Does the Weather Influence Global Stock Returns?

Ming Dong, Andréanne Tremblay*

October 21, 2019

Abstract

We hypothesize that weather's emotional effects depend on climate and season, and examine the relation between weather (sunshine, wind, rain, snow, and temperature) and daily index returns separately for each region (cold, hot, and mild countries) and month. In a large sample from 49 countries from 1973 to 2012, we find strong effects on stock returns of all five weather variables and all but the sunshine effect vary across temperature regions and seasons. The systematic patterns of weather effects across climates and seasons suggest that weather influences stock returns through investor mood, and that the emotional effects of the weather are stronger and more pervasive than previously documented. Our results reveal two contrasting themes of the weather-return relationship: comfortable weather conditions promote positive affect and lead to higher returns especially during seasons of increased outdoor activity, but extreme low temperature in the winter elevates risk-taking and leads to higher returns.

JEL: G00, G11, G14, F39

Keywords: weather, stock returns, temperature region, season, behavioral economics, investor psychology

* Ming Dong is from Schulich School of Business, York University, Toronto, M3J 1P3, Canada; e-mail: mdong@schulich.yorku.ca; phone: (416) 736-2100 ext. 77945. Andréanne Tremblay is from Laval University, Quebec City, G1V 0A6, Canada; e-mail: andreanne.tremblay-simard@fsa.ulaval.ca. We thank the Editor (Ivo Welch) for valuable suggestions, Andrew An, Shiu-Yik Au, Kee-Hong Bae, Jason Berkowitz, Melanie Cao, Doug Cumming, George Georgopoulos, Bing Han, David Hirshleifer, Harrison Hong, Mark Kamstra, Ambrus Kecskés, Tim Loughran, Tyler Shumway, Lin Sun, Qiguang Wang, seminar participants at the Society for the Advancement of Behavioral Economic conference at Lake Tahoe, the Financial Management Association conference in Nashville, the Research in Behavioral Finance conference in Rotterdam, the Australasia Banking and Finance conference in Sydney, the Midwest Finance Association conference in Chicago, and York University for helpful comments, Roy Shelef for excellent research support and discussions, and the Social Sciences and Humanities Research Council of Canada (SSHRC) for financial support.

1. Introduction

The question of whether daily weather influences financial market behavior is of great interest to financial economists as well as psychologists. Because daily weather is exogenous to the economic system and has hardly any relation to economic fundamentals, it is a convenient instrument for studying the effects of emotion on decision making. Despite the large literature on the relation between weather and stock returns,[1] prior research falls short of producing convincing evidence that weather affects stock returns through investor emotion. Most prominently, prior research assumes that weather has a static and uniform effect on asset prices. However, if the effects of weather on mood vary across climates and seasons, we should also expect the effects of weather on stock prices to differ across geographical regions and seasons.

In addition, the existence and prevalence of a relation between weather and stock returns remain controversial. On the one hand, there is quite strong evidence of a positive association between sunshine (by far the most researched weather variable) and stock returns (Saunders (1993), Hirshleifer and Shumway (2003) and Goetzmann et al. (2015)). On the other hand, it has been argued that this relationship is either spurious or sample-specific (e.g., Trombley (1997), Kamstra, Kramer, and Levi (2003), Loughran and Schultz (2004), and Dowling and Lucey (2008)). Evidence on the effects of other weather variables such as temperature, rain, or snow is either negligible or more controversial.

This paper employs a new approach to investigating the effects of weather on stock returns. Unlike prior research, we allow weather effects to vary across climates and seasons. There are

[1] There is also a literature on the effects of the weather on trading activity and volume (e.g., Goetzmann and Zhu (2005) and Schmittman et al. (2015)). Several papers investigate the effects of weather on the returns of individual stocks in a particular country instead of at the aggregate index level, and most often focus on the sunshine effect (e.g., Loughran and Schultz (2004) and Goetzmann et al. (2015)). In contrast, we examine the effects of five weather variables on country index returns. Because we examine index returns, our results are not driven by idiosyncratic risk.

strong reasons to expect that the psychological effects of weather on optimism or risk-taking will be highly dependent on regional and seasonal conditions, which implies that the same weather variable could be expected to have opposite mood effects in different climates. If so, prior research, which assumes uniform effects across geographical regions and seasons, may not adequately capture the true weather effects. In addition, we consider five weather variables (sunshine, wind, rain, snow and temperature) simultaneously, in line with the psychology literature that recommends multiple variables to describe a "complete weather picture" (e.g. San-Gil, Gonzalez De Rivera, and Gonzalez (1991), p. 402). Consequently, we find that the effects of weather on returns are much more pervasive than previously documented, and each of the five weather variables has unique ways of influencing returns.

There are strong reasons to believe that the effects of the weather on mood depend on geographical regions, and more precisely, regions defined by their annual average temperature. First, the psychology literature shows that the valence of mood (e.g., good versus bad mood) is positively associated with temperature, except in very high or low temperature environments (e.g., Wyndham (1969), Allen and Fisher (1978), and Howarth and Hoffman (1984)). Second, other weather variables may also have a climate-specific impact on affect. For example, rain and wind may adversely influence mood in cold countries because they tend to exacerbate the perceived temperature, but in hot countries, rain and wind may be much less disruptive or even be utility increasing, if they reduce the effective temperature.

Similarly, to the extent that weather conditions (such as snow) depend on temperature, their psychological effects should vary across the seasons. Also, there is psychological evidence of seasonal shifts in mood (e.g., Keller et al. (2005), Kamstra, Kramer, and Levi (2003)). Furthermore, as we discuss below, if the weather effects are felt more strongly in the outdoors, the strength of these effects should be stronger in seasons in which individuals allocate more outdoor time.

Two additional considerations support the approach of conducting separate tests by climate and season. First, this approach isolates non-weather return seasonality from the weather effects. For example, since winter tends to have higher returns than summer (e.g., Jacobsen and Marquering (2008)), pooling summer and winter observations could mute the effect of snow on returns, even after controlling for non-weather related seasonality. Second, this approach allows us to capture climate and season-specific weather effects. For instance, wind and rain have opposite effects on summertime returns between cold countries and hot countries, such effects cannot be detected in a pooled all-months or all-regions test, even if we allow nonlinearity in the specification.

We make two hypotheses about the weather effects. First, comfortable weather should lead to an upbeat investor mood and therefore high stock returns. This Comfortable Weather Hypothesis offers a basic guidance as to the *sign* of each weather variable in different seasons and regions. Second, the weather effects on returns should be stronger when people spend more time outdoors or when the marginal utility of outdoor time is higher. This Outdoors Hypothesis offers guidance about the *strength* of the weather effects and the times when we are more likely to observe them. Owing to the contingent nature of the weather effects, the purpose of these hypotheses is to provide a general guidance of expectations from the tests. We estimate the average time spent outdoors following the methodology of Graff Zivin and Neidell (2014), and confirm the intuition that for all temperature regions, the outdoor time is longest in the summer and shortest in the winter, and that the hot region has considerable outdoor time in the winter.

To test these hypotheses, we investigate the effects of weather on nominal index returns across 49 countries from 1973 to 2012. Following Hirshleifer and Shumway (2003), we use daily weather variables observed in the city of the main exchange for each country as proxies for the most relevant weather conditions, and conduct both ordinary least squares regressions (of daily returns) and logit regressions (of the probability of a positive return) on the weather variables, with standard errors clustered by both country and day to account for possible error correlations. We sort the countries into three temperature regions (cold, mild, and hot), shift the timing of countries in the Southern Hemisphere by six months to align the seasons, and conduct month-by-month tests for each temperature region. In our final cleaned sample, each region has at least 84,000 daily return observations with non-missing weather variables. Since stock returns are primarily driven by non-weather economic events, a large sample is necessary to neutralize various economic effects and detect the weather effects.[2]

The empirical results indicate pervasive statistical significance of all five weather variables. To verify that the relation between weather and returns is real rather than spurious, we examine whether the patterns of relationships between weather and returns in both the OLS and logit tests can be interpreted in a systematic way that is consistent with economic and psychology theories.

Most of the weather effects appear to be consistent with our Comfortable Weather Hypothesis and Outdoors Hypothesis. The following are our salient findings:

- Sunshine has a positive effect on daily returns for all temperature regions, and across all seasons. However, all the other weather effects are region and season-specific.

[2] Trombley (1997) also conducts month-by-month tests on the relation between U.S. index returns and cloud cover, but fails to establish a clearly positive relationship between sunshine and returns, presumably because the sample used is only one index series spread across the 12 calendar months.

- In the cold region, wind and rain have a negative effect on returns in summer and spring, suggesting a negative effect of windy or rainy conditions on mood in those months, possibly because wind and rain are disruptive to outdoor activity during the long-awaited warmer seasons. In the hot region, summertime wind and rain have a positive effect on returns, consistent with the cooling effects they provide, and in sharp contrast to the cold region.
- Snow (applicable to cold countries from December to March) has a negative effect on returns.
- Temperature exhibits nonlinear effects on mood, some of which are consistent with the Comfortable Weather Hypothesis. In the cold region, returns are negatively related to summertime temperature, suggesting a preference for cooler weather in the summer. In September, however, returns are positively related to temperature, suggesting a preference of longer summer in the cold climate. In hot countries, returns are higher on cool days in summer and on warm days in winter and spring, possibly because people in hot countries welcome warmer but not sweltering weather.
- However, in cold and mild countries, stock returns and temperature are strongly negatively correlated in the winter (December to February). This is incompatible with the Comfortable Weather Hypothesis, but it is consistent with evidence from experimental psychology that at very low temperatures, subjects tend to exhibit increased aggression or risk-seeking behaviors (e.g, Howarth and Hoffman (1984) and Schneider et al. (1980)).

In summary, the preponderance of our results supports the hypothesis that comfortable weather conditions promote investor optimism and lead to high stock returns, especially during seasons of increased outdoor activity. The sole exception, but one that is also consistent with psychological evidence, is our finding that in cold environments, low temperature is associated with high returns. This finding is consistent with freezing temperature stimulating risk seeking and stock buying. The existence of systematic patterns of the weather effects on returns suggests that weather impacts stock returns through investor emotion.[3]

As an application of our findings, we calculate a comfort index for the weather in our sample cities using the observed weather-return relationship and the historical average of weather variables. To our knowledge, this is the first time a comfort index is constructed for cities around the world based on how investors react to weather conditions.

Hypothesizing that weather's effects on returns depend on region and season is most critical to our findings. By conducting separate tests for each region-month, we find new, previously undocumented weather effects, while explaining why weather effects are often insignificant in papers that pool observations.

Prior research primarily focuses on the effect of sunshine on financial markets (e.g., Hirshleifer and Shumway (2003)), and treats other effects such as temperature as either insignificant or uniform on returns (e.g., Dowling and Lucey (2008)). The relatively consistent effect of sunshine on returns across regions and seasons explains why prior research finds a positive sunshine effect even without conditioning the analysis on region and season.

Our paper is the first that finds significant rain, wind, and snow effects in a global sample (Shu and Hung (2009) find a negative wind effect in some European countries). Hirshleifer and Shumway (2003) find rain and snow are insignificantly related to returns after controlling for sunshine. In light of our paper, their result is understandable because rain and wind have opposing effects in the cold versus hot regions, and even in the same hot region, wind's effect can shift from positive (spring) to negative (fall). The snow effect disappears when Hirshleifer and Shumway

[3] Dong and Tremblay (2018) show that weather-based trading strategies can generate significant profits. Since the null hypothesis predicts no relationship between weather and daily return, finding significant gross profits from this trading strategy indicates that the associations between weather and returns are systematic. Such a conclusion does not rely on detailed climate- and season-specific interpretations of the weather effects.

(2003) pool all countries and months. In contrast, by focusing on the snow season in the cold region instead of assuming a uniform, year-round snow effect, we detect a significant negative snow effect on returns.

Similarly, the negative relationship between temperature and returns first documented by Cao and Wei (2005) hides a much more nuanced structure of the temperature effect. We find that the temperature effect is neither uniformly negative nor constant in strength. In the cold region, the temperature effect is negative in the summer, and even more negative in the winter, but there is a positive temperature effect in September. In the hot region, temperature has a negative effect in the summer but a positive effect in winter and spring. The overall negative temperature effect on returns documented in the prior literature reflects the use by prior research of samples with observations predominantly from the cold countries where a negative temperature effect dominates.

There are further reasons why our testing approach reveals new weather effects. Because we recognize that weather's effects on returns are of secondary importance (relative to economic events), we use a large sample of 49 countries spanning 40 years. We use index returns rather than firm-level data, because individual stock returns are predominantly driven by firm-specific events. We also remove outliers (daily returns in excess of 2.5% in absolute magnitude) in the spirit of Saunders (1993), because such outliers are unlikely the result of weather's influence, yet exert large statistical impact on estimation. As a result, we find more clear-cut weather effects than many prior papers.

2. Hypotheses

We develop two hypotheses about the effects of the weather on stock returns. The first one concerns the sign of the effect of each weather variable on returns, while the second hypothesis is about the strength of the weather effects.

2.1. What Should Be the Sign of Each Weather Effect?

A body of psychology and finance literatures suggests that "comfortable" or "pleasant" weather should promote investor happiness and optimism, and an upbeat mood tends to lead to enhanced "spending" or "buying" tendency. For example, there is a positive relation between pleasant weather and good mood (Keller et al. (2005), Rehdanz and Maddison (2005), and Connolly (2013)). In turn, good mood leads to positive assessment of various outcomes (Wright and Bower (1992), and Kaplanski et al. (2014)), and inducement of positive affect stimulates risk taking (Isen and Patrick (1983)). Similarly, good mood and positive investor sentiment affect financial variables. For example, stock returns are higher before holidays (Ariel (1990)); sports-induced bad moods negatively affect stock returns (Edmans, Garcia, and Norli (2007)); and experimental research finds a positive association between mood and financial risk taking (e.g., Bassi, Colacito, and Fulghieri (2013)).

