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

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

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**Abstract**

Using novel methodology and proprietary daily store-level apparel and sporting goods brand data, I find that, consistent with long-run adaptation to climate, sales sensitivity to weather declines as historical norms and variability of weather increase. Short-run adaptation to weather shocks is dominated by changes in how much people buy on the day of the event. There is little intertemporal substitution. Over four weeks, a one-standard deviation one-day weather shock shifts sales by about 10 percent. While switching between indoor and outdoor stores offsets a small portion of contemporaneous responses, I find no evidence that ecommerce offsets any of the effects.

**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 the backdrop of increasing average temperatures and weather variability, economists have studied the effects of weather and adaptation in a variety of contexts, including agriculture, health, labor, housing, and fisheries. In this paper I study adaptation in the context of retail sales, a sector not typically considered particularly weather-sensitive, that accounts for roughly ten percent of total employment. In addition to potentially affecting firm profitability, retail sensitivity to weather can increase income volatility for low-income 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).) Therefore, increased weather-induced variability in sales is one channel through which climate change could have implications for inequality.

I examine both long-run adaptation to climate and short-run adaptation to weather shocks in the context of one apparel and sporting goods retail brand. Long-run adaptation occurs when more experience with a weather phenomenon reduces sensitivity to it. This may be achieved by investment in durables like 4-wheel drive vehicles or development of human capital like ability to drive in snow. I define short-run adaptation as changes to when, how, and what tasks people accomplish or goods they consume in maximizing utility in response to immediate weather shocks and 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. Whether weather shocks induce people to switch consumption among goods, substitute intertemporally, or shift shopping between indoor and outdoor shopping centers or to online stores can have significant implications for retail stores and their employees.

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 are less responsive to given snowfall levels. Sensitivity to weather shocks is reduced based on both historical norms and standard deviations of weather, suggesting potential for some adaptation to changes in both levels of weather outcomes (like higher temperatures) and increased variability projected under climate change.

I apply novel methodology from Roth Tran (2017) to examine short-run adaptation to the weather shocks that are most important for sales of the firm. 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.) Cross-validation limits over-identification while allowing for flexibility, allowing me to examine how sales gains and losses due to "good" and "bad" weather—determined within specific contexts—are made up, if at all. In particular, I allow a 60F 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 in this context involves only very limited intertemporal substitution, which would involve offsetting sales effects in the weeks before and after shocks. Instead, contemporaneous responses to weather shocks appear to be amplified over time and largely permanent. A one-standard deviation negative (positive) weather shock yields about a 10 percent largely persistent loss (gain) in sales.

I find that short-run adaptation to weather primarily involves changes to *what* people buy and to a leser extent *how* they buy it. In particular, when I limit the analysis only to metropolitan statistical areas with both types of stores, I find some evidence of weather-induced shifting of purchases between indoor and outdoor stores. However, at best 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. However, I 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 unfavorable weather for stores does not appear to affect online sales on net. The limited scope of intertemporal and venue substitution suggests that the main response to weather in this context is to change how much people buy.

Although it is possible that results of similar analyses to 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 while applying current weather responses to future climate projections would overstate effects of climate change on the retail sector, assuming perfect adaption would greatly understate these effects. Third, examining only contemporaneous weather effects could pose problems, as demonstrated by the amplification over time of contemporaneous effects of negative weather shocks.

In terms of contributions, to my knowledge, this is the first paper to use historical data to empirically examine how sensitivity to weather shocks depends on the second moment of weather as well as the first. 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 use high frequency data.[1] In terms of retail sales, this paper is the first to examine differences in weather effects on shopping at indoor and outdoor venues (though some recent work has confirmed some of these findings), intertemporal effects, and shifting from brick-and-mortar stores to online sales with one dataset, especially one that spans the broad range of climates experienced within the United States.

The evidence presented here also suggests that brands may be able to increase resilience to higher weather variability a little bit 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 (2017).)

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 the retail sector. In sections 2 and 3, I describe the data and empirical methodology I use. I follow this with a discussion of results in section 4 and finally a conclusion in section 5.

[1] Addoum, Ng and Ortiz-Bobea (2019) 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.

# 1 Literature

This paper builds upon research examining adaptation to climate change, weather effects in retail spending, and how outdoor activity responds to weather.

Literature empirically examining adaptation to climate change has focused largely on agriculture (see for example Schlenker and Roberts (2009), and Kala (2017)), cyclones (see Hsiang and Narita (2012) and Bakkensen and Mendelsohn (2016)), and health (see for example Deschênes and Greenstone (2011) and Barreca et al. (2015)), with additional works looking at topics like labor (Behrer and Park (2017)), income (Deryugina and Hsiang (2017)), and fisheries (Shrader (2017)). These include several analyses using a similar approach to the one I undertake here of examining long-term adapation by interaction weather shocks with historical norms (see for example, Hsiang and Narita (2012), Barreca et al. (2015), and Behrer and Park (2017)).

