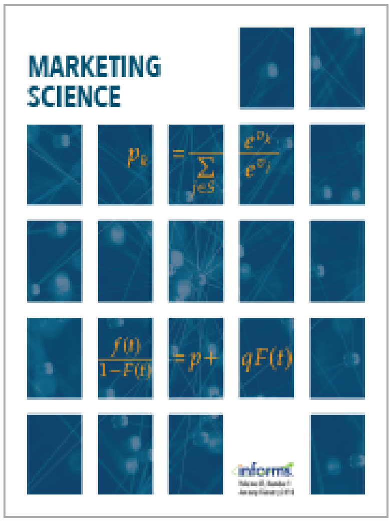

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Sunny, Rainy, and Cloudy with a Chance of Mobile Promotion Effectiveness

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Abstract. Although firms are leveraging weather conditions in promotions, they struggle to quantify the impact. This study exploits field experiment data on weather-based mobile promotions with over six million users. Results find that sunny and rainy weather have first-order main effects. Purchase responses to promotions are higher and faster in sunny weather relative to cloudy weather, whereas purchase responses to promotions are lower and slower in rainy weather. These findings are robust across different measures of weather changes with both backward-looking historical weather and forward-looking forecasts, as well as deviations from normal weather. Also, sunny and rainy weather have second-order interactive effects with ad copies of mobile promotions. Compared with the neutral ad copy, the prevention frame ad copy hurts the initial promotion boost induced by sunshine, but improves the initial promotion drop induced by rainfall. For marketers, these findings imply new opportunities in customer data analytics for more effective weather-based mobile targeting.

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Keywords: mobile • targeting • field experiment • e-commerce • advertising • weather

1. Introduction

Many firms are leveraging weather-based promotions. For example, Burberry rolls out weather-based campaigns promoting products according to London's local weather.[1] Echoing this, Ace Hardware, Taco Bell, Delta Airlines, Farmers Insurance, and others target local weather in their promotions (Rosman 2013). With more than 150 million users of weather apps, there are a total of 2 billion checks of weather each day (Suddath 2014). Thus, over 200 major brands have committed substantial marketing budget to partner with the Weather Channel Company for advertising and promotions (Neff 2014).

However, firms struggle to scientifically quantify the impact of weather on purchase responses to promotions. This difficulty arises mainly because of data limitations. Under traditional promotion settings, it is difficult to compile an observational data set that can simultaneously track individual users' weather, location, and purchase response to promotions. Even with observational data, self-selection and endogeneity may confound estimates from simple correlational approaches. Thus, it is necessary to use an experimental approach to gauge the impact (Sudhir 2016, Gordon et al. 2016).

To overcome this difficulty, we exploit mobile promotions with field experiments. Mobile technologies allow for more precisely identifying individuals' location, weather, and forecast, and digital records on the incident and timing of purchase responses. Furthermore, through field experiments, we randomly assigned different ad copies of mobile promotions. This manipulation generated an exogenous shock and helped gauge the causal impact. We collaborated with a major telecom company who conducted field experiments on over six million mobile users.

Results indicate that purchase responses to promotions are higher and faster in sunny weather, but lower and slower in rainfall, relative to cloudy weather. Better-than-yesterday weather and better-than-forecast weather engender more purchase responses, and vice versa. A good deviation from the expected rainy or cloudy weather with relatively rare events of sunshine would boost purchase responses to mobile promotions.[2] These effects are incremental and robust even after controlling for individual location, time of day, temperature, humidity, visibility, air pressure, dew point, wind, and mobile usage behavior.

Besides such first-order main effects, sunny and rainy weather also have second-order interaction effects with ad copies of mobile promotions. An ad copy with a prevention frame ("do not miss the opportunity to take advantage of this special deal") is more effective in rainfall, yet a neutral frame ad copy ("a general greeting of dear respected customers") is more effective under sunshine; that is, compared against the neutral ad copy, a prevention frame ad copy hurts the initial promotion boost induced by sunny weather, but improves the initial promotion drop induced by rainy weather. To enhance the generalizability in results, we obtained an additional field data set that involved app ads of a different product from the telecom company. The additional data set consistently supported the positive effect of sunny weather and negative rainy weather on incremental mobile ad sales compared with the cloudy weather condition.

Our findings make several contributions. First, they help reveal the effectiveness of a novel approach with weather-based advertising and promotions. Consumers nowadays are inundated with and annoyed by irrelevant ads on their personal devices (Tucker 2014, Bart et al. 2014, Andrews et al. 2016). Our findings suggest that an effective approach is to leverage the relevant, local weather information. Sunny and rainy weather may be viable, costless instruments to boost the sales returns to promotions. Firms should use the prevention frame ad copy on rainy days and the simple neutral frame ad copy on sunny days for more incremental promotion purchases. Thus, weather-based promotions with the appropriate ad copy may attain greater "bang for the buck."

Furthermore, our findings extend prior mobile targeting literature that has focused on location, time, and crowdedness in the environment (Danaher et al. 2015, Ghose et al. 2012, Luo et al. 2014, Fong et al. 2015, Dubé et al. 2017). This is the first study to examine sunny and rainy weather as contextual variables for mobile targeting. Indeed, weather and mobile devices go hand in hand, as checking weather forecasts is one of the most used native applications. Enabled by ubiquitous mobile location technologies and universal accessibility of forecasts on apps, brands may leverage weather conditions for designing promotions and ad copy creatives. Sunny and rainy weather are largely neglected environmental variables in promotions literature in general, and mobile targeting literature in particular.

More broadly speaking, they illustrate the potency of behavioral field study and big data to help tease out the subtle weather effects that would be hard to detect with small samples. Indeed, quantitative researchers may examine how "behavioral message frames based on psychological theories that have been tested in the lab can be leveraged in the field" (Sudhir 2016, p. 5). Similar to the work that uses behavioral theories of sympathy bias to test the effects of advertising content on charitable giving (Sudhir et al. 2016), our study leverages psychological theories of weather and consumer behavior to quantify mobile promotion effectiveness. For marketers, our findings imply fresh opportunities of customer data analytics for effective weather-based mobile targeting.

2. Literature and Hypotheses

Although the marketing literature has hardly investigated the specific role of weather for responses to promotions, prior works in psychology and economics have discussed the general role of weather (Steele 1951, Simonsohn 2007). Weather affects people's mood states, shopping activities, and other daily behaviors. Persinger and Levesque (1983) found that weather accounted for 40% of the variability in people's daily moods. Exposure to sunlight enables the brain to produce more serotonin and thus improves mood like in a "heliotherapy" (Schwarz and Clore 1983). With a better mood, people have more positive evaluations of restaurant services, investments, life satisfaction, products, and shopping activities (Murray et al. 2010). A good mood induced by sunny weather positively influences stock valuation, and hence investors buy more stocks on sunny days (Hirshleifer and Shumway 2003). Similarly, because of positive projection bias, consumers tend to purchase more convertible cars in sunny weather with clear skies (Busse et al. 2015).

By contrast, rainy weather likely creates negative feelings (Klimstra et al. 2011). Exposure to rain can leave individuals wet and uncomfortable and in a lousy mood state (Conlin et al. 2007, Parsons 2001, Zwebner et al. 2014). In a comprehensive meta-analysis, Hsiang et al. (2013) find that people experience more depressive symptoms and negative feelings such as anxiety, nervousness, stress, and fear on rainy days. Also, Rosman (2013) documents that weather app users are in bad moods in rainy and inclement weather such as storms and hurricanes. By contrast, people experience better moods during bright sunny days. Thus, extant literature ties not only sunlight to positive moods but also rainy weather to negative feelings.

The central hypothesis here is that purchase responses to mobile promotions are higher and faster in sunny weather, but lower and slower in rainy weather, relative to a cloudy sky. This claim is consistent with the psychological theory of "affect as information" (Schwarz and Clore 1983, Pham 2009, Pham et al. 2012). Specifically, mood can be an information input to evaluate advertising (Batra and Stayman 1990) and price promotions (Hsu and Liu 1998). People evaluate the same product more favorably when in a good mood, and less favorably when in a bad mood (Stephen and Pham 2008; for reviews, see Isen 2001, Gardner 1985). Also, a state of high affect can lead to more favorable outcomes because consumers are more innovative and prone to variety seeking (Kahn and Isen 1993), so consumers in a better mood are more open to information advertising and promotional discounts. This discussion suggests that, compared to cloudy weather, sunny weather with more exposure to sunlight would enable the brain to produce more serotonin and a better mood, which would then lead to more favorable and spontaneous evaluations of ads and deals, and thus more and faster purchase responses. By contrast, rainy weather would lead to a worse mood state, and thus less favorable evaluations with fewer and slower responses to promotions.

