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# The impact of daily weather on retail sales: An empirical study in brick-and-mortar stores

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ABSTRACT

In this study, we examine the influence of weather on daily sales in brick-and-mortar retailing using empirical data for 673 stores. We develop a random coefficient model that considers non-linear effects and seasonal differences using different weather parameters. In the ex-post analysis using historic weather data, we quantify the explanatory power of weather information on daily sales, identify store-specific effects and analyze the influence of specific sales themes. We find that the weather has generally a complex effect on daily sales while the magnitude and the direction of the weather effect depend on the store location and the sales theme. The effect on daily sales can be as high as 23.1% based on the store location and as high as 40.7% based on the sales theme. We also find that the impact of extreme bad and good weather occurrences can be misestimated by traditional models that do not consider non-linear effects. In the ex-ante analysis, we analyze if weather forecasts can be used to improve the daily sales forecast. We show that including weather forecast information improves sales forecast accuracy up to seven days ahead. However, the improvement of the forecast accuracy diminishes with a higher forecast horizon.

## 1. Introduction

While the weather's impact on business operations has been studied before (Steele, 1951; Bahng and Kincade, 2012), most of the research on the influence of the weather focuses on its impact on strategic decisions, i.e., mid-to long-term decisions (Chen and Yano, 2010; Bertrand et al., 2015). The weather's impact on operations (Parsons, 2001; Steinker et al., 2017) as well as on retail sales (Arunraj and Ahrens, 2016; Appelqvist et al., 2016) has received only limited attention.

Nevertheless, daily weather, which cannot be appropriately anticipated several weeks or even months in advance (Simmons and Hollingsworth 2002), has an immediate effect on daily businesses and sales. Weather, such as precipitation (rain and snow) and temperatures, significantly influence people's behavior (Cao and Wei, 2005; Murray et al., 2010), although it is unclear how shoppers change their shopping behavior in physical stores because of the weather. On one hand, shoppers may choose to exploit good weather, and they may choose to engage in an outside activity instead of visiting retail stores. Accordingly, they will postpone or forgo purchases. This consumer behavior can have major impacts on retailers:

> "Planalytics found that shopper traffic to specialty apparel stores in major cold-weather markets like Philadelphia, Boston, and Chicago fell 6%, 5%, and 4%, respectively, during that time. The firm estimates that, so far this holiday season, apparel-only stores have already lost $343 million through December 12. And that tally doesn't even include the department stores."
>
> – "That Warm Weather You Like Is Costing Retailers Hundreds of Millions", Fortune, Dec 16, 2015

On the other hand, bad weather might cause shoppers to stay at home and purchase through online channels instead of physical stores (Steinker et al., 2017), or it might cause them to change their plans and visit retail stores. Overall, the weather has a significant effect on the economy. According to Lazo et al. (2011) weather accounts for 3.4% of sales variations. However, such numbers have rarely been determined for individual businesses. In particular, it has not been studied which and how factors affect the weather influence, e.g., store location, product categories, etc.

From a managerial perspective, it is important to understand such weather influences in more detail for two reasons: First, managers need to account for the actual weather when analyzing past sales in an *ex-post analysis*. Retailers must understand the nature and impact of the different factors that potentially affected their historical sales. If sales have been affected by particularly good or bad weather, revenues and sales quantities must be corrected accordingly to enable an un-weather-

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biased planning for the future (e.g. to improve order quantities or to avoid unnecessary mark-downs). Second, managers could use weather forecasts in an *ex-ante analysis* to anticipate the impact of the weather on future sales and to improve daily decision making. If the weather is particularly good or bad, managers could change replenishment quantities from warehouses or change staff schedules in stores to better align these activities with the more precise sales forecast.

Studies that examine the influence of weather on businesses often examine the apparel industry (Chen and Yano, 2010; Bahng and Kincade, 2012; Bertrand et al., 2015, Babongo et al., 2018). The weather particularly influences the perception of the offered fashion goods. However, weather also generally affects the shopping behavior, i.e., keeping customers away from or driving customers into a store. Therefore, the weather also affects sales of non-apparel product categories, which has not been studied exhaustively. We aim to close this research gap by explicitly studying the sales of a multi-category retailer that offers a broad range of product categories from apparel to electronics to kitchen accessories and many more. Earning profits in the retail industry is tougher than in other industries (Gaur et al., 1999), and retailers are under pressure to avoid costly mistakes, e.g., over- and/or under-stocking. More accurate forecasts of customer traffic help to improve workforce planning in stores (Mani et al., 2015), price optimization and revenue management (Ferreira et al., 2016), and the inventory planning of stock keeping units (SKUs) (Williams et al., 2014).

Many meteorological service providers offer weather forecasts and weather information to retailers to improve planning, e.g., MeteoGroup, MetraWeather, Netweather. tv, and Planalytics. Although the application of weather information is widely available in practice, the academic research has not yet thoroughly investigated the impact of weather on retail sales (Arunraj and Ahrens, 2016). In this study, we leverage the data of 673 stores from a German retailer to examine the impact of weather on retail sales. We first conduct the ex-post analysis using actual weather data and develop a new empirical model that incorporates non-linearity and seasonality. We use the model to quantify the explanatory power of weather information on daily sales, identify store-specific effects and analyze the influence of specific sales themes across a broad range of different product categories. Next, we leverage our insights to conduct the ex-ante analysis using weather forecasts. We analyze how the model can be used to improve the accuracy of sales forecasts.

The next section reviews the related literature. We describe the data in the third section. Next, we develop our models, analyze the impact of weather on sales, and discuss the implications of the results. Finally, we conclude with our scientific and managerial contributions, limitations, and future research opportunities.

## 2. Literature

This study addresses and extends the stream of research into the weather's influence on sales, in particular on retail sales. To better understand this research issue, we provide an overview about two aspects of the literature. First, we summarize the factors that potentially link weather with sales in brick-and-mortar stores. Second, we discuss the existing studies that analyze the influence of weather on sales.

### 2.1. Factors linking weather with in-store sales

Steele (1951) conducted a seminal study identifying four potential factors linking weather to daily sales: (i) comfortableness, (ii) physical prevention, (iii) psychological effects on shopping habits, and (iv) desirability of certain products during certain weather periods.

*Comfortableness* describes a condition under which the weather does not physically prevent customers from going to a store but creates the feeling that the shopping trip is unpleasant. For example, workers find that bad weather eliminates distractions and allows individuals to focus on their work instead of leisure activities (Lee et al., 2012). The comfortableness effect of weather has been widely studied, e.g., on mood (Keller et al., 2005), automobile plant productivity (Cachon et al., 2012), stock market returns (Hirshleifer and Shumway 2003), helpfulness (Cunningham, 1979), or product valuation (Zwebner et al., 2013).

*Physical preventions* are weather-induced hindrances, e.g., snow drifts, which prevent a customer's trip even though the customer is willing to visit a store. Physical hindrances in retail settings are associated with negative effects on contemporary sales (Agnew and Thornes, 1995).

*Psychological effects* may lead to a change in shopping habits, e.g., bulk buying to hoard supplies. For example, lower prices during an extreme weather occurrence might trigger stock-ups (Gauri et al., 2017). Lower prices during extreme weather occurrences are common in retail settings (Beutel and Minner, 2012). It has been shown that the weather at the time of purchase heavily affects customers' decisions for purchases, e.g., advance sales of outdoor events, when the weather at the time of purchase should be irrelevant (Buchheim and Kolaska, 2017).

Finally, weather might influence the *desirability of certain products*, e.g., umbrellas during rainy periods or barbecue grills during sunny and warm weather. Such desirability is most often observed in the fashion industry (Chen and Yano, 2010; Bertrand et al., 2015). For example, cold winters help the sales of warm winter clothes (Bahng and Kincade, 2012), and sunscreen is sought during warm and sunny weather (Parsons, 2001).

### 2.2. Weather impact on retail sales

Some empirical studies about weather effects adopt a general approach by estimating the weather's influence on the aggregated economy (Starr-McCluer, 2000; Lazo et al., 2011). However, those studies do not draw managerial implications from their findings. The studies that provide managerial implications often consider the weather as a factor in strategic planning or on aggregate levels.

A common theme in studies of the weather effect is the focus on daily aggregated sales. We provide a summarizing overview of relevant studies that apply empirical methodology in Table 1. The table focuses on studies on which our research is built upon and whose findings we want to expand. An overview of the weather factors that are used in retail industry studies is provided by Arunraj and Ahrens (2016, p.737). Most studies find a clear link between the weather and retail sales. For example, Parsons (2001) finds that temperature and rainfall affect shopping behavior and Perdikaki et al. (2012) show that weather and sales link via traffic. However, the results are aggregated for the shopping center location, not for individual stores and/or products within the shopping center. Murray et al. (2010) investigate the weather effect on a single store's daily aggregate tea sales and find that weather, in particular sunshine, triggers psychological mechanisms that increase consumer spending. Steinker et al. (2017) find that temperature, rain, and sunshine have a highly significant effect on daily sales for an online retailers. Verstraete et al. (2019) propose a machine learning approach to handle the impact of both the short-term and the long-term weather uncertainty on the forecast (for the former it is automatically selecting the best prediction model).

