Sellin’ in the Rain: Adaptation to Weather and Climate in the Retail Sector

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Abstract

Consistent with long-run adaptation to climate, I find that weather sensitivity of daily store level sales decreases with increasing historical weather variability and norms at an apparel and sporting goods brand. I examine short-run adaptation to weather shocks using a machine learning based index. I find that weather induces little intertemporal substitution. A one-standard deviation one-day weather shock shifts sales about 10 percent over several weeks. Ecommerce fails to offset weather-induced losses in stores. While diversifying among indoor and outdoor mall stores could protect brands against effects of precipitation, snow events and extreme temperatures appear to decrease sales at both types of stores.

Keywords: adaptation, climate change, weather, machine learning, retail, sales

Keywords: Q54, L81, D12

Portions of this analysis were previously circulated as a working paper and then published as part of a dissertation under the title “Blame it on the Rain: Weather Shocks and Retail Sales” (see Roth Tran (2016).)

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With increasing global temperatures and weather variability,\(^1\) economists have studied the effects of weather and adaptation in a range of outcomes, including agriculture, health, labor, housing, and fisheries. In this paper I study adaptation in retail sales, a sector not typically considered particularly weather-sensitive but which accounts for roughly ten percent of total employment in the United States. Retail sensitivity to weather can affect firm profitability, increase income volatility for retail workers,\(^2\) weaken the link between worker effort and outcomes at the core of principal agent problems, and affect the ability of firms to forecast demand for inventory and investment purposes.

I examine both short-run adaptation to weather shocks and long-run adaptation to climate in the context of one apparel and sporting goods retail brand. I define short-run adaptation as changes to when, how, and what tasks people accomplish or goods they consume to maximize utility in response to immediate weather shocks net of any responses by profit-maximizing retailers. Examples include postponing a shopping trip in order to hike on an unusually warm winter day or spending money on heat instead of clothes during a severe winter storm. Long-run adaptation occurs when more experience with a weather phenomenon reduces sensitivity to it, decreasing the need for short-run adaptations. This can be achieved through investment in durables like air conditioning and 4-wheel drive vehicles or development of human capital like ability to drive in snow. If consumers simply shift the timing or method of making purchases, then weather shocks may simply pose inconvenience. However, if instead consumers change what they buy, this suggests that weather affects relative utility of

\(^1\)Variability in precipitation is likely to increase, as indicated in the 2018 National Climate Assessment, which states that “The frequency and intensity of heavy precipitation events across the United States have increased more than average precipitation... and are expected to continue to increase over the coming century.... These trends are consistent with what would be expected in a warmer world, as increased evaporation rates lead to higher levels of water vapor in the atmosphere, which in turn lead to more frequent and intense precipitation extremes.” (Hayhoe et al. (2018), p.88) However, while climate models suggest that temperature variability is likely to increase in the summer months (June - August), temperature variability is currently expected to decrease over the year as a whole in most of the United States (Bathiany et al. (2018).)

\(^2\)Workers whose hours and wages depend on daily sales activity and whose economic well-being can be negatively impacted by unpredictable income (see Board of Governors of the Federal Reserve System (2019).) This suggests that increased weather-induced variability in sales is one channel through which climate change could have implications for inequality.
activities in a meaningful way, whether it is recreational shopping or sports. Weather induced changes to what consumers buy also has greater implications for stores and their employees, as their net sales over time and across venues are more sensitive to weather.

Using a unique proprietary data set of a national brand’s daily store-level sales that enables me to address a variety of attenuation bias concerns, I find evidence of long-run adaptation to climate in retail sales. For example, stores in locations more accustomed to large snowfall events are less responsive to given snowfall levels. Sensitivity to weather shocks declines as historical means and standard deviations of elements like precipitation and maximum temperature increase, suggesting potential for some adaptation to changes in both levels of weather outcomes (like higher temperatures) and increased variability (like more severe snowfall events) projected under climate change.

I apply novel methodology to examine short-run adaptation to the weather shocks most important for sales of the firm’s stores. In particular, I use the lasso machine learning method in a residuals-on-residuals framework to create a weather index that predicts how favorable weather conditions are for daily store-level sales in a given region, season, and shopping location type (indoor versus outdoor.) By examining out-of-sample prediction errors in random subsamples of the data, this method limits over-identification while allowing for flexibility, so that I can examine how sales gains and losses due to “good” and “bad” weather—determined for specific contexts—are made up, if at all. For example, I allow a 60°F winter day to be good for shopping in Los Angeles but bad for shopping in Minneapolis. I also allow an unusually warm day to be good for shopping in summer but bad in winter and for a rainy day to be good for shopping in indoor but not outdoor venues. By algorithmically selecting among thousands of residualized nonlinear weather variables those that optimize prediction of contemporaneous sales, this method agnostically chooses which aspects of weather have the largest effect on sales given a particular context.

I find that short-run adaptation to weather involves only very limited intertemporal substitution, which would in the week before and weeks after a shock offset sales effects
on the day of the weather event. Instead, the responses in the days before and after a weather shock boost the contemporaneous response, which is largely permanent. A one-standard deviation negative (positive) weather shock yields about a 10 percent largely persistent loss (gain) in sales.

I find little evidence that people do respond to weather shocks by changing where or how they buy products. In particular, when I limit the analysis only to metropolitan statistical areas with both indoor and outdoor stores, I find some evidence of weather-induced shifting of purchases between the two types of stores. However, this venue substitution only partially tempers immediate effects of disruptive weather, for example offsetting about 12 percent of weather effects in the Northeast but none (on average) in the Midwest. I also find no evidence of sales being shifted to the online space when weather is bad for shopping in stores. Instead, the most favorable weather for shopping in stores also increases online sales, while weather that is unfavorable for stores has no net discernible impact on online sales. The limited scope of intertemporal and venue substitution suggests that the main response to weather in this context is to change what people buy, not within the brand but to other expenditures entirely.  

Although it is possible that results of similar analyses using data for other retail brands could yield qualitatively different outcomes, the findings I present here have significant implications. First, I show that weather can induce large and largely permanent swings in retail sales for stores, implying that short-run adaptation to weather shocks can potentially affect firm profitability in addition to worker wages, even when smoothing over time and diversifying across venues. Second, my results suggest that there is adaptation in retail sales, which should be accounted for when applying current weather responses to future climate projections. Third, examining only contemporaneous weather effects could pose problems, as demonstrated by the amplification over time of contemporaneous effects of negative weather shocks.

