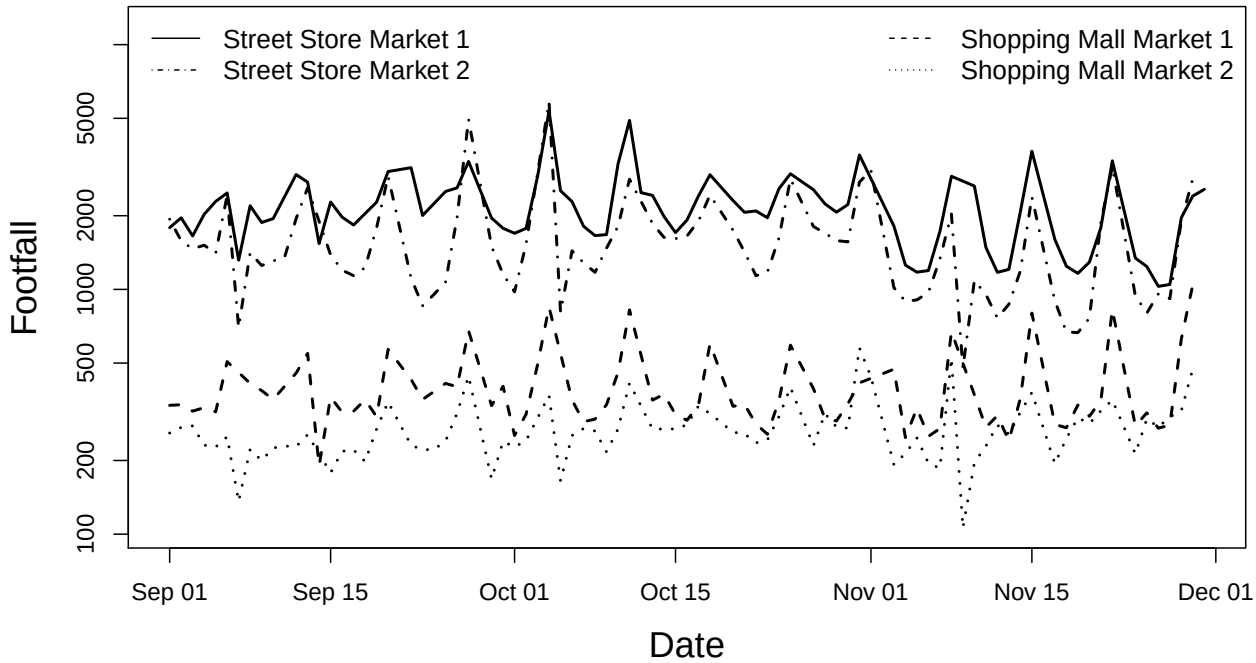

Figure 2: Comparison of daily footfall over three months of 2014 for four different stores.

most cases were the same in all cities within a country. In particular, they did not use weather as an input, thereby allowing us to take weather as exogenous shocks and hence interpret our estimates of weather effects as causal.

To compute discount levels, we used two sources of information suggested by the retailer. First, we obtained merchandizing information about discounts planned for each store and family of products, during the full-price selling season (March to June and September to December). We found that planned discounts always applied per store and family (e.g., discount of 20% for coats). There were also instances other kinds of discounts that applied generally to all products within a store (e.g., 20% for the second unit purchased). Since our model considers aggregate sales, we use as a covariate in our model the average discount within a category. Second, we computed the discount applicable to a store-family-day triplet, which was not easy to retrieve from the merchandizing plan. We obtained the total income per product per store per day from transaction data. Using this information, we estimated the discount applied per family per store per day. Specifically, we first calculated for every day, product and store the income per unit of product sold. That is, if we denote INC_{ist} the total income for product i, in the store s and day t and S_{ist} the number of units sold we could obtain the average unit price, denoted as $\hat{p}_{ist} = \frac{INC_{ist}}{S_{ist}}$. This value might not coincide with the product price on that day due to the general discount rules described above (e.g., 20% for the second unit purchased). With this time series it was possible to estimate the regular price of a product as the maximum of the time series, denoted $\hat{p}_{is} := \max_t \hat{p}_{ist}$. With this

Families	Total number of products	Average number of products in a store	Average units sold in a store
Dress	410	66.3	13.7
T-shirt	571	84.7	22.1
Skirt	87	12.3	2.4
Shirt	51	9.3	2.2
Denim trousers	46	9.9	2.1
Pullover	126	19.6	4.6
Coat	163	26.8	4.2

