Whether Weather Matters: Impact of Exogenous Factors on Customers Channel Choice

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Abstract Many customers today shop across multiple channels. Previous literature has documented the importance of endogenous factors, such as retailers' operational strategies, new store openings, and customer demographics on customers' channel choice in an omnichannel setting. In this paper, we shed light on the impact of an exogenous factor—weather conditions—on retailers' B&M store and online sales as well as on customers' channel choice. Using online and B&M store data from a worldwide winter apparel retailer and daily weather and climate normals data at the zip code level, we find the following: (1) Negative (positive) temperature deviations, i.e., cold (hot) days, lead to a significant increase (decrease) in sales both for online and offline channels. The effects are stronger for the offline channel. (2) Cold days induce customers to migrate to the offline channel, whereas hot days and snowy days lead them to purchase through the online channel. Moreover, our findings indicate that although weather significantly affects retailers store traffic and sales, retailers' staffing practices are suboptimal; they understaff on cold days and overstaff on hot days. We also discuss the implications of our findings for retailers' omnichannel strategies.

Keywords Omnichannel retailing · Quasi-experimental methods

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S. Gallino, A. Moreno (eds.), *Operations in an Omnichannel World*, Springer Series in Supply Chain Management 8, https://doi.org/10.1007/978-3-030-20119-7_10

1 Introduction

It is prevalent in the retail industry to attribute the discrepancy between anticipated and realized performance to unexpected weather conditions. Coca-Cola's Chief Financial Officer Gary Fayard recognized this when he stated, "I hate to use the weather, but a lot of it was the weather," to explain low sales volume in 2013 (TheWeatherChannel 2013). In 2016, the British Retail Consortium blamed warmer weather in August for retailers' poor performance (Woods 2016). In 2017, the U.K.'s Office for National Statistics attributed the increase in retail sales to a particularly warm June in Britain (Jackson 2017). Walmart claimed unseasonably warm weather hurt its performance in the USA in fall 2016 (Bose 2016). By contrast, brewing company Lion fell behind on deliveries due to demand spikes induced by a particularly hot summer in 2017 (Shaw 2017). On the other hand, Macy's had to offer big discounts to sell winter inventory that was piling up because of a warm 2015 winter (Tabuchi 2015).

As the myriad of examples show, unexpected weather is a major factor that impacts retailers. The effects of weather on sales, however, are rather intricate and not well understood. Importantly, with the increasing prominence of omnichannel retailing, understanding how weather events affect retailers requires an integral analysis of the effects of weather shocks on both offline and online channels, as well as their interaction.

The primary focus of this paper is to empirically study how omnichannel retailers are impacted by weather conditions. To this end, we collaborated with a worldwide outdoor apparel and gear company specializing in outerwear, coats, footwear, and equipment, such as backpacks. Our analysis is composed of two parts. First, we look at how weather conditions impact traditional brick-and-mortar (B&M) stores and the online channels. We analyze the effects of weather conditions (temperature deviations, rain, and snow) on sales volume in both B&M stores and the online channel. Theoretically, it is not a priori clear how different channels are affected by prevailing weather conditions. Unfavorable weather conditions, such as low temperatures and rain, might make outdoor activities less attractive, thus inducing a decrease in B&M store traffic and sales. Online stores might partially absorb part of this foregone offline demand. By contrast, low temperatures and snow increase the salience of a winter product's instrumental utility, which can lead to an increase in sales of winter items. Our results show that negative (positive) temperature deviations lead to a significant increase (decrease) in both online and offline sales. The effects are stronger for offline stores.

Second, we examine how customers' channel choice depends on weather conditions. Specifically, we study how weather affects the share of sales that comes from the online channel in an area. As discussed above, unfavorable weather conditions might increase the offline transportation cost and convenience of online shopping. However, conspicuous capabilities, such as the instantaneous gratification obtained by purchasing a winter product offline, might have a larger effect on the shopping process in low temperatures and on snowy days. Our analysis indicates that weather has a significant effect on customers' channel choice. Negative temperature deviations—i.e., unusually cold days—lead to an increase in the share of sales coming from the offline channel. By contrast, positive temperature deviations lead to a decrease in the share of sales coming from the offline channel. These results suggest that the instantaneous gratification effect induced by an unusually cold weather might outweigh the store-visit discouragement effect.

Our paper makes three important contributions. First, it studies the effects of weather on retailers' offline and online channels. Several papers have studied the impact of weather shocks on retailers (Bertrand et al. 2015; Steinker et al. 2016; Belkaid and Martínez-de Albéniz 2017), but in all cases they analyze either the online or the offline channel. Second, by analyzing the impact of weather on customers' channel choice, we contribute to the literature on the competition between online and offline channels. Previous studies analyze the effects of endogenous factors—such as population demographics, store openings, and the introduction of cross-channel functionalities—on online–offline channel substitution. By contrast, in this study we exploit the exogenous component of weather shocks to uncover the online–offline channel substitution patterns within a major retailer. Finally, despite recent advances in weather analytics, to this day most retailers do not incorporate weather information effectively into their decision-making process. Anecdotal evidence suggests, in line with our results, that weather conditions directly influence store traffic. While a recent stream of literature documents the importance of a sales force on converting store traffic to store sales, our results suggest that store staffing is not efficiently adjusted to respond to weather-induced volatility in store traffic. Based on our analysis, we suggest several ways in which firms can leverage granular, high-frequency weather data to improve staffing-level decisions.

The rest of the paper is organized as follows: In Sect. 2, we summarize the relevant literature. Section 3 describes the data we received from the retailer and the weather-data collection process. We present the details of our empirical analyses and our findings for B&M stores in Sect. 4, for the online channel in Sect. 5, and for customers' channel choice in Sect. 6. In Sect. 7, we discuss improvements that can be generated by incorporating weather into retailers' decision-making process.

2 Literature Review

In this paper, we identify the effects of weather on both the online and offline channels of a major retailer, as well as on customers' channel choice. We also discuss the implications of these weather-induced effects for labor planning. Each of these topics—impact of weather shocks, cross-channel competition, and labor planning—has been studied in different fields. In this section, we discuss the relevant literature in these areas.

2.1 Weather

The effects of weather on customer mood and behavior is a long-studied topic in psychology. Previous research shows that sunlight significantly improves mood (Keller et al. 2005; Kripke 1998; Lambert et al. 2002; Leppämäki et al. 2003), whereas cloudiness decreases it (Cunningham 1979; Hirshleifer and Shumway 2003). In turn, good mood increases customer spending and leads to more favorable product evaluations (Isen et al. 1988; Bitner 1992; Underwood et al. 1973).