Another stream of research studies study unexpected deviations from seasonal patterns and explore deviations in daily temperature. Bertrand et al. (2015) show that seasons have different exposure to temperature anomalies, and men, women, and kid's clothing show different results in response to the same weather risk. They develop a method to assess weather-related risk in sales and show how managers can use weather derivatives to hedge against such risk. In a similar setting, Choi et al. (2011) find that apparel companies can minimize the cost that is associated with weather risks by studying consumer behavior. Through a demand prediction model, they calculate a cost

**Table 1**
Empirical studies of daily weather effects in retailing.

| Reference | Data | | Weather Effect(s) | | | |
|---|---|---|---|---|---|---|
| | Sample | Dependent variable(s) and level of aggregation | Non-linear | Seasonal | Store Location specific | Key findings |
| Steele (1951) | 1 department store for 7 weeks before Easter from 1940 to 1948 | Daily total store sales | No | No | No | Weather is correlated with sales. |
| Parsons (2001) | 1 mall location for 6 months from 1995 through 1996 | Aggregated daily shopper count | No | No | No | Rainfall and temperature affect the shopping behavior. |
| Murray et al. (2010) | 1 independent retail store with 6 years data | Aggregated total daily sales of the store | Only for temperature, no analysis | No | No | Weather affects consumers' behavior. As exposure to sunshine increases, negative effects decrease and consumers tend to spend more. |
| Choi et al. (2011) | 100 apparel stores for 2004–2010 | Aggregated daily sales of t-shirts and down jumpers per store | No | Yes | No | Apparel companies with understanding of consumer behavior with respect to weather are able to minimize cost from weather risks. |
| Bahng and Kincade (2012) | 52 stores in Seoul and Kyunggi areas for 2007–2008 | Daily aggregated sales | No | No | No | Seasonal garments are affected by temperature fluctuations. Daily temperature fluctuations did not affect sales of the whole season. |
| Bertrand et al. (2015) | Fashion retail data from France for 2000–2013 | monthly sales in volume per distribution channel and garment type | No | Yes | No | Relationship between temperature and sales anomalies. Weather derivatives can be used to offset risks from unseasonal weather. |
| Arunraj and Ahrens (2016) | 3 retail stores (2 food, 1 fashion) in lower Bavaria, Germany for 2010–2014 | Total number of daily transactions, daily sales data for the fashion store | No | No | No | Weather effects on store traffic depend on the store type (fashion vs. food). Sales in fashion retail stores depend on the weather. |
| Belkaid and Martinez-de-Albeniz (2017) | 98 fashion retail stores in 4 European countries in 13 cities | store footfall and conversion of visits into product category sales per store | No | Yes | Only mall/non-mall | Rain has a large effect on store traffic and while temperature drives conversion, i.e., increases sales. Weather-based pricing allows for revenue increases. |
| Steinker et al. (2017) | 32 months of online order data for customers in one state in Germany | Aggregated daily online sales | No | Yes | No | Weather information increases forecast accuracy. Weather has seasonally different effects on sales. |
| This study | 673 retail stores across Germany for 2013 and 2014 | Aggregated daily sales per store and sales theme | Yes | Yes | Yes | Weather effects are seasonally different and non-linear. Weather effects depend highly on the affected location and products. |

minimizing demand level. Babongo et al. (2018) analyze how apparel demand forecasts for the upcoming season could be made more accurate by taking into account the weather of the previous sales season using an extensive data set for winter sports equipment.

All prior literature is typically limited in terms of weather variables considered, non-linearity of the weather impact and data used for the analysis. Most research does not consider weather parameters other than temperature, e.g. sunshine or rain. While there are some studies that apply machine learning techniques to investigate the impact of weather on businesses, more traditional statistical approaches do not include non-linearity and seasonality as comprehensively in their considerations. When machine learning approaches were used, those studies did not further investigate the results to gain more insights about the impact of non-linearity and seasonality on the weather effect on retail sales. When other parameters are used, the traditional statistical models do not include non-linear effects or seasonality. Finally, the unit of analysis is often either a single store/shopping mall or single product categories, e.g. textile, across multiple stores. To the best of our knowledge, Belkaid and Martinez-de-Albeniz (2017) is the only other study that also considers how the weather effect on sales can differ by location, season, and product categories. They demonstrate that retailers could increase revenue by up to 2% through weather-contingent pricing. Their study is embedded in the fashion industry and neglects non-linearity. Furthermore, they do not quantify the differences in weather effect on sales that occur due to store-specificity. Our study is closely related to Belkaid and Martinez-de-Albeniz (2017) with respect to the modeling. While they emphasize revenue optimization through weather-contingent pricing, we aim to quantify the difference between linear and non-linear weather effects as well as store- and sales theme-specific effects. By studying aggregated data, most studies do not incorporate relevant nuances in the weather effect. Our study seeks to fill this gap by providing a way to determine both aggregate and store-specific weather effects to contribute to the planning of retail sales on different levels.

## 3. Data

For our data set we combine two data sources. We use retail data from a major German retailer and weather data from a public source. Next, we describe the data in more detail.

### *3.1. Retail data*

The first source of data is the daily sales of 673 stores of a German retailer. The stores are typically small, with an average size of 80 $m^2$, and they are located on pedestrian streets and in shopping malls. The retailer employs a business model with a constantly changing product portfolio. Each week the retailer starts and promotes one new sales theme of a product category in all of its stores, i.e., the same sales theme across all stores at the same time. Generally, the sales themes consist of 80–300 new SKUs that fit common product categories, e.g., rain clothing and accessories. A sales theme is sold for six weeks (36 days, Monday to Saturday for 6 weeks) before it is retired, i.e., the retailer removes all of the associated products (SKUs) from its stores. Thus, each week, a different combination of six sales themes is sold within each store. The offered sales themes vary and cover a broad range of products. For example, in one six-week window, the offerings were: (1) summer clothing, (2) car accessories, (3) microfiber linen and silver, (4) children's beach fashion, (5) bathroom and household articles, and (6) watches. All of the sales themes are distinct from one another to offer a broad range of product categories.

The sales data include information about the daily sales of 673 retail stores in Germany for 2013 and 2014. The information includes both daily revenue in Euros as well as the number of SKUs sold per store and article. Because we have such disaggregated sales information, we can examine both the daily aggregated sales per store as well as the sales by sales theme per store per day. This offers us additional insights about how weather affects different products. In total, we have 104 different sales themes in our data (one new per week, retired after 6 weeks). Furthermore, the retailer provides detailed data about each store location. For instance, the information includes a store's size (in $m^2$) and address, and whether the store is located inside a mall. A particularly important aspect of the sales data is that this retailer does not offer any price discounts on current sales themes in its physical retail stores before products are retired from the store, i.e., our data do not suffer from price promotion effects. Furthermore, the retailer applies a constant advertising effort, i.e., the sales are not actively affected by advertisement effects. While the retailer uses different channels for advertisements, e.g., an e-mail newsletter and printed catalogs, they are used in a constant and regular manner, e.g., newsletters are sent out on the same day every week.

### *3.2. Weather data*

The second data source is the weather data for Germany. We gather the data on the weather from Deutscher Wetterdienst (DWD), which offers daily aggregate information on numerous weather parameters free of charge on its FTP servers. We collected the weather information for a period of 30 years (1985–2014). Because the weather is not the same throughout the country but can vary significantly, we collect the weather information for 79 weather stations. We select the weather station for each 2-digit zip code, which results in the above mentioned 79 stations. If a station's weather parameters are missing, we exclude the specific day. Next, we match each store to its weather station based on the 2-digit zip code. By using the 2-digit zip code, we account for the fact that the weather is different across regions; however, we assume that, on average, the weather is the same within each region. We acknowledge that a 2-digit zip code can be a spacious area, and some might argue that it does not offer enough location-specific weather information for different stores within such regions. However, Steinker et al. (2017) show that the weather within Germany is homogenous enough to use as few as six cluster regions to sufficiently model differences between locations in Germany with regard to the weather. Therefore, using as many as 79 weather stations to account for location-specific weather information will provide sufficiently specific information for each location. The data available covers numerous parameters such as the minimum, average, and maximum temperature, precipitation (rain and snow), sunshine duration, barometric and steam pressure, and average wind speed. Fig. 1 shows the location of the weather stations ($o$) and that of the retailer's stores ($x$) across Germany.