This paper contributes to the literature by showing that not only weather means

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3Unfortunately, with the data available, I am not able to observe what households are spending money on instead of the products sold by this brand. However, when sales at stores (or online) for this brand drop, I view this as a change in what people are buying.
but weather variation affect consumer purchases. It examines both short- and long-term adaptation in one context and with novel methodology that can answer whether the weather that matters in specific contexts induces substitution or yields permanent shifts. It is also one of the first papers in the adaptation literature to focus on the retail sector, and, to my knowledge, the first in this area to examine these questions using high frequency (daily) and spatially granular data. In terms of retail sales, this paper builds on a significant literature examining weather effects by using a data set that spans a broader range of climates but still with spatially and temporally granular data to look cohesively in one context at long- and short-run adaptation and specifically how weather affects intertemporal spending, shopping at indoor versus outdoor venues, and shifting from physical stores to ecommerce (versus examining in-store sales only.)

The evidence I present suggests that weather conditions affect not only how people spend their time but also their money. This may be through changes to underlying demand for goods but also due to impulse shopping as an activity in and of itself. The results have implications for brands, which may be able to increase resilience to higher weather variability somewhat by diversifying the types of stores they operate and accounting for weather-induced intertemporal sales shifts when determining compensation and inventory planning. In this spirit, recent literature in the field of operations management has suggested that firms adjust pricing and inventory in response to weather (see Belkaid and de Albéniz, 2020.)

The remainder of this paper is laid out as follows. In section 1, I provide a brief overview of some of the relevant literature on adaptation and on weather effects in retail. I next provide a theoretical framework for thinking about adaptation and consumption in section 2. In sections 3 and 4, I describe the data and empirical methodology, respectively. I follow this with a discussion of results in section 5 and a conclusion in section 6.

Addoum, Ng and Ortiz-Bobea (2020) use annual sales data to examine whether responses to temperature differ for establishments whose average annual temperatures are in the top versus bottom half of the distribution. They find only one specification shows a significant difference between responses for these two groups and no significant effect for either group alone.

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1 Literature

This paper builds upon research examining adaptation to climate change, weather effects in retail spending, and outdoor activity responses to weather. It contributes to non-retail work on adaptation by exploring the role of adaptation in consumption or spending, which is an important driver of the economy. It contributes to examinations of weather effects in retail by applying a novel methodology (the predictive weather index) to perform a comprehensive analysis of adaptation, both long and short run in various forms, that this one data set spanning a broad range of climates (e.g. across the U.S. rather than within one European country) with great granularity (e.g. daily store level data rather than annual, sector-wide, or national data) enables.

Empirical studies have shown found evidence of various forms of adaptation to climate in the agriculture and fisheries sectors (see for example Schlenker and Roberts, 2009, Kala, 2017, and Shrader, 2017), in response to events like cyclones (see Hsiang and Narita, 2012 and Bakkensen and Mendelsohn, 2016), and in terms of outcomes like health (see for example Deschenes and Greenstone, 2011 and Barreca et al., 2015), labor (Behrer and Park, 2017), and income (Deryugina and Hsiang, 2017). Some of these studies use a similar approach to the one I undertake here in examining long-term adaptation by interacting weather shocks with historical norms (see for example, Hsiang and Narita, 2012, Barreca et al., 2015, and Behrer and Park, 2017). From this literature, we know that people can adapt to different climates, but that this adaptation is partial.

A significant body of literature examining how weather affects retail sales dates back to Steele (1951). Largely oriented toward marketing and operations management, this work has primarily relied on data available at either very small temporal or geographic ranges or at large aggregated scales. Maunder (1973) established early on that abnormal temperature and precipitation effects on retail sales vary by season. Looking at macroeconomic impacts, Starr-McCluer (2000) showed although cold winter weather depresses retail sales in some categories, these effects are offset by in subsequent...
months, yielding no meaningful net quarterly effects. Parsons (2001), Bahng and Kincade (2012), Bertrand, Brusset and Fortin (2015), Parnaudeau and Bertrand (2018), and Aladangady et al. (2016) are recent examples of studies showing that weather has significant effects on retail sales. In contrast, Addoum, Ng and Ortiz-Bobea (2020) find only energy sector sales respond meaningfully to temperature fluctuations when using annual data on firm establishment sales. However, unable to observe daily or even weekly or monthly sales, their data may make it difficult to measure responses to weather that could still affect individual firms, stores, and workers in meaningful ways in shorter time frames.

Recent work by Belkaid and de Albéniz (2020) shows that daily sales for an apparel brand in four European countries increase in indoor stores and decrease in outdoor stores in response to precipitation. They further show this effect is primarily driven by decreased foot traffic and that conditional upon entering a store, individuals in outdoor stores are more likely to make purchases when it is raining. They also find that warmer temperature increases sales of dresses in summer and decreases sales of coats in winter. My results complement this work by also exploring long-run adaptation to climate and the short-run adaptations to weather of intertemporal and brick-and-mortar to e-commerce, with the latter analyses facilitated by the weather index methodology I employ.

Another strand of literature has shown that weather can have psychological impacts on purchases (see for example, Howarth and Hoffman, 1984, Levi and Galili, 2008, Conlin, O’Donoghue and Vogelsang, 2007, and Busse et al., 2014, and Li et al., 2015) and mood more generally (see for example, Baylis, 2020.) Weather has also been shown to affect outdoor activity. Smith (1993) shows that beach use, swimming, golf and tennis all respond to temperature, with some nonlinearity. Graff Zivin and Neidell (2014) show that high temperatures decrease time allocated to outdoor leisure, while Chan and Wichman (2020) find that leisure cycling activity is very responsive

\footnote{For quarterly analyses, they impute establishment sales patterns using national quarterly sales patterns and annual establishment level sales.}
to temperature and precipitation. Tucker and Gilliland (2007) review 37 studies on how weather and seasonality affect physical activity and find that 73 percent of the articles examined report significant impacts. This body of work suggests that weather can may affect underlying demand for apparel and sporting goods products as well as the utility of shopping in exposed outdoor versus covered indoor venues.

2 Theoretical Model

To explain how weather shocks can cause rational shifts in time, venue and channel of consumer purchases as well as permanent changes in demand for products, I build on the Starr-McCluer (2000) approach which adds a weather component to the Ghez and Becker (1975) household-production model.

In this model, an individual produces $n$ household “commodities” $C_{it}$ in period $t$. These commodities are broadly defined and include activities like golfing, going to the beach, eating dinner, and recreational shopping. A commodity is produced through a combination of household labor $h_{it}$ and purchased goods vector $q_{it}$ as follows:

$$C_{it} = C_i(q_{it}, h_{it}, \theta_{it})$$  \hspace{1cm} (1)

The vector $\theta_{it}$ was introduced by Starr-McCluer (2000) to represent “factors that shift the productivity of goods or labor in the production of $C_{it}$.” Weather is an important component of $\theta_{it}$.