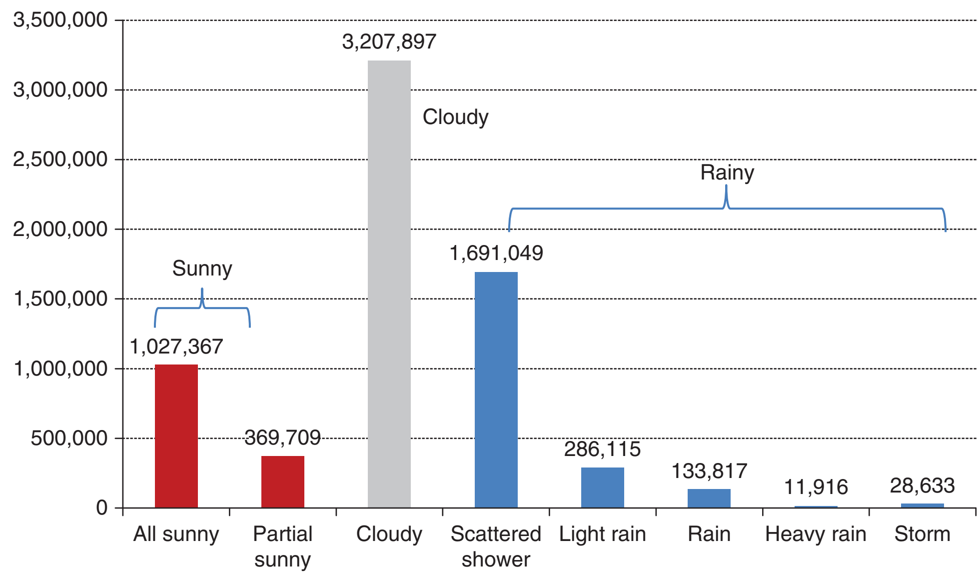
Another hypothesis in our study is that sunny and rainy weather have interaction effects with ad copies of mobile promotions. A prevention frame ad copy hurts the initial promotion boost induced by sunshine, but improves the initial promotion drop induced by rainfall. This claim is also consistent with the theory of affect as information, which holds that feeling interpretations are subject to a response-mapping dependency (Pham 2009, p. 178). People in good moods pay more attention to nonnegative information in messages. This is because people in good mood states generally try not to expose themselves to negative information, hoping that they can remain blissful (Isen 2001). On the other hand, people in bad moods pay more attention to negativity in messages because they are more vigilant and psychologically more available for such messages (Mayer et al. 1992, Schwarz and Clore 1983). Indeed, Pham and Avnet (2009) find that the effects of positive mood are attenuated by a prevention frame because positive mood mismatches the negativity in loss-avoidance prevention frame. Consistent with this, the ad copy with a prevention frame attenuates the initial promotion boost induced by sunshine, because sunny-weather-induced positive mood mismatches the negative information in a prevention frame. Reversely, because rainy-weather-induced negative mood matches the negative information, the ad copy with a prevention frame improves the initial promotion drop induced by rainfall.

3. Field Data

Our field experiment data were provided by a large mobile telecommunications company. The ideal test of weather effects is to conduct a randomized field experiment by manipulating weather. Yet, random assignments of sunny and rainy weather are impossible. However, we can randomly assign different ad copies of promotions and then match the data with weather records, i.e., augmented field data. Thus, we conducted a quasi field experiment to explore the effect of sunny and rainy weather on purchase responses to mobile promotions. The mobile campaigns promote the add-on service of video streaming to smartphone users. The basic mobile services, such as call service and short message service (SMS), are provided by the telecom company when users subscribe to specific cell phone plans. However, the add-on services must be purchased. This promoted product allows mobile users to watch videos on their smartphone devices on the go. Randomized promotions were sent to over six million (6,744,884) mobile users via push-open SMS notification campaigns from September 2, 2013, through October 3, 2013. The mobile promotions had two ad copies: one with a prevention frame and one with a neutral frame. For the prevention frame ad copy, the message began with "Do not miss the opportunity to take advantage of this special deal!" This ad copy emphasized preventing the users from losing the deal, i.e., a negative tone with the wording of *not missing* in ad copy. For the neutral frame ad copy, the message began with a general greeting of "Dear respected customer." This ad copy emphasized a generic salutation, a nonnegative tone in ad message.[3] Variations in message length could be a confound, given the small screen sizes of mobile phones. Yet the original messages of the two ad copies in Chinese had similar length (see Appendix A for message length). The rest of the promotion content was the same: "Subscribe to the mobile video-streaming service of [the Wireless Service Provider] for only ¥3 per month! Watch video episodes of the most popular TV series on your mobile devices on-the-go! The regular price is ¥6. Purchase by replying "Yes" to this SMS within the next 48 hours!" All these campaigns were promoting the same mobile product with the same price, and all SMS messages were sent to users at 9 A.M. every day consistently. Interested users could respond by purchasing the service with promoted prices. The purchase prices would be charged immediately to the users' wireless phone bill. All SMS campaigns were randomly sent. For the randomization procedures, the SAS software's random number generator and RANUNI function were used to generate a random value from a uniform distribution. After that, the random numbers were sorted in sequence to extract the sample to send to mobile users. The targeted users did not subscribe to this video-streaming service, nor did they receive a similar mobile promotion from the wireless service provider.

To identify the incremental effect, there were 20,000 similar users in the control group who did not receive any promotions during our field experiment time window.[4] These users are regarded as the holdout baseline group. Also, tests of descriptive statistics with covariates (weather, location, mobile usage behavior) find

Figure 1. (Color online) Distribution of Weather Conditions in Data



insignificant differences across the three groups (prevention frame, neutral frame, and holdout group; all $p > 0.18$), thus passing the randomization checks and supporting that the control groups are indeed suitable and represent what the treatment groups would have done had they not been treated.

We complement the promotion data with data from a rich database of weather variables across cities of mobile users at both daily and hourly levels. We develop an algorithm to automate the data scraping process to collect the weather data online from Weather Underground. In this study, we focus on the effects of sunny weather (all sunny and partial sunny), cloudy weather (cloudy days without much sunlight or clear sky), and rainy weather (scattered showers, light rain, rain, heavy rain, and storms). Figure 1 presents the frequency of individual daily exposure to the distribution of weather conditions. As shown in Figure 1, there are enough variations, since, for instance, "sunny" has over 1.3 million observations and "cloudy" has over 3.2 million observations.

Figures 2(a) and 2(b) depict model free evidence for the incremental effect of mobile promotions. The purchase rate of the holdout group (without promotion) is zero. This is reasonable because the mobile company provides over 200 add-on mobile service packages. It is quite difficult for users to notice the video-stream service package without promotions. Thus, the promotion responses are incremental, and the control group is not included in the subsequent model tests. This also supports that the responses are not due simply to more mobile usage on sunny days. Figure 2(b) suggests that the purchase response rate is the highest (1.05%) for sunny weather, and the lowest (0.64%) for rainy weather. The baseline cloudy weather (0.78%) has a response rate in between.

3.1. Data Analyses and Identification Strategies

Our data analyses have multifaceted identification strategies. First, we take self-selection into account since people may self-select the geographic locations to live in. Locations with certain latitude and longitude measures are naturally correlated with weather conditions. Thus, it may not be weather, but rather locations or the types of residents at these locations that drive purchase responses. To deal with this confound, our model controls for location fixed effects of 31 provinces covering 344 cities (see the online appendix). Also, we exploit the within-person weather variations in terms of both backward-looking historical weather and forward-looking forecasts. We further test deviations from the normal weather given the geographical area, since each geographical area has normally expected weather. Then, we conduct a falsification test on the interactions with temperature. Finally, we replicate the main effects of sunshine and rain with a different mobile product through app ads.

4. Analysis and Results

Our econometric models start from the most basic analyses. We estimate individual user's $likelihood_i$ to respond to a mobile promotion by making a purchase. The latent likelihood is a logit function of weather conditions and covariates

$$Mobile\ Promotion\ Response\ Likelihood_i^{\text{weather}} = \frac{\exp(U_i)}{1+\exp(U_i)},$$

$$U_i^{\text{weather}} = \alpha_0 + \alpha_1 Sunny_i + \alpha_2 Rainy_i + \beta Ad\ Copy\ Frame_i + \Delta ControlVars + \mu\Omega_{\mathrm{R}(i)} + \rho\mathbf{X}_\mathrm{i} + \varepsilon_i, \quad (1)$$

where i indicates the mobile user. The *promotion response* equals 1 if the user responds to mobile promotions by making a purchase and 0 otherwise. We