Our methodology uses actual weather on a given day to measure the weather's influence on sales, i.e., we use observations for $temperature_{d,m,y,l}$, $precipitation_{d,m,y,l}$, and $sunshine_{d,m,y,l}$ for day $d = 1 \ldots 28$ $(30, 31)$ (depending on the number of days of the month), month $m = 1 \ldots 12$, year $y = 1985 \ldots 2014$, and weather station $l = 1 \ldots 79$. To account for climate changes, we use a linear trend calculation and calculate detrended weather parameters based on 30 years of data, i.e., we detrend all of the weather parameters in the regression models (Bertrand et al., 2015). The World Meteorological Organization (WMO) defines 30 years as the timespan to calculate normal weather that is not affected by climatic change.

The weather perception on a given day is a combination of weather parameters. For example, temperature, precipitation, and sunshine are most often used by studies in different combinations. However, thus far there is no objective measure available to determine how weather is perceived by humans based on the combination of different weather parameters. To classify the weather perception on a given day, we derive a classification for each of the three weather parameters based on the classification of a given day relative to other days of the same season, i.e., the historical distribution. We do this individually for each season and each weather station. The 10% percentile represents days with abnormally bad weather (low temperature, low sunshine and high

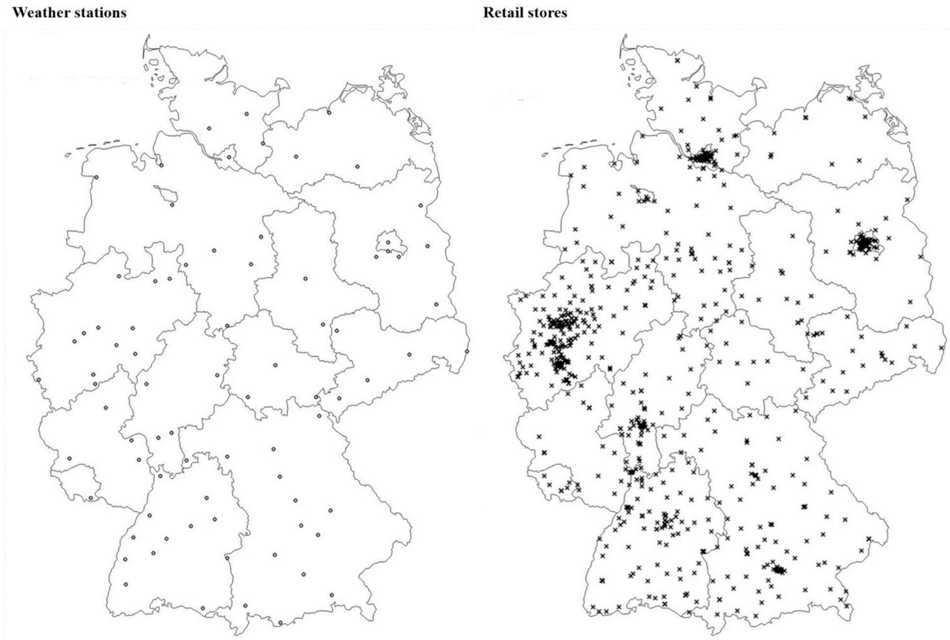


**Fig. 1.** Location of weather stations and retails stores in Germany.

precipitation), whereas the 90% percentile represents days with abnormally good weather (hot, no precipitation, and a great deal of sunshine). Each weather parameter is equally weighted with its respective percentile. We measure the difference from expected weather represented by the 50% percentile (median weather). Therefore, all of the plots are adjusted and show no effect from weather for days at the 50% percentile. We assume theoretical days in which all three weather parameters are observed in parallel, e.g., a 60% percentile day has temperature, precipitation and sunshine of 60%. In this way, we are able to calculate an aggregated weather effect for moderate weather occurrences as well as for extreme ones, e.g., the 10% worst/best days.

A real day can also have a temperature that is ranked at 50%, rainfall at 30%, and sunshine at 70%. To classify the realized occurrence of weather conditions, we draw on the historical weather distribution to individually classify each parameter of our 2013–2014 sample for each weather parameter. We then derive the percentile rank from the historical distribution. After determining each day's rank for historical temperature, sunshine duration, and precipitation, we calculate the average percentile rank of the given day.

Fig. 2 shows the histogram of weather classifications based on their historical percentile rank. A low percentile rank indicates an abnormally bad weather, and a high percentile rank indicates abnormally good weather, i.e., days with average percentile ranks that are below 10% represent abnormally bad weather, whereas days with average percentile ranks that are above 90% represent abnormally good weather. We find that only 1.8% of the observed days fall into an average percentile rank that is less or equal to 10%, and only 5.4% fall into an average percentile rank of 90% or above. If we broaden the definitions for extreme weather to 20%, we find that 7.7% of days fall into a percentile rank of up to 20% and that 14.7% fall into a percentile rank of 80% and above.

## 4. Model development

In this section we introduce our empirical models, which extend the insights gained in previous studies on weather effects. We amend previous models by including non-linear and seasonally differenced effects. For our models, we use a log-linear formulation, i.e., we use the log-transformed daily store sales in Euro as our dependent variable. We apply a log-linear model because AIC and BIC favor such model specification over a log-log specification and it provides the semi-elasticities of the weather influences for ease of interpretation, i.e., a change in sales is expressed as a percentage change while a change in weather parameters is expressed in absolute values (e.g., percent change in sales by hour of sunshine), which is more intuitive than a log-log formulation that used a percentage change in the weather parameters (e.g., percent change in sales by percent change of hour of sunshine). In addition, an alternative log-log model would require a rescaling of weather variables (e.g., 0 precipitation or sunshine could not be interpreted right away) to ensure positive values which would affect the ease of the interpretation.