Therefore, weather can affect financial outcomes through its influence on investor mood. Indeed, sunshine positively predicts returns around the world (Hirshleifer and Shumway (2003)), and is associated with higher credit approvals (Cortés, Duchin, and Sosyura (2016)) and buying propensities of institutional or retail investors (Goetzmann et al. (2015) and Schmittmann et al. (2015)). We therefore predict a positive relation between "comfortable" weather conditions and stock returns:

H1 (The Comfortable Weather Hypothesis): Comfortable and pleasant weather conditions lead to higher stock returns.

Our definition of "comfortable" weather is not fixed, but rather is climate- and season-specific. Similarly, owing to the contingent nature of the weather effects on mood, it is not feasible to pin down effects to each climate and each month. However, for our five weather variables, we can make broad testable predictions as follows.

First, sunshine is well-known in the literature to lead to an upbeat mood (e.g., see Hirshleifer and Shumway (2003) and their extensive literature review). We therefore expect a positive sunshine effect on returns. Second, wind and rain are generally disruptive to the outdoor experience, but when the temperature is extremely high, rain and wind may be preferred cooling conditions (e.g. Keller et al. (2005)). Third, snow cover on the ground exacerbates the winter toughness and hinders outdoor activity. We therefore expect a negative effect of snow depth on stock returns. Finally, temperature should have a contingent effect on mood. Research suggests that people prefer higher temperatures in the coldest months and lower temperatures in the hottest months (Rehdanz and Maddison (2005)). We therefore expect low (high) temperature during summer (winter) times to promote happiness.[4]

2.2. Does Increased Outdoor Time Strengthen Weather Effects?

Because happiness is positively related to leisure time spent outdoors (e.g., MacKerron and Mourato (2014)), and also because the effects of the weather on mood are felt more strongly in the outdoors than indoors (Keller et al., (2005)), we expect that conditions conducive to a pleasant

[4] Research in psychology also finds that individuals exhibit risk-taking and aggression behaviors during extreme low temperatures (Howarth and Hoffman (1984) and Schneider et al. (1980)). Such effects are not in our basic Comfortable Weather Hypothesis, but may still exert an influence on investor mood.

outdoor experience should be especially effective in promoting investors' emotions when investors are likely to spend more time outdoors. Our second hypothesis is thus:

H2 (The Outdoors Hypothesis): The effects of the weather on returns are stronger when individuals expect to spend more time outdoors and when they assign a high marginal benefit to outdoor time.

The relevance of this hypothesis rests on an estimation of the time people spend outdoors each month. We adopt the methodology of Graff Zivin and Neidell (2014), who estimate the relationship between daily maximum temperature and daily leisure time spent outdoors, based on American Time Use Survey (ATUS) data. The ATUS data contain information about how people living in various regions of the U.S. spent their time during 2003-2006. Since the temperatures in the ATUS data cover a wide range, from 25°F to 105°F, we use Graff Zivin and Neidell's (2014) estimated relationship to provide a baseline of the time spent outdoors for all months and for all three temperature regions.

Specifically, the estimation of the outdoor leisure time is a three-step process. First, leisure time spent outdoors as a function of the maximum daily temperature is retrieved from Graff Zivin and Neidell (2014). Second, for each country and each month, we calculate the average maximum daily temperature. For each country-month, we then estimate the time spent outdoors relative to when the temperature is between 76°F and 80°F. Third, we use the unconditional daily average outdoor leisure time (0.73 hours) estimated in Graff Zivin and Neidell (2014) to convert the relative outdoor leisure time into the total outdoor leisure time, in minutes, and we compute the average outdoor leisure time for each month by temperature region. Table A2 contains the daily maximum temperature and estimated time spent outdoors for each month and each temperature region. It also outlines several patterns of outdoor time across the regions.

Our two hypotheses only offer general guidelines for what to expect for the weather effects on returns. Ideally, one could construct a "comfort" index of the weather conditions that would allow precise predictions about the weather-return relation. However, developing a "comfort" index would necessarily require imposing assumptions on the sign and strength of weather effects.

Indeed, multiple forces may affect how a specific weather condition is perceived, and even large average populations can have variable feelings towards the same weather conditions.[5] These feelings can fluctuate during the year and depend on other concomitant weather conditions. Furthermore, we cannot draw on the psychology literature to infer the signs of the weather effects, as the psychology literature does not have a consensus on whether and how the weather influences mood or comfort.[6]

Instead of attempting the infeasible task of predicting exact weather effects for each region and season, we use the "big data" approach: we let the data show the patterns of the effects of weather variables. Adopting the "big data" approach represents a trade-off between avoiding spurious multiple testing results and letting the data reveal weather effects, without imposing ex ante a rigid structure to the results.

In this context, and with the caveat that multiple testing could impact the significance of our results, we take the holistic approach (i.e., put more weights on effects that form stronger patterns). We interpret the results in light of the Comfortable Weather and Outdoors Hypotheses. Such a big

[5] For example, while it is reasonable to expect wind to be disliked in the cold regions, the a-priori answer to the question whether the wind effect should be stronger in winter or summer is ambiguous: the wind chill effect should make wintertime wind feel especially rough and uncomfortable, while in the summer, wind may be more disliked because it disturbs outdoor activities (people spend more outdoor times in the summer). In addition, the feelings towards the weather are likely heterogeneous across the population: for instance, Conolly (2013) finds that women are more sensitive to weather conditions than men.

[6] For instance, Wright and Bower (1992), Keller et al. (2005), Rehdanz and Maddison (2005), Connolly (2013), and Kaplanski et al. (2014) find a positive relation between pleasant weather and mood, but Huibers et al. (2010), Klimstra et al. (2011), and Lucas and Lawless (2013) find much more nuanced relations. A further reason that a comfort index approach may not be feasible is that certain weather effects involve psychological origins incompatible with the Comfortable Weather Hypothesis.

data approach offers a practical way to deal with complex relationships between weather and returns when there is no simple a-priori hypothesis based on first principles.

3. Sample and Research Design

3.1. Sample

We retrieve daily index returns from Datastream. We include in the sample all countries for which Datastream's Global Equity Index is available. Table 1 lists the countries included in our sample, as well as the coverage period where both the returns and weather data are available. For some countries, there are gaps in coverage; hence the varying numbers of valid of observations. Table 1 also shows each country's mean and standard deviation of percentage daily returns over that coverage period. All returns are nominal returns in local currency and include dividends.

We collect weather data from the Integrated Surface Database (ISD) managed by the National Climatic Data Center (NCDC, http://www.ncdc.noaa.gov/data-access/quick-links#dsi-3505). For each country included in our sample, we select the weather station closest to the country's main stock exchange. If the selected series have a gap in coverage, we complement the weather data series with data from the second-nearest weather station, if available, as long as the complementing weather station is within a distance of 50 kilometers from the country's main stock exchange. However, our results remain if we do not complement the principal weather series, or if we take the average of the observations from the weather station closest to the financial exchange and the second-nearest station.

We sort our full sample into three geographical regions. Specifically, we classify cold, mild, and hot countries using the 33rd and 67th percentiles of the full sample's distribution of annual temperature. Panel A of Table 2 lists the countries included in each region.

We retrieve sky cover, temperature, wind speed, precipitation, and snow depth data from the ISD. We construct all weather variables based on the average value of hourly observations of each weather condition between 6:00 AM and 4:00 PM local time, following Hirshleifer and Shumway (2003). We transform the qualitative sky cover variable into a categorical variable (SKC), by following Hirshleifer and Shumway (2003) and assigning a value of 0 to clear skies, a value of 2.5 to scattered cloud cover, a value of 6 to broken cloud cover, and a value of 8 to completely overcast skies. Wind speed (WIND) is measured in miles per hour and temperature (TEMP) is in Fahrenheit. RAIN is an indicator variable that is equal to one if some liquid precipitations were recorded between 6:00 AM and 4:00 PM local time on the day of the measurement.[7] Otherwise, RAIN is equal to zero.

We measure snowiness condition by snow depth (SNOW), which is the five-day moving average of the mean daily snow cover in inches on the ground measured between 6:00 AM and 4:00 PM. Using the five-day moving average minimizes the impact of missing or inaccurate average daily snow cover readings. Non-zero or non-missing snow related variables are sparse in the mild and hot regions. We thus exclude SNOW from the regression models for the mild and hot countries. Likewise, for the cold countries, we omit SNOW in the regression tests from April through November owing to the sparse and sometimes implausible non-zero records for those months.

We run tests for each calendar month, which automatically takes into account any seasonality. We shift the timing of Southern Hemisphere countries by six months, so that seasons in both hemispheres are synchronous. We do not deseasonalize weather variables (Hirshleifer and

[7] We construct the variable RAIN using the PCP06 raw variable, as this variable is the one with the least missing observations. PCP06 records the liquid precipitations (in inches) in the 6 hours immediately preceding the weather record. As such, RAIN is defined based on the average observed precipitations between 12:00 AM and 4:00 PM local time.

Shumway (2003)) or control for the length of daylight (Kamstra, Kramer, and Levi (2003)) because of the minimal within-month variations in hours of daylight and climate.

Panel B of Table 2 reports the mean, median and standard deviation of the annual average temperatures of the countries included in each region. Panel B also shows the number of observations with non-missing weather and returns data by region, and reveals that countries with shorter coverage periods are almost exclusively mild or hot countries. Panel C reports the mean, median and standard deviation of our main weather variables and of percentage daily returns, by region. Cold countries are significantly cloudier, windier and rainier than hot countries. The highest pairwise correlation among weather variables is 0.289 (between SKC and RAIN in cold countries). Section 5.2 discusses further tests for multicollinearity, all of which suggest that multicollinearity is not a concern in our sample. Panel C also shows that cold countries have mean returns that are lower and less volatile than hot countries, although the difference in mean returns is not significant.

3.2. Regression Test Design

Our *Comfortable Weather* hypothesis predicts that comfortable weather leads to optimistic investor mood, which in turn leads to positive index returns. Based on the literature, we anticipate that the effects of the weather on investor mood vary with the geographic regions and seasons. This prediction motivates our methodological design. Our second hypothesis, the *Outdoors Hypothesis*, predicts that the effects of the weather on investor mood are strongest when people spend more time outside (e.g., in the summer of the cold region) or when the utility of outdoor time is highest.

We sort our sample by region and month (rather than by country and month, to allow for a sufficient sample size in each region-month group), and estimate the following panel regression of daily index returns of countries in each region-month group:

$$r_{it} = \alpha_t + \beta_1 SKC_{it} + \beta_2 WIND_{it} + \beta_3 RAIN_{it} + \beta_4 SNOW_{it} + \beta_5 TEMP_{it} + \varepsilon_{it}, \quad (1)$$

where *i* indexes countries in a particular region-month group and *t* denotes trading day. For the mild and hot countries and for the months from April through November in the cold countries, we estimate a reduced form of this model and drop SNOW from the regression, to reflect the absence of snow cover in these periods and regions. In addition, because it is possible that weather effects are related to the sign of the returns and not their magnitude, we estimate the following logit model:

$$P(r_{it} > 0) = \frac{1}{1+e^{-(\alpha+\beta_1 SKC_{it}+\beta_2 WIND_{it}+\beta_3 RAIN_{it}+\beta_4 SNOW_{it}+\beta_5 TEMP_{it})}}, \quad (2)$$

where $P(r_{it} > 0)$ is an indicator variable that is equal to 1 if the returns of country *i*'s market index on day *t* is positive, and zero otherwise.

For both the OLS and the logit regressions, in addition to estimating the model on a month-by-month basis, we also run an "all-months" regression by pooling all months together, to see the net effect of the weather on daily returns by region only. In both the OLS and the logit regressions, standard errors are clustered by country and day to account for the regression residuals' contemporaneous correlation for each region-month group and within-group autocorrelation across time, in line with the recommendations of Petersen (2009) and Cameron, Gelbach, and Miller (2011).

A technical point in detecting the effects of the weather on stock returns is the treatment of return outliers. Our purpose is to examine the effects of *non-economic*, weather variables. If extreme daily returns are primarily caused by economic events, it seems necessary to remove extreme return outliers from our tests, because such outliers are least likely caused by the weather while exerting the largest impact on regression results. We therefore follow Saunders (1993) and remove returns with absolute value greater than a certain threshold, and assess the robustness of our results by varying this threshold. The selection of the threshold value reflects a tradeoff: a stricter (i.e., lower) threshold eliminates non-weather driven observations, but if we remove too many large return observations, we risk omitting valuable signals and making our tests influenced by noises (i.e., small returns) caused by liquidity trading.

When we do not apply any filter and keep all observations, we find significant effects of the weather variables, at least for certain regions and months. (The OLS and logit regression results for the full sample with no filter rule applied are available from the authors upon request.) We obtain our base case results, presented in this paper, when we apply a 2.5% filter rule (corresponding to filtering out 4.9% of all observations). Our results are fairly robust to the specific filters we use: results strengthen (relative to using no filters) if we apply the 3% filter rule, and vary only slightly if we impose a 2% filter rule. Section 5.1 has more details.