Table 1: Descriptive statistics of product categories. The interpretation is the following: in the sample we observed 410 different dresses; in a given store on a given day, there were 66.3 dresses offered on average (with a much higher average inventory depth) and 13.7 units were sold.

value, we estimated the discount applied for the product $\hat{d}_{ist} = 1 - \frac{\hat{p}_{is}}{\hat{p}_{ist}}$. We defined the discount per family as the average of the discount estimated per product. That is, the discount per family j is $\hat{d}_{jst} = \underset{i \in j}{\text{mean}}\{\hat{d}_{ist}\}$. This procedure might be problematic in the cases where we did not have any unit sold on that day for a family (in this case, the total income is zero for all the products of the family, as well as the units sold; it occurs approximately 10% of the time). In this situation we used the fact that normally, discounts were applied for all products of the store, not only for one single family. Indeed, correlation between discounts across families is around 0.60. Hence, we defined $\hat{d}_{jst}$ as the average discount for the other families in that store.

Weather. We used meteorological data from historical records at different airports in the four countries of interest, from Weather Underground (*http://www.wunderground.com*). To this end, for each store, we collected historical weather data from the nearest airport. Since our stores are all located in major cities, this provides accurate weather conditions about each store. Note that the mean of the distances between the airports and the city of the store is 18 km, with a standard deviation of 11 km.

There are many weather variables that one could use, such as maximum, mean and minimum for temperature, humidity, barometric pressure, the amount of precipitation and/or snow. In the previous literature, different types of weather variables have been used: Parsons (2001) only found significant associations of footfall in a shopping mall with temperature and rain, although humidity and sunlight were also considered, Murray et al. (2010) focused on sunlight only and Bertrand et al. (2015) and Bahng and Kincade (2012) only considered temperature.

In this study, we focused our attention on temperature and rain, because snow and cloud cover (equivalent to sunlight) where highly correlated with them, so they were removed to avoid collinearity issues in our empirical analysis. We defined temperature as the absolute deviation between mean daily temperature in Celsius and the historical mean on that calendar day between 1996 and 2012. Taking this variable instead of the absolute temperature entails some advantages over using absolute temperature. First, the absolute temperature has a substantial seasonal variation, so that the effect of absolute temperature cannot be easily distinguished from seasonality. Instead, temperature deviation is uncorrelated with calendar seasonality. Second, temperature deviation is by construction the deviation from the norm, which is unpredictable at the time of product design.

Hence, this variable will not capture endogenous effects due to retailer decisions. Third, there is a psychological aspect that is worth noting: it might seem that centering the temperature variable is simply a numerical manipulation, but given that people are aware of historical temperatures, temperature deviation captures the deviation of actual temperature from expectations of shoppers, hence the response to deviations from the "normal". In addition, rain was taken as a binary variable that indicates whether there was presence of rain. We report in Table 2 the descriptive statistics of these variables.

		Temperature	**Rain**
Germany	Mean	0.24	0.61
	Sd	3.82	
	Min	-13.13	0
	Max	12.27	1
France	Mean	-0.02	0.50
	Sd	3.45	
	Min	-11.88	0
	Max	9.00	1

		Temperature	**Rain**
Italy	Mean	0.30	0.39
	Sd	2.92	
	Min	-11.88	0
	Max	11.24	1
Spain	Mean	0.47	0.30
	Sd	2.94	
	Min	-10.00	0
	Max	10.65	1

Table 2: Descriptive statistics of the selected weather variables.

3.3 Hypotheses

As mentioned before, rain causes discomfort in a direct way and reduces the sense of comfort of pedestrians (Miranda-Moreno and Lahti 2013). In addition, it has also an impact on mood for two reasons. First, rain is associated with more cloud cover, which results in a reduction of sunlight, and hence reduces positive mood. Second, rain increases humidity, which has been associated negatively with mood (Howarth and Hoffman 1984, Sanders and Brizzolara 1982): this implies that rain again reduces positive mood.