In my model, I allow utility in period $t$ to depend on the production of household commodities in surrounding periods as well as the current one. I denote vectors of commodity production levels over time, as anticipated during period $t$, as $C^t_i$, which is defined as

$$C^t_i = \{C_{i0}, \ldots, C_{i(t-1)}, C_{it}, E_t[C_{i(t+1)}], \ldots, E_t[C_{iT}]\}. \hspace{1cm} (2)$$
Then individual utility in period $t$ is

$$U_t = U(C^t_1, C^t_2, \ldots, C^t_n).$$  \hspace{1cm} (3)

This reflects that an individual may prefer a mix of activities over doing the same thing day after day and allows enjoyment of an activity to change with anticipation of future activities. For example, an individual may enjoy shopping for golf clubs when it is snowing if she expects to go on a golf vacation in the coming summer. An individual may get less utility from a beach outing if he has just spent the last five days on the beach than if he has been in the office all week.

The individual maximizes the discounted utility stream

$$\max_{h, q} U = \max_{h, q} \sum_t \delta^t U_t,$$  \hspace{1cm} (4)

subject to the budget constraint

$$\sum_t \frac{1}{(1+r)^t} \left[ \sum_i \sum_j p_{jt} q_{ijt} \right] = A_0 + \sum_t \frac{1}{(1+r)^t} w_t H_t,$$  \hspace{1cm} (5)

where $r$ is the interest rate, $p_{jt}$ and $q_{ijt}$ the price and quantity for good $j$ at time $t$ (for commodity $i$), $A_0$ the initial assets, $w_t$ the wage rate, and $H_t$ the hours of paid work. The time budget constraint requires total time $L_t$ to equal paid work time plus household production time as follows:

$$L_t = H_t + \sum_i h_{it}$$  \hspace{1cm} (6)

Given some basic tractability assumptions, optimal levels of goods $(q^*_{ijt})$ and household labor $(h^*_it)$ will be functions of current and expected future wage rates $w_t, \ldots, w_T$, prices $P_t, \ldots, P_T$, and household productivity factors $\theta_t, \ldots, \theta_T$ (including weather),

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Note that $q_{ijt}$ may be durable or non-durable. In the case of a durable good, if the individual already owns the item, it may not be necessary to purchase the good at time $t$ in order to use it then. However, every use contributes to some depreciation of the good, thus in effect imposing a cost on use of the good at time $t$. 

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as well as the interest and discount rates $r$ and $\delta$.

\[
q^*_t = q^*_t(w_t, \ldots, w_T; P_t, \ldots, P_T; \theta_t, \ldots, \theta_T; \delta; r)
\]
\[
h^*_t = h^*_t(w_t, \ldots, w_T; P_t, \ldots, P_T; \theta_t, \ldots, \theta_T; \delta; r),
\]

In this model, a shock to current or expected future weather can affect sales of good $q_{i,j}$ in the following ways:

1. **Intertemporal substitution**: A weather shock that shifts productivity of labor and goods allocated to commodity $C_{it}$ relative to $C_{it+h}$ may cause an individual to produce commodity $C_i$ in a different period and purchase good $x \in q_i$ at a different time.

2. **Channel substitution**: A weather shock can affect the relative productivity of different types of shopping commodities, leading to a change in venue of purchase for good $x$. For example, suppose that $C_{it}$ is a mall shopping trip, while $C_{lt}$ is online shopping, with $x \in q_{it}$ and $x \in q_{lt}$. Inclement weather, like heavy rain that makes roads dangerous to travel, can reduce the relative productivity of $C_{it}$, making online shopping more attractive and causing individuals who otherwise would have purchased $x$ at the mall to make the transaction online. Similar substitution can occur between purchasing a good at an indoor mall versus a store in an outdoor shopping area.

3. **Sales gained from or lost to outside options**: A weather shock may result in substitution between commodities $C_{it}$ and $C_{lt}$, where good $x$ is an element of $q_{it}$ but not $q_{lt}$. This weather-induced substitution to or from an alternative activity may increase or decrease sales for good $x$ without corresponding intertemporal or channel substitutions.
2.1 Illustrative example

Suppose an individual is considering the following commodities:

\[
\begin{align*}
C_{1t}(q_{1t}, h_{1t}, \theta_{1t}) &= \text{shopping in indoor malls for sandals} \\
C_{2t}(q_{2t}, h_{2t}, \theta_{2t}) &= \text{shopping at outdoor malls for sandals} \\
C_{3t}(q_{3t}, h_{3t}, \theta_{3t}) &= \text{wearing sandals at the beach} \\
C_{4t}(q_{4t}, h_{4t}, \theta_{4t}) &= \text{shopping online for sandals} \\
C_{5t}(q_{5t}, h_{5t}, \theta_{5t}) &= \text{alternative activity}
\end{align*}
\]

Suppose there is an unexpected downpour, reflecting a shift in \(\theta_{it}\). One can imagine that:

\[
\begin{align*}
\frac{\partial C_{1t}}{\partial \theta_{1t}} &> 0 \text{ (shopping in indoor malls for sandals)} \\
\frac{\partial C_{2t}}{\partial \theta_{2t}} &\geq 0 \text{ (shopping at outdoor malls for sandals)} \\
\frac{\partial C_{3t}}{\partial \theta_{3t}} &< 0 \text{ (wearing sandals at the beach)} \\
\frac{\partial C_{4t}}{\partial \theta_{4t}} &= 0 \text{ (shopping online for sandals)} \\
\frac{\partial C_{5t}}{\partial \theta_{5t}} &\gg 0 \text{ (alternative activity)}
\end{align*}
\]

These relationships could result in an individual shopping for sandals sooner than originally planned, as he reschedules his beach outing to a later date. It could result in the individual shifting from buying sandals (still needed for next week’s vacation) in the downtown shopping district to doing so at an indoor mall. Or he could simply buy them online. Finally, the consumer could abandon the sandal purchase entirely, as he decides that he really needs a good pair of rain boots or umbrella instead.

2.2 Long-run adaptation

The same weather occurrence on the same day will affect sales heterogeneously across regions due to differences in (1) infrastructure (e.g. storm drainage systems that minimize flooding, air conditioning, snow plows), (2) individual adaptability (e.g. ability to drive in rain or snow, four-wheel drive, rain gear for hiking), or (3) local weather norms, where rarer events are likely to be more disruptive (e.g. warm and sunny day in...
January in Minneapolis vs. Los Angeles). These three adaptation elements are likely to be highly correlated. Infrastructure and individuals are likely to be well-adapted to weather that is within regional norms.

I represent these adaptation elements with $\eta_{it}$. To account for the fact that weather will impact household commodity production differentially, I update equation 1 as follows:

$$C_{it} = C_i(q_{it}, h_{it}, \theta_{it}, \eta_{it})$$

(10)

3 Data

I use proprietary daily store level sales data for over 100 U.S. locations of an apparel and sporting goods brand. I have identified each store location as either outdoor, where consumers enter stores through the outside and exposed to weather conditions, or indoor, where consumers can move freely between stores without braving the elements. Outdoor locations include strip malls and metropolitan shopping districts, while indoor locations are generally in fully enclosed malls. These store sales data span the period of April 2010 through December 2013.