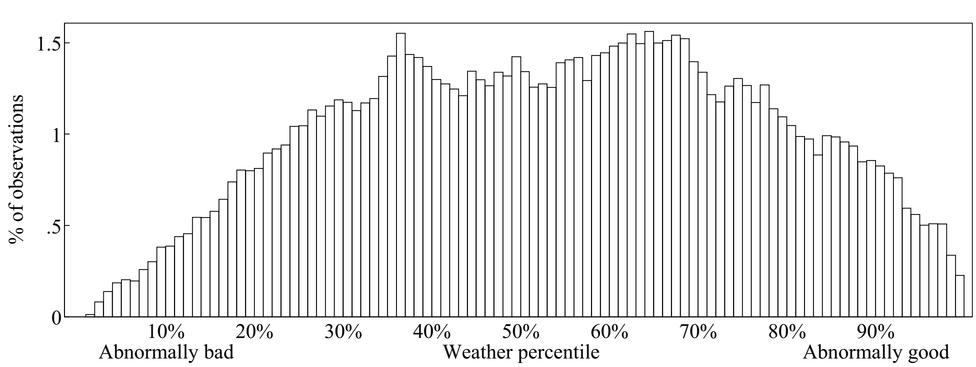


**Fig. 2.** Histogram of weather classifications.

**Table 2**
Regression results for weather effect on daily retail sales.

| | (i) Control | | (ii) Weather | | (iii) Weather (non-linear) | | (iv) Weather (seasonal) | | (v) Weather (complete) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Temperature | | | −0.0100*** | (-54.10) | 0.0023*** | (5.41) | | | | |
| **Precipitation** | | | −0.0069*** | (-32.20) | −0.0113*** | (-27.29) | | | | |
| **Sunshine** | | | −0.0130*** | (-49.42) | −0.0232*** | (-33.47) | | | | |
| **Temperature$^2$** | | | | | −0.0007*** | (-33.79) | | | | |
| **Precipitation$^2$** | | | | | 0.0002*** | (10.11) | | | | |
| **Sunshine$^2$** | | | | | 0.0010*** | (20.09) | | | | |
| **Temperature Spring** | | | | | | | −0.0153*** | (-52.21) | −0.0289*** | (-37.66) |
| **(Temperature Spring)$^2$** | | | | | | | | | 0.0012*** | (27.71) |
| **Temperature Summer** | | | | | | | −0.0179*** | (-67.84) | −0.0121*** | (-17.30) |
| **(Temperature Summer)$^2$** | | | | | | | | | −0.0003*** | (-11.84) |
| **Temperature Fall** | | | | | | | −0.0026*** | (-8.85) | 0.0154*** | (19.98) |
| **(Temperature Fall)$^2$** | | | | | | | | | −0.0013*** | (-32.11) |
| **Temperature Winter** | | | | | | | 0.0094*** | (20.33) | 0.0198*** | (25.70) |
| **(Temperature Winter)$^2$** | | | | | | | | | −0.0017*** | (-18.72) |
| **Precipitation Spring** | | | | | | | −0.0127*** | (-29.44) | −0.0288*** | (-30.17) |
| **(Precipitation Spring)$^2$** | | | | | | | | | 0.0009*** | (18.05) |
| **Precipitation Summer** | | | | | | | −0.0039*** | (-13.49) | −0.0046*** | (-6.96) |
| **(Precipitation Summer)$^2$** | | | | | | | | | 0.0000 | (0.61) |
| **Precipitation Fall** | | | | | | | 0.0021*** | (5.38) | 0.0004 | (0.52) |
| **(Precipitation Fall)$^2$** | | | | | | | | | −0.0000 | (-0.87) |
| **Precipitation Winter** | | | | | | | −0.0118*** | (-16.87) | −0.0238*** | (-14.98) |
| **(Precipitation Winter)$^2$** | | | | | | | | | 0.0013*** | (7.76) |
| **Sunshine Spring** | | | | | | | −0.0141*** | (-34.83) | −0.0385*** | (-31.06) |
| **(Sunshine Spring)$^2$** | | | | | | | | | 0.0022*** | (21.14) |
| **Sunshine Summer** | | | | | | | 0.0029*** | (7.06) | 0.0008 | (0.70) |
| **(Sunshine Summer)$^2$** | | | | | | | | | 0.0002* | (2.53) |
| **Sunshine Fall** | | | | | | | 0.0020*** | (4.22) | −0.0011 | (-0.85) |
| **(Sunshine Fall)$^2$** | | | | | | | | | 0.0005*** | (3.81) |
| **Sunshine Winter** | | | | | | | −0.0080*** | (-10.58) | 0.0005 | (0.23) |
| **(Sunshine Winter)$^2$** | | | | | | | | | −0.0014*** | (-4.73) |
| **Intercept** | 7.1952*** | (317.02) | 7.3655*** | (319.18) | 7.3539*** | (318.34) | 7.3423*** | (318.17) | 7.3597*** | (316.63) |
| Controls | | Yes | | Yes | | Yes | | Yes | | Yes |
| Observations (#Stores) | 396,246 (673) | | 396,246 (673) | | 396,246 (673) | | 396,246 (673) | | 396,246 (673) | |
| AIC/BIC | 409,337/409,403 | | 377,669/377,767 | | 373,930/374,061 | | 350,223/350,419 | | 342,883/343,210 | |
| MAPE | 28.4% | | 26.2% | | 25.9% | | 24.2% | | 23.6% | |
| Adjusted $R^2$ | 62.7% | | 66.8% | | 67.5% | | 70.5% | | 71.9% | |
| Δ Adjusted $R^2$ | n.a. | | 4.1% | | 4.8% | | 7.8% | | 9.2% | |

$t$ statistics in parentheses, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ Note: Coefficients of the Random Coefficient Model are the means of the store-specific coefficients (BLUPs).

Our models include three weather parameters to model the weather effect on daily store sales. We consider the values of average daily temperature in °C, precipitation in mm per $m^2$, and sunshine duration in hours, as is outlined in the data section. These weather parameters are identified, developed, and proven by the prior studies of the weather effect on sales (e.g., Murray et al., 2010; Steinker et al., 2017). To verify the fit of the variables in our data, we examine our model specification for multicollinearity and find that the mean variance inflation factor (VIF) is 2.1 with a maximum VIF of 5.6 when excluding squared terms. VIFs below a threshold of 10 commonly do not raise significant concerns about multicollinearity (O'Brien, 2007). Further, our own examination of various model specifications indicates that temperature, precipitation, and sunshine are the most relevant parameters with regard to statistical significance. We also tested model specifications that include only combinations of the three variables (e.g., only temperature, only precipitation, or sunshine and precipitation without temperature); however, those models are prone to endogeneity issues because leaving out temperature, precipitation, and/or sunshine induces an omitted variable bias and biases the coefficients of the model.

The prior literature on weather effects suggests seasonal differences in the weather effect (Murray et al., 2010; Choi et al., 2011). For example, more sunshine has a different effect on sales in the winter than in the summer. Therefore, we run our models with seasonal variables per weather parameter. Finally, we include the squared terms because we expect the weather effect on sales to be a non-linear function of the parameters (Murray et al., 2010; Arunraj and Ahrens, 2016). While using a log-linear specification with a log-transformed dependent variable induces non-linearity in the model, it does not entirely account for possible non-linear shapes in the relationship between sales and weather, e.g., (inverse) u-shapes. Therefore, we include squared terms to capture such relationships. We additionally tested including a cubed term and do not find that the relationship between weather and sales are significantly different when we include cubed terms in comparison to squared terms.

We formulate a random coefficient model (Swamy, 1970) that is suitable for panel data and takes into account the distinction between the stores (Poi, 2003; Greene, 2012). We use Stata 13 to run the model. It accounts for the stochastic variation of the parameter heterogeneity. This provides qualitatively similar aggregate results to a fixed-effects model but also provides store-individual weather effects:

$$\begin{aligned}\ln(Daily\ \ Sales^{i,t}) \quad &= \alpha^i + \beta_1^{i,s} * temperature_{i,t} + \beta_2^{i,s} * (temperature)_{i,t}^2 \\ &+ \beta_3^{i,s} * precipitation_{i,t} + \beta_4^{i,s} * (precipitation)_{i,t}^2 \\ &+ \beta_5^{i,s} * sunshine_{i,t} \\ &+ \beta_6^{i,s} * (sunshine)_{i,t}^2 \\ &+ \gamma^{i,w} * weekday_{i,t} + e^{i,t}\end{aligned}$$

where $i = 1, \ldots, 673$ indicates the $i$th store unit, and $t = 1, \ldots, 624$ indicates the time period, i.e., the day. $\alpha^i$ is the store-specific intercept, $\beta^{i,s}$ are the respective coefficients for the explanatory variables for each season [spring (March, April, May), summer (June, July, August), fall (September, October, November), and winter (December, January, February)] with $s = 1, \ldots, 4$ and store location $i$. $\gamma^{i,w}$ are the coefficients for the control variables that indicate the weekday $w$ (Monday, Tuesday, … Saturday; stores are closed on Sundays). The weather parameters that we use are the daily *temperature* (°C), *precipitation* (mm per $m^2$), and *sunshine* (hours) for each day $t$ and for each store $i$. We apply store-specific coefficients, $\beta^{i,s}$, for the explanatory variables for each season to account for the fact that the weather affects each store differently. Not all of the sales influencing factors are observable to the researcher; the effect of those factors is captured by the error terms $e^{i,t}$ as proposed by Mani et al. (2015). Note that the omission of unobservable variables might cause endogeneity. Because the independent variables for weather are not included in the retailer's planning process and hence not linked to the other sales affecting variables, we do not encounter correlation between our independent variables for the weather and the error term. More specifically, this specific retailer does not react to day-to-day weather in any way. Obviously, the weather is not influenced by daily sales of the retailer. Hence, simultaneity is not a cause of endogeneity. Finally, measurement errors are the third source of potential endogeneity. However, we use daily sales data directly from the retailer and weather data from the DWD, both of which are not subject to systematical measurement errors. Therefore, we do not encounter immediate endogeneity.

Table 2 shows the aggregated results of the random coefficient model. Because we are only interested in the weather effect, we present the corresponding coefficients for the weather parameters and omit control variables. To gather more insight about the value of weather information on explaining retail sales, we compare five other model specifications: (i) a control model without the weather as explanatory variables including only the control variables ("control"), (ii) a model with weather parameters without seasonality or non-linearity of the weather effect ("weather"), (iii) a model with non-linearity but not seasonality of the weather effect ["weather (non-linear)"], (iv) a model with seasonality but not non-linearity of the weather effect ["weather (seasonal)"], (v) and a model with seasonality and non-linearity of the weather effect ["weather (complete)"].

The coefficients for the random effects model in Table 2 are the arithmetic mean of store-specific best linear unbiased predictions (BLUPs), which are similar to the best linear unbiased estimators (BLUEs) from fixed effects models. Convention distinguishes between BLUEs for fixed effects and BLUPs for random effects (Robinson, 1991). We also conduct the analysis with a fixed-effects model specification, i.e., coefficients without distinction for the store, and the results show that the arithmetic mean of the BLUPs is similar in size and equal in direction to the BLUE coefficients that are calculated by the fixed effects model; thereby providing robustness to the aggregate empirical results with regard to the weather effect on sales. We find that temperature, precipitation, and sunshine duration all influence daily retail sales. Most of the squared terms are significant, and we can conclude that the effects of temperature, precipitation, and sunshine are non-linear. Furthermore, the seasonal coefficients are significantly different and support the notion that the weather affects daily retail sales differently depending on the time of the year.