In addition to altering mood, weather has been found to change how people allocate their time to different activities. Connolly (2008) shows people on average shift 30 min from leisure to work on rainy days. Moreover, weather events induce substitution among different leisure activities. Graff Zivin and Neidell (2014) uncover a U-shaped relationship between temperature and indoor leisure activities and a corresponding inverted-U shape for outdoor leisure activities. This implies that outdoor activities are less appealing on days with unfavorable weather conditions—i.e., days of extreme heat or cold.

Another relevant stream of literature argues that prevailing weather conditions impact the perceived utility of different alternatives. Using data on advanced ticket orders for an outdoor cinema, Buchheim and Kolaska (2016) show that advance ticket orders increase up to 50% on sunny days relative to cloudy days. Conlin et al. (2007) argue that customers are more likely to return cold weather items ordered on cold days. Furthermore, such weather-induced utility adjustments take place even in high-stakes environments, as shown by Busse et al. (2015). They analyze the effects of weather on car purchases and find customers are more likely to purchase a four-wheel-drive car right after a snow storm. By contrast, customers tend to opt for convertibles on days with sunny and warm weather. Finally, Simonsohn (2010) shows that cloud coverage on the day of campus visits strongly impacts students' university enrollment decisions.

In comparison, less attention has been devoted to analyzing the effects of weather on company operations. Notable exceptions include Cachon et al. (2012) and Lee et al. (2014). Using production data from automobile plants, Cachon et al. (2012) show that severe weather conditions, such as snowstorms, lead to significant production loss. Lee et al. (2014), on the other hand, demonstrate that worker productivity is higher on bad weather days. Chen and Yano (2010) study weather-rebate contracts for seasonal products with weather-sensitive demand. Divakar et al. (2005) and Kök and Fisher (2007) incorporate weather as a covariate into their demand model. Moreover, Bertrand et al. (2015) show that weather significantly impacts apparel retailers' sales volume. Belkaid and Martínez-de Albéniz (2017) analyze the effects of temperature and rain on store traffic and conversion rates in B&M stores. They show that store traffic is affected by rain, whereas conversion rates depend on both temperature and rain. Steinker et al. (2016) analyze the effects of weather on online sales, and show that including seven-day weather forecasts significantly improves the forecast accuracy of online orders.

To the best of our knowledge, previous literature on the effects of weather on retailers has focused on either only the online (Steinker et al. 2016) or the offline (Bertrand et al. 2015; Bahng and Kincade 2012; Belkaid and Martínez-de Albéniz 2017) channel. By contrast, we disentangle the effects of weather on both channels separately using highly granular daily zip code-level and store-level data. In addition, we exploit the exogeneity of weather shocks to identify how customers' channel choice is affected by weather. Finally, we discuss the implications of these results for labor planning. Whereas Steinker et al. (2016) leverage weather forecasts to inform online retailers warehouse workforce planning decisions, we discuss how weather information can be used to adjust staffing in B&M stores.

2.2 *Channel Choice*

Previous studies have shown that customers' channel choice is affected by endogenous factors that shape their offline world, such as the availability of offline options (Forman et al. 2009; Brynjolfsson et al. 2009), population demographics in an area (Choi and Bell 2011), and sales taxes (Anderson et al. 2010). Online sales are higher in places with fewer offline alternatives (Forman et al. 2009; Brynjolfsson et al. 2009) and in areas where local market customers have minority preferences (Choi and Bell 2011). However, most of these studies (Forman et al. 2009; Brynjolfsson et al. 2009; Choi and Bell 2011) focus on the online–offline channel substitution across, rather than within, firms. A notable exception is Wang and Goldfarb (2017). They analyze the effects of B&M store openings on the online sales of an omnichannel retailer. They suggest that in areas where a retailer has a strong brand presence, offline stores cannibalize online sales. By contrast, in places where a retailer does not have a strong presence, offline stores lead to an increase in online sales. Similarly, Bell et al. (2017) show that introducing showrooms increases overall demand. Moreover, Gallino and Moreno (2014) show that introducing cross-channel BOPS (buy-online, pickup-in-store) functionalities reduces online sales and increases B&M store sales.

More generally, a long stream of literature studies online–offline channel competition across firms, rather than within a firm. The studies that do analyze customers' channel choice within a firm analyze the effects of endogenous changes. Thus, we depart from existing literature by analyzing how an exogenous factor—weather shocks—affects customers' channel choice within a firm. Our results indicate significant impact of weather on customers' channel choice. We find that customers move to offline channels on extremely cold days and snowy days, whereas they prefer the online channel more strongly on extremely hot days.

2.3 Labor Planning

As our results and numerous accounts by executives reveal, weather directly impacts store traffic. In addition, a recent stream of literature documents the importance of sales force on customer satisfaction and sales (Fisher et al. 2006; Kesavan et al. 2014; Ton and Huckman 2008). Kesavan et al. (2014) show that the relationship between fitting-room traffic and sales follows an inverted-U shape. Increasing the fitting-room staff by one person has a significant positive impact on conversion rates. Moreover, Fisher et al. (2018) develop a methodology for retailers to systematically set the labor level in each store. They demonstrate that a 10% increase in labor levels in understaffed stores increases sales by 5.1%. We complement this literature by discussing how weather information can be incorporated into B&M stores' labor-planning process to better respond to weather-induced volatility in traffic patterns and to maximize conversion rates.

3 Data and Empirical Setting

We obtain a proprietary data set from a large worldwide outdoor gear and winter apparel retailer covering B&M stores and an online channel between January 2016 and August 2017. We augment this data with daily weather data as well as climate normals data per zip code to study how weather impacts the customers' channel choice.

The retailer operates 63 stores all over the United States. For B&M stores, we observe sales, store traffic, labor hours, and number of transactions at day-store level. Moreover, in the online channel we observe all transactions that took place in the USA during our period of observation, which total more than 1.6 million transactions. For each online transaction, we observe the transaction date, the customer's zip code, the SKU, price, and quantity of the items in the order.

3.1 Weather

We collect daily weather data for all 63 stores and over 29,000 zip codes where the online orders originated. We utilize two different data sets for collecting zip code-level weather data. First, using WeatherSource.com's API, we obtain daily weather information for every zip code where a store is located or an online order originated, from January 2016 to August 2017.[1] For each day and zip code, we collect the

[1]WeatherSource.com provides high accuracy weather data using OnPoint weather technology. For more information, see [https://weathersource.com].

following weather variables: precipitation and snowfall in inches, and maximum, average, and minimum values for temperature, cloud coverage, relative humidity, and wind speed.

Second, we gather data on daily climate normals, specifically, daily normal average temperatures and their standard deviation at the weather station level. We use 1981–2010 USA. Climate Normals data sets from the National Oceanic and Atmospheric Administration's (NOAA) website to construct our climate normals for each zip code. NOAA generates daily normals for temperature variables at day-weather station level by averaging the last 30 years' average temperatures for that particular day-weather station. We identify the latitude and longitude of each zip code closest to the weather station for which the climate temperature normals information is available for each zip code in our dataset.[2] The mean, median, and maximum distance between each zip code and its corresponding weather stations are 11.3, 12.1, and 58.7 miles, respectively.