I also use daily zip code level ecommerce sales data for the same brand. However, I only have the dates when the sales were fulfilled by the firm, not when the orders were actually placed online. Because fulfillment did not regularly occur on weekends during this period, I aggregate these data at a weekly level, with the week starting on Tuesdays. The zip codes correspond to delivery addresses.

I combine these sales data with airport and weather forecast office weather station data from NOAA, National Centers for Environmental Information (NCEI). To obtain store-level weather data, I inverse-distance weight observations from all such weather stations within 70 miles and 400 meters elevation of each store location. The weather elements I use in this analysis include maximum temperature, minimum temperature, precipitation, snowfall, and snow depth.\(^7\) I also average over maximum and minimum

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\(^7\)Data on humidity or wind were completely unavailable or frequently missing.
temperature to calculate average temperature for a day.

In working with the weather data, I exclude stations missing more than 5 percent of precipitation or temperature observations during my time frame. This yields anywhere up to seven weather stations per location and causes me to drop several stores due to insufficient observations. I furthermore use OLS regressions of weather station observations on nearby weather station observations to impute remaining missing weather observations. Finally, I replace missing snowfall and snow depth data with zeros when national monthly snowfall maps indicate that there was no snow at the weather station locations in the applicable months.

To allow for heterogeneous responses to weather events based on different climates, I assign each store location to the corresponding climate region in the National Climate Assessment (Melillo, Richmond and Yohe, 2014.) With national representation, my data include a wide range of climates. For example, while Northwest locations have the highest share of days with positive precipitation, they are far less likely to experience daily precipitation over 2 inches than Southeast locations. My data also include significant variation in observed temperature, snowfall, and snow depth distributions. Figure 1 shows the wide variety of distributions of weather observations I observe by region.

I calculate historical means and standard deviations using NOAA, National Centers for Environmental Information (NCEI) weather station level observations ranging from 1980-2009. For each calendar day \( d \) (e.g. January 18), I apply a Bartlett weighting kernel over the historical observations for days \( d - 14, ..., d + 14 \) (e.g. January 4 - February 1) to calculate the daily historical mean and standard deviation for each element at each station. This kernel places the greatest weight on historical observations on day \( d \), with the weights on the surrounding days \( d \pm h \) diminishing linearly with \( h \). Smoothing over 870 historical observations for each day \( d \) reduces noise in daily historical means and standard deviations from rare events like large rainfalls, avoiding large discrete jumps from one day to the next. This method also avoids discrete jumps at the start and end of each month that would be introduced by calculating means
and standard deviations for each calendar month and allows the mean temperature to gradually increase or decrease over the course of a month.

The data include a wide range of historical means and standard deviations, which tend to be correlated, so that locations and seasons where large swings in precipitation are more common are also more likely to have higher means. However, there is some variation in these relationships. This relationship can be seen in the scatter plots of precipitation and snowfall means and standard deviations in Figure 2. For example, a location in the Northwest might have similar mean precipitation but much lower standard deviation relative to a location in the Southeast, where the former sees frequent low levels of precipitation and the latter experiences less frequent but more intense precipitation events.

4 Empirical Strategy

4.1 Baseline model

I estimate the effect of weather shocks by controlling for a variety of fixed effects that capture seasonal trends both in weather and in sales. Through these controls I avoid, for example, attributing to cold weather the increases in sales that are due to December holiday shopping. Specifically, using panel data for stores $i$ and days $t$, I estimate the following model:

\[
\ln(Sales_{it}) = \omega \cdot weather_{it} + \alpha + \alpha_i + \alpha_y + \alpha_{im} + \alpha_{iw} + \beta_1 i \cdot store_i \cdot t + \beta_2 i \cdot store_i \cdot t^2 + \beta_3 \cdot holiday_t + \beta_4 \cdot store\_closure\_or\_opening_{it} + \varepsilon_{it}.
\] (11)

I model weather in a variety of ways, as discussed below, and in each case, $\omega$ the vector of their coefficients. The fixed effects include store ($i$), year ($y$), store-by-calendar month ($im$), and store-by-day-of-week ($iw$) fixed effects. I also include store-specific

\footnote{Note that I now use $i$ to indicate the store, not the commodity as in section 2.}
holiday and linear and quadratic trend effects as well as indicators for the first or last week or month of a store’s existence.\footnote{My data include observations with 0 sales, which occur when stores are closed. These closures may result from extreme weather events. To be conservative and maintain a focus on non-extreme events, I exclude these observations because the ln(0) is undefined.}

### 4.2 Long-run adaptation

When estimating long-run adaptation to climate, I start with the approach in Dell, Jones and Olken (2014) by estimating

\[
\ln(\text{Sales}_{it}) = \alpha + \alpha_i + \beta X_{it} + \phi_1 \cdot ELEM_{it} + \phi_2 \cdot \overline{ELEM}_{it} \cdot ELEM_{it} + \varepsilon_{it},
\]  

(12)

where \(X_{it}\) is the set of fixed effects from equation 11, \(ELEM_{it}\) is the weather element of interest, and \(\overline{ELEM}_{it}\) is the daily historical normal of the weather element. Long-run adaptation is indicated by \(\phi_1\) and \(\phi_2\) having opposite signs. This relationship indicates people living in climates more accustomed to a particular type of weather are also less sensitive to that weather. As \(\overline{ELEM}_{it}\) increases, the absolute effect of \(ELEM_{it}\) decreases.

In addition to examining the effects of historical means, I build on the Dell, Jones and Olken (2014) specification in equation 12 by adding standard deviations to see how acclimation to more variable weather affects weather sensitivity. This is important because climate change projections suggest that weather will become more extreme and variable, an increase in the standard deviation of observed weather. I model this by adding the historical standard deviation version of the interaction term as follows:

\[
\ln(\text{Sales}_{it}) = \alpha + \alpha_i + \beta X_{it} + \phi_1 \cdot ELEM_{it} + \phi_2 \cdot \overline{ELEM}_{it} \cdot ELEM_{it} + \phi_3 \cdot \sigma^ELEM_{it} \cdot ELEM_{it} + \varepsilon_{it}.
\]

(13)

As before, opposite signs on \(\phi_1\) and \(\phi_3\) are consistent with long-run adaptation.
4.3 Weather index

Weather effects are nonlinear, sensitive to context, and dependent upon interactions between the elements. For example, I observe a contemporaneous response of sales to temperature in the shape of an inverted U (see Figure 3.