In contrast, the impact of temperature occurs via the channel of thermal comfort (Fanger 1973). The comfort sensed in a given environment depends on many variables but it has been observed that temperature has a unimodal relationship with comfort: very hot or very cold temperatures produce discomfort, while intermediate temperatures are more comfortable. For example, Keller et al. (2005) shows that temperature has an inverted U-shaped relationship with mood. Zivin and Neidell (2014) find that, in several cities in the United States, the number of pedestrians on the street increase with temperatures below 25°C and decrease above. Attaset et al. (2010) finds that the peak occurs at 27°C for pedestrians at a certain county in California. Specific behaviors also seem to have U-shaped relationships with temperature (Rotton and Cohn 2000). Given this background, and the fact that in our data, historical average temperatures range from -5 to 26°C, we assume that the sensitivity of shopping variables to temperature variation may change from the cold to the hot season. However, in the majority of our sample temperature falls in the region where higher temperatures increase thermal comfort. In other words, the effect of higher temperature should be opposite of that of rain.

Finally, the main difference between rain and temperature is that rain creates large changes in comfort, while temperature only brings small changes, which furthermore have an intensity that depends on the base temperature level from which these deviations occur.

Footfall. Whether to go into a store or not is a decision that should be affected by the current weather. This is particularly true for shopping of fashion items, a hedonic consumption which should be more sensitive to the context (as opposed to grocery shopping when your fridge is empty). We could even consider store visits as a form of leisure.

Previous research indicates that one should separate indoor and outdoor leisure, pointing out that when there is more comfortable weather people prefer outdoor activities (Zivin and Neidell 2014, Spinney and Millward 2011). These results suggest that when it rains, a shift to indoor activities occurs (Miranda-Moreno and Lahti 2013). This implies that rain should increase visits to shopping mall stores, and decrease them in stores located on the street.

The effect of temperature is slightly more complex, as described in §2. Indeed, outdoor activities exhibit an inverted U-shape with temperature. Hence, in cold periods (winter), when temperature increases, a shift to outdoor activities occurs (Zivin and Neidell 2014), as one should expect from thermal comfort theory (Nikolopoulou et al. 2001), thereby decreasing shopping activity; indeed it has been reported that physical outdoor activities and sports also increase with temperature (Tucker and Gilliland 2007, Izquierdo Sanchez et al. 2016), as well as other recreational activities such as going into nature, beach, golf or sailing (Loomis and Crespi 1999, Mendelsohn and Markowski 1999, Loomis and Richardson 2006, Li 2014). In contrast, in warm periods (summer), outside temperature might make people uncomfortable and increases in temperature should lead to an increase in shopping visits. We thus hypothesize that the effect of temperature is decreasing in moments where historical temperature is low, and increasing when it is high. In other words, the coefficient of the interaction of temperature deviation with historical absolute temperature is positive.

In summary, we construct two hypotheses, for rain and temperature:

> H_1: Rain increases footfall on shopping center stores and decreases it in street stores.
> H_{2a}: For a given historical absolute temperature, temperature decreases footfall.
> H_{2b}: The effect of temperature on footfall is more negative with lower historical absolute temperatures.

Category sales. In addition to the effect on footfall, people will also take actions during the shopping process to reduce thermal discomfort. The choice of clothing is an act that can increase thermal comfort (Humphreys et al. 2007). In particular, some types of clothes provide more or less insulation than others. As one should obviously expect, Humphreys et al. (2007) show that people wear warmer clothes (with more insulation properties) during colder conditions. Bertrand et al. (2015) also find that sales of winter collection products decrease with temperature while they increase for summer collection products. We expect the same effect in sales: people will feel more attracted to product families like dresses in warmer conditions and families like coats in colder conditions. This variation is due to higher thermal comfort of these products which increase the perceived attractiveness of the product.

> H_3: Sales of "summer" clothes (e.g., dresses) increase with higher temperature deviations, and sales of "winter" clothes (e.g., coats) decrease with higher temperature deviations.

Finally, we should determine the impact of rain on sales. Given that there is no particular effect related to comfort once in the store, we do not make any particular hypothesis in this respect.

Sensitivity to discounts. Finally, in addition to the impact on footfall and sales, the weather can also moderate the effect of discounts. This moderating effect is particularly relevant because pricing seems to be the most actionable lever that a retailer can use to react to changes in weather.

It has been suggested that mood affects evaluations of people and objects in the same direction of their current mood (Forgas and Bower 1987, Gardner 1985, Gorn et al. 1993). This effect is a consequence of the fact that people in positive mood can remember more easily and pay more attention to positive information (Bower 1981, Blaney 1986, Tamir and Robinson 2007). Hence we expect that people on positive mood are more capable of integrating discounts into their decision-making and, since mood bias evaluations in a positive direction, consumers will perceive a better monetary transaction, so that even a small extra discount may increase their utility significantly. Indeed, Hsu and Shaw-Ching Liu (1998) found in a lab experiment that people in positive mood are more sensitive to discounts than those in negative mood. Given the relationship between temperature and rain with mood (positive and negative respectively), we expect that:

H_4: Rain decreases discount sensitivity.
H_5: Temperature increases discount sensitivity.