Figure 2. (Color online) Purchase Response Rates of Mobile Promotions

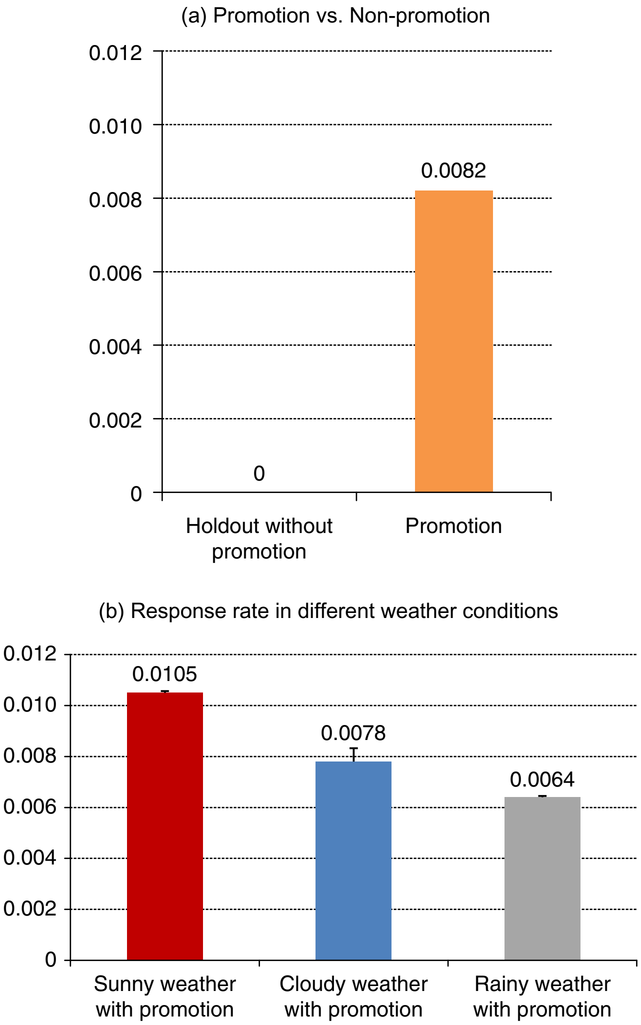


Table 1. Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Mobile Promotion Response	6,744,884	0.0078	0.0881	0	1
Sunny	6,744,884	0.2068	0.4050	0	1
Rainy	6,744,884	0.3184	0.4659	0	1
Ad Copy Frame	6,744,884	0.5541	0.4971	0	1
Temperature	6,744,884	27.1813	3.3350	5	37
Temperature Range	6,744,884	9.7772	3.5308	2	23
Visibility	4,251,825	7.1485	3.6572	0	19
Dew Point	4,321,404	60.9009	10.9377	−14	78
Humidity	4,321,404	66.7555	15.0454	7	98
Air Pressure	4,198,892	29.9411	0.1076	29.08	30.37
Wind Speed	6,756,524	2.2465	0.5340	1	5
Wind Direction	6,614,522	3.0949	2.7234	1	10
Rural	6,744,884	0.4873	0.4998	0	1
Province	6,744,884	18.2299	7.9071	1	31
Day	6,744,884	17.5310	10.5274	1	23

Notes. Mobile Promotion Response is a dummy variable equal to 1 if the user purchased the mobile promotion and 0 otherwise. *Sunny* is equal to 1 if the weather was sunny on the day that individual i was exposed to the mobile ads and 0 otherwise. *Rainy* is equal to 1 if the weather was rainy on the day that individual i was exposed to the mobile ads and 0 otherwise. The weather condition is the baseline cloudy weather. *Ad Copy Frame* is equal to 1 for the mobile promotion with prevention frame ad copy, and 0 for neutral frame ad copy. *Wind Speed* (kilometers per hour), *Temperature* (highest, in degrees Celsius), *Temperature Range* (highest minus lowest), *Visibility* (in kilometers), *Dew Point* (in degrees Celsius), *Humidity* (in percentage), and *Air Pressure* (in hectopascals) are continuous variables. *Rural* is a dummy variable for rural or urban area, and there are nine dummies for wind direction. There are 31 provinces and 23 weekdays in the field data.

have two dummies, $Sunny_i$ and $Rainy_i$, for the three weather conditions: sunny, cloudy, and rainy weather of the day (or hour). The baseline weather is cloudy. $Ad\ Copy\ Frame_i$ equals 1 for the prevention frame ad copy and 0 for the neutral frame ad copy of the mobile promotion. We control for weather-related variables of highest temperature, temperature range, humidity, dew point, air pressure, wind speed, and wind direction. Correlations among variables are not high, with the largest correlation being less than 0.15 in the data. We control for temperature variables because prior studies have found that temperature has a significant effect on consumer behavior (Conlin et al. 2007), i.e., temperature premium (Zwebner et al. 2014). Temperature range equals the highest temperature minus the lowest temperature in degrees Celsius, indicating the uncertainty of temperature. Also, we control for wind variables because they influence people's moods and feelings (Denissen et al. 2008) and the behavior of animals (Hayes and Huntly 2005). We control for location-based fixed effects with $\Omega_{\mathbf{R(i)}}$, a vector of 30 geographical dummies (31 provinces). Also, we control for *rural*, which equals 1 if the user lives in a rural area and 0 otherwise. This helps control for income differences between rural and nonrural areas. Finally, we consider the behavioral differences between weekdays and weekends. On weekends, people may have more freedom to choose to go out if it is sunny and stay inside if it is rainy. Yet, on weekdays, people may have less freedom to do so if they need to go to work whether it is sunny or rainy. Relatedly, we consider the confounding day effect. As our field experiment is implemented for one month, people may purchase more at the beginning (versus the end) of one month because of budget limitations. Hence, we control for the day fixed effect with X_i, a vector of day fixed effects (22 dummies for the 23 weekdays) during the promotion period.[5] Table 1 reports the summary statistics of the data. The mean value of consumer responses shows the purchase rate is about 0.78%. This purchase rate is consistent with the rate between 0.6% and 2% for mobile promotions in Asia (eMarketer 2014).

As Table 2 shows, across all models, sunny weather consistently has a significant and positive effect, while rainy weather has a negative effect on purchase likelihood. Thus, there is an increase in consumers' likeli-

Table 2. Sunny (Rainy) Weather Increases (Decreases) Consumer Response to Mobile Promotion

	(1)	(2)	(3)	(4)	(5)
Sunny	0.3684***	0.1782***	0.4327***	0.1880***	0.1880***
	(0.014)	(0.022)	(0.026)	(0.038)	(0.037)
Rainy	−0.1243***	−0.0814**	−0.4621***	−0.1068**	−0.1068**
	(0.017)	(0.031)	(0.036)	(0.035)	(0.037)
Ad Copy Frame	0.5238***	0.7414***	0.8217***	0.7814***	0.7814***
	(0.017)	(0.070)	(0.034)	(0.084)	(0.087)
Temperature			−0.0524***	−0.0191**	−0.0191**
			(0.005)	(0.006)	(0.006)
Temperature Range			0.0072	−0.0226***	−0.0226***
			(0.006)	(0.007)	(0.007)
Visibility			−0.0039	−0.0114**	−0.0114**
			(0.004)	(0.004)	(0.004)
Dew Point			0.0238***	0.0006	0.0006
			(0.002)	(0.002)	(0.002)
Humidity			0.0005	0.0044***	0.0044***
			(0.001)	(0.001)	(0.001)
Air Pressure			1.1496***	−0.0214	−0.0214
			(0.131)	(0.140)	(0.139)
Wind Speed			0.1542***	0.2812***	0.2812***
			(0.034)	(0.040)	(0.039)
Rural			0.2344***	0.0889**	0.0889**
			(0.028)	(0.028)	(0.027)
Intercept	−5.4551***	−5.0080***	−39.9486***	−4.9052	−4.9052
	(0.062)	(0.178)	(3.962)	(4.263)	(4.216)
Wind direction	No	No	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes	Yes
Day fixed effect	No	Yes	No	Yes	Yes
N	6,744,884	3,321,575	3,321,575	3,321,575	3,321,575
Log likelihood	−290,404.56	−168,922.52	−166,772.56	−162,413.8	−162,413.8
AIC	580,875.1	337,923	333,641.1	324,939.6	324,939.6
BIC	581,328	338,431.9	334,275.5	325,668.5	325,668.5
LR chi-squared	37,565.79	18,012.36	20,694.18	17,339.23	17,343.91
Prob. > chi-squared	0.0000	0.0000	0.0000	0.0000	0.0000

Notes. This table reports the logistic regression coefficients, Model (5) is with robust standard error in estimation. The sample size reduces from Model (1) to Model (2) because of missing data on weather covariates of temperature, dew point, humidity, visibility, air pressure, and wind speed. AIC, Akaike information criterion; BIC, Bayesian information criterion; LR, likelihood ratio.

$^{**}p < 0.01$; $^{***}p < 0.001$.

hood to respond to promotions in sunny weather and a decrease in rainy weather, compared with the baseline cloudy weather. Table 2 also supports the effect of ad copy frame. Compared with the neutral ad copy, the prevention frame ad copy has a positive direct effect on purchase response, as expected.

Besides statistical significance, there is material economic significance. Specifically, in terms of the odds ratio, sunny weather leads to 1.21 ($= e^{0.1880}$) times more purchases of promotions compared with cloudy weather. By contrast, rainy weather leads to 0.9 ($= e^{-0.1068}$) times fewer purchases. As the company who conducts field experiments has over 300 million smartphone users, scaling up would produce a substantial amount of sales revenue. Even for firms with a small number of customers, 1.21 times more purchase responses per individual in sunny weather is still meaningful and economically profitable, because firms incur no costs for sunshine but could attain more purchase responses to promotions on sunny days.