There is also a significant body of literature examining how weather affects retail sales, dating back to Steele (1951). This literature is largely oriented toward marketing and operations management and has to date primarily been performed on 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, while Starr-McCluer (2000) showed although weather affects national monthly retail sales, these effects are offset by in subsequent months, yielding no meaningful effects at the quarterly level. Parsons (2001), Bahng and Kincade (2012), Bertrand, Brusset and Fortin (2015), and Parnaudeau and Bertrand (2018) are additional examples of studies showing that weather has significant effects on retail sales. In contrast, Addoum, Ng and Ortiz-Bobea (2019) find that temperatures are generally unrelated to non-energy sector sales when using annual data on firm establishment sales. However, it is possible that their null results are sensitive to the low frequency of outcomes, their definition of extreme temperatures, and other biases I discuss in section 3.3.

With an emphasis on operations management, the recent working paper Belkaid and de Albéniz (2017) shows that daily sales for an apparel brand in Europe increase in indoor stores and decrease in outdoor stores in response to precipitation. They further show that this effect is primarily driven by decreased footfall 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.

There is a strand of literature that 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 (2019).) Weather has also been shown to affect outdoor activity. Particularly, Smith (1993) shows that beach use, swimming, golf and tennis all respond to temperature, with some nonlinear effects. Graff Zivin and Neidell (2014) use the American Time Use Survey to show that high temperatures decrease time allocated to outdoor leisure, while Chan and Wichman (2018) examine data on 27 million weekend bikeshare trips and find that leisure cycling activity is very responsive 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 supports both the idea that underlying demand for apparel and sporting goods products could be affected by weather and that the utility of shopping in exposed outdoor versus covered indoor venues is also likely affected by weather.

## 2 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, which I define as requiring consumers to enter the store 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. I also average over maximum and minimum 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 7 weather stations per location and causes me to drop 3 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 have allocated each of the store locations to one of the climate regions defined the National Climate Assessment (Melillo, Richmond and Yohe (2014).) With national representation of the stores, my data include a wide range of distributions of weather observations. For example, while locations in the Northwest have the highest share of days with positive precipitation, observed precipitation levels at the high end of the distribution are much lower than those in the Southeast. My data also include significant variation in observed temperature, snowfall, and snow depth distributions. Figure A.1 in the appendix 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. I apply a Bartlett weighting kernel to smooth over the 14 days before and after a particular day of the year in order to calculate the daily normal and standard deviation for each element at each station. This kernel places the greatest weight on the day of interest with the weights on the surrounding days diminishing linearly with distance from the day of interest. This smoothing incorporates rare events without introducing too much day-to-day noise in normals and avoids discrete jumps in normals at the start and end of each month.

As in the case of distributions of daily weather observed in the time frame for which I have sales data, my data include a wide range of historical norms and standard deviations. While the means and standard deviations 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, there is some variation in these relationships, as demonstrated by the scatter plots of precipitation and snowfall means and standard deviations in Appendix Figure A.2. This is consistent with the previously described scenario where some areas like the Northwest, for example, see frequent low levels of precipitation and others like the Southeast experience less frequent but higher levels of precipitation.

# 3 Empirical Strategy

## 3.1 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, I estimate the following model:

$$\begin{aligned} \ln(\text{Sales}_{it}) = {} & \boldsymbol{\omega} \cdot \mathbf{weather}_{it} + \alpha + \boldsymbol{\alpha_i} + \boldsymbol{\beta_1} \cdot \text{year}_t \\ & + \boldsymbol{\beta_{2i}} \cdot \text{store}_i \cdot t + \boldsymbol{\beta_{3i}} \cdot \text{store}_i \cdot t^2 \\ & + \boldsymbol{\beta_{4i}} \cdot \text{store}_i \cdot \text{month}_t \\ & + \boldsymbol{\beta_5} \cdot \text{holiday}_t \\ & + \boldsymbol{\beta_{6i}} \cdot \text{store}_i \cdot \text{weekday}_t \\ & + \boldsymbol{\beta_7} \cdot \text{store\_closure\_or\_opening}_{it} + \varepsilon_{it}. \end{aligned} \tag{1}$$

Weather can be modeled in a variety of ways in this setup, with $\boldsymbol{\omega}$ the coefficient of interest. The fixed effects include store, year, store-by-trend, store-by-quadratic trend, store-by-calendar month, specific holiday, and store-by-day-of-week fixed effects. I also allow for the first or last week or month of a store's existence to yield different sales effects.[2]