4. Impact on Footfall

4.1 Model description

We use a reduced-form log-linear model to adjust the daily store footfall: as dependent variable, we use the logarithm of the footfall, which can handle better size effects (e.g., seasonal variations in a larger store will be larger in absolute terms). Thus, the regression estimated coefficients can be interpreted as a change in the percentage of footfall.

As mentioned in §3.3, stores have been classified according to their location: in a shopping mall or on the street. We expect a different impact of weather on footfall depending on the location. Moreover, previous descriptive analysis shows different seasonality depending on the type of store (cf. Figure 2). Given these facts, we use the following independent variables in our model. First, we include X_{st} a seasonality factor, which includes interactions of s the store, and w the week number factor (1 to 52) and d the weekday (Monday to Sunday). This incorporates a store fixed effect, to take into account fixed store properties (e.g., location, market population, accessibility, etc.), as well as store-dependent seasonality patterns. We hence consider very detailed seasonality controls to avoid attributing seasonal variations to weather effects. We also consider a linear trend t that captures evolution in footfall over time. Note that t is measured in years, so α can be interpreted as the growth per annum. Second, we consider the possible impact of discounts on footfall, even though price information is usually provided within the store and should not affect the decision of customers to visit the store. We thus include d_{st} the average price discount across all products. Finally, W_{st} is the set of weather variables (including rain, temperature deviation and interaction of temperature deviation and historical absolute temperature). Letting $l \in \{Street, Mall\}$, the resulting model can be written using the following vectorial form for coefficients and covariates:

$$\log(N_{st}) = \alpha t + \beta' X_{st} + \gamma d_{st} + \delta_{l(s)} W_{st} + e_{st} \tag{1}$$

where $l(s)$ is the type of store s, and e_{st} is the residual, which we assume to be normally distributed. Note that we use vector notation, e.g., $\beta' X_{st} = \beta_{swd}$ if t is the d-th day of weeknumber w.

Given that we use a large number of seasonality controls, we can use the difference of log-traffic between a given t and the same date of the previous year (same weekday in same weeknumber). We can thus rewrite the model as

$$\text{Model F1:} \quad \Delta \log(N_{st}) = \alpha + \gamma \Delta d_{st} + \delta_{l(s)} \Delta W_{st} + e'_{st} \tag{2}$$

where $\Delta Q_{st} := Q_{st} - Q_{st-1}$ is the variation of any variable Q_{st} between years and $e'_{st} = \Delta e_{st}$ is a Normal residual. This specification can easily be estimated with ordinary least squares, with a few variables. Namely, since we have two years of data (2013 and 2014), this formulation allows us to work with the difference between 2014 and 2013 of the relevant variables, without worrying about seasonality. Note that this differentiation might be problematic if a certain date, e.g., Wednesday of week 15, was different in 2014 compared to 2013, which might be the case if that date was a holiday in 2014 but not in 2013. In these cases, the store would be closed in 2014, so the difference $\Delta \log(N_{st})$ would be missing, and hence would be omitted from the estimation, thereby not biasing our results.

4.2 Results

We estimate this model via ordinary least squares, although we report robust errors to avoid issues with heteroscedasticity. We compare model F1 in (2) to a more basic model F0 where $l \equiv 0$. Table 3 shows the results of the estimation.

We can see that rain has a different impact depending on the location, as discussed in §3.3. The impact of rain on footfall is significant and strong: when it rains all day, it implies a change of approximately $e^{-0.074} - 1 = -7.4\%$ of footfall in street stores and an increase of $e^{0.052} - 1 = 5.2\%$ in shopping mall stores. Hence, hypothesis H_1 cannot be rejected. Moreover, we see that introducing weather variables in F1 improves model fit compared to the benchmark F0, although the amount of remaining variability is still high ($R^2 = 0.023$ and residual standard error of 0.355). Note finally that the goodness of fit of the model should not be considered low. Indeed, the dependent variable here is variation of log-footfall, while a regular forecast model for footfall would regress $\log(N_{st})$ directly; in this case, regressing $\log(N_{st})$ against $\log(N_{st-1})$, Δd_{st} and ΔW_{st} (the same variables as in F1) results in a R^2 of 0.79.