We report the OLS and logit regression results in Tables 3 and 4, respectively. For each of these regression tables, Panels A, B, and C report results for the cold, hot, and mild region, respectively. For both the OLS and logit regressions, we report the estimates of the coefficients, their associated *p*-values (in parentheses) and the economic impact [in square brackets]. For ease of reporting, all variables (except the indicator variable RAIN) are expressed in percentages. The economic impact estimation procedures are described in Section 4.2, following a discussion of the results in Section 4.1.

4. Discussion of the Weather Effects

4.1. Regression Results

Tables 3 and 4 present the OLS and logit panel regression results, respectively, with the 2.5% filter rule applied. For brevity we indicate the statistical significance in Tables 3 and 4, with specific *p*-values included in the Internet Appendix Tables IA.1 and IA.2. To provide an overall picture of the effects of all five weather variables, we summarize both the OLS and logit test results in Table A1 by keeping only results that are significant at the 20% level or higher.[8]

Table 5 provides tests of the Comfortable Weather Hypothesis (H1) and the Outdoors Hypothesis (H2). We test whether significant seasonal variations exist for WIND, RAIN and TEMP, against the null of no seasonal variations of weather effects, for each temperature region. The claim that the SNOW effect is season-specific holds trivially.

Before discussing the possible interpretations, two caveats are in order. First, given the large number of regressions and the fact that the "pure" emotional weather effects are inevitably mixed with fundamental economic effects as reflected in index returns, it is possible that some regressions are contaminated by non-weather information. When interpreting these regression results, we take a holistic approach: we put more weight in weather effects that tend to form systematic patterns across regions and seasons. Because it is highly unlikely that random noises can cause systematic patterns of weather effects, our holistic approach helps gain insights into these effects in the light of our hypotheses.

[8] Although the overall patterns of the weather effects do not rely on the cut-off significance levels, keeping results significant at the 20% level (rather than a higher significance level) is helpful in obtaining a more comprehensive picture of the weather effects. For instance, in the cold region, WIND (OLS) has a negative effect on returns in July that is significant at the 20% level (p = 0.148). Viewed in combination with the negative WIND effect for June and August, this result strengthens the pattern of a negative wind effect on returns in the cold region summer. Also in the cold region, RAIN (logit) negatively influences the likelihood of a positive return in July (p = 0.184), which, together with the OLS evidence of a negative July RAIN effect (p = 0.041), strengthens the case of a negative rain effect in the cold region July.

Second, while the usual season classification (e.g., spring is March-May, summer is June-August) is a good starting point to describe seasonal weather effects, the actual effects may be more intricate for a variety of reasons: The frequency of large impact weather conditions (e.g., days of heavy rainfall or heavy wind) may vary across a season, and a particular month may exhibit certain unique weather effects. For example, in the cold region and in contrast to August and October, high temperatures could be mood-lifting in the September transition from summer to fall, if people in cold countries prefer a long summer than a short one.

Therefore, it is not feasible to predict a priori the exact sign and strength of the monthly weather effects. Instead, we present the empirical patterns of the weather-return relation across the seasons and interpret them in light of our hypotheses. We recognize, however, that ex post interpretation is subject to the multiple testing problem. This should especially be borne in mind for those tests in which the results are only marginally significant.

4.1.1 Sunshine (SKC)

We first examine the effect of sunshine. Considering the pooled results (column 13) of Table 3 and Table 4, we confirm that the magnitude of the daily market index returns is negatively related to the current cloudiness (a negative proxy for sunshine), consistent with the Comfortable Weather Hypothesis. Results are particularly strong for cold countries, both in the OLS ($p < 0.001$) and in the logit specification ($p = 0.002$).[9] Judging by the OLS results of Table 3, there is clear evidence of a sunshine effect in hot countries ($p = 0.001$) and weaker evidence in mild countries ($p = 0.089$), but the logit results of Table 4 indicate much weaker significance levels of SKC for

[9] For brevity, we do not report *p*-values in Tables 3 and 4. Tables IA.1 and IA.2 of the Internet Appendix are the same as Tables 3 and 4, but show the *p*-values of all coefficients.

hot and mild countries. These results suggest that while sunshine has a global positive effect on returns, this effect is strongest and most consistent in the cold region. We do not detect significant differences in the sunshine effect across seasons in any region, suggesting an all-year effect of sunshine in creating an upbeat mood.

4.1.2 Wind

When we examine the effects of wind, we find evidence in support of both the Comfortable Weather and the Outdoors hypotheses for all three temperature regions. Considering the pooled results (Column 13), we find that WIND is generally negatively associated with returns in cold (Table 3: $p = 0.045$) and mild countries (Table 4: $p = 0.052$). This is consistent with the comfortable weather hypothesis in that the wind's cooling and disruptive effects make the weather uncomfortable.

In line with the Outdoors Hypothesis, we find in the OLS tests of Table 3 that there is a significant negative wind effect in cold countries in March ($p < 0.001$) and in the summer ($p = 0.052$, 0.148, and 0.078 for June, July and August, respectively). It appears that the wind's cooling effect is especially unwelcome in the spring, when the marginal utility of outdoor time is possibly at its highest, and in the few months of warmer weather that cold countries enjoy. As shown in Table 5, result R1 (the spring and summer period has a more negative WIND effect than fall and winter) is confirmed in the OLS test ($t = 2.11$). In contrast, and in line with both the Comfortable Weather and the Outdoors hypotheses, the same cooling effect of wind appears to be appreciated in the hot countries' warmer months; we find a positive wind effect in June (Table 4: $p = 0.015$) and in April (Table 3: $p = 0.024$) in hot countries. Wind's disruptive effect appears to dominate in November (Table 3: $p = 0.048$) and in late summer (Table 3: $p < 0.200$ in both August and September). The late summer negative wind effect may also be related to the tropical storms.[10] The varying effects of wind across the seasons result in an insignificant all-months wind effect in the hot region. Table 5 corroborates result R9 (August-November has a more negative WIND effect than spring and summer) at the 10% level for the difference in the OLS test (t = 1.76).

In the mild region, in line with the cold region, there is a pattern of negative wind effects in the spring and summer. However, there seems to be a positive effect in June (p = 0.195), possibly because of the comfortable cooling effect of wind when temperatures soar in June (Table A2). Table 5 shows this seasonal difference (R5: spring and summer except June have a more negative WIND effect than June) is confirmed in the logit test (t = 2.05).

4.1.3 Rain

In cold countries, RAIN is negatively associated with returns in the summer (Table 3: p = 0.041 in July) and spring (Table 3: p = 0.16 for April; Table 4: p = 0.217 for May). Rain has an overall negative effect on returns (Table 3, all-months regression: p = 0.102). Table 5 corroborates result R2 (spring and summer have a more negative RAIN effect than fall and winter) in the OLS test (t = 2.01).

There is a noteworthy pattern about the sign of the wind and rain effects in the cold region. In the OLS regressions of Table 3, the negative signs of both WIND and RAIN concentrate in the warmer portion of the year, in line with the Outdoors Hypothesis. Out of the eight months from March through October, WIND has a negative sign in all months except April, and RAIN is

[10] Tropical hurricanes and tropical storms, both in the Atlantic and Eastern Pacific basins, tend to peak on September 10; see http://www.nhc.noaa.gov/climo/.

negative in all eight months.[11] This pattern reinforces the idea that in the cold region, the negative effect of wind and rain on mood is stronger when people expect to spend more time outdoors.

However, in line with our Comfortable Weather Hypothesis, and in sharp contrast with the negative rain effect observed in the summer of cold countries, in hot countries, and especially when average maximum daily temperatures are higher than 85°F (June-August; see Table A2), rain is positively perceived (Table 3: $p = 0.002$ and 0.083 for July and August, respectively; Table 4: $p = 0.016$ for June). Accordingly, RAIN in the hot region has an overall positive effect on returns as shown in the all-months regression (Table 3: $p = 0.016$; Table 4: $p = 0.045$). Result R10 (summer has a more positive RAIN effect than the rest of the year) is confirmed both in the OLS test (Table 5: $t = 2.30$) and in the logit test (Table 5: $t = 1.76$).

The temperature-contingent rain effect also exists in mild countries. In the logit tests, RAIN has a negative sign in 10 out of the 12 months, which suggests that rain is disliked in the mild region, and in the spring in particular (Table 4: $p = 0.025$ and 0.035 for March and April, respectively). On the other hand, rain positively affects returns in the warm month of June (Table 3: $p = 0.016$; Table 4: $p = 0.056$), possibly because it provides a cooling effect similar to the one observed in hot countries. The all-months logit regression indicates a strong negative effect of RAIN (Table 4: $p < 0.001$), confirming the overall negative emotion associated with RAIN in mild countries and lending support to the Comfortable Weather Hypothesis. Result R6 from Table 5 (June has a more positive RAIN effect than spring) is confirmed in the logit test ($t = 2.28$).

4.1.4 Snow

[11] If each of the 16 signs was independently binomial ($p = 0.5$) as implied by the null hypothesis of zero weather effects, the probability of observing 15 negative WIND and RAIN coefficients would be 0.00024. We confirm in unreported tests that the RAIN coefficient for the warmer part of the year (March-October) is different from the coefficient for the rest of the year, both in the OLS ($t = 2.61$) and the logit test ($t = 1.74$).

Results regarding snow depth are in line with both the Comfortable Weather and the Outdoors hypotheses. In the all-months regression, SNOW has a negative impact on returns in the cold region (Table 4: $p = 0.073$). The month-level regressions further reveal that this effect is significant after December (Table 3: $p = 0.011$ for March; Table 4: $p = 0.044$, 0.10, and 0.003 for January, February and March, respectively). This suggests that snow accumulations may hinder daily activities and make outdoor experiences less pleasant.

4.1.5 Temperature

The Comfortable Weather and Outdoors hypotheses also explain at least part of our findings regarding the daily average temperature. The hypotheses are consistent with the negative TEMP coefficients observed in the summer of cold and mild countries (Table 3 and Table 4: $p < 0.05$ for at least one test for June), as cooler temperatures are more comfortable in the summer (in line with the observations of Keller et al. (2005) and Connolly (2013)). The hypotheses' predictions are also consistent with the positive TEMP coefficient observed in September in cold countries (Table 3: $p = 0.004$; Table 4: $p = 0.001$). This positive temperature effect suggests that people in cold countries favor warmer weather that permits enjoyable outdoor activity in the summer-fall transition.[12] Table 5 shows that result R3 (summer has a more negative TEMP effect than September) is confirmed in both the OLS ($t = 3.61$) and logit test ($t = 3.67$) for the cold region. Table 5 corroborates a similar finding, result R7, in the logit test ($t = 2.32$) for the mild region.

In the hot region, returns are negatively affected by average daily temperature in the summer, particularly in June (Table 3: $p = 0.109$; Table 4: $p = 0.018$) and August (Table 3: $p = 0.005$; Table 4: $p = 0.015$). Investors may find the hot countries' maximum temperatures of above 85°F (Table A2) too hot for the outdoors to be enjoyable, thus explaining the negative temperature effect on returns.[13] However, returns are positively related to temperature in the winter

[12] Temperature in the cold region has a negative effect on returns in October ($p < 0.05$ in Tables 3 and 4). A plausible interpretation is that a lower temperature in October alerts people of the cold weather to come, leading to increased risk-seeking behaviors. Therefore, nearly half of the negative TEMP effects in the cold/mild regions (October through February) may be related to the risk-seeking-under-low-temperature effect. Future research is needed to confirm this interpretation.

[13] The insignificant (rather than significantly negative) temperature effect in July for the hot region seems to be consistent with findings in psychology that in extreme hot temperature, individuals experience apathy and inactivity (e.g., Wyndham (1969)). Cao and Wei (2005) cite this literature in explaining the less negative effect of temperature on returns during the summer than during the winter across all countries in their sample, but we find here that the summertime negative effect of temperature on returns is strongest in the hot region, which suggests that the overall

(Table 3: $p = 0.119$ for December; Table 4: $p < 0.001$ for December and $p = 0.197$ for January) and spring ($p < 0.10$ in April and May in at least one test), when investors possibly want warmer temperatures, so that they can enjoy more of the outdoors. Table 5 confirms result R11 (summer has a more negative TEMP effect than spring and summer) in the logit test ($t = 2.76$).

However, the highly consistent and negative TEMP coefficients that we observe in both the cold and mild regions between December and February (for the cold region, in Tables 3 and 4, $p < 0.05$ in five out of the six TEMP coefficients; in the mild region, $p < 0.10$ in five out of the six TEMP coefficients, with three less than 0.01) are not consistent with the basic Comfortable Weather Hypothesis, but rather with the explanation that in extremely cold temperatures, individuals exhibit risk-seeking behaviors (Cao and Wei (2005), Howarth and Hoffman (1984) and Schneider et al. (1980)).[14] That the negative TEMP effect in the winter months of cold and mild region is stronger than in other times is confirmed in results R4 (cold region) and R8 (mild region), both reported in Table 5. The strong association between extremely low temperature and high stock returns is a major departure from the nearly ubiquitous "positive-emotion-promotes-optimism" theme, and confirms the complex relation between mood and risk assessment (Isen (2000)).[15]

Overall, as seen in the summary of Table A1, the signs and patterns of the weather effects on returns are broadly consistent with both the Comfortable Weather Hypothesis and the Outdoors

---

summertime negative effect of temperature is more consistent with the comfortableness rather than the apathy interpretation.

[14] The link between extreme low temperature and stock returns can potentially be attributed to two reasons: a more optimistic attitude of investors under very low temperatures, and/or a more risk-seeking attitude under such low temperatures. Since the former stretches credulity (e.g., the financial press often blames the cold winter weather for a slow pace in economic activity), the latter seems to be the more logical reason.