In our analysis, we focus on temperature, cloud coverage, precipitation, and snowfall. We want to understand how weather impacts customers' channel choice. However, daily temperature in a spatial area is endogenous and follows a seasonal pattern. Therefore, instead of daily temperature, we use local temperature variations to identify the effect of temperature on customers' channel choice. Our identification strategy relies on analyzing the impact of idiosyncratic local temperature anomalies (i.e., abnormally hot days and cold days). Moreover, we focus on temperature deviations from the mean instead of using temperature in levels (i.e., in Fahrenheit). This enables us to focus on temperature-level changes not in an absolute sense but proportional to an area's usual variation. Specifically, we calculate temperature deviations at the day-zipcode level by subtracting daily average temperature from corresponding day-zipcode historical average temperatures and dividing this difference by the standard deviation of daily historical temperatures of that area. We refer to this value as temperature variation ($TemperatureDeviation_{zd}$). We categorize local temperature shocks into hot and cold day categories; specifically, we designate a day as hot (cold) if the temperature variation is greater (less) than 2 (-1.5). Selecting these thresholds enables us to classify approximately 5% of the days at both tails as local temperature shocks.

Instead of focusing on an exact amount of rainfall and snowfall, we classify a day as rainy (snowy) if precipitation (snowfall) is positive. Moreover, we want to identify the effect of rain at the seasonal level; thus, we interact rain with cold-season variable, which denotes the fall and winter seasons. Cloud coverage is denoted in percentages: 0 denotes a completely clear day, whereas 100 represents a completely cloudy day. Although previous research identifies the effect of all these weather variables on customer behavior, we do not include cloud coverage in our analysis due to correlation between rain and cloud coverage (see Table 1).

[2]NOAA provides climate temperature normals for 7501 weather stations in the United States. The selection is more limited than the GHNCD-Daily data set.

Table 1 Correlation between weather variables

	Cloud coverage	Hot	Cold	Rain	Snow
Cloud coverage	1.00				
Hot	−0.01	1.00			
Cold	0.01	−0.04	1.00		
Rain	0.48	−0.02	0.02	1.00	
Snow	0.20	−0.04	0.07	0.24	1.00

4 Evaluating the Impact of Weather on B&M Stores

A naive way to analyze the impact of weather on offline and online channels is to look at the correlation between average temperature on a given day and sales. However, this approach would fail to identify the true impact of weather on sales, since daily temperature in an area is endogenous to that region. For instance, 50 °F is the average temperature in San Francisco. By contrast, 50 °F in Chicago in January can be categorized as a hot day. Instead, we focus on idiosyncratic local temperature anomalies, as discussed in Sect. 3.1. Thanks to our detailed online order and B&M store data, we can use date and zip code as our level of analysis. Moreover, stores and zip codes might have systematically different sales than others. Therefore, we include store fixed effects to study the offline channel, and zip code fixed effects to study the online channel.

The main specification we use for the offline channel analysis is the following:

$$\begin{aligned} log(Sales_{s,d}) = \alpha + \mu_{w(d),y(d)} + \beta_1 hot_{s,d} + \beta_2 cold_{s,d} + \beta_3 rain_{s,d} \\ \times coldseason_d + \beta_4 snow_{s,d} + \tau_s + \tau_1 weekend_d + \tau_2 holiday_d \\ + \epsilon_{s,d} \end{aligned} \tag{1}$$

We control for seasonal patterns with week–year fixed effects $\mu_{w(d),y(d)}$, where $w_{(d)}$ denotes the week pertaining to date d, and $y_{(d)}$ denotes the year. τ_s denotes the store fixed-effects. $weekend_d$ takes value 1 if date d is a weekend, and $holiday_d$ takes value 1 if date d is a federal holiday. Moreover, $hot_{s,d}$ ($cold_{s,d}$) equal 1 if $TemperatureDeviation_{zd}$ of store s located on zip code z is higher (lower) than 2 (−1.5) on date d. $rain_{s,d}$ ($snow_{s,d}$) is equal to 1 if there is any rainfall (snowfall) in the zip code of store s on date d.

We take the logarithm of the dependent variable (sales). We use logarithms for ease of interpretation, but our qualitative results hold if we use levels. Our main variable of interest is the β coefficient. We cluster standard errors at the store level to control for arbitrary correlation of observations within clusters.

Table 2 Impact of weather on offline sales

	(1)	(2)	(3)	(4)
Cold	0.30***	0.18***	0.29***	0.17***
	(0.02)	(0.01)	(0.02)	(0.02)
Hot	−0.21***	−0.14***	−0.23***	−0.14***
	(0.04)	(0.02)	(0.03)	(0.02)
Cold season	0.09**	0.04	0.09***	0.03
	(0.04)	(0.03)	(0.03)	(0.03)
Rain	0.12***	0.07***	0.13***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Cold season × Rain	−0.15***	−0.05***	−0.17***	−0.05***
	(0.03)	(0.02)	(0.02)	(0.02)
Snow	0.13***	0.17***	0.13***	0.16***
	(0.03)	(0.02)	(0.02)	(0.02)
Visitors		0.99***		1.00***
		(0.02)		(0.01)
Store FE	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes	Yes
Store-Month–Year FE	No	No	Yes	Yes
Observations	33,733	33,733	33,733	33,733

Note: Robust standard errors are in parentheses, clustered at store level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.1 Results

The results of our analysis are given in Table 2. All columns include store, weekend, federal holiday, and week–year fixed effects. The third and fourth columns include store-month–year fixed effects to control for store-specific seasonal patterns. Moreover, the second and fourth columns also include the number of visitors as a control variable. The table shows that prevailing weather conditions in an area have a significant and sizable impact on sales with and without including the store traffic control. Our results indicate that unusually cold days increase sales, whereas hot days decrease sales. When weather is unusually cold on a given day, sales increase by 35% on average. By contrast, on unusually hot days sales decrease by 19%. Similarly, in the summer and spring sales increase by 12.7% on rainy days, and on snowy days sales increase by 13.9%. Moreover, the weather's impact on sales varies according to store characteristics. For instance, hot days affect outdoor stores less (see columns 1 and 2, Table 3) and the increase in sales on cold days and rainy days is larger for stores located in shopping malls (see columns 3 and 4, Table 3).