Temperature generally has a negative effect on footfall, of about -0.0104 per degree. However, this effect is moderated by the historical temperature, and is milder during the warm season, because the coefficient of the interacted term is positive, equal to 0.000501. That is, when the average historical temperature is zero, i.e., in the winter, any increase in temperature results in a drop of 1% per degree in footfall ($e^{-0.0104} - 1$). In contrast, when the average historical temperature is 20°C, i.e., in the summer, temperature does not affect footfall, because a variation of one degree provides a variation of $e^{-0.0104 + 20 \times 0.000501} - 1 \approx 0$. At the extreme, in very hot days, e.g., June in Madrid, higher temperatures increase footfall. This can be interpreted as customers escaping outside heat and seeking refuge in air-conditioned stores. In sum, temperature impacts footfall differently depending on the "normal", historical temperature, and the impact changes sign at

about 20°C, consistently with previous studies. Hence, these findings are in line with hypotheses H_{2a} and H_{2b}, which cannot be rejected.

4.3 Robustness Checks

To establish the robustness of our model, we introduce here further interactions between weather variables and other time and location variables, by further studying the variation of the coefficients across day types and countries. These are denoted models F2 and F3 in Table 3. We also tested other possible variations of the model (rain intensity instead of rain occurrence, memory effects) but they did not provide any additional insight so we omit them.

Differences between weekday and weekend. We argued that the effect of weather on footfall is based on how leisure time is allocated between shopping and outdoors based on actual weather. Thereby, we should expect that the impact is stronger in days where people have more leisure time, i.e., on weekends. Model F2 includes the interaction of weather variables with day type: the results show that the impact of rain is indeed stronger on weekends compared to weekdays, e.g., the effect of rain is more than three times stronger on weekends compared to weekdays in street stores, and twice as strong in shopping mall stores. On the other hand, the effect of temperature is weaker, suggesting that while rain is a strong determinant of weekend leisure choices, temperature only has a second-order effect.

Differences between countries. Model F3 introduces interactions of the weather variables with the location of the stores across the four countries for which we have data: Spain, Germany, France and Italy. We see that the insights from model F1 all remain true with the further observation that Germany is the least sensitive to rain, see non-significant coefficient of impact of rain in shopping malls (this is also the country with the most frequent occurrence), while Italy is the most sensitive to it.

5. Impact on Sales

5.1 Model description

To model the retail sales for a given category, we should first note that there is a high positive correlation between that and store footfall. As a result, we focus on conversion, defined as the ratio of units sold in category j, defined as U_{stj}, to store visitors N_{st}. Conversion is driven by store conditions, including discounts, number of products offered in the category or number of units stocked in the store (Boada-Collado and Martínez-de-Albéniz 2019). Although conversion might take values equal to zero, in our sample the number of units sold per category per day is equal to 9.2, so we focus our analysis on the log of conversion $C_{stj} = (1 + U_{stj})/N_{st}$. We adopt a reduced-form specification where

$$\log(C_{stj}) = \lambda_j t + \nu_j' Y_{stj} + \mu_j Z_{stj} + \phi_{l(s)j} W_{stj} + \varepsilon_{stj} \tag{3}$$

where Y_{stj} includes seasonality controls as in Equation (1), and Z_{stj} includes log-visitors N_{st} (to account for non-linearities due to store congestion, see Perdikaki et al. 2012), assortment breadth and total number of units stocked in category j in that store on that day. Furthermore, W_{stj} contains

the weather variables, taken directly as independent variables and also interacted with discounts, to capture the moderating effect of the weather on discount sensitivity and test hypotheses H_4 and H_5. We assume that errors are normally distributed, after checking that $\log(C_{stj})$ is indeed distributed in a unimodal fashion in the sample.

As before, we use the difference of log-conversion between a given t and the same date of the previous year (same weekday in same weeknumber). We can thus rewrite the model as

$$\text{Model C1:} \quad \Delta \log(C_{stj}) = \lambda_j + \mu_j \Delta Z_{stj} + \phi_{l(s)j} \Delta W_{stj} + \varepsilon'_{stj} \tag{4}$$

where $\varepsilon'_{stj} = \Delta\varepsilon_{stj}$ is again a Normal residual.

Observe that in our formulation we ignore substitution across categories, but, as in Boada-Collado and Martínez-de-Albéniz (2019), conversion probabilities are quite small (of the order of 0.01), so substitution effects can be safely ignored.