[15] Novy-Marx (2014) documents that New York City temperatures are correlated with the monthly returns of a number of asset pricing anomaly strategies. He also notes the apparently contradictory interpretations of the negative temperature effect of Cao and Wei (2005) and the positive sunshine effect of Hirshleifer and Shumway (2003). Our comprehensive approach of studying five weather effects on daily returns makes it clear to what extent the Comfortable Weather Hypothesis holds among all these effects.

Hypothesis, with the main exception of a strong negative effect of wintertime temperature in the cold and mild regions. Furthermore, Table 5 provides evidence that the effects of wind, rain, and temperature exhibit seasonal variations, with each region possessing unique weather patterns. In sum, the notion in prior literature that all weather conditions have a static and uniform mood effect is strongly rejected.

4.2. Economic Impact

We verify that our weather effects are economically significant. More precisely, in the OLS tests, we estimate the economic impact of a continuous weather variable (SKC, WIND, SNOW or TEMP) as the change in stock returns (in terms of annualized returns) that results from a change in that weather variable from the 25th percentile to the 75th percentile, holding all other variables at their sample mean values.[16] Similarly, the impact of an indicator variable (RAIN) is the change in annualized returns caused by a change from 0 to 1 of the indicator variable, keeping all other variables at their sample means.

For example, to estimate the impact of SKC in the cold region in January, we follow a 3-step procedure. First, we compute the change in daily return (denoted as d) caused by a change in SKC from the 25th to the 75th percentile (for the cold region in January) and holding other variables at their sample means. Second, we compute the mean daily index return (denoted as r) of all cold countries in January, and estimate the range of the daily return caused by a change in SKC to be $(r - d/2, r + d/2)$. Third, we calculate the economic impact as the corresponding change in annualized returns (using 250 trading days per year) in absolute value. Economic impact is expressed in percentages.

[16] We use the same calculation method for SKC as for other continuous variables, because our operationalized SKC variable is the daily mean cloud cover observed between 6:00 AM and 4:00 PM local time and as such, it can take any value between 0 and 8.

In the logit tests, the economic impact of a weather variable is the change in the dependent variable (the probability of a positive daily return) as a result of a change in that weather variable from the 25th to the 75th percentile (or for RAIN, from 0 to 1), holding all other variables at their sample mean values.

The figures [in brackets] in Tables 3 and 4 indicate substantial economic impacts of the weather on stock returns. For example, based on the OLS results in Table 3, in the cold region, SKC, WIND, RAIN, and TEMP all have a significant impact on stock returns, with an annualized return impact as high as 6.3% for SKC in February, 8.3% for WIND in March, 12.7% for RAIN in July, and 12.9% for TEMP in October. In comparison, SNOW has a relatively low economic impact, reaching as high as 0.6% in March, although this may partly be due to the smaller number of valid snow depth observations. Similar conclusions hold based on the logit test in Table 4. For instance, a decrease in February TEMP from the 75th to the 25th percentile increases the probability of a positive daily return by 2.8%.

We highlight the weather variables that have the highest economic impacts for each geographical region as follows. In the cold region, the top weather effect based on the OLS test is TEMP in October [–12.9%]; based on the logit regression, the top effect is February TEMP [–2.8%]. In the mild region, February TEMP has the largest return effect [–16.3%] based on the OLS while December TEMP has the top effect [–3.8%] based on the logit test. In the hot region, OLS- and logit-based top effects are, respectively, July RAIN [21.2%] and June RAIN [3.8%]. Even though sunshine has the most consistent positive effect across regions and months, temperature often exerts the highest economic impact on returns, with rain's effect comparable to sunshine's, on an individual region-month basis. Despite the differences in the way weather affects stock returns across regions and seasons, the economic magnitude of the weather effects on investor behavior is comparable across the geographical regions.

Of course, what we label as "weather effects" may be partly fundamental economic effects. For example, snow removal is costly, and tornadoes destroy powerlines. While we cannot completely rule out the possibility that the weather effects we document reflect fundamentals, several considerations argue against this interpretation. First, we examine the effects of daily weather fluctuations rather than long-term weather trends, so normal daily weather variables do not convey permanent shifts in climate and therefore should have limited impact on fundamental asset value. Second, when we remove extreme conditions—which have the best chance to exert an economic impact, we find our results remain similar (see Section 5.2), suggesting at least a good portion of the weather effects does not rely on a fundamental channel. Third, economic impacts are unlikely to vary with season and region in ways consistent with our two hypotheses. For example, the adverse effect of wind occurring only in the spring and summer of cold countries rather than in the winter, and the positive effect of wind in the spring and summer of hot countries, are difficult to reconcile with a fundamental channel.

Finally, if weather's impact on asset prices are a result of fundamental principles, it is impossible to form profitable trading strategies based on weather. However, Dong and Tremblay (2018) document substantial profits from weather-based trading strategies in global equity markets, which is consistent with weather influencing returns through emotional channels.

4.3. Comfort Index of Sample Countries

As an application of the weather-return relationship, we construct a comfort index (CI) for the weather in our sample cities. Even though it is infeasible to form an ex ante comfort index for testing the weather effects (as explained in Section 2), an ex post CI is useful to measure the comfort level of each country.

The logic for computing a CI for each country is that if the weather-return relationship is fully consistent with the Comfortable Weather Hypothesis, then the daily expected return of a country using the OLS model directly reflects the comfort level of each day. Averaging all the daily expected returns should then give the overall comfort level of each country. In reality, however, the OLS regression results in Table 3 are not fully consistent with the Comfortable Weather Hypothesis, with the main exception being the negative TEMP effect for October through February in the cold/mild regions—in cold winter days, a warmer TEMP should indicate a higher comfort level (see footnote 11). We therefore adjust the TEMP coefficient by inverting its sign for the winter months (December-February) as well as October and November for the cold and mild regions.

More specifically, the comfort index is calculated as follows: for each country, we use this country average monthly weather over the full sample period and the significant ($p < 0.2$) monthly coefficients from Table 3. For each country *i* (in temperature region *j*) and month *m*, we compute the CI as:

$$CI_{im} = \alpha_{jm} + \beta_{1,jm}\overline{SKC}_{i,m} + \beta_{2,jm}\overline{SPD}_{i,m} + \beta_{3,jm}\overline{RAIN}_{i,m} + \beta_{4,jm}\overline{SNOW}_{i,m} + \beta_{5,jm}\overline{TEMP}_{i,m},$$

where the coefficients are those from Table 3, with the exception that $\beta_{5,jm}$ is equal to the negative of the TEMP coefficient for October through February for the cold and mild regions.

Finally, since the regressions in Table 3 are run separately for each region, we can only compare the CI for countries within each temperature region. Table 6 presents the CI and CI rank within each respective temperature region for the sample countries. Figure 1 shows a "heat map" of the annual CI categories of the sample countries in the three temperature regions.

5. Robustness Tests

We provide various robustness tests by using alternative filter rules for the sample, variable measurement, or temperature region definitions.

5.1. Filter Rules

Our OLS and logit results are not highly sensitive to the filter rules used to control for the effect of return outliers: our results remain if we use filters ranging from 1.5% to 3%, and some results remain when we do not filter out return outliers. Tables IA.3 and IA.4 report the results from the OLS and logit regressions when we do not filter out return outliers, and Tables IA.5 and IA.6 show the results of filtering out absolute returns greater than 3%.

5.2. Alternative Weather Variable Measurement and Test Design

We find that the weather effects become weaker, with many effects disappearing, when we define our weather variables in terms of deviations from their monthly country mean. Tables IA.7 and IA.8 report the results from the OLS and logit regressions, respectively. We interpret these findings as evidence that individuals respond to current weather conditions.

As a further robustness test, we exclude observations with extreme weather conditions. Specifically, we exclude observations for which WIND and SNOW are higher than the historical country-month 95th WIND and SNOW percentiles, and observations for which SKC and TEMP are either above the historical country-month 95th SKC or TEMP percentiles, or below the 5th SKC or TEMP percentiles, respectively. Tables IA.9 and IA.10 present the results from the OLS and logit tests. Our main results are robust to the exclusion of such observations, suggesting that the weather effects we document are not driven by extreme weather conditions.

Because rain and cloudiness are concurrent weather phenomena, we verify that multicollinearity is not a concern in our sample. In the OLS regressions of Table 3, none of the

Variance Inflation Factors is higher than 1.5, which alleviates concerns of multicollinearity. In addition, we estimate a reduced form of our models where the independent weather variables are SKC, WIND, SNOW (where applicable), and TEMP only. In an all-months setting, coefficients of these variables as well as their statistical significance are very similar to their full-model coefficients. Tables IA.11 and IA.12 report the results.

5.3. The Sell-In-May (SIM) and Seasonal Affective Disorder (SAD) Variables

We account for the possibility that the effect of any weather variable may be caused by a seasonal weather pattern such as the Seasonal Affective Disorder (SAD) as presented in Kamstra, Kramer, and Levi (2003) or certain unidentified non-weather related seasonality factor. Therefore, for the "all-months" pooled regression, we follow Jacobsen and Marquering (2008) and include a Sell-in-May (SIM) variable as an additional independent variable. SIM is an indicator variable equal to 1 during the months of January, February, March, April, November and December, and it is equal to 0 otherwise. Columns 1, 4, and 7 of Tables IA.13 and IA.14 show that the all-months OLS and logit weather effects are robust to the inclusion of SIM, indicating that the weather effects we document are not caused by unknown seasonality factors.

The weather effects in the all-months regressions are also invariant when we use the daylight-related Seasonal Affective Disorder (SAD) variable, as defined in Kamstra, Kramer and Levi (2003), instead of the Sell-In-May indicator variable. Columns 2, 5, and 8 of Tables IA.13 and IA.14 present the results. In addition, since we examine the weather effects on country index returns, the effects we study are different from the seasonality in cross-sectional returns documented in Heston and Sadka (2010).

We verify our results remain if we include country fixed effects in the all-months regression, even though country fixed effects could absorb some of the weather effects we intend to capture.

Columns 3, 6, and 9 of Tables IA.13 and IA.14 show the results for the all-months regressions with country fixed effects included.

5.4. Classification of Temperature Regions

The definition of temperature regions reflects a trade-off: Sorting the full sample into more temperature subsamples makes each region more uniform, but reduces the sample size of each region. In addition to our baseline classification into hot, mild, and cold regions, we also conduct tests using a 2-region or 4-region classification. Tables IA.15 through Tables IA.18 report the results. In both schemes (especially the 2-region one), the results for the cold region are very much in line with our baseline; all results with respect to the five weather variables remain unaffected with only minor changes in magnitude and significance levels. The results for the hot region are also quite similar to our baseline, with the only exception that the temperature effect tends to be noticeably weaker, especially under the 4-region scheme.

5.5. Northern and Southern Hemispheres

In our baseline specification, we shift the timing of variables of the Southern Hemisphere countries by six months to align the season with the Northern Hemisphere. However, one issue arising from this shift is that the clustering of standard errors by day implies clustering together errors of day t (for the Northern Hemisphere countries) and day t + *6 months* (for the Southern Hemisphere countries). To deal with this issue, we repeat our tests using observations of the Northern Hemisphere countries only. OLS and logit results (Tables IA.19 and IA.20) indicate that all the baseline weather effects are preserved for the cold region. The calendar patterns of the weather effects for the mild region is less pronounced regarding WIND and RAIN. For the hot region, which suffers the largest sample size reduction, the effects of SKC and WIND are little affected relative to the baseline results, the effect of RAIN is weakened but remains positive in

June and July, and TEMP shows a substantially weakened pattern. Therefore, while including both hemispheres tends to strengthen our OLS and logit test results, the identification of weather effects is unaffected by whether we include the Southern Hemisphere countries in our analysis.

5.6. Geographical Dispersion of Countries

Because we measure the weather of each country by that of the city of the main exchange, it is possible that our methodology introduces a measurement error problem in geographically large countries. In unreported tests, we sort our sample countries into high- and low-dispersion countries. We use two proxies for dispersion: the ratio of the exchange city population to the country population, and the total area of the country. We find that weather effects are generally stronger when the population is highly concentrated near the exchange, or when the country's area is small.

However, including countries with large geographical dispersion helps to increase sample size and gain statistical significance of the weather effects. In addition, including high-dispersion countries introduces measurement error in the weather variables, which should weaken our results. Our reported results therefore represent a lower bound on the weather effects.

6. Conclusion

We test the effects of five weather variables (sunshine, wind, rain, snow, and temperature) on stock index returns across 49 countries from 1973 to 2012 by sorting our sample by temperature region and calendar month. We hypothesize that the weather effects on investor mood are contingent on climate and season, and uncover a number of new weather effects on stock returns. We find that while sunshine has a universally positive effect on mood for all temperature regions, the effects of other weather conditions vary across seasons and temperature regions. The prevalent weather effects across climates and seasons suggest systematic rather than spurious patterns, and are consistent with two themes. First and primarily, comfortable weather conditions promote positive affect and optimism, and lead to higher returns, especially during seasons when individuals like to spend time outdoors. Second, in a cold environment (i.e., winter times in cold or mild regions), low temperature elevates the risk-taking tendency and leads to higher returns.

We recognize that a study of the effects of weather on stock returns has, by construction, limitations. Even though our research design tries to detect the weather effects (by allowing effects to vary with climate and season, removing return outliers, using a large sample to neutralize non-weather effects, and looking for patterns consistent with psychology theory), returns are primarily affected by economic events. Also, given the latitude in interpreting our hypotheses, further independent research is needed to confirm our findings.