Next, we analyze how the effects of temperature and other weather variables—such as snow and rain—vary across seasons for brick-and-mortar stores. As can be observed in Table 4, the effect of temperature deviations is statistically significant

Table 3 Impact of weather on offline sales for outdoor and indoor stores

	(1) Indoor store	(2) Outdoor stores	(3) Street stores	(4) Shopping mall
Cold	0.32*** (0.04)	0.29*** (0.03)	0.22*** (0.04)	0.35*** (0.03)
Hot	−0.34*** (0.05)	−0.16*** (0.04)	−0.22*** (0.05)	−0.21*** (0.05)
Cold season	0.12** (0.05)	0.07 (0.05)	0.05 (0.07)	0.11*** (0.04)
Rain	0.16*** (0.02)	0.09*** (0.02)	0.08*** (0.03)	0.13*** (0.01)
Cold season × Rain	−0.19*** (0.05)	−0.13*** (0.03)	−0.21*** (0.05)	−0.12*** (0.03)
Snow	0.09* (0.05)	0.15*** (0.03)	0.23*** (0.04)	0.08* (0.04)
Store FE	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes	Yes
Store-Month–Year FE	No	No	No	No
Observations	11,564	22,169	12,234	21,499

Note: Robust standard errors are in parentheses, clustered at store level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4 Impact of weather on offline sales across different seasons

	(1) Fall	(2) Spring	(3) Summer	(4) Winter
Cold	0.31*** (0.06)	0.26*** (0.03)	0.20*** (0.03)	0.33*** (0.04)
Hot	−0.26*** (0.05)	−0.19*** (0.04)	−0.07* (0.03)	−0.28*** (0.04)
Rain	0.01 (0.02)	0.15*** (0.02)	0.09*** (0.02)	−0.06** (0.03)
Snow	0.12*** (0.04)	−0.01 (0.04)		0.16*** (0.03)
Store FE	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes	Yes
Store-Month–Year FE	Yes	Yes	Yes	Yes
Observations	5,402	10,577	8,262	9,492

Note: Robust standard errors are in parentheses, clustered at store level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

for every season but smallest in summer. The effect is largest in the winter season. Our collaborating retailer is famous for its outdoor gear and winter items. The benefits of a cold weather product might be more salient on a cold day in winter, thus driving up sales.

The effects of extreme temperature deviations on B&M store sales differ across seasons. This suggests that the effects of temperature deviations on sales might be heterogeneous across different temperature deviations. To analyze the heterogeneous impact of temperature deviations on offline store sales, we reestimated Eq. 1 by replacing $hot_{s,d}$ and $cold_{s,d}$ with indicator variables for different temperature deviation bins into which the daily $TemperatureDeviation$ falls. We use 11 indicator variables for temperature deviation bins ranging from (≤ -2.5) to (≥ 2.5). We leave the days with $TemperatureDeviation$ between $(-0.5, 0.5)$ as our left-out group.

We plot the regression results in Fig. 1. For each bin, the estimated coefficient is represented by a dot and the 95% confidence interval around the estimated coefficient is represented by error bars. As the deviation of daily temperatures from the normal range increases, the estimated coefficients increase both on cold and hot days. This trend is stronger for cold days. For example, when $TemperatureDeviation$ is between $(-1.5, -1)$, offline channel sales increase by

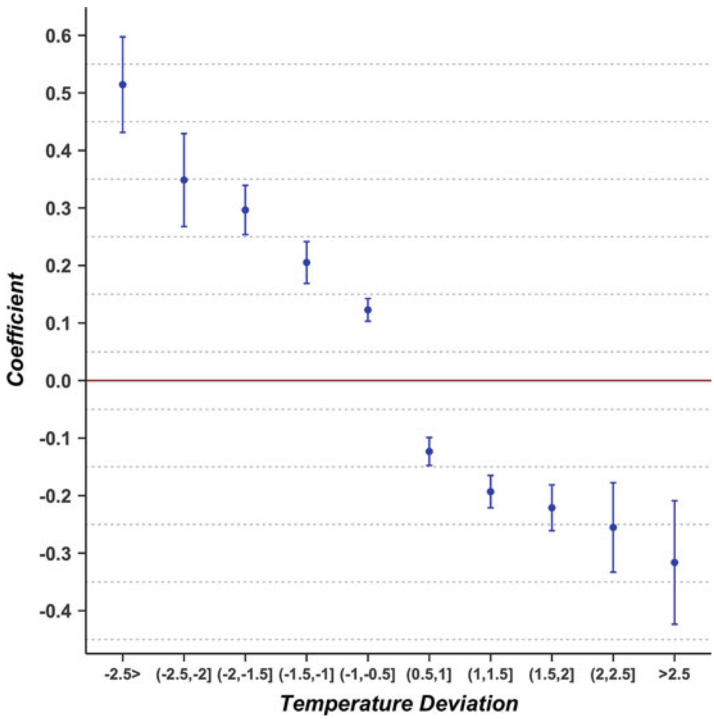

Fig. 1 Effect of temperature deviations on sales

20% relative to the baseline group. When the $TemperatureDeviation$ of a day falls into the $(-2, -1.5)$ category, the increase in sales reaches 29% relative to the baseline group.

4.2 Mechanisms

Our analyses show that weather conditions in an area impact sales in B&M stores significantly. In this section, we explore the mechanisms behind the observed effects.

4.3 Impact on Store Traffic and Conversion Rates

There might be several reasons leading up to the increase (decrease) in sales during cold (hot) days.

How customers substitute between shopping and other leisure activities might depend on prevailing weather conditions. Moreover, an increase in store traffic might lead to an increase in sales. First, we test for this mechanism by using the following regression (the definitions of the independent and control variables are explained in detail in Sect. 4.1):

$$\begin{aligned} log(Outcome_{s,\,d}) = \alpha &+ \mu_{w(d),y(d)} + \beta_1 hot_{s,d} + \beta_2 cold_{s,d} + \beta_3 rain_{s,d} \\ &\times coldseason_d + \beta_4 snow_{s,d} + \tau_s + \tau_1 weekend_d \\ &+ \tau_2 holiday_d + \epsilon_{s,d} \end{aligned} \tag{2}$$

Following the analysis in Sect. 4.1, the standard errors are clustered at the store level. Our results show that prevailing weather conditions in an area significantly impact store traffic. As can be observed in Table 5, store traffic increases (decreases) on cold (hot) days by 12.7% (7%). Similar to results for store sales, the traffic is lower on rainy days in cold seasons. Moreover, for snowy days, we observe that although store traffic is 3% lower, sales are 13.9% higher. This result shows that the impact of weather conditions on customer behavior is intricate.

Next, we analyze how weather conditions impact the conversion rates in the stores. We calculate the conversion rate by dividing the number of orders placed by the store traffic. Conversion rate is restricted between 0 and 1; thus, we use a fractional logit model (Papke and Wooldridge 1996). Our results are robust to using OLS instead of fractional logit. The results of our analysis are given in Table 6. Weather has a significant impact both with and without the store traffic inclusion as a control variable. The conversion rates increase by 1.2% points on extremely cold days and decrease by 0.5% points on extremely hot days. In addition, snowy days increase conversion rates by 0.7% points.