Finally, although our model can be applied to any definition of category, we consider the retailer's main product families (dress, t-shirt, shirt, skirt, denim trousers, pullover and coat). We illustrate the results for the more distinctive summer product (dress) and winter product (coat). For robustness, we include additional interactions in the model and discuss them in §5.3.

5.2 Results

Table 4 presents the estimation results. As before, we compare model C0 without weather effects to model C1 described in Equation (4). As we can see, many of the covariates are non-significant, which is why we provide a simplified model C1b, where we removed the interaction with store type (mall or street) and historical temperature. We discuss model C1b in detail, and compare it to the theoretical predictions described in §3.3.

We can see from the table that most of the coefficients related to the weather are non-significant, thereby confirming that a priori outside weather has a weak influence on the in-store conversion decision. The only significant effect is related to the type of goods that are purchased: we find that higher temperature increases sales for dresses and decreases them for coats, as expected from hypothesis H_3. Note that this effect is quite strong: a variation of 5°C produces an increase of 11% of sales for dresses and a reduction of 9% in the case of coats. The same insight of the hypothesis H_3 holds true for the rest of categories, not shown here, with only one exception, pullovers: in winter season, pullover conversion increases with positive temperature deviations; the opposite is true for the warm season. Therefore, pullovers, which one would associate with winter clothing, have a summer-type behavior in the cold season. Indeed, we looked for samples of these products and found that pullovers of this brand are not the typical thick, warm pullovers that one may imagine: they are instead thin-fabric products that resemble woolen dresses, most of them without a high neck. This suggests that one could infer the nature of the product category directly from its sensitivity to weather, as opposed to using an intuitive, traditional categorization.

In addition, note that the impact of rain on sales is non significant, which suggests that while temperature directly influences apparel's utility for the consumer, rain does not seem to impact it, which is consistent with the retailer's offering being related to high fashion rather than functional aspects such as water resistance; things would of course be different if umbrellas and raincoats were part of the assortment.

Moreover, the effect of weather on discount sensitivity is non-significant. In fact, as seen in the robustness section, it turns out that the moderating effect of the weather might change signs across

countries, suggesting that sensitivity is indeed weakly or not at all affected by the weather. This invalidates hypotheses H_4 and H_5. This finding suggests that in-store conditions indeed neutralize any outdoor weather influences. As a matter of fact, anecdotal evidence suggests that indeed thermal conditions are actively managed by retailers to communicate brand positioning (Salkin 2005).

Finally, we can also comment on the impact of the controls on conversion. We see that the coefficient for discounts is positive and significant, although this might be an endogenous variable and might be biased. We also see that store footfall has a significant effect and decreases conversion, which is consistent with the findings of Perdikaki et al. (2012) that attribute more congested points of sales to less effective store assistance, thereby lowering conversion. Similarly, more inventory in the category significantly increases conversion, as also shown in Boada-Collado and Martínez-de-Albéniz (2019). In contrast, category assortment breadth does not seem to affect conversion, which is in opposition with most choice models such as the multinomial logit. Also note that the strength of all coefficients differ across categories, and we observed that assuming homogenous categories leads to severe biases in the estimation of the different effects.

5.3 Robustness

We check here the robustness of model C1b, by separating the influence of weather by different control variables, as we did in §4.3: between midweek and weekends, and between countries. We denoted these models C2 and C3 in Table 5.

Differences between weekday and weekend. We check possible differences in the coefficients between between weekdays and weekends in C2. We observe that there are no qualitative differences from previous results. Interestingly, on weekends we find customers to be more price-sensitive under the presence of rain and when temperature is warmer. This would invalidate hypothesis H_4. In fact, to be consistent with theory, the results suggest that shopping during rainy days raise customer's moods, which would lead to higher price sensitivity. On the other hand, H_5 is consistent with the results, during weekends. In contrast, effects during weekdays are not significant.

Differences between countries. The comparison between countries corresponds to model C3. Again, the effect of temperature on conversion remains similar to the base model. The moderating effect of the weather on price sensitivity is not significant.

6. Conclusions and Further Research

In this paper, we empirically studied the effect of weather, through temperature and rain, on different stores types at a mass-market fashion retailer. We decomposed the analysis on two key metrics of the retailer: footfall (the number of visitors on a store) and conversion (the probability of purchasing an item in a given category). We proposed reduced-form log-linear specifications with fine-grained seasonality controls. Despite the large number of controls, we transformed the base model into an expression using differences, that allowed us to estimate the effect of weather on the variables of interest. We estimated the models using a large data set with daily observations over 2 years and 98 stores in 13 European markets.