We also test the interaction effects between weather and ad copy frame

$$\begin{aligned} U_i^{\text{weather}} = \alpha_0 &+ \theta_1 \mathit{Ad\ Copy\ Frame}_i \times \mathit{Sunny}_i \\ &+ \theta_2 \mathit{Ad\ Copy\ Frame}_i \times \mathit{Rainy}_i + \alpha_1 \mathit{Sunny}_i \\ &+ \alpha_2 \mathit{Rainy}_i + \gamma \mathit{Ad\ Copy\ Frame}_i \\ &+ \Delta \mathit{ControlVars} + \mu \Omega_{\mathrm{R(i)}} + \rho \mathbf{X}_{\mathrm{i}} + \varepsilon_i. \end{aligned} \tag{2}$$

Results in Table 3 show that when the weather is sunny, the prevention frame ad copy leads to a decreased purchase likelihood compared with the neutral ad copy. Interestingly, when the weather is rainy,

Table 3. Mobile Promotions with Prevention Frame Ad Copy Are Less Effective in Sunny Weather, Yet More Effective in Rainy Weather, in Terms of Purchase Likelihood

	(1)	(2)	(3)	(4)
Sunny	0.6632***	0.8314***	0.3131***	0.3131***
	(0.023)	(0.038)	(0.051)	(0.049)
Rainy	−0.2452***	−0.5841***	−0.2829***	−0.2829***
	(0.034)	(0.059)	(0.072)	(0.074)
Ad Copy Frame	0.7001***	1.0151***	0.8113***	0.8113***
	(0.023)	(0.044)	(0.086)	(0.090)
Sunny × Ad Copy Frame	−0.5225***	−0.7098***	−0.2350**	−0.2350**
	(0.030)	(0.048)	(0.080)	(0.077)
Rainy × Ad Copy Frame	0.1835***	0.2393***	0.2239**	0.2239**
	(0.038)	(0.067)	(0.060)	(0.063)
Temperature		−0.0397***	−0.0180**	−0.0180**
		(0.006)	(0.006)	(0.006)
Temperature Range		0.0023	−0.0236***	−0.0236***
		(0.006)	(0.007)	(0.007)
Visibility		−0.0091*	−0.0144***	−0.0144***
		(0.004)	(0.004)	(0.004)
Dew Point		0.0199***	0.0004	0.0004
		(0.002)	(0.002)	(0.002)
Humidity		0.0028***	0.0045***	0.0045***
		(0.001)	(0.001)	(0.001)
Air Pressure		0.8092***	−0.0222	−0.0222
		(0.133)	(0.141)	(0.139)
Wind Speed		0.2036***	0.2806***	0.2806***
		(0.034)	(0.040)	(0.039)
Rural		0.1798***	0.0740**	0.0740**
		(0.028)	(0.028)	(0.028)
Intercept	−5.5971***	−30.3986***	−4.9523	−4.9523
	(0.064)	(4.034)	(4.264)	(4.217)
Wind direction	No	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	No	No	Yes	Yes
N	6,744,884	3,321,575	3,321,575	3,321,575
Log likelihood	−290,193.29	−166,627.46	−162,404.18	−162,404.18
AIC	580,456.6	333,354.9	324,924.4	324,924.4
BIC	580,936.9	334,015.7	325,679.3	325,679.3
LR chi-squared	37,988.33	20,984.38	17,358.47	17,346.25
Prob. > chi-squared	0.0000	0.0000	0.0000	0.0000

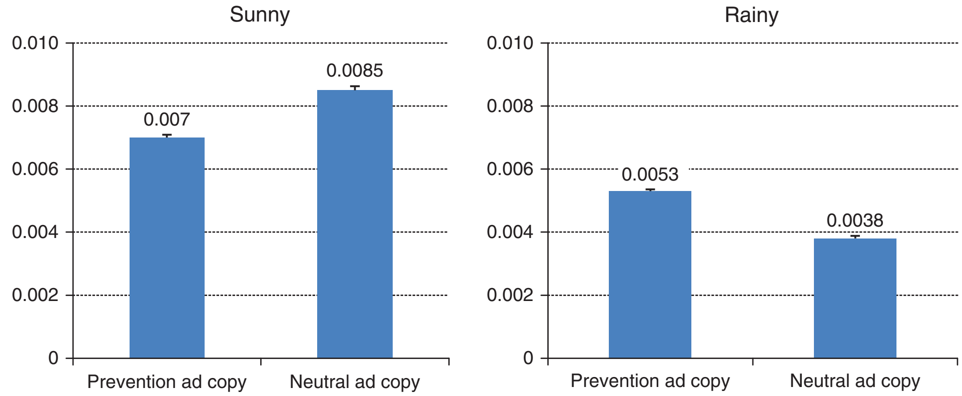
Notes. This table reports the logistic regression coefficients, Model (4) is with robust standard error in estimation. The sample size reduces from Model (1) to Model (2) because of missing data on weather covariates of temperature, dew point, humidity, visibility, air pressure, and wind speed. AIC, Akaike information criterion; BIC, Bayesian information criterion; LR, likelihood ratio.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

the prevention frame leads to an increased purchase likelihood. Because it is difficult to interpret interactions in logistic regression, we follow the procedure by Ai and Norton (2003, p. 124) to calculate mean marginal effects of the interaction effects. As shown in Figure 3, compared with the neutral ad copy, the prevention ad copy indeed has a lower mean marginal effect in sunny weather. The reverse is observed in rainy weather, where the prevention ad copy has a higher mean marginal effect than the neutral ad copy.

Now, we conduct hour-by-hour survival analyses of response hazard, or purchase speed. The time stamps in digital purchase records before deal expiration allow us to test how *fast* consumers purchase at the hourly level. Also, as the weather condition may change every hour, we collect weather data at the hourly level and develop an hour-by-hour hazard model. Table 4 indicates that the promotion purchase rate is the highest (0.00022) in hourly sunny weather and the lowest (0.00013) in hourly rainy weather, thus adding more evidence for our main conclusion even at the hourly level. The Kaplan–Meier plot in Figure 4 suggests that the slope of the line for sunny weather is steeper than that for cloudy weather, meaning that in sunny

Figure 3. (Color online) Mean Marginal Effects of Weather and Ad Copy Interaction Effects

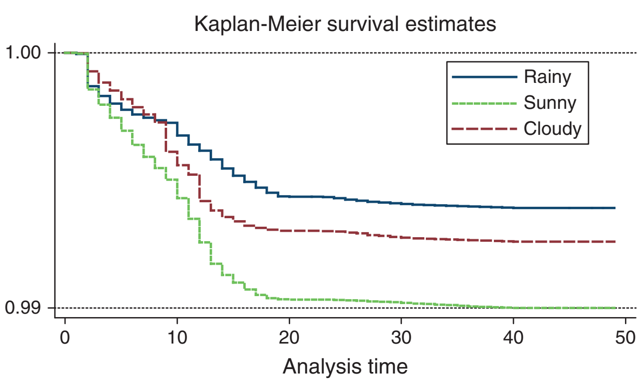


Notes. For the prevention frame ad copy, the mobile promotion message begins with "Do not miss the opportunity to take advantage of this special deal!" This ad copy emphasizes preventing the users from losing the deal, i.e., a negative tone with wording about not missing out in the ad copy. For the neutral frame ad copy, the mobile promotion message begins with a general greeting of "Dear respected customer." This ad copy emphasizes a generic salutation, a nonnegative tone in ad message content.

Table 4. Response Rates of Hourly Weather Conditions

	Hourly purchase rate	Number of observations
Hourly Sunny	0.00022	2,643,566
Hourly Cloudy	0.00016	2,847,163
Hourly Rainy	0.00013	2,834,813
Total	0.00017	8,325,542

Figure 4. (Color online) Response Hazard in Different Weather Conditions



weather, consumers make faster purchase responses to promotions. Also, the slope of the line for cloudy weather is steeper than that for rainy weather, suggesting that consumers have slower purchase responses in rainy weather if they make purchases. However, the Kaplan–Meier plot presumes time-invariant weather, assuming that what matters is the weather at the time of receiving the deal. Thus, we also conduct hour-by-hour analyses with hazard model in a panel style with time-varying weather. Hazard analyses account for the weather at the time of receiving the deal *and* at the time of purchasing it.

The proportional hazard model is shown below

$$\begin{aligned} h(t) &= h_0(t)\exp(U_{it}^{\text{weather}}),\\ U_{it}^{\text{weather}} &= \alpha_0 + \alpha_1 \mathit{HourlySunny}_{it} + \alpha_2 \mathit{HourlyRainy}_{it}\\ &\quad + \beta \mathit{Ad\ Copy\ Frame}_i\\ &\quad + \gamma_1 \mathit{Ad\ Copy\ Frame}_i \times \mathit{HourlySunny}_i\\ &\quad + \gamma_2 \mathit{Ad\ Copy\ Frame}_i \times \mathit{HourlyRainy}_i\\ &\quad + \Delta \mathit{ControlVars} + \mu\Omega_{\text{R(i)}} + \rho \mathbf{X}_{\text{i}} + \varepsilon_{it}, \end{aligned} \tag{3}$$

where the dependent variable is $h(t)$, the hazard rate for purchase response at hour t. The baseline hazard $h(0)$ represents the cloudy weather condition when all variables in the function of U_i^{weather} are equal to 0. Weather-related covariates here are also at the hourly level. To further control for the behavioral effects of weather, we analyze data in the daytime hours during weekdays. During the nighttime period, the weather effects should go away because there is no sunlight after dark. Also, people will be less affected by rain when they are indoors at night (see Appendix B). Taking this into account, our hazard models use the hourly weather data of daytime hours (from 9 A.M. to 5 P.M.). Results of Cox proportional hazard models are presented in Table 5. As an hour-by-hour analysis across individuals, the number of observations in the hazard models (55,164,292) is larger than that in the logit model (6,744,884).[6] The results in Table 5 indicate significant positive effects of sunshine (coefficient = 0.5481, $p < 0.05$) and negative effects of rainfall (coefficient = −0.5247, $p < 0.05$) on purchase hazard; that is, the hazard rate of purchase responses in sunny weather is 73% faster than that in cloudy weather. By contrast, the hazard rate of purchasing in rainy weather is 59% slower than that in cloudy weather. Table 5, column (4), results support that when the weather is sunny, the prevention frame ad copy

Table 5. Hourly Sunny (Rainy) Weather Increases (Decreases) Response Hazard (9 a.m. to 5 p.m.)