Table 5 Impact of weather on number of visitors and average order value for offline channel

	(1) Visitors	(2) Avg. order size
Cold	0.12***	0.10***
	(0.02)	(0.01)
Hot	−0.07***	−0.12***
	(0.02)	(0.02)
Cold season	0.05***	−0.0004
	(0.02)	(0.03)
Rain	0.04***	0.05***
	(0.01)	(0.01)
Cold season × Rain	−0.10***	−0.04***
	(0.02)	(0.01)
Snow	−0.03	0.12***
	(0.03)	(0.02)
Visitors		0.10***
		(0.01)
Store FE	Yes	Yes
Weekend FE	Yes	Yes
Week–Year FE	Yes	Yes
Store-Month–Year FE	No	No
Observations	33,733	33,733

Note: Robust standard errors are in parentheses, clustered at store level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.4 Impact on Average Order Value

Although rational customers should evaluate how much utility they will derive from a product under all states of the world, the previous literature has documented that customers are exposed to different psychological biases—such as projection bias and salience effect—that impact their purchasing behavior. Therefore, weather shocks in an area might impact the products customers purchase as well as their willingness to pay for different products. For example, Busse et al. (2015) show that customers are more likely to purchase cars with convertible tops on warm and sunny days, and four-wheel-drive vehicles on cold days. Furthermore, Busse et al. (2012) find that houses with swimming pools that go under contract sell for $1600 more in the summer compared to wintertime.

Following these examples, we next analyze the impact of prevailing weather conditions on customers' purchase behavior. Our data set includes information on total daily sales and number of transactions at the store level. However, we do not know the items purchased at each transaction. Therefore, we focus our attention on average basket values, which are calculated by dividing total daily sales by number of transactions at the store.

Table 6 Impact of weather on conversion rates for offline channel

	(1) Conversion	(2) Mrg. Eff.	(3) Conversion	(4) Mrg. Eff.
Cold	0.070*** (0.010)	0.009*** (0.001)	0.087*** (0.010)	0.012*** (0.001)
Hot	−0.028** (0.011)	−0.004** (0.001)	−0.042*** (0.010)	−0.005*** (0.001)
Cold season	0.037** (0.018)		0.044** (0.018)	
Rain	0.029*** (0.007)	0.003*** (0.001)	0.036*** (0.006)	0.002*** (0.001)
Cold season × Rain	−0.020** (0.008)		−0.037*** (0.007)	
Snow	0.057*** (0.011)	0.008*** (0.002)	0.053*** (0.011)	0.007*** (0.002)
Visitors			−0.157*** (0.017)	−0.020*** (0.002)
Store FE	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes	Yes
Store-Month–Year FE	Yes	Yes	Yes	Yes
Observations	33,733	33,733	33,733	33,733

Note: Robust standard errors are in parentheses, clustered at zip code level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Our results indicate that on cold (hot) days, customers who make a purchase spend more (less) on average. Average basket sizes increase (decrease) by 10.5% (12.7%) on cold (hot) days and increase 12.7% on snowy days (see Table 5).

Thus, we conclude that sales increases on cold days and sales decreases on hot days can be explained by a combination of all three mechanisms: changes in store traffic, conversion rates, and basket sizes.

5 Evaluating the Impact of Weather on Online Channels

In Sect. 4, we show that prevailing weather conditions in the area have a strong impact on B&M store sales, store traffic, conversion rates, and average basket sizes. In this section, we analyze the impact of weather on the online channel. We observe all orders placed through our collaborator's online channel during our period of observation. For each order, we know the date the order was placed, the zip code the order is coming from, SKUs, prices, and quantities of the items ordered. We observe more than 1.6 million online transactions during this period. Observing the transaction data at the zip code level enables us to use the zip code and date as our units of analysis. First, we analyze how weather conditions impact online channel sales. We analyze idiosyncratic local temperature anomalies—namely, hot and cold days, rain, and snow. We define hot and cold days as explained in Sect. 4.

The main specification we use for analyzing the impact of weather conditions on the online channel is the following:

$$log(Sales_{z,\,d}) = \alpha + \mu_{w(d),\,y(d)} + \beta_1 hot_{z,\,d} + \beta_2 cold_{z,\,d} + \beta_3 rain_{z,\,d} \times coldseason_d + \beta_4 snow_{z,\,d} + \tau_1 weekend_d + \tau_2 holiday_d + \tau_z + \gamma_{z,\,m(d),\,y(d)} + \epsilon_{z,\,d} \quad (3)$$

We include zip code fixed effects, τ_z, to account for systematic differences across zip codes. Moreover, we control for seasonal patterns at the week–year level, $\mu_{w(d),y(d)}$, and for zip code-specific seasonal patterns at the month–year level, $\gamma_{z,m(d),y(d)}$. The detailed definition of weather variables is given in Sect. 4. We use the logarithm of the dependent variable for ease of interpretation, and our coefficient of interest is β. We cluster standard errors at the zip code level.

5.1 Results

The results of our main analysis are presented in Table 7. In both columns, zip code, weekend, federal holiday, week–year, and month–year zip code fixed effects are included. As can be observed in the first column, prevailing weather conditions in an area significantly impact online sales of the focal brand. Similar to our results for B&M stores, we observe that online sales increase by 8.3% on cold days, and by 5.3% on snowy days. Online sales decrease by 4.5% on hot days. Although the impact of weather on online channels is in line with the results for offline channels, the magnitude of the effects is much larger in the offline channel. In addition, we observe that the effect of cold days on online sales is larger for areas that have a store within 20 miles. However, this result does not explain how customers' channel choice is impacted by weather conditions, as zip codes with a store nearby might be systematically different from zip codes without a store. We analyze the impact of weather conditions on customers' channel choice in detail in Sect. 6.

Similar to our analysis in Sect. 4.1, we study how this effect varies across seasons. In parallel to our results for B&M stores, we observe that weather conditions have the largest effect on sales in the winter season and the smallest effect in the summer season (see Table 8). Sales increase on average by 10.5% on cold days in the winter season. The increase in sales on cold days in the summer season is, by contrast, only 3%. Moreover, rain decreases sales in the fall and winter seasons but does not have any impact in the spring and summer seasons.