Nonetheless, our results do indicate that there exist substantial weather effects on stock returns, that the patterns of the effects vary across climates and seasons, and that the strength of the weather effects tends to increase with the time spent outdoors. These findings suggest that weather influences asset prices, and that temporary emotional states influence individuals' judgment about long-term prospects. Future research appears fruitful to reveal novel patterns and sources of the weather effects on mood.

References

Allen, A.M. and G.J. Fisher, 1978. Ambient temperature effects on paired associate learning. *Ergonomics* 21, 95–101.

Ariel, R. A., 1990. High stock returns before holidays: Existence and evidence on possible causes. *Journal of Finance* 45, 1611-1626.

Bassi, A., R. Colacito, and P. Fulghieri, 2013. 'O Sole Mio: An experimental analysis of weather and risk attitudes in financial decisions, *Review of Financial Studies* 26, 1824-1852.

Cameron, A. C., J.B. Gelbach, and D.L. Miller, 2011. Robust inference with multiway clustering, *Journal of Business & Economic Statistics* 29, 238-249

Cao, M. and J. Wei, 2005. Stock market returns: A note on temperature anomaly, *Journal of Banking and Finance* 29, 1559-1573.

Connolly, M, 2013. Some like it mild and not too wet: The influence of weather on subjective well-being. *Journal of Happiness Studies*, 14, 457-473.

Cortés K.R., R. Duchin, and D. Sosyura, 2016. Clouded Judgment: The Role of Sentiment in Credit Origination. *Journal of Financial Economics* 121, 392-413.

Dong, M. and A. Tremblay, 2018. Are weather-based trading strategies profitable? Working paper, York University.

Dowling, M. and B.M. Lucey, 2008. Robust global mood influences in equity pricing, *Journal of Multinational Financial Management* 18, 145-164.

Edmans, A., D. Garcia, and O. Norli, 2007. Sports sentiment and stock returns, *Journal of Finance* 62, 1967-1998.

Graff Zivin, J. and M. Neidell, 2014. Temperature and the allocation of time: Implications for climate change, *Journal of Labor Economics* 32, 1-26.

Goetzmann, W.N., D. Kim, A. Kumar, and Q. Wang, 2015. Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies* 28, 73-111.

Goetzmann, W.N., and N. Zhu, 2005, Rain or shine: Where is the weather effect?, *European Financial Management* 11, 559-578.

Heston, S.L. and R. Sadka, 2010. Seasonality in the cross section of stock returns: The international Evidence. *Journal of Financial and Quantitative Analysis* 45, 1133-1160.

Hirshleifer, D. and T. Shumway, 2003. Good day sunshine: Stock returns and the weather. *Journal of Finance* 58, 1009–1032.

Howarth, E. and M.S. Hoffman, 1984. A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology* 75, 15–23.

Huibers, M. J., L.E. de Graaf, F.P. Peeters, and A. Arntz, 2010. Does the weather make us sad? Meteorological determinants of mood and depression in the general population. *Psychiatry Research*, *180*, 143-146.

Isen, A., 2000. Positive affect and decision making. In *Handbook of Emotion*. Eds. M. Lewis and J. Haviland-Jones. New York: Guilford.

Isen, A. and R. Patrick, 1983. The effect of positive feelings on risk taking: When the chips are down. *Organizational Behavior and Human Performance* 31, 194–202.

Jacobsen, B. and W. Marquering, 2008. Is it the weather? *Journal of Banking and Finance* 32, 536-540.

Kamstra, M. J., L.A. Kramer, and M.D. Levi, 2003. Winter Blues: A SAD stock market cycle, *The American Economic Review* 93, 324–343.

Kaplanski, G., H. Levy, C. Veld, and Y. Veld-Merkoulova, 2014. Do happy people make optimistic investors? *Journal of Financial and Quantitative Analysis,* forthcoming.

Keller, M. C., B.L. Fredrickson, O. Ybarra, S. Côté, K. Johnson, J. Mikels, A. Conway, A. and T. Wager, 2005. A warm heart and a clear head, *Psychological Science* 16, 724–31.

Klimstra, T. A., T. Frijns, L. Keijsers, J.J. Denissen, Q.A. Raaijmakers, M.A. Van Aken, and W.H. Meeus, 2011. Come rain or come shine: Individual differences in how weather affects mood. *Emotion*, *11*, 1495-1499.

Loughran, T., and P. Schultz, 2004. Weather, stock returns, and the impact of localized trading behavior, *Journal of Financial and Quantitative Analysis* 39, 343-364.

Lucas, R. E., and N.M. Lawless, 2013. Does life seem better on a sunny day? Examining the association between daily weather conditions and life satisfaction judgments. *Journal of Personality and Social Psychology*, *104*, 872-884.

MacKerron G. and S. Mourato, 2014. Happiness is greater in natural environments. *Global Environmental Change*. Forthcoming.

Novy-Marx, R., 2014. Predicting anomaly performance with politics, the weather, global warming, sunspots, and the stars. *Journal of Financial Economics 112*, 137-146.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies* 22, 435-480.

Rehdanz, K. and D. Maddison, 2005. Climate and happiness. *Ecological Economics* 52, 111–125.

Rind, B., 1996. Effects of beliefs about weather conditions on tipping. *Journal of Applied Social Psycholog*y 26, 137–147.

San-Gil, J., J. L. Gonzalez de Rivera and J. Gonzalez, 1991. Biometeorology of psychiatric disorders. In *European Textbook of Psychiatry*. Ed. A. Seva. Barcelona: Anthropos.

Saunders, E.M.J., 1993. Stock prices and Wall Street weather. *American Economic Review* 83, 1337–1345.

Schmittmann, J.M., J. Pirschel, S. Meyer, and A. Hackethal, 2015. The impact of weather on German retail investors. *Review of Finance* 19, 1143-1183.

Schneider, F.W., W.A. Lesko, and W.A. Garrett, 1980. Helping behavior in hot, comfortable and cold temperature: A field study. *Environment and Behavior* 2, 231–241.

Shiller, R. J., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* 71, 421-436.

Shu, H-C. and M-W. Hung, 2009. Effect of wind on stock market returns: Evidence from European markets. *Applied Financial Economics* 19, 893-904.

Trombley, M.A., 1997. Stock prices and Wall Street weather: Additional evidence, *Quarterly Journal of Business and Economics* 36, 11-21.

Wright, W. F. and G.H. Bower, 1992, Mood effects on subjective probability assessment, *Organizational Behavior and Human Decision Processes* 52, 276-291.

Wyndham, H.C., 1969. Adaptation to heat and cold. *Environmental Research* 2, 442–469.

Table 1. Summary Statistics by Country

This table lists the countries and cities included in our sample. Stock return and standard deviation are in percentage points. Average year-round temperatures are in Fahrenheit and come from the Integrated Surface Database (ISD) managed by the National Climatic Data Center. For each country, the begin date (Column 4) is the first year for which neither the returns nor the weather information is missing. Series for all countries end on December 31, 2012. Columns 5 and 6 list the mean and standard deviations of percentage returns in local currency for each country. Column 7 shows the number of observations with valid daily return and hourly weather data for each country. Returns are in percentages.

Country (1)	City (2)	Avg. Temp., °F (3)	Begin Date (4)	Mean Daily Return (5)	Std. Dev., Daily return (6)	N (7)
Argentina	Buenos Aires	60.7	1988	0.048	1.05	5,364
Australia	Sydney	63.7	1973	0.035	0.85	10,163
Austria	Vienna	52.1	1973	0.036	0.69	10,132
Belgium	Brussels	52.2	1973	0.039	0.74	10,151
Brazil	Sao Paolo	67.1	1994	0.075	1.03	4,373
Bulgaria	Sofia	53.2	2000	0.033	0.93	2,860
Canada	Toronto	45.1	1979	0.045	0.73	9,651
Chile	Santiago	52.6	1989	0.070	0.81	5,941
China	Shanghai	63.1	1991	0.003	1.05	4,753
Colombia	Bogotá	53.0	1992	0.057	0.75	5,308
Denmark	Copenhagen	49.0	1973	0.046	0.74	10,099
Finland	Helsinki	43.6	1988	0.033	1.04	5,676
France	Paris	54.6	1973	0.045	0.93	9,942
Germany	Frankfurt	51.3	1973	0.047	0.82	9,869
Greece	Athens	67.8	1988	0.012	1.04	5,775
Hong Kong	Hong Kong	75.7	1987	0.064	1.03	9,278
Hungary	Budapest	54.4	1996	0.036	1.01	5,080
India	Mumbai	84.8	1990	0.071	1.00	5,406
Indonesia	Jakarta	85.6	1990	0.047	0.99	5,384
Ireland	Dublin	50.9	1973	0.041	0.84	9,903
Israel	Tel Aviv	73.4	1993	0.055	0.97	4,914
Italy	Milan	57.5	1973	0.041	0.98	9,751
Japan	Tokyo	61.0	1996	0.024	0.84	10,067
Korea	Seoul	54.2	1996	0.010	1.07	5,737
Luxemburg	Luxemburg	50.1	1992	0.033	0.87	5,180
Malaysia	Kuala Lumpur	83.2	1986	0.042	0.82	6,688
Mexico	Mexico City	56.2	1988	0.074	0.95	6,074
Netherlands	Amsterdam	52.1	1973	0.039	0.83	10,046
New Zealand	Wellington	54.1	1988	0.020	0.81	6,369
Norway	Oslo	42.4	1980	0.057	0.99	7,947
Pakistan	Karachi	84.9	1992	0.072	0.98	4,730
Peru	Lima	65.5	1994	0.052	0.83	4,754
Philippines	Manila	82.3	1987	0.046	0.94	6,192

Table 1 (Continued). Summary Statistics by Country

Country (1)	City (2)	Avg. Temp., °F (3)	Begin Date (4)	Mean Daily Return (5)	Std. Dev., Daily Return (6)	N (7)
Poland	Warsaw	49.5	1994	0.021	1.05	4,362
Portugal	Lisbon	62.2	1996	0.021	0.77	5,817
Romania	Bucharest	55.6	1996	0.047	1.05	3,567
Russia	Moscow	44.4	1998	0.081	1.14	2,964
Singapore	Singapore	82.3	1973	0.019	0.89	9,851
South Africa	Johannesburg	65.3	1973	0.076	0.94	9,881
Spain	Madrid	59.4	1987	0.046	0.96	6,325
Sri Lanka	Colombo	84.2	1987	0.030	0.81	6,390
Sweden	Stockholm	46.8	1982	0.059	0.98	7,270
Switzerland	Zurich	50.5	1979	0.042	0.72	9,657
Taiwan	Taipei	74.2	1987	0.024	1.07	5,653
Thailand	Bangkok	85.2	1987	0.018	1.05	6,019
Turkey	Istanbul	60.9	1988	0.040	1.20	4,988
UK	London	53.3	1973	0.039	0.86	10,091
USA	New York	51.1	1973	0.034	0.85	10,112
Venezuela	Caracas	72.4	1990	0.040	0.89	5,399

Table 2. Classification of Countries According to Yearly Average Temperature

This table describes the composition of the temperature regions. Panel A lists the countries included in each region. We define cold, mild, and hot regions based on the 33rd and 67th percentiles of the full sample's distribution of annual temperatures. Average year-round temperature (in Fahrenheit) is in parentheses. Panel B shows the mean, median and standard deviation of the annual temperature (in Fahrenheit), by region. N is the number of observations with valid return and weather data for each region. Panel C reports summary statistics for each of the temperature regions. All weather variables are based on the average of hourly readings between 6:00 AM and 4:00 PM local time on the day of the measurement. SKC is the average sky cover. WIND is the average wind speed (in miles per hour). RAIN is an indicator variable that is equal to 1 if the average of the hourly records of liquid precipitations (in inches) registered in the 6 hours prior to any hourly readings is positive; and zero otherwise. SNOW is equal to the depth (in inches) of the snow cover on the ground. SNOW is set to zero in summer months and in hot and mild countries. RET is each country's daily percentage returns of Datastream's Global Equity Index, in local currency. All weather variables come from the Integrated Surface Database (ISD) managed by the National Climatic Data Center (NCDC). The last two columns of Panel C show the difference in means of the weather variables and the returns, between cold and hot countries, and between mild and hot countries. Returns are in percentages. ***; **, * indicate that the hypothesis of the equality of means was rejected using a standard *t*-test at the 1%, 5%, and 10% level, respectively.