	(1)	(2)	(3)	(4)
Hourly Sunny Weather	0.5485***	0.6304***	0.5481***	0.7135***
	(0.018)	(0.019)	(0.022)	(0.016)
Hourly Rainy Weather	−0.7733***	−0.4465***	−0.5247***	−0.9240***
	(0.049)	(0.051)	(0.053)	(0.024)
Hourly Sunny × Ad Copy Frame				−0.3844***
				(0.031)
Hourly Rainy × Ad Copy Frame				0.3296***
				(0.033)
Ad Copy Frame			0.1244***	0.1429***
			(0.018)	(0.020)
Temperature			−0.1518***	−0.5343***
			(0.005)	(0.003)
Dew Point			0.1264***	0.4895***
			(0.004)	(0.003)
Humidity			−0.0530***	−0.2130***
			(0.002)	(0.001)
Air Pressure			−0.4277**	−8.0703***
			(0.155)	(0.072)
Visibility			−0.0459***	−0.0807***
			(0.003)	(0.002)
Rural			−0.0584**	−0.1120***
			(0.019)	(0.011)
Wind Speed			0.0580***	0.6138***
			(0.003)	(0.003)
Wind direction	No	No	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	No	Yes	Yes	Yes
N	59,814,313	59,814,313	55,164,292	55,164,292
Log likelihood	−409,198.47	−398,471.57	−367,346.64	−362,932.8
AIC	818,460.9	797,025.1	734,817.3	766,007.7
BIC	818,970	797,677.3	735,798.5	767,148
LR chi-squared	9,962.50	31,416.30	38,775.47	42,059.18
Prob. > chi-squared	0.0000	0.0000	0.0000	0.0000

Notes. The table shows proportional hazard model results. AIC, Akaike information criterion; BIC, Bayesian information criterion; LR, likelihood ratio.

$^{**}p < 0.01$; $^{***}p < 0.001$.

leads to slower purchase hazard (coefficient = −0.3844, $p < 0.001$) than the neutral ad copy. By contrast, when the weather is rainy, the prevention frame ad copy leads to faster purchase hazard (coefficient = 0.3296, $p < 0.001$) than the neutral ad copy. These results add more evidence for the interaction effects between weather conditions and ad copies.

4.1. Additional Analyses

Furthermore, we considered two types of changes in weather, backward looking and forward looking, to test the effects of sunny and rainy weather relative to cloudy weather on purchase responses (i.e., to extend the results in Table 2 with changes in weather). For the backward-looking weather changes, if the weather yesterday was rainy, people may possibly suppose it will still be rainy today. Yet, if the weather turns out to be sunny, then this change to better weather (from rain to sunshine) will put consumers in a better mood than no weather change (sunny–sunny in a row), thus likely inducing more responses. To test this, we code *Better than Yesterday* as 2 if the weather changes from rainy to sunny and 1 if from cloudy to sunny or from rainy to cloudy. We coded *Worse than Yesterday* in a similar way. The baseline here is no change in weather (i.e., sunny–sunny, rainy–rainy, or cloudy–cloudy in a row). The results in Table 6 confirm that *Better than Yesterday* indeed increases the purchase response likelihood, and *Worse than Yesterday* decreases it. Additionally, column (3) in Table 6 shows that after controlling for the backward-looking changes in weather, the effects of current sunny and rainy weather are still consistent and significant (all $p < 0.05$).

For the forward-looking weather changes, we test whether consumers are less (more) likely to respond to promotions when the real weather is worse (better) than forecast. We code *Better than Forecast* as 2 if the forecast is for rainy weather but it turns out to be sunny,

Table 6. Changes in Weather Matter (Backward Looking)

	(1)	(2)	(3)
Better than Yesterday	0.1135***	0.0960***	0.0869***
	(0.012)	(0.012)	(0.012)
Worse than Yesterday	−0.2086***	−0.2644***	−0.1578***
	(0.012)	(0.014)	(0.018)
Sunny			0.2118***
			(0.015)
Rainy			−0.0484*
			(0.023)
Ad Copy Frame	0.9173***	1.0573***	1.0662***
	(0.046)	(0.061)	(0.059)
Weather covariates	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes
Day fixed effect	No	Yes	Yes
N	5,820,418	5,820,418	5,820,418
Log likelihood	−360,207.3	−343,946.09	−360,088.82
AIC	720,482.6	687,984.2	720,251.6
BIC	720,944.2	688,607	720,754
LR chi-squared	32,236.01	31,606.06	32,472.95
Prob. > chi-squared	0.0000	0.0000	0.0000

Notes. This table reports the logistic regression coefficients. AIC, Akaike information criterion; BIC, Bayesian information criterion; LR, likelihood ratio.
$^{*}p < 0.05$; $^{***}p < 0.001$.

Table 7. Changes in Weather Matter (Forward Looking)

	(1)	(2)	(3)
Better than Forecast	0.0767***	0.0679**	0.0332
	(0.021)	(0.021)	(0.022)
Worse than Forecast	−0.1459***	−0.1753***	−0.0960***
	(0.022)	(0.022)	(0.024)
Sunny			0.3325***
			(0.037)
Rainy			−0.1008***
			(0.031)
Ad Copy Frame	0.9632***	1.0260***	1.0507***
	(0.055)	(0.066)	(0.063)
Weather covariates	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes
Day fixed effect	No	Yes	Yes
N	1,414,148	1,414,148	1,414,148
Log likelihood	−117,074.77	−110,874.42	−110,830.69
AIC	234,245.5	221,850.8	221,767.4
BIC	234,848	222,471.1	222,412
LR chi-squared	12,293.17	7,226.75	7,314.23
Prob. > chi-squared	0.0000	0.0000	0.0000

Notes. This table reports the logistic regression coefficients. AIC, Akaike information criterion; BIC, Bayesian information criterion; LR, likelihood ratio.
$^{**}p < 0.01$; $^{***}p < 0.001$.

and 1 if the forecast is for rainy weather but it turns out to be cloudy or if the forecast is for cloudy weather but it turns out to be sunny. We code *Worse than Forecast* in a similar fashion. With modern technologies, weather forecasts are 70% accurate and 30% inaccurate (thus there are some variations in forward-looking weather changes). Results in Table 7 support that *Better than Forecast* indeed increases the purchase response likelihood, and *Worse than Forecast* decreases it. Also, we find consistent and significant effects of sunny and rainy weather on purchase responses, even after controlling for forward-looking unexpected changes.

Next, we test how deviation from normal weather matters. If a certain area has a normal, expected weather with rainfall or a cloudy sky, a good deviation with relatively rare events of *sunny* days would lead to better moods and thus more responses. According to climate conditions, China can be divided into northern and southern regions with the Qinling–Huaihe line. The northern region, with 16 provinces, belongs to the temperate zone, while the southern region, with 15 provinces, belongs to the subtropical zone. Figure 5 depicts the normal weather frequency across the regions. In the north, sunny weather is the normal weather with the highest frequency, followed by cloudy and then rainy weather. In the south, the normally expected weather is cloudy, followed by rainy and sunny. The Table 8 results support the consistent positive effect of sunny and the negative effect of rainy. Also, results in both logit and linear probabilistic models suggest that the interaction term *Sunny* × *South* is positive and significant. Thus, good sunshine deviation from the normal cloudy weather in the south (a relatively rare event of *sunny* weather) indeed engenders more purchase responses than in the north.

As a falsification test, we check the robustness via the interaction between weather and temperature. Although sunshine is usually associated with nice weather, when the temperature is too hot, sunlight may have a negative effect on mood (Cohen 2011, Zwebner et al. 2014).[7] Results in column (1) of Table 9 indeed show that the interaction between sunny weather and temperature (highest degree of the day) is significantly negative, as expected. Also, the results support the positive interaction effect between rainy weather and the highest temperature. This finding also passes the falsification test because a warmer rainy day is relatively better weather compared with a colder rainy day to consumers.