As the effects of weather conditions on online sales differ by season, we next analyze whether the effects of weather conditions, specifically temperature deviations, are heterogeneous. Following our analysis in Sect. 4.1, we replace

Table 7 Impact of weather on online sales

	(1)	(2)
Cold	0.081***	0.041***
	(0.004)	(0.006)
Hot	−0.046***	−0.043***
	(0.005)	(0.007)
Cold season	0.096***	0.096***
	(0.009)	(0.009)
Rain	0.009***	0.010***
	(0.003)	(0.003)
Cold season × Rain	−0.028***	−0.028***
	(0.004)	(0.004)
Snow	0.052***	0.051***
	(0.004)	(0.004)
Cold×Any store		0.072***
		(0.008)
Hot×Any store		−0.006
		(0.009)
zip code FE	Yes	Yes
Weekend FE	Yes	Yes
Week–Year FE	Yes	Yes
zip code-Month–Year FE	Yes	Yes
Observations	1,081,689	1,081,689

Note: Robust standard errors are in parentheses, clustered at zip code level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8 Impact of weather on online sales across different seasons

	(1) Fall	(2) Spring	(3) Summer	(4) Winter
Cold	0.069***	0.037***	0.030***	0.100***
	(0.012)	(0.010)	(0.010)	(0.005)
Hot	−0.090***	−0.040***	−0.035**	−0.034***
	(0.011)	(0.013)	(0.014)	(0.007)
Rain	−0.012***	0.021***	0.005	−0.018***
	(0.004)	(0.005)	(0.004)	(0.003)
Snow	0.050***	0.007		0.051***
	(0.008)	(0.016)		(0.005)
Zip code FE	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes	Yes
Zip code-Month–Year FE	Yes	Yes	Yes	Yes
Observations	316,624	157,567	167,708	415,053

Note: Robust standard errors are in parentheses, clustered at store level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

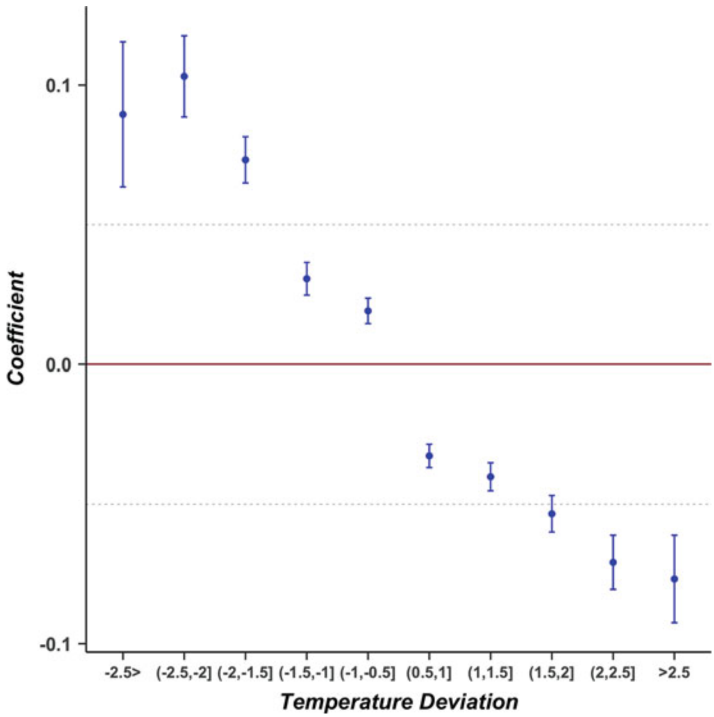

Fig. 2 Effect of temperature deviations on online sales

$hot_{s,d}$ and $cold_{s,d}$ with indicator variables for the 0.5 temperature deviation bins into which the daily $TemperatureDeviation$ falls by using 11 indicator variables described in detail in Sect. 4.1. The regression results are plotted in Fig. 2, where each dot represents the estimated coefficient for that $TemperatureDeviation$ bin and error bars depict the 95% confidence interval around the estimated coefficient. The magnitude of the estimated coefficients increases as a day is colder relative to the historical weather. For example, for cold days when the temperature deviation ($TemperatureDeviation$) is between $(-1.5, -1)$, sales increase by 3% relative to the baseline group. The increase in sales reaches 7.2% when $TemperatureDeviation$ goes down to $(-2, -1.5)$ in the online channel. Next, we focus on the mechanism behind the observed effect of weather on online channel sales.

5.2 Mechanism

In Sect. 4.2, we show that the effect of weather on the offline channel can be explained by the effect of weather on store traffic, conversion rates, and average order sizes. For instance, on cold days, store traffic, conversion rates, and average order value increase in B&M stores. However, the data on the number of daily visits to a website at the zip code or area level is not available. Therefore, we cannot quantify the change in website traffic and conversion rates driven by local weather conditions. Nevertheless, we have detailed data at the order level for the online channel. Thus, we can calculate how much the average basket size, average number of items in the basket, and average price of an item in the basket change as a function of prevailing weather conditions in an area.

In this section, we use the following specification

$$\begin{aligned} log(Outcome_{z,\,d}) = \alpha + \mu_{w(d),\,y(d)} + \beta_1 hot_{z,\,d} + \beta_2 cold_{z,\,d} + \beta_3 rain_{z,\,d} \\ \times coldseason_d + \beta_4 snow_{z,d} + \tau_1 weekend_d \\ + \tau_2 holiday_d + \tau_z + \gamma_{z,m(d),y(d)} + \epsilon_{z,d} \end{aligned} \quad (4)$$

Our results are reported in Table 9. As we observe in column 1 of Table 9, the number of orders placed increases on cold days by 6.9%, whereas it decreases by 3% on hot days. Moreover, on snowy days, the number of orders placed increases by 3.8%. Similar effects are observed for average order value, average price of items in

Table 9 Effect of weather on number of orders, average basket size, average item price, and average number of items in orders for online sales

	(1) Num. orders	(2) Avg. order value	(3) Avg. item value	(4) Avg. number of items
Cold	0.067***	0.014***	0.007**	0.007***
	(0.002)	(0.003)	(0.003)	(0.002)
Hot	−0.029***	−0.017***	−0.024***	0.007***
	(0.002)	(0.004)	(0.004)	(0.003)
Cold season	0.059***	0.037***	0.023***	0.014***
	(0.004)	(0.008)	(0.007)	(0.005)
Rain	0.001	0.008***	0.009***	−0.001
	(0.001)	(0.003)	(0.002)	(0.002)
Cold season×Rain	−0.013***	−0.014***	−0.012***	−0.002
	(0.002)	(0.003)	(0.003)	(0.002)
Snow	0.038***	0.014***	0.007**	0.007***
	(0.002)	(0.003)	(0.003)	(0.002)
Zip code FE	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes	Yes
Zip code-Month–Year FE	Yes	Yes	Yes	Yes
Observations	1,081,689	1,081,689	1,081,689	1,081,689

Note: Robust standard errors are in parentheses, clustered at zip code level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

an order, and average number of items in each order, albeit the effects are smaller in magnitude. Therefore, we conclude that the impact of weather conditions on online sales can be explained through the impact of weather conditions on the number of online orders and the average order value.