Panel A: Countries in Each Temperature Region

Cold	**Mild**	**Hot**
Austria (52.1)	Argentina (60.7)	Australia (63.7)
Belgium (52.2)	Bulgaria (53.2)	Brazil (67.1)
Canada (45.1)	China (63.1)	Greece (67.8)
Chile (52.6)	Colombia (53.0)	Hong Kong (75.7)
Denmark (49.0)	France (54.6)	India (84.8)
Finland (43.6)	Hungary (54.4)	Indonesia (85.6)
Germany (51.3)	Italy (57.5)	Israel (73.4)
Ireland (50.9)	Japan (61.0)	Malaysia (83.2)
Luxemburg (50.1)	Korea (54.2)	Pakistan (84.9)
Netherlands (52.1)	Mexico (56.2)	Peru (65.5)
Norway (42.4)	New Zealand (54.1)	Philippines (82.3)
Poland (49.5)	Portugal (62.2)	Singapore (82.3)
Russia (44.4)	Romania (55.6)	South Africa (65.3)
Sweden (46.8)	Spain (59.4)	Sri Lanka (84.2)
Switzerland (50.5)	Turkey (60.9)	Taiwan (74.2)
United States (51.1)	United Kingdom (53.3)	Thailand (85.2)
		Venezuela (72.4)

Table 2 (Continued). Classification of Countries According to Yearly Average Temperature

Panel B: Summary Statistics of Temperature, in Fahrenheit, by Region			
	Cold	**Mild**	**Hot**
Mean	49.78	57.56	76.31
Median	50.59	56.64	80.00
Standard deviation	15.06	13.55	10.90
N	124,069	84,176	101,755

Panel C: Summary Statistics of Weather and Returns in the Cold, Mild, and Hot Regions

Variable		Cold (1)	Mild (2)	Hot (3)	Difference (1 – 3)	Difference (2 – 3)
SKC	Mean	4.98	4.31	4.59	0.40***	–0.29***
	Median	5.43	4.47	5.13		
	Standard deviation	2.15	2.29	2.23		
WIND	Mean	9.20	7.85	6.98	2.22***	0.87***
	Median	8.36	6.78	6.25		
	Standard deviation	5.30	5.34	4.32		
RAIN	Mean	0.17	0.10	0.11	0.06***	–0.01***
	Median	0.00	0.00	0.00		
	Standard deviation	0.37	0.30	0.31		
SNOW	Mean	0.50	0.00	0.00	0.50***	N/A
	Median	0.00	0.00	0.00		
	Standard deviation	2.44	0.00	0.00		
RET (Daily)	Mean	0.045	0.044	0.041	0.00	0.00
	Median	0.009	0.000	0.000		
	Standard deviation	0.844	0.941	0.961		
RET (Annual)	Mean	12.98	11.25	13.84	–0.87	–1.33
	Median	12.36	10.27	14.72		
	Standard deviation	25.34	29.78	29.92		

Table 3. Ordinary Least Square (OLS) Regressions of Daily Return on Weather Variables

Description: This table presents the results of the following OLS panel regression: $r_{it} = \alpha + \beta_1 SKC_{it} + \beta_2 WIND_{it} + \beta_3 RAIN_{it} + \beta_4 SNOW_{it} + \beta_5 TEMP_{it} + \varepsilon_{it}$. Observations with the absolute value of daily index return greater than 2.5% are removed. All weather variables are based on the average hourly readings between 6:00 AM and 4:00 PM local time on the day of the measurement. SKC is the average sky cover. WIND is the average wind speed. RAIN is an indicator variable that is equal to 1 if the average of the hourly records of liquid precipitations registered in the 6 hours prior to any hourly readings is positive. SNOW is the average depth of the snow cover on the ground; it is set to zero in summer months and in hot and mild countries. TEMP is the daily average temperature. Panels A, B, and C present the results for the cold, mild, and hot countries, respectively. Figures in brackets indicate the economic significance of the independent variables. The economic impact of a variable is the change in annualized return as a result of a change in that variable from the 25th to the 75th percentile (or for RAIN, from 0 to 1), holding all other variables at their sample mean values. Standard errors are clustered by day and country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, two-tailed tests, respectively. The superscript ^{a} indicates significance at the 20% level. Returns, economic impact, and R^2 are in percentages.

Interpretation: Each temperature region has distinctive weather effects. The OLS regression results in this table combined with the logit regression results (Table 4) provide patterns of the weather effects across the temperature regions and seasons. These patterns are more succinctly summarized in the Appendix Table A1 and are broadly consistent with the Comfortable Weather Hypothesis (H1) and the Outdoors Hypothesis (H2), with the exception of the negative TEMP effect in the winter of the cold and mild regions.

Panel A: Cold Countries

	Jan (1)	**Feb (2)**	**Mar (3)**	**Apr (4)**	**May (5)**	**Jun (6)**	**Jul (7)**	**Aug (8)**	**Sep (9)**	**Oct (10)**	**Nov (11)**	**Dec (12)**	**All (13)**
SKC	–0.63^a	–0.55*	–0.45	–0.67^a	0.08	–0.65	–0.61	–0.69*	0.00	–0.25	–0.48	–0.34	–0.57***
	[6.34]	[6.32]	[4.55]	[6.24]	[0.74]	[5.17]	[5.40]	[6.18]	[0.03]	[1.98]	[3.73]	[2.83]	[5.23]
WIND	–0.11	–0.26^a	–0.36***	0.16	–0.06	–0.42*	–0.36^a	–0.38*	–0.21	–0.14	0.22	0.07	–0.10**
	[3.11]	[6.68]	[8.34]	[3.25]	[1.01]	[6.65]	[5.62]	[5.88]	[3.35]	[2.67]	[4.76]	[1.69]	[2.01]
RAIN	0.01	0.03	–0.02	–0.03^a	–0.02	–0.00	–0.05**	–0.03	–0.01	–0.03^a	0.02	0.00	–0.01^a
	[2.86]	[9.59]	[6.25]	[9.32]	[4.25]	[0.29]	[2.70]	[7.26]	[2.43]	[6.57]	[5.09]	[0.55]	[2.74]
SNOW	–0.02	–0.14	–0.49**									0.25^a	–0.01
	[0.07]	[0.72]	[0.60]									[0.10]	[0.00]
TEMP	–0.18***	–0.24**	–0.23	–0.02	0.13	–0.34**	–0.10	–0.20^a	0.51***	–0.50***	–0.24	–0.13	–0.18***
	[8.50]	[1.36]	[8.10]	[0.82]	[3.77]	[9.56]	[2.69]	[5.04]	[0.65]	[2.90]	[7.39]	[4.85]	[1.26]
Intercept	0.21***	0.23***	0.22**	0.11	–0.04	0.32***	0.17	0.23**	–0.30**	0.29***	0.12	0.12***	0.17***
R^2	0.10	0.15	0.18	0.06	0.02	0.11	0.12	0.10	0.17	0.22	0.07	0.05	0.11
N	10,549	9,827	10,660	9,734	10,592	9,842	10,157	10,718	10,342	10,423	10,386	10,833	124,063

Table 3 (Continued). Ordinary Least Square (OLS) Regressions of Daily Return on Weather Variables

Panel B: Mild Countries

	Jan (1)	**Feb (2)**	**Mar (3)**	**Apr (4)**	**May (5)**	**Jun (6)**	**Jul (7)**	**Aug (8)**	**Sep (9)**	**Oct (10)**	**Nov (11)**	**Dec (12)**	**All (13)**
SKC	–0.61	0.34	–1.07**	0.36	–0.54	–0.96[a]	–0.12	–0.39	–0.15	–0.43	–0.23	0.35	–0.32*
	[7.95]	[4.12]	[2.17]	[3.92]	[4.76]	[9.01]	[1.21]	[3.72]	[1.29]	[3.86]	[2.44]	[4.16]	[3.20]
WIND	0.13	–0.25[a]	0.06	–0.31[a]	–0.03	0.11	–0.27[a]	–0.30	0.02	–0.10	–0.08	–0.40**	–0.11[a]
	[2.92]	[5.34]	[1.21]	[6.37]	[0.48]	[1.70]	[4.78]	[4.96]	[0.24]	[1.57]	[1.44]	[8.05]	[1.95]
RAIN	0.00	–0.00	0.02	–0.01	0.02	0.06**	0.04**	0.00	–0.04	–0.03	0.02	–0.03	0.00
	[0.79]	[0.77]	[4.53]	[4.17]	[6.01]	[5.36]	[0.23]	[1.07]	[9.92]	[7.71]	[5.91]	[7.65]	[0.58]
TEMP	–0.24*	–0.43***	–0.20	–0.30	–0.02	–0.23**	0.03	–0.10	0.00	–0.27	–0.05	–0.18	–0.14***
	[9.66]	[6.34]	[6.01]	[7.92]	[0.57]	[8.17]	[1.23]	[4.13]	[0.06]	[7.15]	[1.27]	[7.05]	[7.62]
Intercept	0.20***	0.28***	0.20*	0.26	0.04	0.22***	0.05	0.14	0.01	0.20	0.06	0.14**	0.15***
R^2	0.06	0.18	0.07	0.08	0.01	0.07	0.03	0.04	0.02	0.06	0.01	0.14	0.05
N	6,989	6,572	7,066	6,799	6,984	7,006	7,220	7,146	7,040	7,088	7,007	7,251	84,168

Panel C: Hot Countries

	Jan (1)	**Feb (2)**	**Mar (3)**	**Apr (4)**	**May (5)**	**Jun (6)**	**Jul (7)**	**Aug (8)**	**Sep (9)**	**Oct (10)**	**Nov (11)**	**Dec (12)**	**All (13)**
SKC	–0.62[a]	–1.21**	–0.10	–0.45	–1.22**	–0.35	–0.89	–0.73[a]	–1.15[a]	0.52	–0.19	–0.90***	–0.59***
	[6.43]	[2.69]	[0.93]	[4.42]	[9.21]	[2.81]	[7.00]	[5.73]	[8.87]	[4.76]	[1.71]	[9.45]	[5.46]
WIND	0.14	0.15	–0.37[a]	0.46**	–0.01	–0.00	0.22	–0.37[a]	–0.39[a]	0.12	–0.39**	–0.13	–0.03
	[2.10]	[2.38]	[5.31]	[6.94]	[0.13]	[0.02]	[3.33]	[5.07]	[5.43]	[1.48]	[4.65]	[1.96]	[0.40]
RAIN	0.01	0.05	–0.01	0.02	0.02	0.04	0.07***	0.04*	0.02	–0.02	0.00	0.01	0.02**
	[2.19]	[4.16]	[1.87]	[6.29]	[6.06]	[2.54]	[1.16]	[2.15]	[6.48]	[4.27]	[0.82]	[1.84]	[6.78]
TEMP	–0.02	–0.02	–0.07	0.15*	–0.04	–0.24[a]	0.05	–0.42***	–0.17	–0.05	–0.03	0.13[a]	–0.04
	[1.64]	[1.07]	[4.50]	[8.46]	[1.68]	[8.27]	[1.61]	[0.68]	[4.96]	[1.89]	[1.41]	[8.19]	[1.69]
Intercept	0.09	0.12	0.12	–0.09	0.12	0.26*	0.03	0.44***	0.26**	0.03	0.07	0.02	0.10**
R^2	0.03	0.11	0.03	0.09	0.06	0.07	0.1	0.14	0.09	0.02	0.03	0.09	0.02
N	8,497	8,051	8,547	8,358	8,433	8,505	8,585	8,328	8,431	8,446	8,397	8,634	101,212

Table 4. Logit Regressions of the Probability of a Positive Daily Return on Weather Variables

Description: This table presents the results of the logit estimation of the following model: $P(r_{it} > 0) = \frac{1}{1+e^{-(\alpha+\beta_1 SKC_{it}+\beta_2 WIND_{it}+\beta_3 RAIN_{it}+\beta_4 SNOW_{it}+\beta_5 TEMP_{it})}}$, where $P(r_{it} > 0)$ is an indicator variable that is equal to 1 if the market return in country *i* on day *t* is positive, and zero otherwise. Observations with the absolute value of daily index return greater than 2.5% are removed. All weather variables are based on the average hourly readings between 6:00 AM and 4:00 PM local time on the day of the measurement. SKC is the average sky cover. WIND is the average wind speed. RAIN is an indicator variable that is equal to 1 if the average of the hourly records of liquid precipitations registered in the 6 hours prior to any hourly readings is positive. SNOW is the average depth of the snow cover on the ground; it is set to zero in summer months and in hot and mild countries. TEMP is the daily average temperature. Panels A, B, and C present the results for the cold, mild, and hot countries, respectively. Figures in brackets indicate the economic significance of the independent variables. The economic impact of a variable is the change in the independent variable (the probability of a positive daily return) as a result of a change in that variable from the 25th to the 75th percentile (or for RAIN, from 0 to 1), holding all other variables at their sample mean values. Standard errors are clustered by day and country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, two-tailed tests, respectively. The superscript [a] indicates significance at the 20% level. Returns, economic impact, and R^2 are in percentages.

Interpretation: Each temperature region has distinctive weather effects. The logit regression results in this table combined with the OLS regression results (Table 3) provide patterns of the weather effects across the temperature regions and seasons. These patterns are more succinctly summarized in the Appendix Table A1 and are broadly consistent with the Comfortable Weather Hypothesis (H1) and the Outdoors Hypothesis (H2), with the exception of the negative TEMP effect in the winter of the cold and mild regions.