5. Another Randomized Field Experiment on App Ads

The second field experiment tackles two main objectives: generalizability of the main effects of sunny and rainy weather and a possible mood explanation for the effects. This experiment uses a different mobile product with a book-reading digital service (similar to Kindle but on a mobile app platform). The app is one of the most popular mobile reading applications in China, providing more than 400,000 e-books to over 300 million users. Randomized app notification ads were sent to 45,733 app users nationwide on May 7, May 19, and June 4, 2015. From the 45,733 app users, 40,266

Figure 5. (Color online) Distributions of Weather Conditions in the North and South

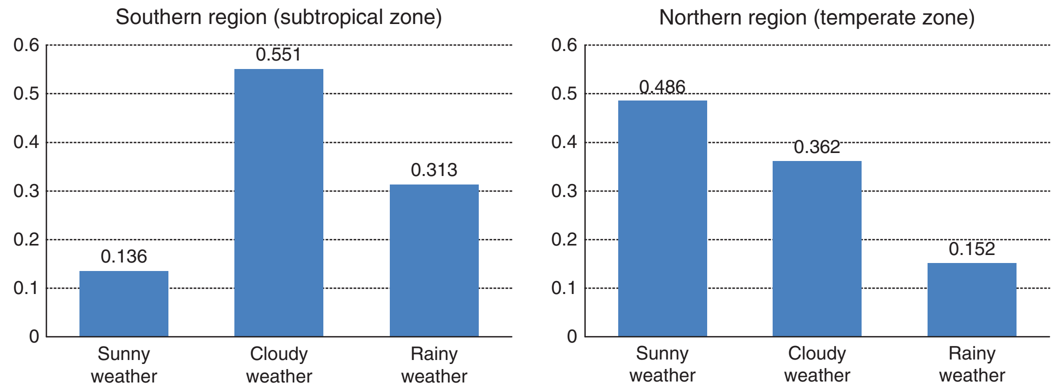


Table 8. Deviations from Normal Weather Matter

	South (logit)	North (logit)	Full (logit)	Full (OLS)
Sunny	0.2904***	0.0406**	0.0326**	0.0003**
	(0.016)	(0.015)	(0.011)	(0.000)
Rainy	−0.0665***	−0.0921***	−0.1193***	−0.0008***
	(0.019)	(0.021)	(0.019)	(0.000)
Sunny × *South*			0.3287***	0.0044***
			(0.020)	(0.000)
Rainy × *South*			−0.0278**	−0.0007**
			(0.006)	(0.000)
Intercept	−6.5763***	−5.9477***	−4.8007***	−0.0000
	(0.095)	(0.098)	(0.077)	(0.016)
Weather covariates	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes
N	4,788,301	5,009,603	9,797,904	9,797,904
Log likelihood	−235,383	−263,560	−524,665	
AIC	470,825.1	527,182	1,002,899	
BIC	471,213.2	527,598.2	1,003,547	
LR chi-squared	22,838.43	28,421.56	46,524.81	
Prob. > chi-squared	0.0000	0.0000	0.0000	
R^2				0.005

Notes. AIC, Akaike information criterion; BIC, Bayesian information criterion; LR, likelihood ratio.
$^{**}p < 0.01$; $^{***}p < 0.001$.

of them were in the ad groups, and 5,467 were in the control group. The control group (without ad) is a randomized holdout control, so the control has ex ante holdout samples that are similar to the treated groups (with ads). Also, indirectly identifying the psychological mood effect of weather, this experiment has two app ads: one recommending mood-related romantic book titles and one recommending mood-neutral biographical book titles.[8] After receiving app ads, interested users could respond by making an in-app purchase. Here we also are able to control for mobile usage behavior with app launch (how many times the user opens the reading app each day) and app session (how many minutes the user reads conditional on opening the app). The two field experiment data sets differ in terms of products (video streaming versus book reading), marketing instruments (price discounts versus pure ads), and delivery mobile technologies (SMS versus app). However, this experiment did not test the speed of response or the effect of ad copy frame. Thus, it serves at least as a replication of the positive effect of sunny weather and negative effect of rainy weather on incremental mobile ad sales compared with cloudy weather.

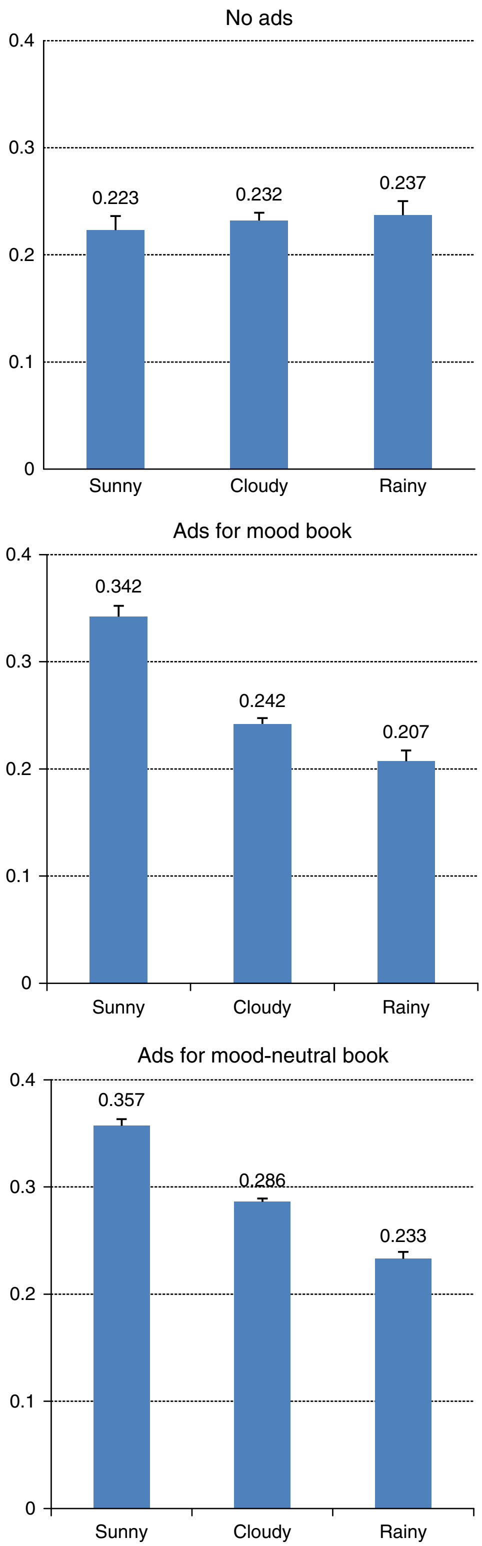
Table 9. Robustness Check of Interactions Between Weather and Temperature

	(1)	(2)
Sunny	1.3508***	0.2919***
	(0.114)	(0.067)
Rainy	−0.2827**	−0.1117*
	(0.092)	(0.051)
Sunny × *Temperature*	−0.0437***	
	(0.004)	
Rainy × *Temperature*	0.0160***	
	(0.005)	
Sunny × *Temperature Range*		−0.0078
		(0.005)
Rainy × *Temperature Range*		0.0107
		(0.006)
Ad Copy Frame	1.1984***	1.1976***
	(0.042)	(0.040)
Intercept	32.7511***	−6.0606***
	(2.058)	(0.177)
Weather covariates	Yes	Yes
Location fixed effect	Yes	Yes
Day fixed effect	Yes	Yes
N	6,428,845	6,428,845
Log likelihood	−307,275.45	−314,137.84
AIC	614,652.9	628,369.7
BIC	615,350.4	629,014
LR chi-squared	28,046.59	28,253.25
Prob. > chi-squared	0.0000	0.0000

Notes. This table reports the logistic regression coefficients. AIC, Akaike information criterion; BIC, Bayesian information criterion; LR, likelihood ratio.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 6 suggests that the effects are incremental. As reported in Appendix C, panel A, formal statistical t-test results consistently support the positive effect

Figure 6. (Color online) Response Rates in Different Weather Conditions



of sunny weather ($p < 0.001$) and the negative effect of rainy weather ($p < 0.001$) on incremental mobile ad sales, compared with cloudy weather. According to the logit, ordinary least squares (OLS), and

Table 10. Consumer Responses to App Ads (Mobile Book in Second Field Experiment)

	Purchase likelihood (logit)	Purchase amount (OLS)	Purchase amount (Tobit)
Panel A: Effects of weather conditions on incremental sales			
Cloudy × No Ads		Baseline	
Sunny × No Ads	−0.0323	0.0248	0.0134
	(0.104)	(0.048)	(0.160)
Rainy × No Ads	−0.2098*	−0.0079	−0.2104
	(0.091)	(0.043)	(0.142)
Sunny × Ads	0.5685***	0.2562***	0.9284***
	(0.061)	(0.030)	(0.096)
Cloudy × Ads	0.2467***	0.1276***	0.4372***
	(0.050)	(0.024)	(0.078)
Rainy × Ads	−0.2060**	−0.0170	−0.2015*
	(0.065)	(0.031)	(0.102)
Intercept	−26.0154***	−7.5074***	−35.8773***
	(4.144)	(2.024)	(6.537)
Weather covariates	Yes	Yes	Yes
Mobile usage behavior	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes
N	45,733	45,733	45,733
Panel B: Differences between weather conditions and ad types			
Cloudy × No Ads		Baseline	
Sunny × No Ads	−0.0404	0.0222	0.0012
	(0.104)	(0.048)	(0.160)
Rainy × No Ads	−0.2064*	−0.0063	−0.2050
	(0.091)	(0.043)	(0.141)
Sunny × Mood book	0.4870***	0.2385***	0.8266***
	(0.074)	(0.037)	(0.117)
Cloudy × Mood book	0.0775	0.0619*	0.1627†
	(0.057)	(0.027)	(0.089)
Rainy × Mood book	−0.2988***	−0.0658	−0.3762**
	(0.087)	(0.041)	(0.135)
Sunny × Neutral book	0.5813***	0.2553***	0.9355***
	(0.063)	(0.031)	(0.099)
Cloudy × Neutral book	0.2865***	0.1437***	0.5011***
	(0.050)	(0.024)	(0.079)
Rainy × Neutral book	−0.1969**	−0.0102	−0.1811†
	(0.067)	(0.032)	(0.105)
Intercept	−25.7482***	−7.4210***	−35.4984***
	(4.144)	(2.024)	(6.534)
Weather covariates	Yes	Yes	Yes
Mobile usage behavior	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes
N	45,733	45,733	45,733

†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Tobit regression models reported in Table 10, panel A, and the coefficient tests of logit models reported in Appendix D, the results also support the positive sunny weather effect (coefficient difference = 0.3534, $p = 0.0009$) and the negative rainy weather effect (coefficient difference = −0.1061, $p = 0.011$) relative to cloudy weather on incremental sales of mobile ads. The test in Appendix D, panel A, also shows that sunny weather with ads and cloudy weather with ads both generate incremental sales, while rainy weather with ads does not increase sales, and that the sunny effect is bigger than the cloudy effect, which in turn is bigger than the rainy effect. Results of difference-in-differences tests also support the statistically significantly incremental effects over the control group (see Appendix E). Thus, results from both the model-free t-test and the regression model indeed replicate the positive effect of sunny weather and the negative effect of rainy weather on incremental mobile ad sales relative to cloudy weather.