One can model weather nonparametrically by binning element realizations in order to estimate responses at different ranges. This popular method originated in agricultural analyses, where a biological mechanism underlies productivity responses. However, in the context of shopping, households are optimizing utility across activities and products and the physical link between particular temperature ranges and outcomes is less fixed. What matters may be whether a temperature is unusually warm or cold and that depends on both location and time of year. Averaging effects from temperature ranges across time and space can introduce attenuation bias. For example, Figure 3 shows these types of U-shaped temperature effects on sales differ by season such that relative to days with average temperatures in the 70-75 degree range, a 45-60 degree range day appears to lower sales in summer but increase them in the winter. Averaging across these effects without accounting for season might suggest that 45-60 degree days don’t affect sales.

One might choose instead to model weather in terms of deviations from the mean (see for example Herrnstadt and Muehlegger, 2014.) However, when compared to alternatives, an unusually hot day in summer may make shopping—particularly in an air conditioned indoor mall—relatively attractive, while an unusually warm winter day could make shopping relatively unattractive, and again particularly in an indoor mall. Averaging across these heterogeneous responses to above- and below-mean weather could yield attenuation bias and make sales appear insensitive to weather.

Interactions between elements can introduce further bias. For example, precipitation during warm weather can make shopping at an enclosed mall attractive, while precipitation during extremely cold weather can make roads icy and reduce willingness to travel to any store. The above approaches using nonparametric binning or devia-
tions from mean can both yield attenuation bias when seeking to measure how much weather affects outcomes in the face of offsetting effects along one dimension due to interactions with another.

To address the concerns described above, I prefer to examine short-run adaptation to weather shocks using the following weather index method, performed separately for indoor and outdoor stores. First, I regress sales and weather variables on the fixed effects in equation 11 in order to generate residuals for each variable. The set of weather variables is extensive and includes polynomials, interactions between elements, and interactions with indicators for season and region. I then use lasso to select among residuals of weather variables that are most predictive of residual sales. I next predict sales residuals using the model selected by lasso. Finally, I standardize the predicted sales residuals to create a weather index $W$ with a mean of 0 and a standard deviation of 1 across all stores and seasons but separately for indoor and outdoor stores. A high positive (negative) value indicates that weather conditions are very (un)favorable for sales in the given store type, region, and season. As I describe below, I use this index to examine how weather affects sales across time, venues, and online versus brick-and-mortar stores.

Figure 4 illustrates an example of weather index values side by side with observed weather over the course of a year in a city in the Northeast. The upper panel shows the indoor and outdoor weather index values, where positive (negative) values indicate that local current weather conditions are (un)favorable for sales. The gray shaded areas highlight the periods during which the two indexes are negatively correlated, consistent with adaptation via change in venues. The lower panel shows the observed weather on those days. The gray bars show precipitation levels, which tend to correspond to a positive index for indoor stores and negative for outdoor stores. The thin solid line shows snow depth while the black dots show snowfall. While snowfall yields negative index values for both indoor and outdoor stores, the region appears to adapt to high snow depth levels fairly well in terms of resuming sales shortly after snow fall events. Maximum and minimum temperatures, shown by the dashed and dash-dotted lines,
have less obvious obvious impact on the weather index, though a spike in temperature in the spring appears to drive to boost the outdoor sales index and lower the indoor sales index.

4.4 Short-run adaptation

Without data on individual shoppers or individual transactions, I am unable to say what individuals do instead of buying a product from the brand or the extent to which they change what products they buy from the brand. However, I am able to examine the extent to which contemporaneous gains and losses are offset at other times and places. These offsets would be consistent with intertemporal and venue substitution, particularly from the firm’s perspective.

I test first for intertemporal weather shock effects. I follow the structure of equation 11, but specifically using the weather index $W$ instead of the weather elements, and add lags and leads of weather index values. Recall that by construction the weather index has a mean of zero and standard deviation of 1, with positive values indicating weather favorable for shopping. Negative coefficients on lags and leads are thus consistent with intertemporal substitution from the firm’s perspective.

Next I examine shifting sales between indoor and outdoor stores. Looking only at metropolitan statistical areas (MSAs) with both indoor and outdoor stores, I separately aggregate daily MSA-level sales and weather at indoor and outdoor stores by averaging over those types of stores within each MSAs to produce $W_{\text{outdoor,mt}}$ and $W_{\text{indoor,mt}}$. I define the following indexes:

\[
W_{\text{own,jmt}} = \frac{W_{\text{outdoor,mt}} \cdot \mathbb{1}[j = \text{outdoor}]}{\sum_{j = \text{outdoor,indoor}} W_{\text{outdoor,mt}} \cdot \mathbb{1}[j = \text{outdoor}]} + W_{\text{indoor,mt}} \cdot \mathbb{1}[j = \text{indoor}]
\]

\[
W_{\text{other,jmt}} = \frac{W_{\text{outdoor,mt}} \cdot \mathbb{1}[j \neq \text{outdoor}]}{\sum_{j = \text{outdoor,indoor}} W_{\text{outdoor,mt}} \cdot \mathbb{1}[j \neq \text{outdoor}]} + W_{\text{indoor,mt}} \cdot \mathbb{1}[j \neq \text{indoor}].
\]
the indoor stores in the same MSA $m$ on the same day. I use these indexes to estimate the following equation:

$$\ln(\text{Sales}_{jmt}) = \alpha + \alpha_m + \beta X_{jmt} + \gamma_1 \cdot W_{\text{own},jmt} + \gamma_2 \cdot W_{\text{other},jmt} + \varepsilon_{jmt}. \quad (15)$$

Sales$_{jmt}$ is the aggregate sales at type $j$ stores within MSA $m$ on day $t$. $X_{jmt}$ include the non-weather fixed effects and controls from equation 11 along with a variable for the number of stores in the MSA at time $t$ to allow sales to shift with entry and exit of stores. A negative $\gamma_2$ coefficient indicates that there is offsetting behavior consistent with substitution between venue types.

Finally, I look for evidence of substitution between in-store and online sales by regressing weekly MSA-level e-commerce sales on weekly in-store weather index values. Negative coefficients would indicate substitution.

5 Results

5.1 Long-Run Adaptation

Panel A of Table 1 shows that, on average, sales increase with temperature and decrease with precipitation, snowfall, and snow depth. Consistent with long-run adaptation to climate, the estimates of $\phi_1$ and $\phi_2$ from equation 12 have opposite signs in all cases except minimum temperature, which is only significant at the 10 percent level. Overall, these results indicate that sensitivity to weather declines with higher historical means. For example, column 4 shows that one inch of snowfall typically decreases sales by 17 percent. However, because the coefficient on the interaction between snowfall and mean snowfall is positive, this effect is weaker for areas and times when snowfall is historically more common.

Adding the equation 13 interactions between current weather and historical standard deviations, Panel B shows that areas accustomed to more variable weather are generally less sensitive to given weather shocks. In particular, in all columns except
column 1 for maximum temperature, variability displaces historical mean in decreasing sensitivity to weather shocks.