## 3.2 Long-run adaptation

When estimating long-run adaptation to climate, I follow the approach in Dell, Jones and Olken (2014). In particular, I estimate

$$\ln(\text{Sales}_{it}) = \alpha + \boldsymbol{\alpha_i} + \boldsymbol{\beta X}_{it} + \phi_1 \cdot ELEM_{it} + \phi_2 \cdot \overline{ELEM}_{it} \cdot ELEM_{it} + \varepsilon_{it}, \quad (2)$$

where $\boldsymbol{X}_{it}$ is the standard set of fixed effects from equation 1, $ELEM_{it}$ is the weather element of interest, and $\overline{ELEM}_{it}$ is the daily historical normal of the weather element. An estimate with opposite signs on $\phi_2$ and $\phi_1$ would be consistent with long-run adaptation because it indicates that people living in climates that are 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 specification in equation 2 by adding standard deviations to see how acclimation to more variable weather affects sensitivity to weather events. This is important because climate change predictions not only suggest that temperatures will increase but also that weather will become more extreme and variable, an increase in the standard deviation of observed weather. I model this by adding

[2] 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.

a standard deviation version of the interaction term as follows:

$$\begin{aligned}\ln(\text{Sales}_{it}) =& \alpha + \boldsymbol{\alpha_i} + \boldsymbol{\beta X}_{it} + \phi_1 \cdot ELEM_{it} + \phi_2 \cdot \overline{ELEM}_{it} \cdot ELEM_{it} \\ & + \phi_3 \cdot \sigma_{it}^{ELEM} \cdot ELEM_{it} + \varepsilon_{it}.\end{aligned} \tag{3}$$

## 3.3 Weather index

Weather effects are nonlinear, sensitive to context, and dependent upon interactions between the elements. For example, the contemporaneous average response of sales in this data to temperature is that of an inverted U-shape.

One way to model weather nonparametrically is to bin element realizations 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 here 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.[3]

An alternative approach might be to model weather in terms of deviations from the mean. However, when compared to alternatives, an unusually warm day in summer may make shopping–particularly in an indoor mall–relatively attractive, while an unusually warm day in winter may make shopping relatively unattractive, and again particularly so in an indoor mall. Averaging across these effects could yield attenuation bias.

[3]For example, Figure A.3 in the appendix 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.

Another complication is that interactions between elements can matter. 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 the mall in the first place. The approaches using nonparametric binning or deviations 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.

For the reasons described above, my preferred method for examining short-run adaptation to weather shocks is to use the weather index method described in Roth Tran (2017). Using the lasso machine learning method in a residuals-on-residuals framework to select from among thousands of variables while limiting risk of overfitting, this index flexibly evaluates how favorable weather conditions are for sales. It allows for non-linear, heterogeneous responses based on context and interactions between weather elements. The index has been standardized to have a mean of 0 and a standard deviation of 1, where a high positive (negative) value indicates that weather conditions are very (un)favorable for sales in the given store type, region, and season.

## 3.4 Short-run adaptation

Because I do not have data on individual shoppers, I am limited in my ability to say what individuals do instead of buying a product at one of the stores in my data. However, I examine the extent to which contemporaneous gains and losses are offset at other times and places, which would be consistent with intertemporal and venue substitution.

I begin by testing for intertemporal effects of weather shocks. Here I follow the structure of equation 1 and add lags and leads of weather index values.

Because the weather index has been structured to have a mean of zero and standard deviation of 1, with positive values indicating weather that is favorable for shopping, negative coefficients on lags and leads are consistent with intertemporal substitution from the firm's perspective. When examining leads and lags of weather index quantile bins, offsetting and substitution is indicated by positive coefficients on low weather index values and negative coefficients on high ones.

Next I examine relationships between indoor and outdoor stores. Looking only at MSAs with both indoor and outdoor stores, I separately aggregate daily MSA-level sales at indoor and outdoor stores and define the following indexes:

$$\begin{aligned} W_{own,jmt} &= W_{outdoor,mt} \cdot \mathbb{1}[j = outdoor] + W_{indoor,mt} \cdot \mathbb{1}[j = indoor] \\ W_{other,jmt} &= W_{outdoor,mt} \cdot \mathbb{1}[j \neq outdoor] + W_{indoor,mt} \cdot \mathbb{1}[j \neq indoor] \end{aligned} \tag{4}$$

I then estimate the following equation:

$$\ln(\text{Sales}_{jt}) = \alpha + \boldsymbol{\alpha_j} + \boldsymbol{\beta X}_{jt} + \gamma_1 \cdot W_{own,jt} + \gamma_2 \cdot W_{other,jt} + \varepsilon_{jt} \tag{5}$$

Because the analysis is no longer performed at the store level, $\text{Sales}_{jt}$ is the aggregate sales at indoor or outdoor stores within MSA $j$ on day $t$. $\boldsymbol{X}_{jt}$ are the non-weather fixed effects from equation 1. I also add an indicator for the number of stores in the MSA, allowing the sales to shift with entry and exit of stores in the area. The index that corresponds to the store type of location $i$ is represented by $W_{own,it}$, with the index for the other store type represented by $W_{other,it}$. 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.