6 Impact of Weather on Customers' Channel Choice

In Sects. 4 and 5, we show daily weather conditions in an area have a significant impact on customers' shopping behavior both for the offline and online channels, albeit the effects are smaller for the online channel. However, analyzing offline and online channels separately does not explain whether and how weather conditions impact customers' channel choice. Previous studies show endogenous factors, such as companies' operational policies, opening of new stores, availability of options in the physical world, and population demographics, affect customers' online shopping behavior. In all of these settings, online shopping behavior is affected by endogenous factors that depend on either the policies of the focal retailer or its competitors, or are shaped by the characteristics of the area in which the customer lives. However, in this study we analyze how an exogenous factor—namely, weather shocks—affects customers' choice between the online and offline channels.

Our collaborator has 63 brick-and-mortar stores in the United States. Hence, many customers live in areas where the retailer has no physical store within a reasonable travel distance, so traveling to one of our collaborator's B&M stores is not practical for them. Thus, we assume these customers do not choose between the online and offline channels and therefore exclude customers who do not have a physical store within 15 miles of their zip code from our analysis of channel choice. In order to analyze how weather conditions in an area impact customers' channel choice, we focus on customers who live in the area of influence of a B&M store, as explained in Gallino and Moreno (2014). We assume that the area of influence of a B&M store covers a radius of 15 miles, but our results are robust to different definitions of the influence area.

If the distance between two stores is less than 15 miles, we assume these stores are located in the same influence area. All the zip codes within a 15-mile radius of these stores are in the influence area of these stores. In total, we have 46 influence areas and 5,149 zipcodes that are served by at least one store. If there is more than one store within a 15-mile distance of one zip code, we assume that zip code is served by the closest store. The mean, median, and maximum distance between the zip codes and the store serving these zip codes is 7.42, 7.17, and 14.99 miles, respectively. Moreover, we assume that weather conditions in the zip code where the store is located represent the weather conditions in the influence area. If more than one store is serving an influence area, prevailing weather conditions of the store that is serving the highest number of zip codes are considered representative of the daily weather in the influence area. The radius of influence areas is small enough to make sure that weather conditions in the zip codes where customers live and where the store is located are very similar on a given day.

To analyze how weather conditions affect the channel choice of customers who live in an influence area, we use the following specification:

$$\begin{aligned} log(PercentageOfflineSales_{i,d}) = \alpha + \mu_{w(d),y(d)} + \beta_1 hot_{i,d} + \beta_2 cold_{i,d} \\ + \beta_3 rain_{i,d} \times coldseason_d + \beta_4 snow_{z,d} \\ + \tau_1 weekend_d + \tau_2 holiday_d + \tau_i + \epsilon_{i,d} \end{aligned} \tag{5}$$

where for influence area i, our dependent variable $PercentageOfflineSales_{i,d}$ represents the ratio of brick-and-mortar store sales to total sales on date d. Moreover, we include influence-area-specific fixed effects τ_i to take systematic differences across influence areas into account. We also control for seasonal patterns at the week–year level, $\mu_{w(d),y(d)}$. We cluster standard errors at the influence-area level.

6.1 Results

The results of our analysis are given in Table 10. As can be seen in column 1 of Table 10, prevailing weather conditions in an area impact customers' channel choice significantly. We observe that on unusually cold days, the share of offline sales increases, whereas on unusually hot days, the share of the online channel sales increases. On average the share of offline sales increases by 2.4% on cold days and decreases by 2.4% on hot days. Moreover, on snowy days and on rainy days in warm seasons—namely, the spring and summer seasons—the share of offline sales increases by 1.3% and 0.7%, respectively. The effect of temperature varies by the number of stores in an influence area. The relative increase in the share of offline sales decreases as the number of stores in the area increases, as can be observed in column 3 of Table 10. However, this result does not necessarily imply that the number of stores in an area is the driving factor behind this result. It might be the case that the influence areas with more than one store differ from others. For example, the areas with multiple stores in an influence area might be more urban and we might be capturing the different impact of weather on urban and rural areas instead of the effect of increasing the number of stores in an area.

Following our analyses in Sects. 4 and 5, we next study how this effect varies across different seasons. Although on cold days the share of offline sales increases in every season, hot days do not significantly impact the share of offline sales on hot days. Similar to our analyses for offline and online channels, we observe the effect of hot and cold days is largest in winter (Table 11).

Table 10 Impact of weather on channel choice

	(1) Perc. offline	(2) Perc. offline	(3) Perc. offline
Cold	0.024*** (0.005)	0.021*** (0.004)	0.032*** (0.008)
Hot	−0.024*** (0.007)	−0.017*** (0.006)	−0.040*** (0.012)
Cold season	−0.031*** (0.010)	−0.033*** (0.010)	−0.031*** (0.010)
Rain	0.007** (0.003)	0.008*** (0.003)	0.007** (0.003)
Cold season × Rain	−0.022*** (0.004)	−0.016*** (0.004)	−0.022*** (0.004)
Snow	0.013** (0.005)	0.009* (0.005)	0.013** (0.005)
Hot×Num. store			−0.012** (0.006)
Cold×Num. store			−0.006* (0.004)
Area FE	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes
Month–Year FE	Yes	Yes	Yes
Observations	25,173	25,173	25,173

Note: Robust standard errors are in parentheses, clustered at the influence-area level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Finally, we analyze whether the effect of temperature deviations is heterogeneous. As discussed in Sects. 4 and 5, to test for heterogeneous effects of temperature deviations we reestimated Eq. (4) by replacing $hot_{i,d}$ and $cold_{i,d}$ with indicator variables for the 0.5 temperature deviation bins into which the daily $TemperatureDeviation$ fall. We use 11 indicator variables for temperature variations bins ranging from (≤ -2.5) to (≥ 2.5). We leave the days with $TemperatureDeviation$ between $(-0.5, 0.5)$ as our left-out group. The results of our analysis are shown in Fig. 3. Similar to the results for B&M stores and online channels, the figure shows that the magnitude of the estimated coefficient increases as the deviation of daily temperature from the area's normal increases. However, the 95% confidence interval around the estimated coefficients overlaps for different bins across the negative and positive temperature deviation areas. Thus, we cannot conclude that there is a statistically significant difference between degrees of negative (positive) temperature deviations.