Panel A: Cold Countries

	Jan (1)	**Feb (2)**	**Mar (3)**	**Apr (4)**	**May (5)**	**Jun (6)**	**Jul (7)**	**Aug (8)**	**Sep (9)**	**Oct (10)**	**Nov (11)**	**Dec (12)**	**All (13)**
SKC	–1.46	–1.24[a]	0.07	–1.26[a]	0.78	–2.51*	–2.09*	–0.99	–0.92	–0.78	–1.24	0.81	–1.19***
	[1.13]	[1.08]	[0.06]	[0.97]	[0.64]	[1.72]	[1.64]	[0.82]	[0.69]	[0.57]	[0.89]	[0.56]	[0.95]
WIND	–0.04	–0.22	–0.51[a]	0.09	0.27	–0.12	–0.34	–0.61	0.05	–0.12	0.42	0.52	0.03
	[0.09]	[0.42]	[1.00]	[0.15]	[0.39]	[0.16]	[0.47]	[0.88]	[0.07]	[0.20]	[0.85]	[1.07]	[0.06]
RAIN	0.08*	0.07[a]	–0.07	0.05	–0.08	0.01	–0.08[a]	0.05	–0.06	–0.05[a]	0.06	–0.05	–0.01
	[1.89]	[1.62]	[1.69]	[1.26]	[1.86]	[0.30]	[1.99]	[1.28]	[1.32]	[1.07]	[1.48]	[1.21]	[0.29]
SNOW	–0.92**	–0.78*	–1.13***									–0.09	–0.50*
	[0.36]	[0.41]	[0.53]									[0.02]	[0.06]
TEMP	–0.35**	–0.78***	–0.41	–0.28	0.51[a]	–0.53[a]	–0.31	–0.10	1.15***	–1.00**	–0.55[a]	–0.79**	–0.49***
	[1.27]	[2.80]	[1.25]	[0.77]	[1.27]	[1.27]	[0.74]	[0.24]	[2.22]	[2.33]	[1.57]	[2.39]	[2.70]
Intercept	0.58***	0.64***	0.47**	0.48*	–0.11	0.65**	0.52**	0.31	–0.59**	0.64***	0.39**	0.55***	0.52***
R^2	0.07	0.20	0.11	0.03	0.05	0.06	0.08	0.03	0.18	0.16	0.08	0.15	0.12
N	10,549	9,827	10,660	9,734	10,592	9,842	10,157	10,718	10,342	10,423	10,386	10,833	124,063

Table 4 (Continued). Logit Regressions of the Probability of a Positive Daily Return on Weather Variables

Panel B: Mild Countries

	Jan (1)	**Feb (2)**	**Mar (3)**	**Apr (4)**	**May (5)**	**Jun (6)**	**Jul (7)**	**Aug (8)**	**Sep (9)**	**Oct (10)**	**Nov (11)**	**Dec (12)**	**All (13)**
SKC	0.23	2.08**	–1.41[a]	0.41	–0.80	–3.96***	0.56	–0.45	0.63	–1.59	–0.45	2.51***	–0.18
	[0.24]	[2.08]	[1.36]	[0.36]	[0.69]	[2.94]	[0.49]	[0.38]	[0.55]	[1.34]	[0.45]	[2.52]	[0.16]
WIND	–0.24	0.01	0.06	–0.57[a]	–0.54[a]	0.85[a]	–0.60**	–0.58[a]	0.19	0.16	–0.41	–1.29**	–0.26*
	[0.43]	[0.01]	[0.11]	[0.91]	[0.84]	[1.08]	[0.94]	[0.88]	[0.28]	[0.24]	[0.69]	[2.11]	[0.42]
RAIN	–0.09	–0.08	–0.10**	–0.13**	0.07	0.08*	0.01	–0.11	–0.16**	–0.02	–0.08	–0.13*	–0.07***
	[2.27]	[1.96]	[2.50]	[3.00]	[1.72]	[1.83]	[0.33]	[2.56]	[4.06]	[0.38]	[1.96]	[3.08]	[1.67]
TEMP	–0.69*	–1.05***	–0.57	–0.87*	–0.19	–0.96***	–0.04	–0.32	0.27	–0.49	–0.05	–1.20***	–0.47***
	[2.23]	[3.22]	[1.43]	[1.80]	[0.55]	[2.69]	[0.13]	[1.18]	[0.84]	[1.22]	[0.13]	[3.77]	[2.22]
Intercept	0.58***	0.60***	0.53*	0.74**	0.27	0.90***	0.19	0.43*	–0.15	0.41	0.17	0.79***	0.46***
R^2	0.13	0.28	0.09	0.12	0.03	0.24	0.03	0.06	0.07	0.05	0.04	0.62	0.11
N	6,989	6,572	7,066	6,799	6,984	7,006	7,220	7,146	7,040	7,088	7,007	7,252	84,169

Panel C: Hot Countries

	Jan (1)	**Feb (2)**	**Mar (3)**	**Apr (4)**	**May (5)**	**Jun (6)**	**Jul (7)**	**Aug (8)**	**Sep (9)**	**Oct (10)**	**Nov (11)**	**Dec (12)**	**All (13)**
SKC	–0.52	–0.65	0.72	–1.10	–1.42	0.23	0.07	–1.77*	–1.60	1.28[a]	0.12	–2.20**	–0.71
	[0.45]	[0.57]	[0.63]	[0.93]	[0.97]	[0.14]	[0.05]	[1.06]	[1.11]	[1.12]	[0.10]	[0.00]	[0.00]
WIND	0.07	0.13	–0.58	0.45	0.13	1.35**	0.49	–0.23	0.29	–0.38	–0.62	–0.34	–0.05
	[0.09]	[0.17]	[0.76]	[0.58]	[0.16]	[1.58]	[0.63]	[0.24]	[0.36]	[0.46]	[0.72]	[0.00]	[0.00]
RAIN	0.10[a]	0.11	–0.00	0.01	0.05	0.17**	0.10	0.06	–0.00	–0.02	–0.06	–0.01	0.04**
	[2.48]	[2.65]	[0.08]	[0.33]	[1.31]	[3.78]	[2.40]	[1.21]	[0.03]	[0.45]	[1.49]	[0.00]	[0.00]
TEMP	0.36[a]	0.06	0.20	0.55*	0.56*	–1.05**	–0.12	–0.92**	0.05	–0.19	–0.11	0.85***	0.05
	[2.00]	[0.36]	[1.10]	[2.56]	[2.05]	[2.70]	[0.29]	[1.77]	[0.12]	[0.66]	[0.52]	[0.00]	[0.00]
Intercept	0.03	0.20	0.03	–0.24	–0.25	0.92**	0.23	0.98***	0.17	0.27	0.24	–0.22	0.18*
R^2	0.07	0.02	0.05	0.12	0.10	0.34	0.04	0.12	0.03	0.03	0.02	0.32	0.01
N	8,497	8,051	8,547	8,358	8,433	8,505	8,585	8,328	8,431	8,446	8,397	8,634	101,212

Table 5. Differences in Weather Effects across Seasons for Each Temperature Region

Description: This table summarizes the seasonal differences in the effects of WIND, RAIN, and TEMP for each temperature region. We provide a short result description for each of the results (labeled R1-R9) in the left-most column. For each weather variable, we compare the effect between two groups of seasons as indicated in each result description. For example, for result R1, Group 1 refers to spring (Feb-Apr) and summer (Jun-Aug), and Group 2 refers to the remaining months. The left three columns show results for the OLS regressions of Table 3 while the right three columns show logit regression results of Table 4. Boldface indicates statistical significance at the 10% level or above based on the t-stat for difference between Group 1 and Group 2. Test of difference is assessed using the *t*-test of difference in coefficients between two groups.

Interpretation: All results are to be interpreted in the two main hypotheses in the paper—the Comfortable Weather Hypothesis (H1), and the Outdoors Hypothesis (H2)—except for results R4 and R8 (temperature has a particularly strong negative effect in the winter in cold and mild countries). For results R3 and R7, we treat September differently from the rest of the year (cold and mild regions) because temperature can have a positive effect on mood during the transition from summer to fall. For results R5 and R6, we treat June differently from the rest of the spring /summer season (mild region) because wind and rain can have a pleasant cooling effect in June, when temperatures soar. Together, these results show that the WIND, RAIN, and TEMP effects vary across the seasons for all three temperature regions, in a way consistent with both H1 and H2, except for the negative effect of TEMP in the winter of the cold and mild regions. Since SNOW only applies to the winter of the cold region, the statement that the SNOW effect varies across the seasons is trivially true.

	OLS			Logit		
	Coefficient (Std. Error) Group 1	Coefficient (Std. Error) Group 2	*t*-stat (1) – (2)	Coefficient (Std. Error) Group 1	Coefficient (Std. Error) Group 2	*t*-stat (1) – (2)
Panel A. Cold region						
R1: WIND: Spring /summer (Mar-Aug, "Group 1") have a more negative WIND effect than fall/winter ("Group 2")	–0.22 (0.06)	0.00 (0.08)	**–2.11**	–0.23 (0.03)	0.27 (0.27)	–1.20
R2: RAIN: Spring/summer (Mar-Aug "Group 1") have a more negative RAIN effect than fall/winter ("Group 2")	–0.02 (0.01)	0.01 (0.01)	**–2.01**	–0.03 (0.03)	0.01 (0.02)	–0.91
R3: TEMP: Summer (Jun-Aug, "Group 1") has a more negative TEMP effect than September ("Group 2")	–0.21 (0.08)	0.51 (0.18)	**–3.61**	–0.32 (0.18)	1.15 (0.36)	**–3.67**
R4: TEMP: Winter (Dec-Feb, "Group 1") has a more negative TEMP effect than rest of year ("Group 2")	–0.18 (0.05)	–0.09 (0.05)	–1.10	–0.51 (0.12)	–0.18 (0.10)	**–2.09**

Table 5 (Continued). Differences in Weather Effects across Seasons for Each Temperature Region

	OLS			Logit		
	Coefficient (Std. Error) Group 1	Coefficient (Std. Error) Group 2	*t*-stat (1) – (2)	Coefficient (Std. Error) Group 1	Coefficient (Std. Error) Group 2	*t*-stat (1) – (2)
Panel B. Mild region						
R5: WIND: Spring/summer (Apr-Aug, minus Jun, “Group 1”) have a more negative WIND effect than June (“Group 2”)	–0.25 (0.32)	0.11 (0.21)	–1.33	–0.53 (0.16)	0.85 (0.65)	**–2.05**
R6: RAIN: June (“Group 1”) has a more positive RAIN effect than spring (Mar-May, “Group 2”)	0.06 (0.02)	0.01 (0.02)	1.47	0.08 (0.04)	–0.06 (0.04)	**2.28**
R7: TEMP: Summer (Jun-Aug, “Group 1”) has a more negative TEMP effect than September (“Group 2”)	–0.09 (0.08)	0.00 (0.12)	–0.64	–0.43 (0.20)	0.27 (0.23)	**–2.32**
R8: TEMP: Winter (Dec-Feb, “Group 1”) has a more negative TEMP effect than rest of year (“Group 2”)	–0.26 (0.07)	–0.09 (0.06)	**–2.03**	–1.01 (0.22)	–0.23 (0.10)	**–3.28**
Panel C. Hot region						
R9: WIND: Fall (Aug-Nov, “Group 1”) has a more negative WIND effect than spring/summer (Apr-Jul, “Group 2”)	–0.19 (0.16)	0.18 (0.13)	**–1.76**	–0.18 (0.39)	0.54 (0.36)	–1.35
R10: RAIN: Summer (Jun-Aug, “Group 1”) has a more positive RAIN effect than rest of year (“Group 2”)	0.05 (0.02)	0.01 (0.01)	**2.30**	0.10 (0.05)	0.01 (0.02)	**1.76**
R11: TEMP: Summer (Jun-Aug, “Group 1”) has a more negative TEMP effect than winter / spring (Dec-May, “Group 2”)	–0.20 (0.10)	–0.02 (0.06)	–1.53	–0.75 (0.32)	0.25 (0.17)	**–2.76**

Table 6. Comfort Indices by Country and Season

Description: This table reports the Comfort Indices (CI) by country and seasons. The comfort index is calculated as follows: For each country, we use this country average monthly weather over the full sample period and the significant ($p < 0.2$) monthly OLS coefficients from Table 3. For each country *i* (in temperature region *j*) and month *m*, we compute the CI as:

$$CI_{im} = \alpha_{jm} + \beta_{1,jm}\overline{SKC}_{i,m} + \beta_{2,jm}\overline{SPD}_{i,m} + \beta_{3,jm}\overline{RAIN}_{i,m} + \beta_{4,jm}\overline{SNOW}_{i,m} + \beta_{5,jm}\overline{TEMP}_{i,m}.$$

During October through February, and for countries in the cold and mild regions only, we invert the sign of the TEMP coefficient. For ease of reporting, we multiply the comfort index by 100. Seasonal comfort indices are the average of the monthly comfort indices for each of the seasons: spring (March to May), summer (June to August), fall (September to November), and winter (December to February). We rank countries along their comfort indices. Ranking is done independently for each temperature region, and each season. Rank 1 (5) indicates the lowest (highest) CI quintile.

Interpretation: Based on the OLS results of Table 3, we construct a comfort index (CI) for each country. The OLS coefficients are consistent with the Comfortable Weather Hypothesis except the negative TEMP effect for October through February in the cold/mild regions because in cold winter days, a warmer TEMP should indicate a higher comfort level. We therefore adjust the TEMP coefficient by inverting its sign for the winter months (December-February) as well as October and November for the cold/mild regions. CI is calculated by using the adjusted OLS coefficients and the average weather variable readings in our sample period. Finally, since the regressions in Table 3 are run separately for each region, we can only compare the CI for countries within each temperature region.