# 4 Results

## 4.1 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 $\phi_2$, the coefficients on the element and interaction terms in equation 2, have opposite signs in all of the columns except for column 2 for minimum temperature. This shows that sensitivity to weather declines with higher norms. 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 normal snowfall is positive, this effect is weaker for areas and times when snowfall is historically more common.

Adding interactions between current weather and historical standard deviations as in equation 3, Panel B shows that areas accustomed to more variable weather also appear to be less sensitive to given weather shocks. In particular, in all columns except column 1 for maximum temperature, it is variability—and not the historical mean—that decreases sensitivity to weather shocks.

These results indicate that there is some long-run adaptation to climate in shopping because sensitivity to weather shocks is lower in areas and times when historical means and standard deviations are greater. However, the coefficients on the $\phi_2$ and $\phi_3$ interaction terms in Table 1 are small relative to the coefficients on the stand-alone weather element terms, suggesting that the potential of adaptation may be limited. For example, column 4 of panel A tells us that a

1-inch snow fall event in a time and location when and where an inch of snow is the norm will see a 16 percent decline in sales, compared to a 17 percent decline in a time and location where the normal snow is just 0.1 inches. According to this analysis, a ten-fold increase in the norm reduces the response to snowfall by just 6 percent.

## 4.2 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. Here I examine intertemporal weather effects using the weather index described in section 3.3 that has a mean of zero and standard deviation of one and allows for nonlinearities, interactions, and context-dependent weather responses.

In Figure 1b, I examine intertemporal substitution in the context of negative and positive realizations of the weather index that allows for heterogeneous and nonlinear effects. I show cumulative effects starting seven days prior to a weather event. Here the positive coefficients shown are applied to negative realizations of the weather index and therefore indicate declines in sales. I find that sales respond in advance of weather events and that the contemporaneous effects are amplified in the days immediately before and after weather shocks. The sales response to negative weather shocks shown in Figure 1a appears to be persistent, with a one-standard deviation unfavorable weather event yielding a loss of about 6 percent of daily sales on the day of the event and amounting to about 12 percent after accounting for the prior and subsequent responses.

Figure 1b shows that effects of positive weather events are also amplified in the days immediately before and after the actual shock. However, here the point estimate of the cumulative effect drops off a bit by the end of three weeks to end up closer to 6 percent, about half of the peak level effect, as there appears to be some intertemporal shifting. This suggests 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 take away that the results shown in Figure 1b raise is that examining just the contemporaneous effect of a weather shock may not accurately reflect total weather effects, because sales start responding to weather before it actually hits and may either continue to grow or diminish over time. This also suggests that individuals, stores, or both are adjusting their behavior based on weather forecasts, which 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 about a 10 percent cumulative shock in terms of one day of sales for the brand I examine.

## 4.3 Substitution between indoor and outdoor stores

I now estimate equation 5 to examine whether people adapt to weather by shifting their shopping activity between indoor and outdoor stores and present the results in Table 2. Here 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. This suggests that venue substitution may not be a major component of short-run adaptation. 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 explore whether weather shocks can yield indoor versus outdoor substitution more in some seasons than others. Here I find some weak evidence of substitution in the fall, though this is significant only at the 10 percent level.

Finally, in column 4 I test whether substitution between indoor and outdoor venues is more likely to occur in some regions than others. Here I do find some evidence that this may be the case. 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, as evidenced by the significantly positive coefficients of a slightly larger magnitude than the base other weather index coefficient, in the Midwest and Southeast there does not appear to be such substitution. 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 2 shows the effects of average temperature, precipitation, snowfall and snow depth on sales at indoor and outdoor stores. Note that in the case of temperature, the results are relative to days with average temperatures in the 70-75°F range, while the other variables show results relative to zero precipitation, snowfall, or snow depth.

Controlling for precipitation, snowfall, and snow depth, Figure 2a 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 be taken with a grain of salt because, as described in section 3.3, temperature effects depend on factors like season and region, so these averages may mask some seasonal substitution-like behavior.

Figure 2b shows that precipitation appears to induce offsetting shopping patterns at indoor and outdoor stores. In particular, any positive level of precipitation appears to drive down sales at outdoor stores. In contrast, 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 3.3.)

Finally, Figures 2c and 2d show that snowfall and snow depth appear to decrease sales in a similar manner at indoor and outdoor stores. While Figure 2c shows that snowfall yields a somewhat stronger negative effect at outdoor stores, Figure 2d shows that snow depth, when controlling for contemporaneous snowfall, has a more consistently negative effect on outdoor stores, but appears to have a larger negative effect percentage-wise at indoor stores for the 2-12 inch range.

On the whole, the non-parametric results shown in Figure 2 suggest that shoppers may adapt in the short run to some weather events by switching between indoor and outdoor stores, while others (particularly snowfall) may simply force them to stay home.