We found that footfall is mostly governed by rain, which has different effect depending on the location of the store, whether it is on the street or within a shopping mall: in a rainy day, footfall is reduced by 7.4% in street stores, while it increases by 5.2% in shopping malls stores. In contrast, conversion is essentially driven by temperature, so that warmer temperatures increase the sales probability of "summer" products such as dresses, and decrease that of "winter" products such as coats. The overall effect on units sold, assuming no variation on prices, follows the same direction: the impact of rain is positive or negative depending on store location, via footfall mainly; the impact of warmer temperatures is positive or negative depending on product characteristics, via conversion mainly.

Our findings are in line with the theoretical work on physiology and psychology. Indeed, the theory predicts that bad weather (rainy, too cold or too hot) produces negative mood and comfort and thereby affects consumer choices. Specifically, it takes customers away from the street on rainy days, while they seek shelter in shopping malls. This affects footfall along the lines of our empirical results. Bad weather also drives customers to choose the products more appropriate for the current weather, as we find. Finally, we also find that customers are more sensitive to discounts when the day is not rainy and they are in better mood, as predicted by the theory. The only deviation from the theoretical hypotheses is that price sensitivity does not increase with warmer temperatures: we do not find support for this statement.

Finally, our work is one of the first attempts to link weather to retail success, using disaggregate data. We hope to inspire future research to better understand the phenomenon. There are several directions worth investigating further. First, there seems to be a transfer of shoppers between street and shopping mall locations. In reality, the transfer should also include online shopping, as suggested by Steinker et al. (2017). We hope to complement our work with online retail data and show that the bad weather drives online traffic and sales up. This also suggests that to make the retailer less sensitive to weather fluctuations, it should seek a balance across channels, so that customer fluctuations balance each other across channels. For instance, in our case, if the retailer would have 41% of footfall coming from street stores and 59% from shopping mall stores, then it would be indifferent to rain in a given market, because $41\% \times (-7.4\%) + 59\% \times (+5.2\%) = 0$. This means that information on weather sensitivity could help retailers build natural operational hedges by balancing store locations properly. In addition, we have found that our empirical sensitivity to weather at the category level reveals the nature of the products within a category. This suggests that these measurements could potentially allow a better classification of products. Also, we worked with large product families where products may not necessarily have the same response to weather variations. Further work could use product characteristics to understand what makes them sensitive to the weather.

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Variable	F0	F1	F2	F3
Intercept	-0.149 (***)	-0.144 (***)	-0.144 (***)	-0.146 (***)
Discount	0.301 (***)	0.312 (***)	0.299 (***)	0.307 (***)
Rain Mall		0.0527 (***)		
Rain Mall FRANCE				0.0175
Rain Mall GERMANY				0.0606 (***)
Rain Mall ITALY				0.0830 (***)
Rain Mall SPAIN				0.0463 (***)
Rain Mall Weekday			0.0426 (***)	
Rain Mall Weekend			0.0834 (***)	
Rain Street		-0.0741 (***)		
Rain Street FRANCE				-0.0777 (***)
Rain Street GERMANY				0.0201
Rain Street ITALY				-0.126 (***)
Rain Street SPAIN				-0.0403 (***)
Rain Street Weekday			-0.0618 (***)	
Rain Street Weekend			-0.112 (***)	
Temp		-0.0104 (***)		
Temp FRANCE				-0.0113 (*)
Temp GERMANY				-0.00451
Temp ITALY				-0.00809
Temp SPAIN				-0.00911 (*)
Temp Weekday			-0.0158 (***)	
Temp Weekend			0.00369	
Temp × HistTemp		0.000501 (**)		
Temp × HistTemp FRANCE				0.000309
Temp × HistTemp GERMANY				-0.000737 (*)
Temp × HistTemp ITALY				0.000226
Temp × HistTemp SPAIN				0.000880 (**)
Temp × HistTemp Weekday			0.000739 (***)	
Temp × HistTemp Weekend			-0.0000142	
Number of variables	2	6	10	18
Degrees of freedom	10579	10575	10571	10563
Residual error	0.359	0.355	0.355	0.354
R2	0.006	0.023	0.027	0.032
F-statistic	59.49	49.98	32.97	20.85

Table 3: Estimates of models F0 (where $l \equiv 0$) and F1 (where l is estimated) from (2), together with alternative models with interactions discussed in §4.3. P-values: *** ($< 0.1\%$), ** ($< 1\%$), * ($< 5\%$). Robust errors are reported.