Next, we compare the explanatory value of weather parameters in empirical models with regard to the level of detail of the weather information. The model comparison provides multiple insights about the weather effect on retail sales. First, our control model that includes controls for the weekday as well as differences between the stores explains 62.7% of the variance in daily sales ("control"). As we add the weather parameters to our control model, we see that the explained variance of the model specifications increases ("weather"). The weather parameters in our model specifications explain approximately 4.1% of the variance in daily retail sales above what is explained by the model without weather information. This number is in line with other studies on the impact of weather on sales (Lazo et al., 2011; Arunraj and Ahrens, 2016). As we further amend the non-linearity and seasonality of the weather effect to our model specification, we find that the AIC (BIC) drop to 373,930 (374,061) for the non-linear model and to 350,223 (350,419) for the seasonal model specification from 377,669 (377,767) for the model with only temperature, precipitation, and sunshine. The adjusted $R^2$ increases by 4.8% (non-linearity) and 7.8% (seasonality), respectively. Finally, we find that the complete model specification with seasonal-different and non-linear weather effect on daily retail sales has a AIC (BIC) of only 342,883 (343,210) compared to 409,337 (409,403) for the model without weather information. Similarly, the adjusted $R^2$ increases by 9.2% for the complete weather information compared to the model without weather information. Hence, we conclude that the model specification controlling for seasonality and

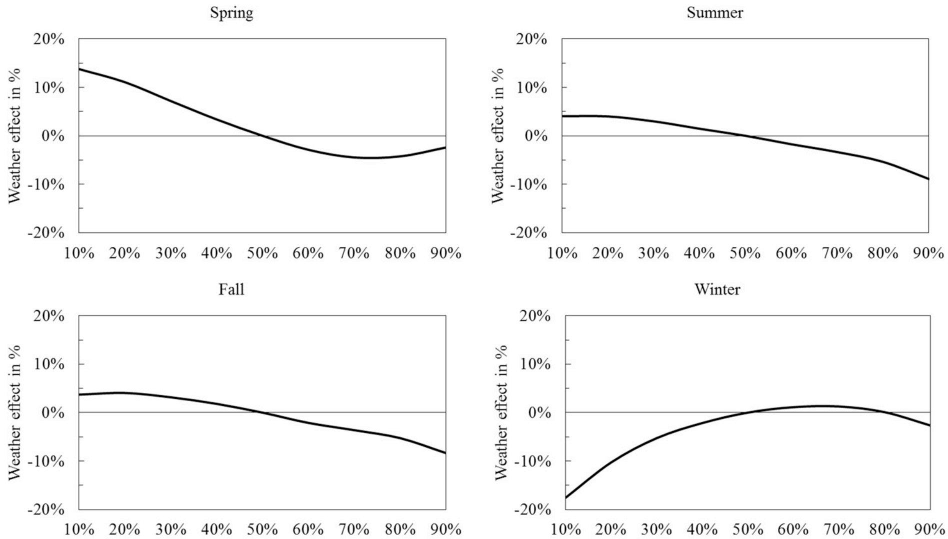


**Fig. 3.** Weather effect on retail sales.

non-linearity of the weather effect explains more variance in daily retail sales compared to models that include only a part of the weather information; and it also provides the best fit of the different model specifications with regard to the AIC and BIC. This is also supported by the MAPE of the different model specifications. In particular, we find that seasonality explains more variance than non-linearity. This is in line with the different theories on how weather affects sales.

To illustrate its impact on daily sales, we calculate the difference between days with bad weather versus days with good weather. We calculate the total daily weather effect based on the coefficients from our regression model. For this purpose, we derive the empirical distribution of the three weather parameters. We do this individually for each season and each weather station. Based on temperature, precipitation, and sunshine, we calculate the weather's impact on daily sales based on the deviation from the median weather. Fig. 3 shows the effect for each season based on the historical weather. The 10% percentile represents days with bad weather (low temperature, low sunshine and high precipitation), whereas the 90% percentile represents days with good weather (hot, no precipitation, and a great deal of sunshine). Each weather parameter is equally weighted with its respective percentile. Because we measure the difference from expected weather as the difference to the median weather of a season, the plot is normalized at the 50% percentile.

Fig. 3 provides a visual understanding of the impact of weather. First, we see that all four seasons show different sales reactions to abnormally good and abnormally bad weather. During the spring, we find the highest positive reaction to bad weather (10% percentile) when sales increase by almost 15%. However, as the weather gets better the positive sales reaction rapidly decreases and shows a negative sales reaction to good weather (90% percentile). Summer and fall are the most similar seasons as both show a positive sales reaction of approximately 4% during bad weather, which decreases to a negative sales reaction of approximately −8% during good weather. In contrast, sales in the winter follow an inverse u-shaped relationship to the weather: bad weather decreases sales by almost 20%; however, as the weather becomes better the sales reaction is almost negligible except for, again, a negative reaction during exceptionally good weather of approximately −2.5%. The results for the weather effect intuitively make sense. As weather gets better, sales in the brick-and-mortar retail stores react negatively. This follows the argument that customers choose different activities during good weather periods and either postpone or drop planned purchases. Conversely, sales increase with bad weather during spring, summer, and fall following a similar argument: customers use physical retail stores relatively more when they do not engage in alternative activities due to bad weather. However, during the winter, exceptionally bad weather also leads to lower sales, which follows the argument that bad weather during winter, when the weather is naturally worse than during other seasons, constitutes a physical obstacle that prevents customers from purchasing in brick-and-mortar retail stores. Therefore, our results empirically support the different theories on how weather affects sales. In particular, we see that customers choose different activities over the purchase and that weather conditions hinder customers from purchases (Steele, 1951; Murray et al., 2010; Stulec, 2013).

Neglecting the non-linearity of the weather effect on sales would impose the risk of over- and underestimating the weather effect when abnormally good or bad weather occurs. To illustrate this issue, we calculate the weather effect using the coefficients from the model that includes the seasonal weather effects ["weather (seasonal)"] but not the squared terms and compare the weather effect size with the weather effect that we calculate from the model specification including squared terms ["weather (complete)"]. Table 3 shows the results of this calculation for abnormally bad and abnormally good weather for each season, i.e., the 10% and 90% weather percentiles, respectively.

**Table 3**
Weather effect on daily sales: difference between linear and non-linear model specifications.

| Weather | Spring | | Summer | | Fall | | Winter | |
|---|---|---|---|---|---|---|---|---|
| | Bad | Good | Bad | Good | Bad | Good | Bad | Good |
| (iv) Linear Model | 12.8% | −16.4% | 2.4% | −6.7% | 2.9% | −0.1% | −10.5% | 0.5% |
| (v) Full Model | 13.8% | −2.4% | 4.0% | −8.9% | 3.7% | −8.3% | −17.6% | −2.6% |
| Absolute Difference | 1.0% | 14.0% | 1.7% | 2.2% | 0.8% | 8.3% | 7.1% | 3.1% |
| | *** | *** | *** | *** | *** | *** | *** | *** |

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

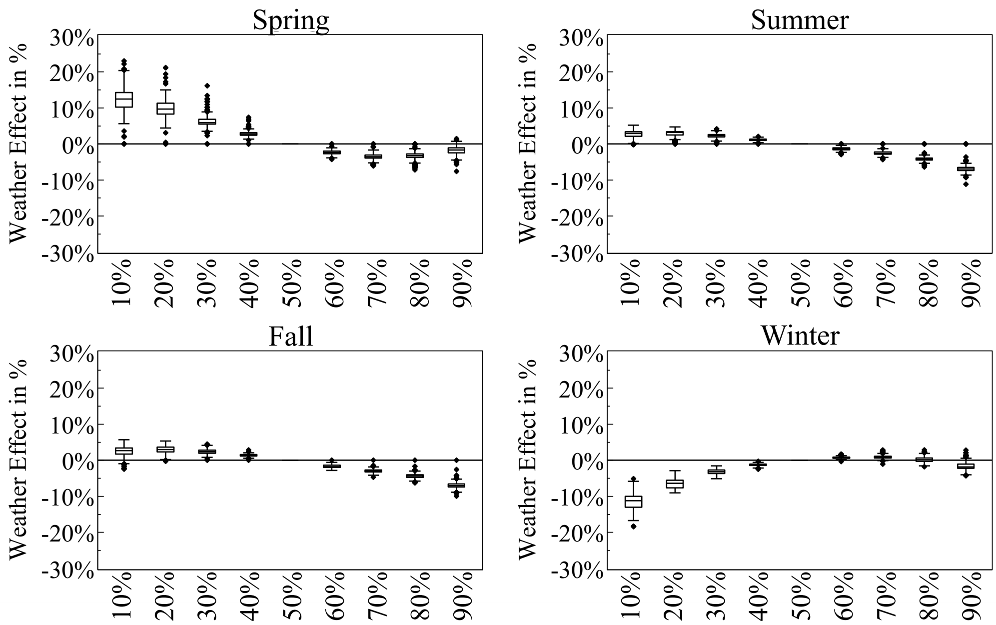


**Fig. 4.** Store-specific weather effect.

We find that the weather effect sizes are significantly different between both model specifications. In particular, we see that the linear model specification underestimates the absolute effect of weather on daily retail sales when the weather is bad. It underestimates a positive sales effect in spring, summer, and fall, and strongly underestimates the negative effect of bad weather in the winter. Meanwhile, the linear specification overestimates the effect of weather when the weather is good in spring. While the full model results in a negative effect of 2.4% of daily sales, the linear model results in a negative effect of up to 16.4%, seriously overestimating the negative effect that the good weather in spring has on daily retail sales. Generally, the linear and non-linear specifications differ between 0.8% and 14.0% with regard to the weather effect size in cases of abnormally bad and good weather. However, the difference becomes marginal when the weather does not occur in abnormally bad or good ways but remains within expectations. As cases of abnormal weather are rare, which also explains the low magnitude of additional explained variance by the squared term extension in the model, a linear model specification suffices in the majority of cases. However, in Fig. 2 we see that on at least 7.2% of days, abnormally bad or good weather occurs. Those are the cases in which retailers should be aware that a linear model specification could significantly misestimate the weather effect.