## 4.4 Substitution from physical store to online sales

When faced with unpleasant weather for shopping, rather than shifting between venues and over time, consumers may instead opt to make purchases online. In

Figure 3, 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 brick-and-mortar 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 this pattern, I observe a flat and somewhat upward sloping curve. It appears that weather that is favorable for shopping in physical stores also drives online sales, while weather that is bad for shopping in physical stores does not have a significant net effect on ecommerce for this brand. This suggests that shopping activity in stores drives 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.

# 5 Conclusion

In this paper, I have implemented novel techniques using daily store-level sales data for a nation-wide apparel and sporting goods brand to show that both short- and long-run adapation partially mitigate responses of retail sales to weather shocks.

In terms of short-run adaptation, while I have found that sales shift somewhat between indoor and outdoor locations in response to some weather shocks, I have found no evidence supporting significant weather-induced substitution between brick-and-mortar sales and online shopping. I have found that timing shifts only partially offset positive weather shock effects, while responses to negative weather shocks tend to instead grow over time. On net, sales in the days immediately before and after weather shocks amplify contemporaneous effects, suggesting that shoppers, stores, or both are adjusting their behavior in response to weather forecasts.

I have also found evidence of long-run adaptation as responses to specific types of weather shocks moderate in locations and times where those shocks are more common. To the best of my knowledge, this is the first paper to show that it is not only the historical mean but also the variance that decreases sensitivity to weather shocks, an important finding as variability of weather is projected to increase due to climate change.

Future work could build upon the results of this paper in a variety of ways. Examining more spending categories using micro data could shed additional light on adaptation. In particular, it is possible that due to the nature of the product, the demand for the apparel and sporting goods brand examined in this paper is more sensitive to weather shocks than other categories or in a different way. Seeing if other retail categories respond in a similar manner would be helpful. It would be interesting to look at a longer time panel to see if responses shift over time, another sign of long-run adaptation. And finally, it would be worthwhile to examine individual responses using the methodology I have applied here but with data like the American Time Use Survey, for example, to see what individuals are shifting their time to as they adapt to weather shocks.

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. 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 adpating to the effects of climate change and also to understanding its potential implications for economic inequality.

## 6 Tables and Figures

Table 1: Adaptation to climate

Panel A: Means

| ln(sales) | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Max Temp | 0.0361*** | | | | |
| Max Temp × Norm Max Temp | -0.000554** | | | | |
| Min Temp | | 0.0152*** | | | |
| Min Temp × Norm Min Temp | | 0.000612* | | | |
| Precipitation | | | -0.130*** | | |
| Precipitation × Norm Precip | | | 0.00663*** | | |
| Snowfall | | | | -0.171*** | |
| Snowfall × Norm Snowfall | | | | 0.0128** | |
| Snow Depth | | | | | -0.0346*** |
| Snow Depth × Norm Snow Depth | | | | | 0.000301** |
| Observations | 124610 | 124606 | 124889 | 133890 | 134626 |
| Adjusted $R^2$ | .8525 | .8521 | .852 | .86 | .8576 |

Panel B: Means and Standard Deviations

| ln(sales) | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Max Temp | 0.0593** | | | | |
| Max Temp × Norm Max Temp | -0.000932** | | | | |
| Max Temp × SD Dev Max Temp | -0.00323 | | | | |
| Min Temp | | 0.0478*** | | | |
| Min Temp × Norm Min Temp | | -0.000170 | | | |
| Min Temp × SD Min Temp | | -0.00592** | | | |
| Precipitation | | | -0.213*** | | |
| Precipitation × Norm Precip | | | -0.00725*** | | |
| Precipitation × SD Precip | | | 0.00723*** | | |
| Snowfall | | | | -0.227*** | |
| Snowfall × Norm Snowfall | | | | -0.00395 | |
| Snowfall × SD Snowfall | | | | 0.00981*** | |
| Snow Depth | | | | | -0.0671*** |
| Snow Depth × Norm Snow Depth | | | | | -0.000902** |
| Snow Depth × SD Snow Depth | | | | | 0.00190*** |
| Observations | 124610 | 124606 | 124889 | 76712 | 89099 |
| Adjusted $R^2$ | .8526 | .8523 | .8522 | .819 | .8231 |

*Note:* Results 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.)

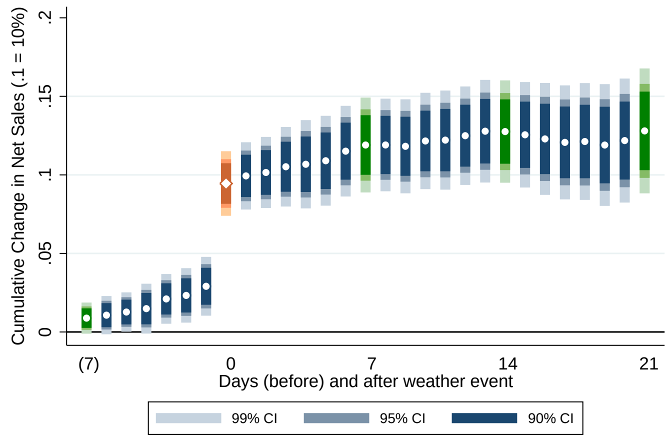
Table 2: Substitution between indoor and outdoor stores