Table 11 Impact of weather on channel choice across different seasons

	(1) Fall	(2) Spring	(3) Summer	(4) Winter
Cold	0.027** (0.013)	0.021** (0.008)	0.024*** (0.008)	0.025*** (0.008)
Hot	−0.023 (0.014)	0.014 (0.009)	−0.029** (0.012)	−0.033*** (0.008)
Rain	−0.011** (0.005)	0.009** (0.004)	0.006 (0.004)	−0.011** (0.005)
Snow	0.027** (0.011)	−0.014 (0.014)		0.015*** (0.005)
Area FE	Yes	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes	Yes
Observations	4009	7908	6135	7121

Note: Robust standard errors are in parentheses, clustered at influence-area level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

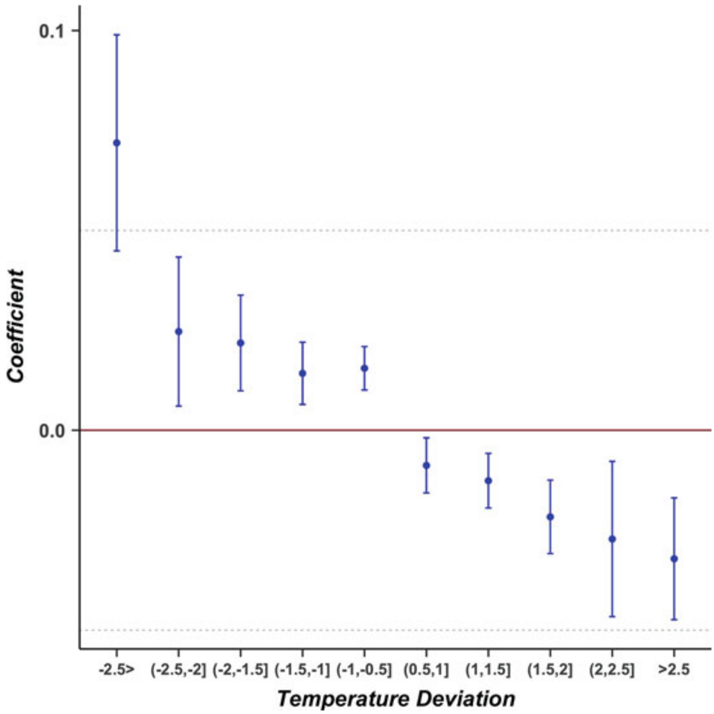

Fig. 3 Effect of temperature deviations on online sales

7 Implications

7.1 Implications for Labor Planning

Previous studies document a significant effect of labor staffing decisions on retailers' sales. Fisher et al. (2006), Kesavan et al. (2014), and Ton and Huckman (2008) show that sales associates play a critical role in turning traffic into sales as they help customers find the products customers are looking for. However, many times sales labor is calculated as a fixed percentage of the sales forecast of the following period (Fisher et al. 2018). Although weather shocks have a significant impact on store traffic and sales, retailers might not fully incorporate these weather shocks in their sales and store traffic forecasts. As retailers use forecast sales information to make their labor staffing decisions, the mismatch between the forecast and realized sales and traffic driven by weather shocks might have spillover effects into the labor staffing decisions. In this section, we test whether the retailers adjust their labor staffing levels by taking weather conditions into consideration.

In previous sections, we show that prevailing weather conditions in an area have a significant impact on store traffic and sales. However, as can be observed in column 1 of Table 12, the retailer is not adjusting the staffing levels depending on weather conditions. Moreover, we observe that once we control for traffic, the planned labor is 4.3% lower on cold days relative to regular days and 4.2% higher on hot days relative to regular days. Although retailers have no control over weather conditions, they would be better off incorporating weather forecasts into labor staffing decisions, which can be adjusted relatively quickly. However, as our results and industry reports show, many retailers do not include weather predictions into their decision-making process. Considering weather forecasts while making labor staffing decisions would help retailers manage the influx of traffic on cold days and reduce the excess labor cost on hot days.

7.2 Implications for Marketing and Assortment Planning

Incorporating weather forecasts into their decision-making process has widespread benefits for retailers. For example, Belkaid and Martínez-de Albéniz (2017) show that by adjusting in-store discounts on rainy days, retailers can improve revenues by 2%. Moreover, Steinker et al. (2016) suggest that including weather forecasts into the online channel's sales forecast can lead to more efficient warehouse-labor planning.

In addition, Murray et al. (2010) document that exposure to sun increases willingness to spend, and Li et al. (2017) show that how customers respond to mobile ads and the effectiveness of different mobile promotion frames varies depending on weather conditions in an area. This kind of weather information is used to design marketing promotions in the industry as well. For example, skin and hair product

Table 12 Impact of weather on labor staffing decisions

	(1)	(2)	(3)
Cold	0.006	−0.043***	−0.041***
	(0.007)	(0.008)	(0.008)
Hot	0.003	0.042***	0.042***
	(0.008)	(0.008)	(0.008)
Rain	0.012**	−0.011	−0.010
	(0.006)	(0.007)	(0.007)
Cold season	−0.029*	−0.053***	−0.053***
	(0.015)	(0.013)	(0.013)
Rain × Cold season	−0.021**	0.026***	0.025***
	(0.008)	(0.007)	(0.007)
Snow	−0.004	0.010	0.012
	(0.008)	(0.007)	(0.007)
Visitors		0.415***	0.637***
		(0.014)	(0.066)
Visitors^2			−0.020***
			(0.006)
Store FE	Yes	Yes	Yes
Weekend FE	Yes	Yes	Yes
Week–Year FE	Yes	Yes	Yes
Store-Month–Year FE	Yes	Yes	Yes
Observations	33,654	33,654	33,654

Note: Robust standard errors are in parentheses, clustered at store level
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

company Neutrogena developed a real-time weather-conditions-driven marketing campaign for its new sunscreens. The firm advertised the product only when the sun was shining (DigitalTrainingAcademy 2016). Outerwear company Timberland coupled the weather forecast for two to three upcoming days with a product needed for those weather conditions in its marketing emails (WeatherUnlocked n.d.). Hair-care purveyor Pantene focused on weather-affected hair problems, displaying different products in ads on humid days and on days with dry heat, as well as providing coupons and giving directions to the closest stores (WeatherAds 2014). All these examples document how much companies can utilize weather conditions to increase brand awareness, increase sales, and cut costs.

8 Conclusion

In this project, we collaborated with a winter and outdoor apparel retailer to analyze the impact of weather conditions on retailers' sales. We have documented the significant impact of weather conditions in both the offline and online channels, as well as customers' channel choice. Our analysis shows that sales increase on extremely cold days and decrease on hot days in both channels. However, the effect of weather on the online channel is much smaller compared to the weather effect on the offline channel. These effects cannot solely be explained by demand shifting. Moreover, weather conditions in an area impact customers' channel choice. Customers tend to move toward the offline channel on extremely cold days and toward the online channel on extremely hot days. Finally, we show an example demonstrating that companies do not sufficiently incorporate weather forecasts into their planning process.

Although this study shows the significant effect of cold days in increasing sales and of hot days in decreasing sales, the effect of weather over different product categories might vary. As our collaborator is a winter apparel retailer, it is possible that cold weather makes the benefits of cold weather items more salient, thus affecting the customer decision-making process. Even if the impact of weather on different products and industries is different, both our study and other industry reports show that companies can increase their profitability by incorporating weather conditions into their decision-making process.

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