Overall, we found that weather explains a share of variance of historical daily retails sales and should be considered to be a factor when daily retail sales in a brick-and-mortar environment are modeled. Furthermore, we find that more elaborate specifications, i.e., including seasonally different weather effects and non-linear weather effects, further increase the model fit and the explained variance for daily retail sales.

## 5. Analysis of the weather impact on retail sales

For our analysis of the weather impact on retail sales, we use a stepwise approach and consider different levels of weather information. First, we use our model to ex-post investigate the location-specificity of the weather effect on historical retail sales, i.e., we examine if and how weather sales reactions differ between stores. Next, we disaggregate daily sales into daily sales for each sales theme to analyze how the weather differently affects sales themes. Then, we apply our model for ex-ante predictions using weather forecasts. We first evaluate hold-out samples and show next, how weather forecasts instead of actual weather information influence the sales forecast accuracy.

### 5.1. *Ex-post weather effect analysis*

#### 5.1.1. *Store analysis*

The retailer locates its stores throughout the country (cf. Fig. 1), which leads to a variety of surrounding conditions. The retailer's store locations possess different characteristics that suggest that the weather affects them differently. On one hand, mall locations have paths between stores that are protected from direct weather influences by roofs, have multiple other stores in close proximity, and provide a large number of nearby parking spaces. On the other hand, non-mall locations have paths between stores that are not protected from the weather, have a smaller number of stores in close proximity and have fewer parking spaces that are not directly attached to the location. All of these traits have a direct influence on customer attainability, which is influenced by the weather, and we cannot claim that the weather has a similar effect on each store (Fergus, 1999). Reporting the 24 BLUPs for each of the 673 stores in our data would be excessive: 16,152 coefficients (673 stores, 4 seasons, 3 weather parameters, linear and squared effect). Therefore, we calculate the weather effect on sales dependent on the retail store location and show the condensed results in Fig. 4.

We use the percentile classification for the distinction between abnormally bad weather (10%), median (expected) weather (50% percentile), and abnormally good weather (90%) as described in the data section. Fig. 4 shows the box plots of the effects for each store for each season for all of the weather classifications. We observe a range over which the store effects differ. During abnormally bad weather the maximum difference in weather effects between stores is 23.0%, i.e., one store experiences a sales increase of up to 23.1%, and another store shows a sales increase of only 0.1%, which results in a difference of 23.0% during abnormally bad weather in spring. This difference between maximum store location specific weather effects differs across the seasons for abnormally bad weather (5.4% in summer, 8.2% in fall, and 13.2% in winter). In spring, the maximum difference between stores is 9.1% for abnormally good weather. For the other seasons, the maximum difference in the weather effects between stores is 7.6% in summer, 7.4% in fall, and 7.1% in winter. Therefore, we find that the general location, surrounding, and setting of a store location affects the

**Table 4**
Effect of abnormally bad and good weather on sales themes.

| Abnormally bad weather (10% percentile) | | Abnormally good weather (90% percentile) | |
|---|---|---|---|
| Weather effect | Sales theme (starting week/year) | Weather effect | Sales theme (starting week/year) |
| 25.9% | 22/2013 | 12.5% | 23/2014 |
| 25.1% | 45/2014 | 10.5% | 12/2013 |
| 22.3% | 30/2014 | 7.8% | 1/2014 |
| 21.9% | 14/2013 | 7.6% | 5/2013 |
| 21.3% | 36/2013 | 7.3% | 2/2013 |
| 19.9% | 14/2014 | 6.6% | 6/2014 |
| 18.8% | 36/2014 | 6.5% | 45/2013 |
| 17.1% | 13/2013 | 5.8% | 9/2013 |
| 16.0% | 9/2014 | 5.6% | 7/2014 |
| 15.7% | 26/2013 | 5.2% | 6/2013 |
| | … | | … |
| | *(84 other sales themes)* | | *(84 other sales themes)* |
| | … | | … |
| −7.7% | 18/2013 | −16.4% | 25/2014 |
| −8.3% | 10/2013 | −16.5% | 42/2013 |
| −9.0% | 5/2013 | −17.6% | 30/2014 |
| −10.0% | 12/2013 | −18.1% | 20/2014 |
| −10.1% | 1/2013 | −18.9% | 30/2013 |
| −11.2% | 9/2013 | −19.3% | 45/2014 |
| −13.2% | 24/2013 | −20.9% | 52/2014 |
| −13.3% | 23/2013 | −22.9% | 22/2013 |
| −13.5% | 49/2014 | −26.0% | 9/2014 |
| −14.8% | 23/2014 | −26.8% | 36/2013 |

weather effect on retail sales significantly with respect to size and in some cases also the direction of the effect.

### 5.1.2. Sales theme analysis

We have examined the weather effect on daily aggregated sales at the firm and the store level. Those daily aggregated sales consist of product sales from six different sales themes. Thus, the daily aggregated sales consist of sales from categories that might react differently to the weather. Therefore, we disaggregate the daily sales into the daily sales per sales theme and run our empirical model on the disaggregated sales to understand the weather effect on sales themes. Thus, we obtain 104 results: one for each category that is sold during the two years that we observe. The dependent variable is the logarithm of a store's daily aggregated sales in Euros attributable to a single theme. This gives us the possibility of comparing the weather reaction between sales themes. Extending our existing model to account for the fact that we analyze the sales theme level, we formulate the model as follows:

The new superscript $c$ indicates the sales theme, which we seek to analyze. $\alpha^{i,c}$ is the store intercept, $\beta^{i,c}$ are the respective coefficients for the explanatory variables per store $i$, and $\gamma^{i,w,c}$ are the coefficients for the binary dummy variables that indicate the day of the week $w$. We include dummy variables with coefficients $\delta^{i,d,c}$ for the day of the sales period $d$ to control for the decreasing daily sales per sales theme during the sales period. We exclude the seasonal superscript $s$ because sales themes last only 6 weeks during which the seasonality of the weather parameter would be difficult to estimate with such short time-series, particularly if we consider the fact that the majority of the total sales occurs within the first two weeks, which is captured by $\delta^{i,d,c}$.

We again use the historical weather distribution to show the effects of abnormally bad and abnormally good weather on the various sales themes. Table 4 shows the effects of abnormally bad (10% percentile) and abnormally good weather (90% percentile). We report the size of the weather effect for the ten sales themes with the highest positive and highest negative reaction in sales dependent on the weather. We find that the reaction to good and bad weather varies widely by sales theme.

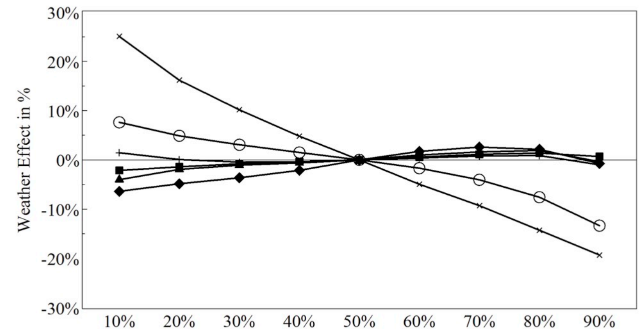


**Fig. 5.** Weather effect on six simultaneous sales themes.

For bad weather, the difference is as large as 40.7% (from −14.8% to 25.9%), and for good weather it is even higher, with a difference of 39.3% (from −26.8% to 12.5%). Nine sales themes that are found to react heavily to bad weather are also found to react heavily to good weather. The direction of their sales reaction is reversed between bad and good weather, i.e., the sales themes that have higher sales during bad weather show lower sales during good weather and vice versa. For example, during sales theme 36/2013 the retailer sold rain clothing and accessories such as umbrellas, which sell well during abnormally bad weather (+21.3%) but in turn sell particularly badly during abnormally good weather (−26.8%). However, the retailer sold summer clothing (t-shirts, shorts, skirts, etc.) for men and women during sales theme 23/2014, which shows the opposite but intuitive reaction that abnormally bad weather decreases sales (−14.8%) and abnormally good weather increases sales (+12.5%). To maintain the anonymity of the data we cannot elaborate about the other sales themes in our data. However, the average difference between abnormally bad and good weather across sales themes is 13.6% and ranges from 48.8% to 0.1%. Hence, we see that the size of the weather effect is highly dependent on the sales themes and product categories. Weather-related product categories such as umbrellas and rain clothing obviously experience a high sensitivity to weather while the weather does not significantly affect other sales themes, e.g., gymnastics and fitness (sales theme 3/2014).