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ln(Net Sales) | | | | |
| 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 | 32036 | 32036 | 32036 | 32036 |
| Adjusted $R^2$ | .943 | .9431 | .943 | .943 |

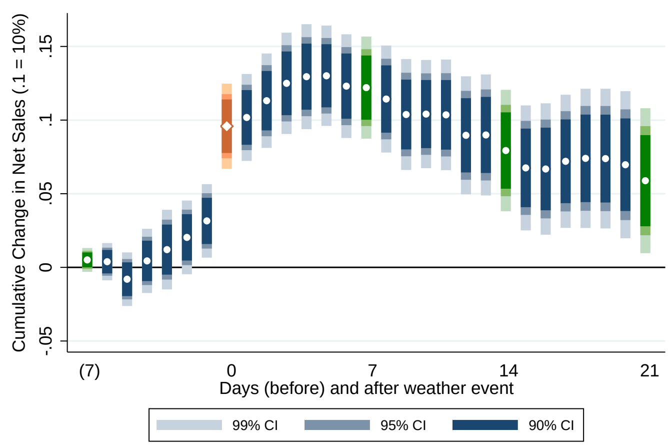
*Note:* Observations are indoor or outdoor sales aggregated at the MSA level. "Own weather index" refers to the indoor (outdoor) weather index for indoor (outdoor) stores, while "other weather index" refers to the outdoor (indoor) weather index for indoor (outdoor) stores. Regressions include only MSAs 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.)

Figure 1: Cumulative Daily Effects of Weather Events

(a) Unfavorable Weather Index Effects



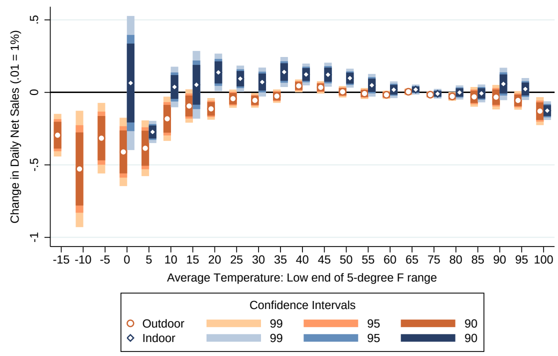

(b) Favorable Weather Index Effects



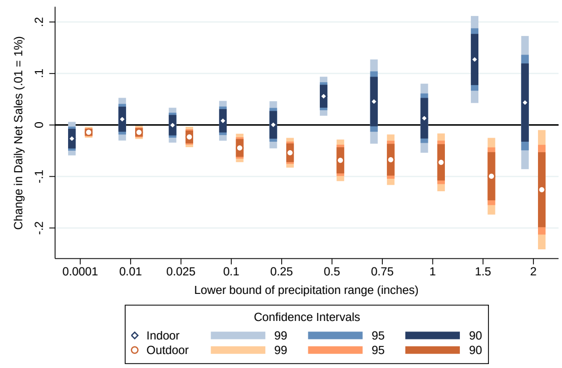

*Note:* Plots show coefficient estimates with confidence intervals for distributed lag regressions of log of daily net sales on the weather index interacted with indicators for whether the index value is positive or negative. The weather index has a mean of zero and standard deviation of 1 and has been constructed separately for indoor and outdoor stores. A positive index value indicates that weather conditions are favorable for contemporaneous sales. In panel (a), the positive cofficients are applied to negative index realizations, so that the cumulative net change reflects the magnitude of a decrease in 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, store opening and store closing fixed effects and control for store-specific linear and quadratic trends. *Source:* proprietary sales data; NOAA, National Centers for Environmental Information (NCEI). *Global Historical Climatology Network Daily.* (Accessed April 22, 2015.)