	Dress			Coat		
Variable	C0	C1	C1b	C0	C1	C1b
Intercept	-0.0318 (***)	-0.0573 (***)	-0.0566 (***)	-0.204 (***)	-0.181 (***)	-0.183 (***)
Discount	0.494 (***)	0.477 (***)	0.480 (***)	0.663 (***)	0.627 (***)	0.633 (***)
logVisitors	-0.333 (***)	-0.324 (***)	-0.322 (***)	-0.609 (***)	-0.612 (***)	-0.616 (***)
logSKU	0.0163	0.0023	-0.0022	-0.0546 (*)	-0.0423	-0.0384
logUnitsStocked	0.315 (***)	0.314 (***)	0.322 (***)	0.296 (***)	0.287 (***)	0.291 (***)
Rain			-0.0148			0.0387 (**)
Rain Mall		-0.0075			0.0244	
Rain Street		-0.0037			0.032	
Rain × Discount		0.0604	0.0543		0.0354	0.0407
Temp		0.000599	0.0227 (***)		0.009	-0.0181 (***)
Temp × HistTemp		0.00162 (***)			-0.00197 (***)	
Temp × Discount		0.0051	-0.00965		-0.0007	0.0159
Number of variables	5	11	9	5	11	9
Degrees of freedom	10572	10566	10568	10572	10566	10568
Residual error	0.671	0.664	0.665	0.712	0.707	0.708
R2	0.052	0.071	0.068	0.105	0.118	0.115
F-statistic	144.11	80.76	96.89	311.44	141.89	171.78

Table 4: Estimates for models C0 (where $\mu_{lj} = 0$) and C1 and C1b (where μ_{lj} is estimated) from model (3). P-values: *** ($< 0.1\%$), ** ($< 1\%$), * ($< 5\%$).

	Dress		Coat	
Variable	C2	C3	C2	C3
Intercept	-0.0581 (***)	-0.0572 (***)	-0.183 (***)	-0.183 (***)
Discount	0.477 (***)	0.462 (***)	0.635 (***)	0.596 (***)
logVisitors	-0.325 (***)	-0.323 (***)	-0.619 (***)	-0.615 (***)
logSKU	-0.00224	-0.00297	-0.0376	-0.0401
logUnitsStocked	0.322 (***)	0.329 (***)	0.289 (***)	0.295 (***)
Rain FRANCE		-0.0363		0.0324
Rain GERMANY		-0.0334		0.0278
Rain ITALY		0.0132		0.000572
Rain SPAIN		-0.0181		0.0519 (**)
Rain Weekday	-0.00193		0.0380 (*)	
Rain Weekend	-0.0670 (**)		0.0344	
Rain × Discount FRANCE		-0.0927		-0.0178
Rain × Discount GERMANY		0.0821		-0.00227
Rain × Discount ITALY		-0.0979		0.186
Rain × Discount SPAIN		0.227		0.142
Rain × Discount Weekday	-0.0873		-0.067	
Rain × Discount Weekend	0.610 (***)		0.406 (*)	
Temp FRANCE		0.0198 (***)		-0.0143 (*)
Temp GERMANY		0.0246 (***)		-0.00851
Temp ITALY		0.0385 (***)		-0.0136 (*)
Temp SPAIN		0.0168 (***)		-0.0249 (***)
Temp Weekday	0.0222 (***)		-0.0178 (***)	
Temp Weekend	0.0243 (***)		-0.0204 (***)	
Temp × Discount FRANCE		-0.00888		-0.0741
Temp × Discount GERMANY		-0.0367		-0.0325
Temp × Discount ITALY		-0.0950 (*)		0.00039
Temp × Discount SPAIN		0.039		0.0835 (**)
Temp × Discount Weekday	-0.0209		-0.00639	
Temp × Discount Weekend	0.0211		0.0895 (*)	
Number of variables	13	21	13	21
Degrees of freedom	10564	10556	10564	10556
Residual error	0.664	0.664	0.707	0.708
R2	0.07	0.07	0.117	0.117
F-statistic	66.04	39.89	116.16	69.82

Table 5: Estimates for models C2 and C3. P-values: *** ($< 0.1\%$), ** ($< 1\%$), * ($< 5\%$).