Even sales themes that are sold during the same time react differently to abnormally good and bad weather. Fig. 5 shows the plotted effect for good and bad weather for sales themes that were sold during six consecutive weeks, i.e., at the same time. Notably, the sales themes that were sold during the same time show reactions to abnormally good and bad weather that move into opposite directions, i.e., half of the six sales themes show positive weather effects and the other negative effects. Two sales themes show a large negative effect on sales while four sales themes do not show a significant sales reaction to abnormally good weather. We also see that product categories show a more linear weather effect on sales than aggregated sales at the firm and store

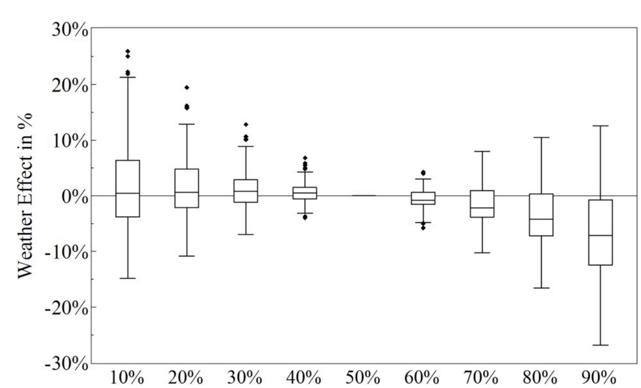


**Fig. 6.** Sales theme-specific weather effect.

levels.

Fig. 6 shows the box plot of the sales theme differentiated weather effects on sales. It is comparable to Fig. 4 for the store level effects. Overall, we find that the difference between sales themes is larger than between store locations. For abnormally bad weather, the maximum difference for the weather effect between sales themes is 40.7% (23.0% for the store-specific effect) with an interquartile range of 10.2% (4.0% for store-specific). For abnormally good weather, the difference between weather effects among sales themes is as large as 39.3% (9.1% for store-specific).

### 5.2. Ex-ante weather effect analysis

In the previous section, we determined that our model offers ex-post explanatory value by including weather information. In this section, we evaluate the model's quality as a mean to ex-ante include weather information in a sales model, i.e., as a forecasting tool. To achieve this, we use two analytical steps. First, we leverage a set of hold-out samples to determine the predictive power of our model using actual weather. Second, we include weather forecast data and compare the model results against the control model without weather and the model with actual weather information. As we use weather forecast data up to 10 days ahead of the actual day, we can further determine up to which point it is beneficial to include weather forecast information. Thus, we can determine beyond which point inclusion of weather forecast information does not benefit the sales model's forecast accuracy.

#### 5.2.1. Hold-out sample evaluation

In Section 4.1 we showed how models with actual weather information, in particular more detailed weather information (i.e., seasonal and non-linear weather effects), provide better fit for historical sales data and can help to increase the explanatory power for ex-post sales analyses. To advance this beyond ex-post analyses, we use a set of hold-out samples and re-estimate the model coefficients without the hold-out sample data and then predict the sales for the hold-out samples.

To create the hold-out samples for 2014, we leave one week of each of the four seasons out of the estimation sample, e.g., week 1, week 14, week 27, and week 40 to create our hold-out sample A (hold-out sample B: week 2, week 15, week 28, and week 41; hold-out sample C: week 3, week 16, week 29, and week 42; etc.). Thereby, we create a total of 13 hold-out samples (hold-out sample A to M). We do this to include one week from each season in each hold-out sample to show that the model works regardless of seasonality. Then, we estimate the model using weather information from the actual weather data without data from the hold-out sample weeks and calculate the predictions for the hold-out samples.

Table 5 shows the results of the hold-out sample estimation with regard to the MAPE of sales in Euro. We find that for 11 of 13 hold-out samples the model with weather information improves versus the control model without weather information in terms of MAPE. On average, the model containing the weather information improves the average MAPE over all hold-out samples by 1.9 percentage points (a 6.7% reduction in MAPE).

**Table 5**
Mean absolute percentage error of predictions for hold-out samples.

| Holdout Sample | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| **without weather** | 24.6% | 35.5% | 23.4% | 37.1% | 24.8% | 27.5% | 24.5% |
| **with weather** | 20.3% | 33.1% | 19.9% | 28.1% | 21.5% | 26.7% | 22.4% |
| **Holdout Sample** | **H** | **I** | **J** | **K** | **L** | **M** | **Ø** |
| **without weather** | 28.0% | 31.2% | 30.2% | 25.4% | 27.3% | 29.9% | **28.4%** |
| **with weather** | 33.6% | 35.5% | 26.9% | 23.0% | 24.4% | 29.0% | **26.5%** |

#### 5.2.2. Weather forecasts evaluation

To evaluate the value of weather information for sales prediction purposes, it is necessary to include weather forecasts instead of actual weather information because actual weather information is only available ex-post but not ex-ante as needed for the predictions. Including weather forecasts induces uncertainty and forecast inaccuracy in the analysis. Exact weather forecasts are nearly impossible for longer time periods (Lorenz, 1963), and model error in weather forecast models increases by approximately 100% every 2.5 days (Orrell et al., 2001).

Thus, we use a subsample of our data for which such weather forecast information is available. While historical, actual weather information is widely available, historical weather forecasts are not available in the same manner. Hence, we only have historic weather forecast data for two cities in our data, Hamburg and Frankfurt/Main, in which 41 of the 673 stores are located. The historic forecasts are available for all three weather variables temperature, sunshine and perception up to ten days ahead.

We re-estimate the model using weather forecasts as replacements for the actual weather data and calculate the MAPE of the hold-out samples from 4.2.1 for our subsample of stores from Hamburg and Frankfurt/Main. We do this for all forecast horizons that are available in the data, i.e., from one day ahead to ten days ahead of the actual sales day. To evaluate the forecast accuracy of the model and the different weather forecast horizons, we compare the results with the control model without weather and the model containing actual weather data calculated on the subsample containing stores from Hamburg and Frankfurt/Main. Table 6 shows the results for the MAPE for the subsample of stores from Hamburg and Frankfurt/Main.

We find that the model containing weather forecast information provides a lower MAPE than the control model without weather information but does not provide lower MAPE than the model containing actual weather information, which is intuitive as the weather forecasts are generally inaccurate. However, we also find that the model containing weather forecast information is on average only marginally better in terms of MAPE than the control model without weather when weather forecasts for more than four days ahead are fed into the model, and that the model performs worse for weather forecast more than seven days ahead.

In summary, the results show that weather information, actual weather as well as weather forecasts, does provide benefits for the prediction but the benefit from weather information diminishes with longer weather forecast horizons and beyond a certain point does not offer benefit for the sales prediction.

## 6. Concluding discussion

A number of prior studies have shown how the weather affects sales in various industries and in different settings. Our study contributes to this stream of research as we propose a new model that includes non-linearity and seasonal differences. Using this model, we extend the previous research (e.g., Arunraj and Ahrens, 2016; Bahng and Kincade, 2012; Bertrand et al., 2015; Chen & Yano, 2010) and show how weather affects retail sales in a large number of German brick-and-mortar stores. Our approach can be used for many different retail settings and across different geographies.