Figure 2: Indoor and Outdoor Responses to Weather

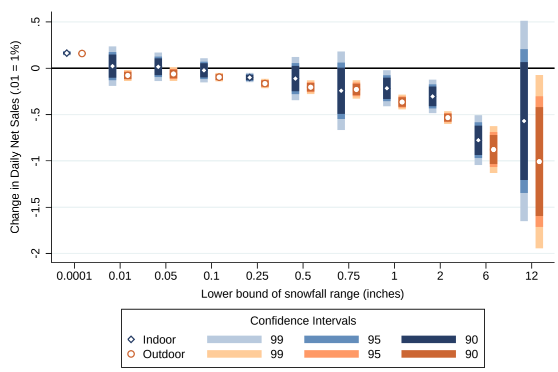
(a) Average Temperature



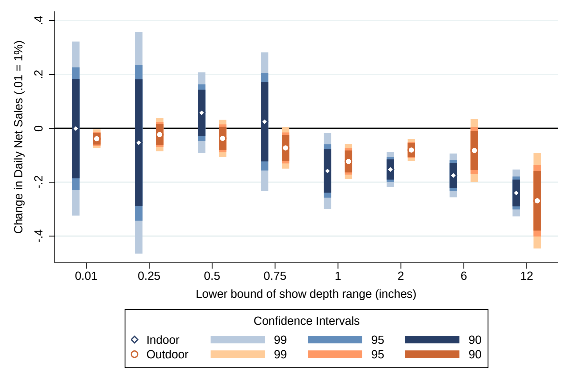

(b) Precipitation




(c) Snowfall

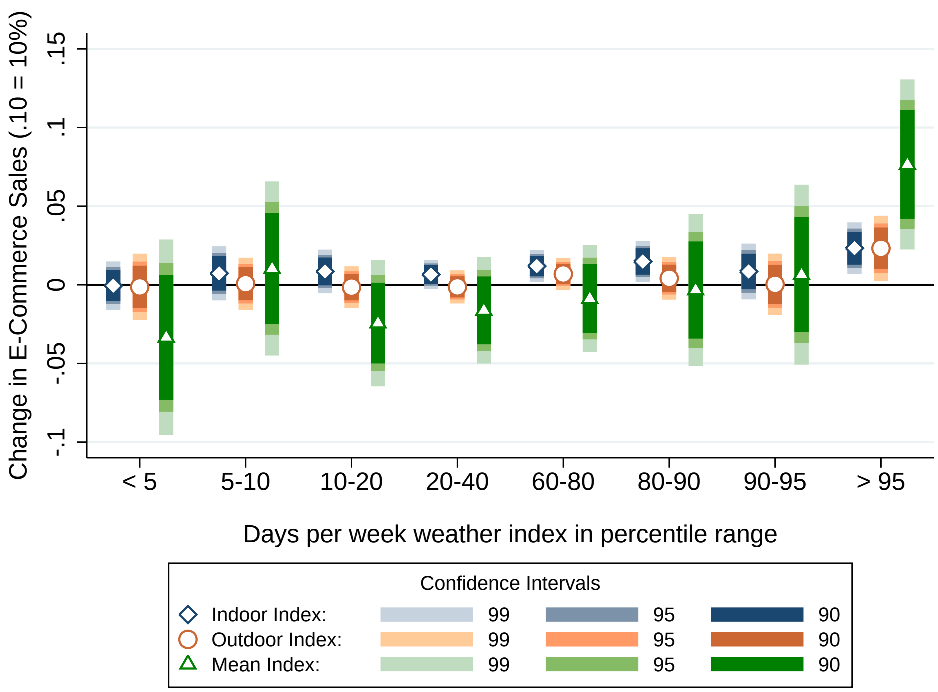



(d) Snow Depth




*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 3: 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.)

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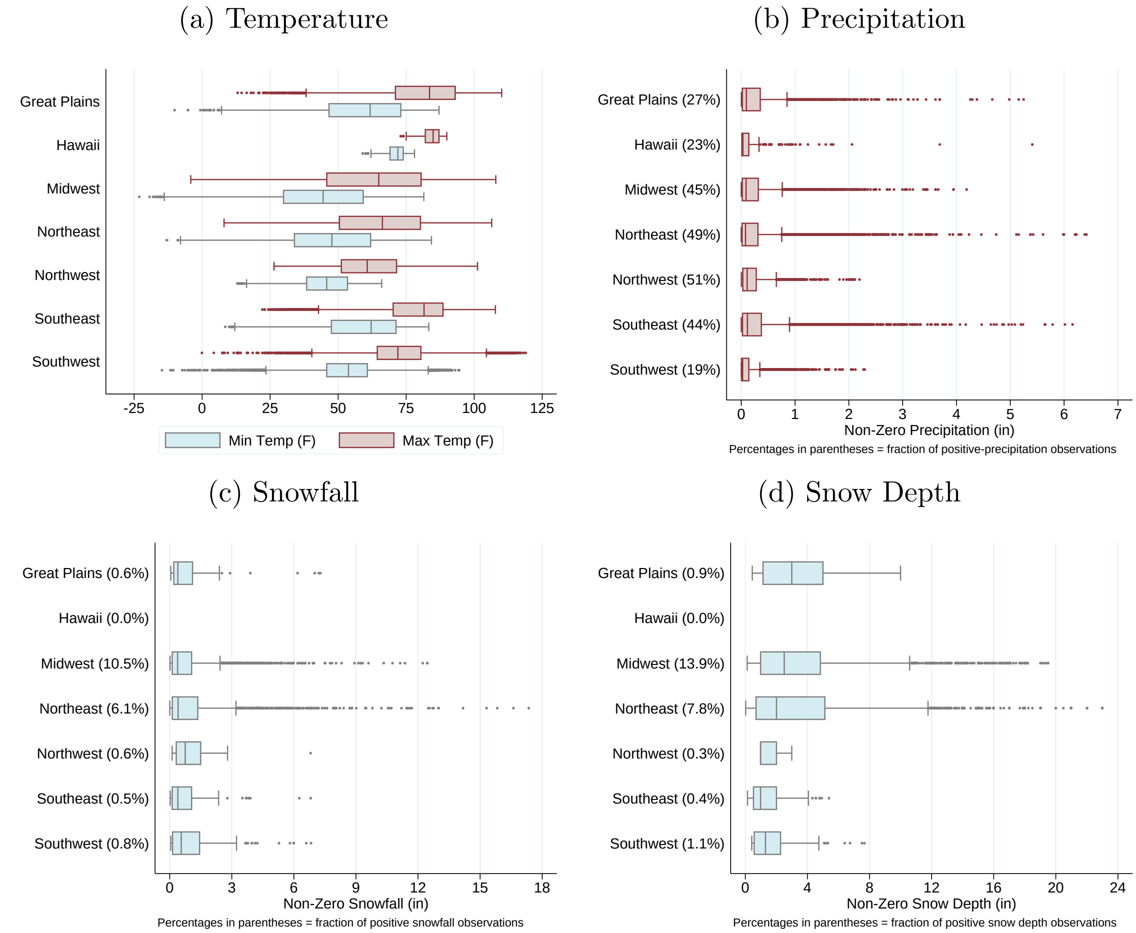
# A Appendix