Although these results show some long-run adaptation to climate in retail, the estimates of the $\phi_2$ and $\phi_3$ interaction terms in Table 1 are small relative to the estimates of the $\phi_1$ stand-alone weather element terms. This implies that the potential of adaptation may be limited. For example, according to column 4 of panel A, one inch of snow yields a 16 percent decline in sales if the historical mean is 1 inch and a 17 percent decline if the historical mean is 0.1 inches. In this analysis, a ten-fold increase in the historical reduces the response to snowfall from 17 to 16 percentage points, or just 6 percent of the response. However, it is possible that the simple linear treatment of weather effects averaged across store types and seasons in this analysis could understate the extent of adaptation.

5.2 Short-run adaptation: Intertemporal substitution

I now examine whether the effects on the day of a weather shock on one day are offset during the week before or the three weeks after the event. I use the weather index described in section 4.3 that has a mean of zero and standard deviation of one and allows for nonlinearities, interactions, and context-dependent weather responses.

The panels in Figure 5 show results from a joint regression that includes leads and lags of weather index values interacted with indicators for whether those index values are negative or positive. I show cumulative effects starting seven days prior to a weather event. With negative (positive) weather index values corresponding to unfavorable (favorable) weather conditions, positive coefficients in Figure 5 indicate cumulative declines (increases) in sales resulting from unfavorable (favorable) weather. I find that sales respond in advance of weather events, with contemporaneous effects being amplified in the days immediately before and after weather shocks.

The sales response to negative weather shocks shown in Figure 5a appears to be persistent. A one-standard deviation unfavorable weather event yields a loss of about
6 percent of daily sales on the day of the event. Although the marginal contributions before and after that event may not be significant, because they tend to go in the same direction, the magnitude of the cumulative effect when accounting for responses in the preceding week and following three weeks is about double that of the contemporaneous effect on the day of the negative weather shock.

In contrast, Figure 5b shows that in the days immediately before and after the actual shock, the marginal effects of positive weather events also move in the same direction as the contemporaneous response. However, about a week after the positive shock, the marginal effect counteracts the initial effect, indicating that some of the initial responses to positive weather shocks may be early harvesting. The point estimate of the cumulative response to a one-standard deviation positive weather shock drops off a bit by the end of three weeks to end up closer to 6 percent, about half of the peak level effect. This tapering off suggests there is some intertemporal offsetting and that some of the boost from favorable weather may be transient. However, the standard errors are large enough that we cannot rule out the possibility that there is no intertemporal substitution of sales after a positive shock.

One key takeaway from Figure 5 is that examining just the contemporaneous effect of a weather shock may not accurately reflect total weather effects. Sales respond to weather before it actually hits and effects may either continue to grow or diminish over time. It appears that individuals (and perhaps stores) adjust their behavior based on weather forecasts, which could therefore have a potentially very meaningful economic impact. On net, it appears that in cumulative terms, a one-standard deviation weather shock at a store on average yields a roughly 10 percent cumulative shock in daily sales.

### 5.3 Substitution between indoor and outdoor stores

In Table 2 I present results from estimating equation 15 to determine whether people adapt to weather by shifting their shopping activity between indoor and outdoor stores. A negative coefficient on *other weather index* is consistent with substitution between
indoor and outdoor venues.

Starting with the simplest specification, column 1 shows that the other weather index does not have a significant effect on store sales. In column 2, I examine venue substitution separately for indoor and outdoor stores in case the substitution goes one direction but not the other. Again, I find no significant effect of the other weather index on sales, although these results do show that outdoor stores are more sensitive to weather effects. In column 3, I examine potential seasonal heterogeneity in weather shocks yielding shifts in sales between indoor and outdoor venues. I find some weak evidence of substitution in the fall which significant only at the 10 percent level.

Finally, in column 4 I test for regional heterogeneity in substitution between indoor and outdoor venues and find some supportive evidence. In particular, in the Northeast (the base region), the Great Plains, Northwest, and Southwest the other weather index appears to partially offset the own weather index. For the Northeast, the coefficients indicate that about 13 percent of effects on sales in one type of store are offset by a shift in sales to the other type of store. However, there does not appear to be such substitution in the Midwest and Southeast. Regional heterogeneity in types of weather that tend to disrupt sales could explain regional heterogeneity in the prevalence of adaptation by way of venue switching. For example, while snowfall might make it difficult for people to go shopping at any location, rain could cause people to switch from outdoor to indoor malls.

To explore whether different forms of weather yield different average sales responses in indoor and outdoor stores, I non-parametrically examine the effects of weather elements on indoor and outdoor stores separately. Figure 6 shows the average effects of temperature, precipitation, snowfall and snow depth on sales at indoor and outdoor stores. In the case of temperature, the results are relative to days in the 70-75°F range for temperature, while the other variables show results relative to zero precipitation, snowfall, or snow depth.

Controlling for precipitation, snowfall, and snow depth, Figure 6a shows that temperatures near the freezing point (20-40°F) may simultaneously drive up sales at indoor
stores (the blue bars with the diamond centers) and drive down sales at outdoor stores (the orange bars with the round centers.) However, these results should be taken with a grain of salt because, as described in section 4.3, temperature effects depend on factors like season and region, so these averages may mask some seasonal substitution-like behavior.

Figure 6b shows that precipitation induces offsetting shopping patterns at indoor and outdoor stores. While any positive level of precipitation appears to drive down sales at outdoor stores, precipitation over 1/2 inch appears to increase sales at indoor stores, though not all of the coefficients in this range are statistically significant (which could be due to heterogeneities or interactions with temperature, as described in section 4.3.)

Figures 6c and 6d show that snowfall and snow depth decrease sales in a similar manner at indoor and outdoor stores. Figure 6c shows that snowfall yields a somewhat stronger negative effect at outdoor stores, though the differences are not generally statistically significant. Figure 6d shows that snow depth, when controlling for contemporaneous snowfall, has a more consistently negative effect on outdoor than indoor stores, but a somewhat larger negative effect at indoor stores in the 2-12 inch range.

In Table 3, I show the results of another examination of weather-induced substitution between indoor and outdoor stores. In this analysis I regress the daily MSA-average weather index for indoor (outdoor) stores on a set of weather indicators in column 1 (3) and then on that set of indicators interacted with the daily MSA-average weather index for outdoor (indoor) stores in the same MSA in column 2 (4). The weather indicators include whether it is hot with max temperature above 90°F, it is freezing, or whether there is positive precipitation, snowfall, or snow depth. The results suggest that while precipitation induces substitution from outdoor to indoor stores both because the coefficients on precipitation in columns 1 and 3 have opposite signs and the coefficients on the interaction term for precipitation in columns 2 and 4 are negative. However, it also suggests that snow and extreme temperatures are unfavorable for both indoor and outdoor stores, which would not be consistent with
substitution between indoor and outdoor stores.