A first key contribution relates to the finding that the effect of temperature, precipitation, and sunshine duration on sales is non-linear. The previous studies have hinted but not included the non-linear effect of weather on sales. We find that weather effect on sales can be over- or underestimated when a linear versus when a non-linear specification is chosen, and the differences between a linear and a non-linear approach can be as high as 14.0%. We also show the significant differences in reactions between seasons, e.g., the sales reaction to bad weather in fall compared to the reaction in spring or summer. The seasonality of the weather effect has been observed by some studies

**Table 6**
Mean absolute percentage error of predictions for hold-out samples including weather forecasts.

| | | Model including | | Weather forecast for | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | No weather | Actual weather | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 |
| **Hold-out sample** | **A** | 28.4% | 22.5% | 22.6% | 22.8% | 22.5% | 22.9% | 23.0% | 23.0% | 23.1% | 23.1% | 23.5% | 27.3% |
| | **B** | 26.2% | 20.3% | 21.4% | 22.1% | 23.0% | 21.9% | 22.8% | 21.6% | 20.5% | 21.1% | 21.3% | 19.8% |
| | **C** | 21.3% | 18.0% | 18.1% | 18.2% | 18.6% | 18.7% | 18.8% | 19.2% | 19.1% | 18.8% | 18.6% | 18.9% |
| | **D** | 35.3% | 28.4% | 28.1% | 28.2% | 28.6% | 28.9% | 30.7% | 30.6% | 30.4% | 31.6% | 30.6% | 34.0% |
| | **E** | 21.0% | 18.0% | 18.5% | 18.6% | 18.5% | 18.8% | 18.6% | 18.9% | 18.9% | 18.8% | 19.7% | 19.6% |
| | **F** | 24.4% | 24.4% | 25.0% | 25.1% | 25.2% | 25.0% | 25.3% | 25.5% | 25.2% | 25.4% | 25.3% | 28.4% |
| | **G** | 25.7% | 21.5% | 28.9% | 30.7% | 31.5% | 33.1% | 31.8% | 30.6% | 33.0% | 34.5% | 34.4% | 33.5% |
| | **H** | 30.3% | 35.2% | 37.4% | 37.7% | 38.3% | 37.8% | 38.1% | 38.3% | 38.1% | 38.4% | 38.5% | 40.3% |
| | **I** | 25.9% | 26.1% | 26.4% | 26.6% | 26.6% | 26.3% | 26.8% | 32.4% | 31.2% | 36.5% | 35.2% | 37.9% |
| | **J** | 29.3% | 26.8% | 27.3% | 27.6% | 27.2% | 28.0% | 27.9% | 27.4% | 28.0% | 28.2% | 28.7% | 30.0% |
| | **K** | 22.3% | 20.3% | 20.3% | 20.8% | 20.8% | 21.6% | 21.2% | 21.4% | 21.9% | 21.7% | 21.7% | 21.8% |
| | **L** | 23.6% | 20.7% | 20.4% | 20.6% | 20.8% | 21.0% | 21.0% | 21.2% | 21.7% | 21.4% | 21.2% | 22.4% |
| | **M** | 27.6% | 25.9% | 26.6% | 26.6% | 26.8% | 27.3% | 27.9% | 27.9% | 28.3% | 28.5% | 28.7% | 30.9% |
| | **Ø** | **26.2%** | **23.7%** | **24.7%** | **25.1%** | **25.3%** | **25.5%** | **25.7%** | **26.0%** | **26.1%** | **26.8%** | **26.7%** | **28.1%** |

(Belkaid and Martinez-de-Albeniz, 2017; Steinker et al., 2017) but has not been stressed and quantified as a necessity for model specifications. The non-linearity and seasonality of weather effects on sales are of particular importance as they affect future studies' approaches, examination, and interpretation of weather influence on sales.

In the ex-post analysis, we provide further insights into store-specific effect and the product-category-specificity of the weather effect. Although it seems intuitive that weather affects stores in different locations in different ways, we are not aware of any previous studies that have explicitly studied this matter. Our model allows for a more distinct approach, i.e., it allows for the aggregation and the disaggregation of the effect size from firm-specific to store-specific effects. We find that sales in different stores can differ by up to 23.0% on the same day for the same weather. Similarly, we show that the weather impact can significantly differ between different sales themes. We find that sales can increase (or decrease) based on the weather and the sales theme by up to 25.9% (26.8).

Adding weather information to our control model increases the explained variance between 4.1% and 9.2%, depending on the level of detail of the weather information that is added. Therefore, we run an ex-ante analysis to analyze how future weather information (i.e. inaccurate weather forecasts) can be used to forecast future sales. Here, our results are interesting but somehow mixed. We find that the hold-out sample benefits from weather information. However, the forecast improvement is relatively low and diminishes with increasing forecast horizons. For one or two days ahead forecasts, the forecast accuracy improves by up to 1.5% on average which relates to a relative improvement of 5.7%. For higher forecast horizons, the benefit decreases, and for seven days ahead, the model falls behind the base model without weather information.

Our results have important managerial implications. For many applications it is essential for managers to obtain full visibility on actual sales and to understand the driving factors behind these sales. We find that the sales can be extremely inflated or deflated based on the weather, and managers could make wrong decisions by just relying on gut feeling and simple explanations such as “our sales were good/bad because of the weather”. Using our methodology, managers would be able to normalize sales data for the weather effect considering the weather on a given day, the store location and the sales theme. Thus, they obtain a better understanding on how the products would have sold without particularly good or bad weather. This could particularly improve decisions on orders for products in the future. From a long-term perspective, managers can leverage these insights and plan product categories accordingly, i.e., plan sales themes that balance each other's reaction to weather. For example, by planning one sales theme that reacts positively to bad weather and one sales theme that reacts negatively to bad weather, a retailer is able to offset negative weather reactions and significantly lower its risk exposure.

Also the results from the ex-ante analysis have managerial implications. In our setting, we find that the improvement decreases as the weather forecast horizon and error increases, i.e., up to four days ahead weather forecasts increase the sales forecast accuracy significantly, but including weather forecasts for more than seven days ahead does not improve the sales forecast accuracy. Thus, we show managers that including weather information in their planning is only applicable and beneficial for short forecast horizons and does not benefit their operational planning more than one week in advance. Accordingly, managers should carefully review the operations decisions that can be based on the next few days.

Although our study presents a number of novel approaches to the examination of the weather effects on sales, some limitations constrain our findings. Some of those limitations also provide new avenues for future research. One aspect of including weather effects in the operational planning process is the availability of weather forecasts. We use publicly available historic weather information from the DWD to quantify the effects. Hence, our results represent Germany; other areas of the world could possibly show different weather effects. Another limitation of our study relates to the availability of other data. In particular, accurate, historical inventory data is not available to us. Hence, we use censored demand data based on realized sales; we are unable to identify lost demand caused by stock-outs. However, exemplary inventory analyses, for a sample of SKUs, showed that stock-out situations are rare, i.e., lost sales should play no or a minor role in our sales data. We also do not possess comprehensive information about customer traffic. Consideration of customer traffic and conversion rates could open up additional analytical topics, e.g., around staff planning and consumer behavior. In particular, based on our study we cannot make more sophisticated claims about consumer behavior in relation with weather effects since we do not have access to the required data. This would pose a valuable question for future research. Experimental research designs as well as survey-based studies could provide more insight about how weather affects consumer behavior and sales for different product categories. Another interesting research path would be to further examine how weather projections affect consumer behavior and sales since anticipation of the weather could affect the consumers' time and shopping planning. Finally, our sales data does not allow for a more sophisticated control model (e.g., Weber et al., 2017), future studies could advance our findings by including other sales variables, e.g., product price changes, and their relation to the weather effect.

Our study provides promising starting points for future research. We want to highlight three promising approaches. First, we show that analysis of the weather effect does yield a significant effect that should be considered at various planning stages in retail stores such as workforce and category planning. However, it is beyond the scope of our study to examine the consequences of weather effects, e.g., on the inventory planning in retail stores. Future research should pick up at this point and use different demand patterns to test in which demand scenarios and at which level of aggregation the consideration and application of the weather effect is called for. Other retailers might observe stronger effects, and certain product categories will be affected to a larger degree. For example, perishable goods in supermarkets can be promising domains for further application of this research because they provide fast-moving, uninterrupted daily sales. Second, sales shift due to the weather are another potentially worthwhile research venue. In particular, we are not aware of any study so far that conclusively investigates how today's weather affects tomorrow's retail sales, the day after tomorrow, and multiple days in advance. Buchheim and Kolaska (2017) conduct such a study on today's weather on future outdoor movie ticket sales and Belkaid and Martinez-de-Albeniz (2017) use memory effects as a robustness check. While we examine the contemporary effect of weather on retail sales, it will be insightful to gather more understanding if retail sales are lost, postponed, or maybe even occur earlier when forecasts are known. Third, with the rising importance of machine learning techniques in research it will also offer a valuable way to further approach the topic of weather effects on retail sales and business impacts in general. While our statistical approach limits the potential non-linear effect to a linear combination, machine learning techniques will allow for a more nuanced view on the impact of non-linearity and seasonality. However, for such approaches a larger sales data foundation is necessary as training data for the model specifications that will allow sensitivity analysis in greater detail about the variables' effect on sales. In this regard we consider our research a starting point for future research by providing proof of the non-linearity and seasonality that calls for more research in the future.

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