Next, we examined the incremental interaction effects between weather and specific book ads. The results in Appendix C, panel B, on t-tests support that sunny weather does have a stronger positive effect on the mood-related (versus mood-neutral) book titles ($p < 0.05$). Yet, rainy weather does not have a different effect on the mood-related (versus mood-neutral) book titles ($p > 0.10$). Consistently, the regression results in Table 10, panel B, and the coefficient tests results show that sunny weather does have a marginally stronger positive effect on the mood-related (versus mood-neutral) book titles (coefficient difference = 0.1147, $p = 0.078$). However, rainy weather does not have a different effect on the mood-related (versus mood-neutral) book titles (coefficient difference = 0.1061, $p > 0.10$). The difference-in-differences results reported in Appendix E also support that sunny weather does have a stronger positive effect on the mood-related (versus mood-neutral) book titles ($p < 0.05$). Also, rainy weather does not have a different effect on the mood-related (versus mood-neutral) book titles ($p > 0.10$). We speculate that mood-related book ads may improve users' mood states, which would match sunny weather but not rainy weather. This might explain why the incremental results here replicate the interaction effects between sunny weather and ad copy of the main study, but not the interaction effects between rainy weather and ad copy. Nevertheless, results in this additional field experiment consistently support the theme that incremental purchase response to mobile ads is greater in sunny weather compared to cloudy weather, and lower in rainy weather compared to cloudy weather. They also show interactions with the specific ad, especially involving sunny weather, albeit not with rainy weather.[9]

6. Conclusion

Firms are leveraging local weather information to increase the relevancy and effectiveness of their promotions. Yet, little causal evidence exists in the literature, especially with field data, on how sunny and rainy weather affect consumer purchase responses to promotions. Using data sets from large-scale field experiments, we find that the following:

- Purchase responses to promotions are higher and faster in sunny weather, but lower and slower in rainy weather, relative to cloudy weather. In terms of odds ratios, sunshine leads to about 1.21 times more response to mobile promotions, and rainfall leads to about 0.9 times less response than cloudy weather.
- Survival models at the hourly level suggest the hazard rate of purchase responses in sunny weather is 73% faster than that in cloudy weather. By contrast, the hazard rate of purchasing in rainy weather is 59% slower than that in a cloudy sky.
- Better-than-yesterday weather and better-than-forecast weather engender more purchase responses, and vice versa. A good deviation from the expected rainy or cloudy weather with relatively rare events of sunny days will substantially boost purchase responses to mobile promotions.
- The ad copy of mobile promotions interacts with sunshine and rainfall. Compared with a neutral frame ad copy, the prevention frame hurts the initial promotion boost by sunshine, but improves the initial promotion drop due to rainfall.

Our study has a number of limitations, which serve as avenues for future research. First, it is limited to the setting of mobile digital services and may not be generalizable to nonmobile settings such as physical products or even desktop platforms. We tested two mobile platforms (SMS versus app) with two digital products (video streaming versus e-book reading). However, both products' valuations are not strictly weather neutral. Valuations for mobile products will be higher if a consumer believes that she will be more likely to spend time outside, where only mobile devices can be used for watching videos or reading books. Also, both products are similar (streaming and reading are both spare-time entertainment) and somewhat weather-related (consumers are more apt to stream or read in bad weather, which means that our results may be more conservative). Thus, it will be important to support generalizable results with other settings and other products that are weather neutral in future research.[10] Also, because of a lack of corporate support, we do not have a happy positive ad copy in the field data. This is a limitation of our study, and future research may test how sunny weather fits a happy, optimistic ad copy. Furthermore, our results suggest that on cloudy days, the neutral ad copy is moderately better than the prevention ad copy. Future tests could reveal more nuanced effects of sunny, rainy, and cloudy weather on consumer response to ads with promotion, prevention, and neutral message frames.

In addition, our research with field experiment datasets cannot directly measure moods and gauge underlying psychological mechanisms. It is not a direct test of theoretical mechanisms, but rather a test with hypotheses motivated by theory. Future research with lab studies may explore the mechanisms of how, on rainy days, consumers may activate mood repair mindsets and engage in more indulgent responses to mobile promotions (Pham et al. 2012, Isen 2001, Schwarz and Clore

1983). Also, it would be interesting for future research to test how weather is related to consumer risk seeking or risk avoidance (Parker and Tavassoli 2000, Reinholtz et al. 2014).

Also, a distinct aspect of weather-based mobile promotions relates to weather awareness and the ability to check weather multiple times using a mobile app. Yet, people are aware of current weather even without checking their mobile devices, especially during daytime (simply by looking out the window). Modern mobile and digital technologies may allow advertisers to access information about consumers' locations and local weather (past, present, forecast) and even competitors' customer activities that were not possible before (Luo et al. 2014, Fang et al. 2015, Andrews et al. 2016, Dubé et al. 2017). Thus, future research may test how such information can be used for optimizing mobile ad message and delivery timing.

Finally, industry practitioners have long argued that advertisers need to integrate weather-related data in online display programmatic environments. Platforms such as Facebook and Twitter (Marshall 2014) are testing how to effectively target users by their local weather.[11] There are also outdoor billboard ads based on real-time, location-based data including weather as tested by Google. In this sense, future research may explore smartphones, the Internet of things, and smart technologies at home, in the office, and in the city toward a broader context of weather-based promotions and ad copy design.

In conclusion, this is an initial step in identifying the causal sales impacts of sunny and rainy weather. We hope it can serve as a springboard for future research to examine how consumers respond to mobile ads and promotions in various weather conditions.

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Appendix A. Mobile Promotion Message

SMS in Field Experiment 1	Message with prevention ad copy frame	Message without neutral ad copy frame
Original version	**别错过占便宜的机会了!** 48 小时内回复“是”购买视频礼包，每月仅需3 元。当月购买后可在手机免费观看精彩视频【公司名称】	**尊敬的客户，您好!** 48 小时内回复“是”购买视频礼包，每月仅需3 元。当月购买后可在手机免费观看精彩视频【公司名称】
English translation	*Do not miss the opportunity to take advantage of this special deal*! Subscribe to the mobile video-streaming service for only ¥3 per month! Watch video episodes of the most popular TV series on your mobile devices on-the-go! The regular price is ¥6. Purchase by replying "Yes" to this SMS within the next 48 hours [Company Name]	*Dear respected customer*, Subscribe to the mobile video-streaming service for only ¥3 per month! Watch video episodes of the most popular TV series on your mobile devices on-the-go! The regular price is ¥6. Purchase by replying "Yes" to this SMS within the next 48 hours [Company Name]
SMS in Field Experiment 2	**Message with mood-related book titles**	**Message with mood-neutral book titles**
Original version	一叶便知秋，一书看世界!【公司名称】百万电子书等您来挑选。**《爱在受伤之后》,《你的孤独，虽败犹荣》**等数百精彩新书上架，不要错过买新书的好机会!	一叶便知秋，一书看世界!【公司名称】百万电子书等您来挑选。**《陈坤的队伍》,《民国名媛的风花雪月》**等数百精彩新书上架，不要错过买新书的好机会!
English translation	Knowing the season from the change of plant, learning the world from reading books. [Company Name] provides more than one million mobile e-books. "*Love after Pain*," "*Loneliness, a Glorious Failure*" and hundreds of new e-books are available now. Don't miss the good opportunity to purchase new books!	Knowing the season from the change of plant, learning the world from reading books. [Company Name] provides more than one million mobile e-books. "*Team of Kun Chen*," "*Story of Old-Time Ladies*" and hundreds of new e-books are available now. Don't miss the good opportunity to purchase new books!

Appendix B. More Robustness Checks

B.1. Smaller Sample Size

We also randomly selected 25% and 50% of observations to test the main weather effects and the interaction effects of weather and ad copy frame (Table B.1). The results show a consistent positive sunny effect and negative rainy effect. Also, the significant interaction terms indicate a consistent negative interactive effect of sunny weather and a prevention frame and positive interactive effect of rainy weather and a prevention frame.

B.2. Weather Effects During Night Hours

If the relevant aspect of weather is the presence of sunlight or rainfall, the promotion effects should vanish after sundown. In other words, at nighttime, people's moods should be less likely to be influenced by outside sunny or rainy weather, because they are likely inside their home, i.e., not exposed to outside sunlight or rainfall. We tested the effects of weather at nighttime (6 P.M.–12 A.M.) with a time-varying hazard model and indeed found that the effects of both sunny and rainy weather are insignificant at night ($p > 0.10$), as expected (Table B.2).