On the whole, the results in Table 2 and Figure 6 indicate that there is regional heterogeneity in the tendency of weather shocks to induce switching between indoor and outdoor stores, with this heterogeneity potentially explained by differences in the types of weather shocks most prevalent in different regions. Further, it appears that while precipitation may induce substitution between indoor and outdoor stores, snowfall does not.

5.4 Substitution from physical store to online sales

When faced with unfavorable weather for shopping, rather than shifting between venues and over time, consumers may instead opt to make purchases online. In Figure 7, I examine how different percentile ranges of weather index values affect online sales. A downward sloping relationship here would be consistent with substitution from shopping in physical stores to online, as unfavorable weather in the lower percentiles of the weather index range (on the left hand side of the chart) increase online sales. Instead of a downward slope, I observe a flat and somewhat upward sloping curve. Weather that is favorable for shopping in physical stores also appears to drive online sales, while weather that is bad for shopping in physical stores does not, on net, affect ecommerce for this brand. This could be explained by weather affecting mood, which in turn drives shopping. Another potential explanation is that shopping activity in stores may drive some online sales, perhaps as customers who find products in stores purchase the particular color or size they like online.

Thus I find no clear evidence of substitution to ecommerce due to bad weather. However, it is possible that the lack of significant effects at low weather index values owes to a boost from substitution to ecommerce being offset by decline in the online sales being driven by shopping in stores.
6 Conclusion

In this paper, I have shown that while there some long-run adaptation to climate and short-run adaptation to weather shocks in daily store level sales, the adaptation appears to be limited. Individual stores can experience large and permanent swings in sales due to unseasonable weather shocks. Firms, investors, and policymakers need to keep in mind that as climate change becomes more pronounced, our economy will not only become increasingly exposed to potential supply chain disruptions and disasters that shut down local economies, but that greater variability in weather can affect consumer purchases in ways that are costly to individual business owners and employees.

With regard to policy, my results suggest that we would overestimate climate change effects if we simply applied current contemporaneous responses to weather to simulated weather from climate change models without accounting for adaptation. However, it would also be incorrect to assume perfect adaptation, as I find that weather shocks are largely persistent and only partially offset through short-run adaptation.

Individuals working in retail with sales-based pay or hourly wages may experience increasingly large income swings as weather becomes more variable and affects sales and hours worked. This type of volatility for relatively low-skilled laborers could present additional hardships if they are credit constrained and already struggling to smooth consumption. Therefore, understanding how climate change will affect the retail sector is an important component to quantifying and adapting to the effects of climate change and also to understanding its potential implications for economic inequality.
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7 Tables and Figures

Table 1: Long-run adaptation to climate

Panel A: OLS regressions on historical means

| Dep var: $ln(NetSales_{i,t})$ | (1)    | (2)    | (3)    | (4)    | (5)    |
|-------------------------------|--------|--------|--------|--------|--------|
| Max Temp                      | 0.0361*** |        |        |        |        |
| Max Temp × Mean Max Temp      |        | -0.0006** |        |        |        |
| Min Temp                      |        |        | 0.0152*** |        |        |
| Min Temp × Mean Min Temp      |        |        |        | 0.0006* |        |
| Precip                        |        |        |        | -0.1300*** |        |
| Precip × Mean Precip          |        |        |        | 0.0066*** |        |
| Snowfall                      |        |        |        |        | -0.171*** |
| Snowfall × Mean Snowfall      |        |        |        | 0.0128** |        |
| Snow Depth                    |        |        |        |        | -0.0346*** |
| Snow Depth × Mean Snow Depth  |        |        |        | 0.0003** |        |
| Observations                  | 124,610 | 124,606 | 124,889 | 133,890 | 134,626 |
| Adjusted $R^2$                | .8525   | .8521   | .8520   | .8600   | .8576   |

Panel B: OLS regressions on historical means and standard deviations

| Dep var: $ln(NetSales_{i,t})$ | (1)    | (2)    | (3)    | (4)    | (5)    |
|-------------------------------|--------|--------|--------|--------|--------|
| Max Temp                      | 0.0593*** |        |        |        |        |
| Max Temp × Mean Max Temp      |        | -0.0009** |        |        |        |
| Max Temp × SD Max Temp        |        |        | -0.0032 |        |        |
| Min Temp                      |        |        |        | 0.0478*** |        |
| Min Temp × Mean Min Temp      |        |        |        | -0.0002 |        |
| Min Temp × SD Min Temp        |        |        |        | -0.0059** |        |
| Precip                        |        |        |        | -0.2130*** |        |
| Precipitation × Mean Precip   |        |        |        | -0.0073*** |        |
| Precipitation × SD Precip     |        |        |        | 0.0072*** |        |
| Snowfall                      |        |        |        |        | -0.2270*** |
| Snowfall × Mean Snowfall      |        |        |        | -0.0040 |        |
| Snowfall × SD Snowfall        |        |        |        | 0.0098*** |        |
| Snow Depth                    |        |        |        |        | -0.0671*** |
| Snow Depth × Mean Snow Depth  |        |        |        | -0.0009** |        |
| Snow Depth × SD Snow Depth    |        |        |        | 0.0019*** |        |
| Observations                  | 124,610 | 124,606 | 124,889 | 76,712  | 89,099  |
| Adjusted $R^2$                | .8526   | .8523   | .8522   | .8190   | .8231   |

Note: Robust standard errors are clustered at MSA level. Regressions include year, month, day of week, holiday, store-trend, store-month, and store-day of week fixed effects. Controls also include indicators for store openings and closures. Temperature observations are in 10 degrees Fahrenheit, while precipitation, snowfall, and snow depth are in inches. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)
Table 2: Substitution between indoor and outdoor stores

Panel A: OLS regressions on historical means

| Dep var: ln(NetSales_{i,t}) | (1)   | (2)   | (3)   | (4)   |
|-----------------------------|-------|-------|-------|-------|
| Own weather index           | 0.0637*** | 0.0520*** | 0.0634*** | 0.0589*** |
| Other weather index         | -0.0022 | 0.0023 | -0.0041 | -0.0075** |
| Outdoor × Own weather index | 0.0294*** |       |       |       |
| Outdoor × Other weather index | -0.0102 |       |       |       |
| winter × Own weather index  |       | -0.0035 |       |       |
| Summer × Own weather index  |       | -0.0035 |       |       |
| Fall × Own weather index    |       | 0.0085 |       |       |
| Winter × Other weather index | 0.0075 |       |       |       |
| Summer × Other weather index | 0.0027 |       |       |       |
| Fall × Other weather index  |       | -0.0146* |       |       |
| Great Plains × Own weather index | 0.0005 |       |       |       |
| Midwest × Own weather index | 0.0067*** |       |       |       |
| Northwest × Own weather index | 0.0301*** |       |       |       |
| Southeast × Own weather index | 0.0046* |       |       |       |
| Southwest × Own weather index | -0.0017 |       |       |       |
| Great Plains × Other weather index | 0.0008 |       |       |       |
| Midwest × Other weather index | 0.0082** |       |       |       |
| Northwest × Other weather index | 0.0031 |       |       |       |
| Southeast × Other weather index | 0.0117** |       |       |       |
| Southwest × Other weather index | 0.0020 |       |       |       |
| Observations                | 32,036 | 32,036 | 32,036 | 32,036 |
| Adjusted R²                 | .943   | .9431  | .943  | .943  |