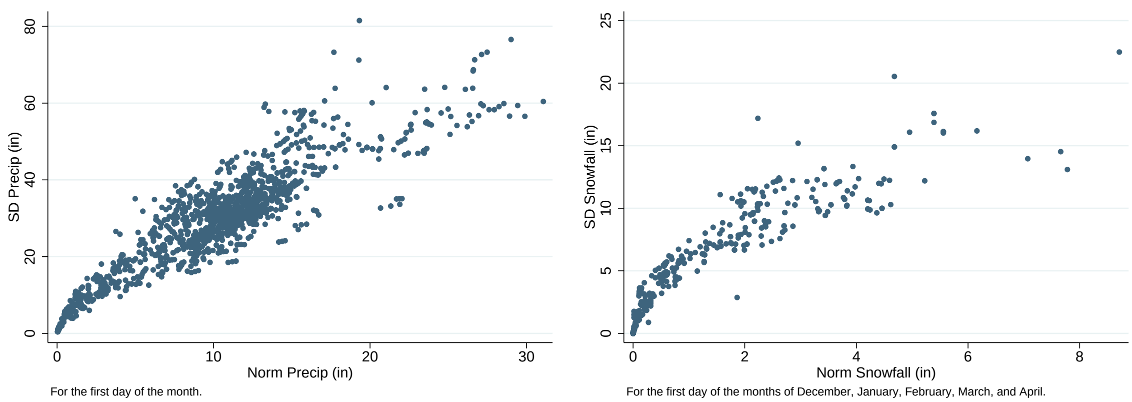
Figure A.1: Weather observations by climate region




*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.)

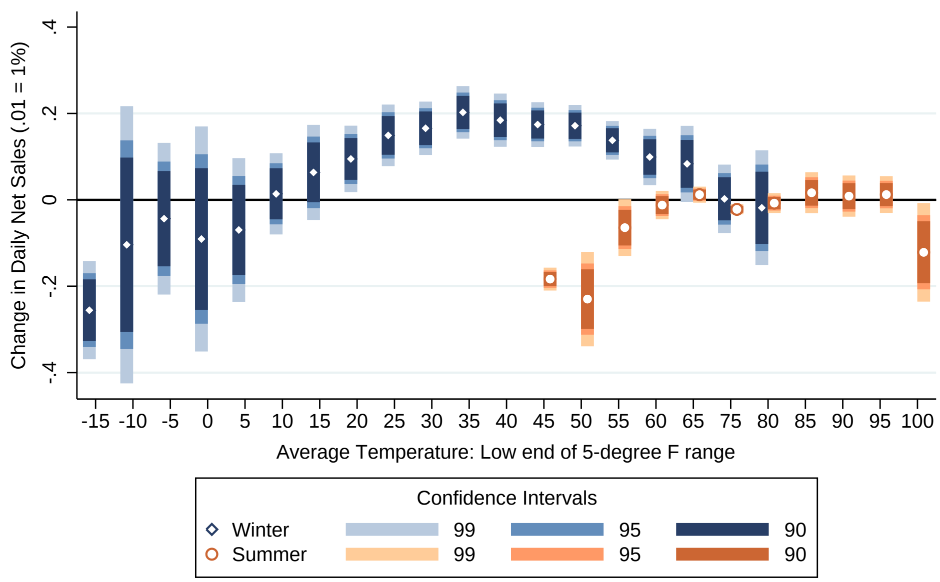
Figure A.2: Historical means and standard deviations of precipitation and snowfall

(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 A.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.)