Table B.2. Falsification Checks with Night Sample

	Nighttime sample
Hourly Sunny Weather	0.0298
	(0.020)
Hourly Rainy Weather	0.0220
	(0.023)
Wind direction	Yes
Location fixed effect	Yes
Day fixed effect	Yes

Table B.1. Robustness Checks with Smaller Sample Size

	(1) Sample 25%	(2) Sample 25%	(3) Sample 50%	(4) Sample 50%
Sunny	0.1734*	0.4195***	0.1569**	0.3335***
	(0.077)	(0.106)	(0.053)	(0.072)
Rainy	−0.1936*	−0.5268***	−0.1284*	−0.4258***
	(0.090)	(0.143)	(0.063)	(0.103)
Sunny × Ad Copy Frame		−0.4563**		−0.3160**
		(0.164)		(0.112)
Rainy × Ad Copy Frame		0.4254*		0.3916**
		(0.179)		(0.128)
Ad Copy Frame	0.9424***	1.0061***	0.6510***	0.6900***
	(0.178)	(0.182)	(0.112)	(0.115)
Wind direction	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes

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

Appendix C. *T*-Test Results (Model-Free Evidence)

P		*Q*	Response rate of *P*		Response rate of *Q*		Difference *P* vs. *Q*
		Panel A: Effects of weather condition on incremental sales					
Sunny with mood book ads	vs.	Sunny with no ads	0.342	minus	0.223	=	0.119***
Sunny with neutral book ads	vs.	Sunny with no ads	0.357	minus	0.223	=	0.134***
Rainy with mood book ads	vs.	Rainy with no ads	0.233	minus	0.237	=	−0.004
Rainy with neutral book ads	vs.	Rainy with no ads	0.207	minus	0.237	=	−0.03†
Cloudy with mood book ads	vs.	Cloudy with no ads	0.242	minus	0.232	=	0.01*
Cloudy with neutral book ads	vs.	Cloudy with no ads	0.286	minus	0.232	=	0.054***
(Sunny with ads) minus (Sunny with no ads)	vs.	(Cloudy with ads) minus (Cloudy with no ads)	0.128	minus	0.044	=	0.084***
(Rainy with ads) minus (Rainy with no ads)	vs.	(Cloudy with ads) minus (Cloudy with no ads)	−0.011	minus	0.044	=	−0.055***

Appendix C. (Continued)

P		Q	Response rate of P		Response rate of Q		Difference P vs. Q
		Panel B: Differences between weather conditions and ad types					
Sunny with no ads	vs.	Cloudy with no ads	0.223	minus	0.232	=	−0.009
Rainy with no ads	vs.	Cloudy with no ads	0.237	minus	0.232	=	0.005
Sunny with mood book ads	vs.	Cloudy with mood book ads	0.342	minus	0.242	=	0.1***
Rainy with mood book ads	vs.	Cloudy with mood book ads	0.207	minus	0.242	=	−0.035**
Sunny with neutral book ads	vs.	Cloudy with neutral book ads	0.355	minus	0.286	=	0.069***
Rainy with neutral book ads	vs.	Cloudy with neutral book ads	0.232	minus	0.286	=	−0.054***
(Sunny with mood book ads) minus (Cloudy with mood book ads)	vs.	(Sunny with neutral book ads) minus (Cloudy with neutral book ads)	0.1	minus	0.069	=	0.031*
(Rainy with mood book ads) minus (Cloudy with mood book ads)	vs.	(Rainy with neutral book ads) minus (Cloudy with neutral book ads)	−0.035	minus	−0.054	=	0.019

$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Appendix D. Coefficient Differences of Logit Models in Table 10

U		V	Coefficient of U		Coefficient of V		Difference U vs. V
		Testing coefficient differences in Table 10, Panel A					
Sunny with ads	vs.	Sunny with no ads	0.5685	minus	−0.0323	=	0.6008***
Rainy with ads	vs.	Rainy with no ads	−0.2060	minus	−0.2098	=	0.0038
Cloudy with ads	vs.	Cloudy with no ads	0.2466	minus		=	0.2466***
(Sunny with ads) minus (Sunny with no ads)	vs.	(Cloudy with ads) minus (Cloudy with no ads)	0.6008	minus	0.2466	=	0.3534***
(Rainy with ads) minus (Rainy with no ads)	vs.	(Cloudy with ads) minus (Cloudy with no ads)	0.0038	minus	0.2466	=	−0.1061*
		Testing coefficient differences in Table 10, Panel B					
Sunny with mood book ads	vs.	Sunny with no ads	0.4870	minus	−0.0404	=	0.5274***
Sunny with neutral book ads	vs.	Sunny with no ads	0.5813	minus	−0.0404	=	0.6217***
Rainy with mood book ads	vs.	Rainy with no ads	−0.2998	minus	−0.2064	=	−0.0934
Rainy with neutral book ads	vs.	Rainy with no ads	−0.1969	minus	−0.2064	=	0.0095
Cloudy with mood book ads	vs.	Cloudy with no ads	0.0775	minus		=	0.0775
Cloudy with neutral book ads	vs.	Cloudy with no ads	0.2865	minus		=	0.2865***
(Sunny with *mood* book ads) minus (Sunny with no ads) minus (Cloudy with *mood* book ads)	vs.	(Sunny with *neutral* book ads) minus (Sunny with no ads) minus (Cloudy with *neutral* book ads)	0.4499	minus	0.3352	=	0.1147†
(Rainy with *mood* book ads) minus (Rainy with no ads) minus (Cloudy with *mood* book ads)	vs.	(Rainy with *neutral* book ads) minus (Rainy with no ads) minus (Cloudy with *neutral* book ads)	−0.3773	minus	−0.4834	=	0.1061

$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{***}p < 0.001$.

Appendix E. Difference-in-Differences Model

	Mood book ad vs. holdout	Neutral book ad vs. holdout	Mood book ad vs. neutral book ad
Sunny vs. cloudy	0.1079***	0.0774***	0.0304*
Rainy vs. cloudy	−0.0403*	−0.0593**	0.0190

Notes. Difference-in-differences estimates are from a linear regression with factors coded to estimate the quantity indicated. Coefficients are reported.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Endnotes

[1] See Creativity (2012) and Hutchings (2012).

[2] We acknowledge the associate editor for the notion that while prior weather studies focus on purchases, we focus on promotion *effectiveness*, or incremental purchase responses to promotions.

[3] As manipulation checks, independent raters with 94 smartphone users confirmed that users indeed interpreted the wording of "do not miss the opportunity" as loss-avoidance-type negative message, i.e., preventing users from the negative outcomes of missing the deal. Also, the neutral frame with the general greeting was confirmed as neutral (smallest interrater correlations = 0.91, $p < 0.001$). Using these two ad copies, there were a total of 38 SMS campaigns. Though not perfectly balanced, 18 prevention and 20 neutral ad copies existed purely because of the corporate agenda, rather than researcher intervention.

[4] The corporate partner tends to keep a randomized holdout control for all field tests. So, the control has ex ante holdout samples that are similar to the treated samples. This control group size is much smaller. This is not totally unexpected because companies oftentimes do not prefer to have a large-size control group, because of the notion that the control group has opportunity costs (since the control group receives no promotions and often does not generate sales, while any promotions generally engender some sales). Indeed, a recent study by Hoban and Bucklin (2015) also had a much smaller control group.

[5] Because our results are robust to hour-by-hour analyses, the case with self-section bias not controlled for would be consumers strategically moving to better climates within one hour, which is not highly feasible for consumers.

[6] In the hour-by-hour survival analyses with over 55 million rows in the hazard model, each run with high-performance computing with parallel processing cost around two weeks.

[7] The interaction effect between weather and wind power is not included in the robustness check as there is no extreme value of wind power in our field data.

[8] Independent raters with 86 app users of the e-books confirmed that the mood-related romance titles (*Love after Pain* and *Loneliness, a Glorious Failure*) were indeed perceived to be moody, feelings-related readings, and the mood-neutral titles (biographical titles of *Team of Kun Chen* and *Story of Old-Time Ladies*) were indeed reported to be feeling-neutral readings (smallest interrater correlations = 0.93, $p < 0.001$). The mood-related book titles could be perceived as depressing at first glance. However, subjects may actually improve their mood upon reading the depressing titles, similar to the case where after watching a depressing or sad movie, people may cry with tears but actually feel better, i.e., have an improved mood. So, mood-related book titles here, with improved mood, would match sunny weather but not rainy weather. This might explain why the incremental results here replicate the interaction effects between sunny weather and ad copy of the main study, but not the interaction effects between rainy weather and ad copy.

[9] We conducted a follow-up survey to explore the underlying mechanism. The survey evidence confirmed that mood partially mediates the effects of weather conditions on mobile promotion responses.

[10] Our work here involves mobile products *relatively* less directly tied to weather (mobile digital services), rather than products (sunglasses or umbrellas) *directly* tied to sunshine or rain. This allows weather-based mobile targeting for more types of digital products.

[11] Many firms run online ads according to weather conditions via Twitter (Beck 2014) and the Facebook ad platform (Robertson 2013). Coors Light and Molson Canadian Cider used the programming interface of Weather Underground. When the weather was sunny and hot, it triggered Facebook mobile ads targeting the local weather.

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