**Note:** Observations are indoor or outdoor sales aggregated at the MSA level. “Own weather index” refers to the indoor (outdoor) weather index for indoor (outdoor) stores, while “other weather index” refers to the outdoor (indoor) weather index for indoor (outdoor) stores. Regressions include only MSAs with indoor and outdoor stores and control for MSA, weekday, month, year, and holiday fixed effects as well as linear and quadratic time trends and number of stores included to adjust for changes in sales due to exit and entry. The omitted season in column 3 is spring, while the omitted region in column 4 is the Northeast. * p < 0.10, ** p < 0.05, *** p < 0.01

**Source:** proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)
### Table 3: Relationship between indoor and outdoor weather indexes

| Dependent variable: Own weather index | Indoor Stores (1) | Indoor Stores (2) | Outdoor Stores (3) | Outdoor Stores (4) |
|--------------------------------------|------------------|------------------|--------------------|-------------------|
| Max Temp > 90°F                      | -0.253***        | -0.191           |                    |                   |
| Max temp below freezing              | -0.347           | -0.968***        |                    |                   |
| it’s raining                         | 0.301***         | -0.133**         |                    |                   |
| it’s snowing                         | -1.299***        | -2.022***        |                    |                   |
| snow on ground                       | -1.034***        | -1.217**         |                    |                   |
| Other weather index                  |                  |                  | 0.770**            | 0.377***          |
| Other weather index \* Max temp > 90°F | 0.046           | 0.175            |                    |                   |
| Other weather index \* Max temp below freezing | -0.242*       | 0.529***         |                    |                   |
| Other weather index \* Positive precipitation | -0.610***     | -0.298***        |                    |                   |
| Other weather index \* Positive snowfall | 0.407           | 0.754***         |                    |                   |
| Other weather index \* Positive snow depth | 0.347***      | -0.040           |                    |                   |

| Observations                         | 16,017           | 16,017           | 16,017             | 16,017            |
| Adjusted $R^2$                       | .0818            | .3267            | .2148              | .4284             |

Notes: Observations are at MSA level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Observations are average indoor or outdoor weather indexes at the MSA level. “Own weather index” refers to the indoor weather index for columns 1 and 2, and the outdoor weather index for columns 3 and 4. “Other weather index” refers to the outdoor weather index for columns 1 and 2, and indoor weather index for columns 3 and 4. Regressions include only MSAs with indoor and outdoor stores and control for MSA, weekday, month, year, and holiday fixed effects as well as linear and quadratic time trends and number of stores included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)
Figure 1: Weather observations by climate region

(a) Temperature

(b) Precipitation

(c) Snowfall

(d) Snow Depth

Note: Plots show regional heterogeneity of distributions of observed weather. For precipitation, snowfall, and snow depth, box plots show distributions of non-zero observations and percentages in parentheses next to region names indicate the fraction of days with positive observations.

Source: NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)
Figure 2: Historical means and standard deviations of precipitation and snowfall

(a) Precipitation

(b) Snowfall

Note: Plots show historical means and standard deviations based on weather observed on the first day of each month from 1980 - 2009. These statistics have been estimated using a Bartlett weighting kernel to smooth over the 14 days before and after a particular day of the year at each station. Station means and standard deviations have then been inverse-distance weighted based on store locations.

Source: NOAA NCDC GHCND weather station observations.
Figure 3: Temperature Effects by Season

Note: Plots show coefficient estimates with confidence intervals for regressions of log of daily net sales on the indicators for weather observations. All regressions include store, year, month, holiday, store-month, and store-trend fixed effects and control for store openings and closings. The regression controls for precipitation, snowfall, and snow depth and shows effects relative to the base category of 70-75°F. Winter is defined as December - February, and summer is defined as June - August.

Source: Proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)
Figure 4: Weather index illustration

Note: The upper panel shows for a city in the Northeast the indoor and outdoor weather index described in section 4.3, where positive (negative) values indicate that local current weather conditions are (un)favorable for sales. The gray shading highlights the periods during which the two indexes are negatively correlated. The lower panel shows the observed weather on those days. The gray bars show precipitation levels. The thin solid line shows snow depth while the black dots show snowfall. Maximum and minimum temperatures are indicated by the dashed and dash-dotted lines.

Source: Proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). *Global Historical Climatology Network Daily*. (Accessed April 22, 2015.)
Figure 5: Cumulative Daily Effects of Weather Events

(a) Unfavorable Weather Effects

(b) Favorable Weather Effects

Note: Plots show coefficient estimates with confidence intervals for distributed lag regressions of log of daily net sales on the weather index interacted with indicators for whether the index value is positive or negative. The weather index has been constructed separately for indoor and outdoor stores and has a mean of zero and standard deviation of one for each of those groups of observations. A positive index value indicates that weather conditions are favorable for contemporaneous sales. Effects shown are cumulative starting one week before the weather shock, which occurs at time 0. Regressions include store, month, weekday, holiday, store-month, store-weekday, and store-trend fixed effects. Controls for store opening and closing indicators.

Source: Proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)
Figure 6: Indoor and Outdoor Responses to Weather

(a) Average Temperature

(b) Precipitation

(c) Snowfall

(d) Snow Depth

Note: Plots show coefficient estimates with confidence intervals for regressions of log of daily net sales on the indicators for weather observations. All regressions include store, year, month, holiday, store-month, and store-trend fixed effects and control for store openings and closings. The regression depicted in panel (a) controls for precipitation, snowfall, and snow depth and shows effects relative to the base category of 70-75°F. Panels (b)-(d) control for maximum temperature and show effects relative to zero precipitation, snowfall, and snow depth. The orange coefficient bar with the diamond marker indicates the cumulative effect on the day of the shock, while the green bars show the effects at one week intervals from the day of the shock.

Source: Proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)
Figure 7: Weather Effects on Online Sales

Note: Regression observations are aggregated at weekly county level, with weeks starting on Tuesdays. Plots show coefficient estimates from three separate regressions estimating the response of ecommerce sales to weather index values based on sales in indoor, outdoor, or averages across both types of stores. A low percentile range weather index value indicates unfavorable weather conditions for shopping in a given store type. Regressions include store, year, month, holiday, MSA-month, and MSA-trend fixed effects. Source: Proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). Global Historical Climatology Network Daily. (Accessed April 22, 2015.)