Panel A. Cold Countries

	Annual		**Winter**		**Spring**		**Summer**		**Fall**	
Country	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**
Russia	13.68	1	19.33	1	3.69	1	8.17	4	23.52	1
Norway	13.81	1	20.81	2	3.27	1	8.92	5	22.22	1
Finland	13.86	1	20.43	1	4.01	1	7.76	3	23.25	1
Denmark	14.62	2	21.65	3	4.61	2	6.82	1	25.38	2
Canada	14.67	2	20.24	1	4.81	3	8.81	4	24.82	2
Poland	14.68	2	21.29	2	4.80	3	7.15	2	25.46	3
Sweden	14.68	3	21.34	2	5.02	4	8.21	4	24.17	2
Austria	15.03	3	22.04	3	4.81	3	6.87	1	26.40	4
Netherlands	15.12	3	22.59	4	4.52	2	6.82	1	26.54	5
Germany	15.16	3	22.15	3	4.99	4	7.83	3	25.67	3
Ireland	15.18	4	23.10	5	4.33	2	7.56	2	25.72	4
Luxemburg	15.28	4	22.47	4	5.13	5	7.99	3	25.53	4
USA	15.37	4	21.97	3	4.93	4	7.21	2	27.39	5
Belgium	15.57	5	22.93	5	4.91	3	7.87	3	26.56	5
Switzerland	15.68	5	22.38	4	5.34	5	9.42	5	25.59	3
Chile	18.15	5	28.61	5	6.32	5	11.29	5	26.38	4

Table 6 (Continued). Comfort Indices by Country and Season

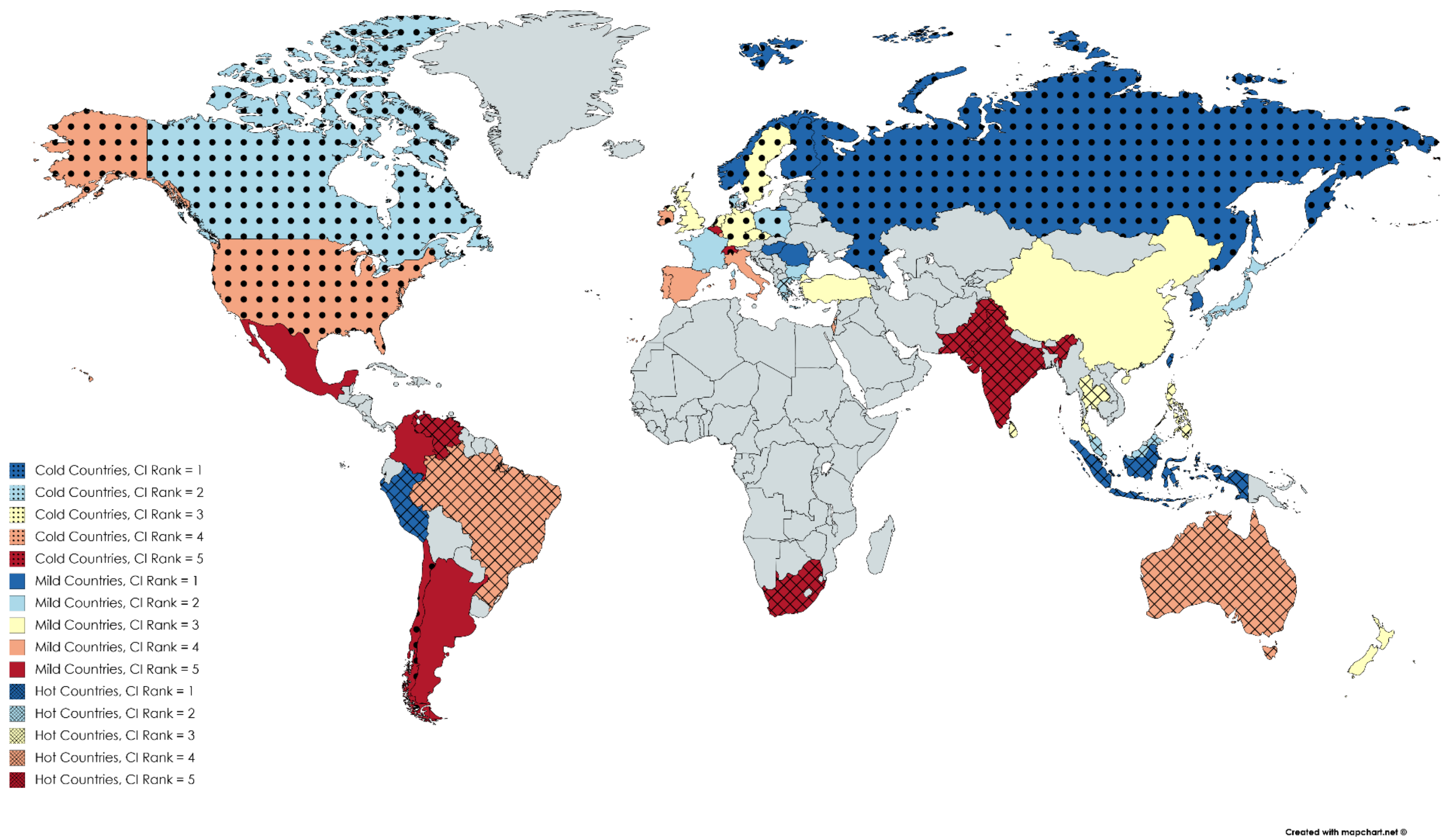
Panel B. Mild Countries

	Annual		Winter		Spring		Summer		Fall	
Country	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**
Hungary	11.86	1	28.71	1	12.45	2	-0.38	2	6.67	3
Korea	11.90	1	28.03	1	13.01	4	-0.11	2	6.67	3
Romania	12.12	1	29.06	1	12.68	3	0.07	3	6.67	3
Bulgaria	12.19	2	29.09	2	12.68	3	0.34	3	6.67	3
Japan	12.24	2	30.99	3	12.16	1	-0.85	1	6.67	3
France	12.43	2	30.24	2	12.30	2	0.51	4	6.67	3
China	12.46	3	31.54	4	12.53	2	-0.88	1	6.67	3
Turkey	12.50	3	30.84	3	12.67	3	-0.16	2	6.67	3
UK	12.50	3	30.56	2	12.21	1	0.54	5	6.67	3
New Zealand	12.52	3	31.33	3	11.96	1	0.13	3	6.67	3
Italy	12.91	4	31.27	3	13.29	5	0.40	4	6.67	3
Spain	13.01	4	32.00	3	13.15	5	0.22	3	6.67	3
Portugal	13.22	4	33.97	5	12.65	3	-0.40	1	6.67	3
Argentina	13.32	5	33.33	4	12.83	4	0.44	4	6.67	3
Colombia	13.88	5	34.61	5	13.00	4	1.25	5	6.67	3
Mexico	14.28	5	34.72	5	14.19	5	1.54	5	6.67	3

Panel C. Hot Countries

	Annual		Winter		Spring		Summer		Fall	
Country	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**	**CI**	**Rank**
Taiwan	3.31	1	4.17	1	1.38	1	3.27	3	4.4	1
Peru	3.74	1	2.85	1	0.58	1	5.97	5	5.57	5
Indonesia	3.84	1	5.45	2	1.87	2	3.44	3	4.6	2
Singapore	3.85	2	5.29	2	1.77	2	3.25	3	5.08	2
Malaysia	3.99	2	5.18	1	1.97	3	3.75	4	5.05	2
Greece	4.02	2	5.29	2	2.02	3	3.09	2	5.69	5
Hong Kong	4.06	2	6.39	3	2.34	4	2.9	2	4.59	1
Philippines	4.24	3	6.73	4	2.79	4	3.09	2	4.34	1
Thailand	4.24	3	6.70	4	2.24	4	2.72	1	5.30	4
Sri Lanka	4.25	3	6.65	4	2.39	4	2.70	1	5.25	4
Israel	4.40	4	6.38	3	3.05	5	2.84	2	5.32	4
Australia	4.71	4	6.48	4	1.86	2	5.59	4	4.92	2
Brazil	4.83	4	6.36	2	1.55	1	6.01	5	5.38	4
Pakistan	4.90	5	8.96	5	4.24	5	1.27	1	5.13	3
Venezuela	4.90	5	6.36	2	1.78	2	5.56	4	5.90	5
South Africa	5.42	5	8.10	5	2.24	3	6.19	5	5.14	3
India	5.77	5	9.81	5	3.35	5	4.67	4	5.25	3

Figure 1. Annual Comfort Index by Temperature Region



This figure shows the annual comfort index (CI) for our sample countries. Each country's weather is presented by the city of the national exchange as shown in Table 1. The comfort index is calculated as follows: For each country, we use this country average monthly weather over the full sample period and the significant ($p < 0.2$) monthly OLS coefficients from Table 3. For each country i (in temperature region j) and month m, we compute the CI as: $CI_{im} = \alpha_{jm} + \beta_{1,jm}\overline{SKC}_{i,m} + \beta_{2,jm}\overline{SPD}_{i,m} + \beta_{3,jm}\overline{RAIN}_{i,m} + \beta_{4,jm}\overline{SNOW}_{i,m} + \beta_{5,jm}\overline{TEMP}_{i,m}$. During October through February, and for countries in the cold and mild regions only, we invert the sign of the coefficient on TEMP so that warmer temperature indicates high comfort level. Seasonal comfort indices are the average of the monthly comfort indices for each of the seasons: spring (March to May), summer (June to August), fall (September to November), and winter (December to February). We rank countries by their comfort indices within each temperature region. Rank 1 (5) indicates the lowest (highest) CI quintile within each region. Countries shaded in light grey are non-sample countries.

Table A1. Summary of Ordinary Least Squares (OLS) and Logit Regression Results

Description: This table summarizes the main findings of the OLS regressions of Table 3 and logit regressions of Table 4. The first (second) row of each weather variable contains results for the OLS (logit) regressions. Only the signs of regression coefficients significant at the 20% level or higher are reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, two-tailed tests, respectively. The superscript [a] indicates significance at the 20% level. The dependent variables of the OLS regression is daily index return, and that of the logit regression is the probability of a positive daily return. All weather variables are based on the average of hourly readings between 6:00 AM and 4:00 PM local time on the day of the measurement. SKC is the average sky cover. WIND is the average wind speed. RAIN is an indicator variable that is equal to 1 if the average of the hourly records of liquid precipitations registered in the 6 hours prior to any hourly readings is positive; and zero otherwise. SNOW is the depth of the snow cover on the ground; it is set to zero in summer months and in hot and mild countries. TEMP is the daily average temperature. Panel A, B, and C summarize results for the cold, mild, and hot countries, respectively. We define cold, mild, and hot regions based on the 33rd and 67th percentiles of the full sample's distribution of annual temperatures. Blue, red, and black colors of the signs indicate results consistent with, inconsistent with, or neutral to the interpretation that comfortable weather leads to higher returns, respectively.

Interpretation: The weather effects are prevalent in all three temperature regions and vary systematically across regions and seasons. Most weather effects (in blue) are consistent with the Comfortable Weather Hypothesis (H1) and the Outdoors Hypothesis (H2). The main exception is the strong negative TEMP effect (in red) in the winter of the cold and mild regions.

Panel A: Cold countries

	Jan (1)	**Feb (2)**	**Mar (3)**	**Apr (4)**	**May (5)**	**Jun (6)**	**Jul (7)**	**Aug (8)**	**Sep (9)**	**Oct (10)**	**Nov (11)**	**Dec (12)**	**All (13)**
SKC	–[a]	–*		–[a]				–*					–***
		–[a]		–[a]		–*	–*						–***
WIND		–[a]	–***			–*	–[a]	–*					–**
RAIN				–[a]			–**			–[a]			–*
	+*						–[a]			–[a]			
SNOW			–**									+[a]	
	–***	–[a]	–***										–*
TEMP	–***	–**				–**		–[a]	+***	–***	–[a]	–[a]	–***
	–**	–***			+[a]	– [a]			+***	–**	–[a]	–**	–***

Table A1 (Continued). Summary of Ordinary Least Squares (OLS) and Logit Regression Results

Panel B: Mild countries

	Jan (1)	Feb (2)	Mar (3)	Apr (4)	May (5)	Jun (6)	Jul (7)	Aug (8)	Sep (9)	Oct (10)	Nov (11)	Dec (12)	All (13)
SKC			−**			−*							−*
		+**	−[a]			−***						+***	
WIND		−[a]		−[a]			−[a]					−**	−[a]
				−[a]	−[a]	+[a]	−**	−[a]				−**	−*
RAIN						+**							
			−**	−**		+*			−[a]			−*	−***
TEMP	−*	−***				−**							−***
	−*	−***		−*		−***						−***	−***

Panel C: Hot countries

	Jan (1)	Feb (2)	Mar (3)	Apr (4)	May (5)	Jun (6)	Jul (7)	Aug (8)	Sep (9)	Oct (10)	Nov (11)	Dec (12)	All (13)
SKC	−[a]	−**			−**			−[a]	−[a]			−***	−***
								−*		+[a]		−**	
WIND			−[a]	+**				−[a]	−[a]		−**		
						+**							
RAIN							+***	+*					+**
	+[a]					+**							+**
TEMP				+*		−[a]		−***				+[a]	
	+[a]			+*	+*	−**		−**				+***	

Table A2. Daily Time Spent Outdoors for Each Month, by Temperature Region

Description: This table reports the averages of daily maximum temperature and daily time spent outdoors for the months, in descending order of time spent outdoors, for each temperature region. We estimate the outdoor leisure time using the relationship between time spent outdoors and maximum daily temperature retrieved from Graff Zivin and Neidell (2014).

Interpretation: The time spent outdoors relates to the Outdoors Hypothesis (H2). Several patterns of outdoor time give specific predictions of the Outdoors Hypothesis. First, in all temperature regions, individuals spend the most and least time outdoors in the summer and winter, respectively. Therefore, we expect most weather effects to be strong around summer time for all temperature regions. Second, individuals spend very limited time outdoors during the winter in the cold and mild countries. Consequently, the marginal utility of outdoor time should be high in the spring when the transition from winter to increasingly mild weather translates into more outdoor opportunity. We thus expect stronger weather effects in the spring than in the autumn in the cold and mild regions. Third, hot countries have the least variation in outdoor time across the seasons, and individuals in hot countries spend considerable time outdoors even during the winter. This implies that we could observe some strong weather effects even in the winter in the hot region. Fourth, the hot region has much higher temperatures and longer outdoor time in all seasons than both the cold and mild regions, but the mild region is closer to the cold than to the hot region in terms of temperature and outdoor time. Therefore, we expect the mild region to have more similar weather effects to the cold region than to the hot region.

Cold Countries			*Mild Countries*			*Hot Countries*		
Month	Maximum Daily Temperature (°F)	Time Spent Outdoors (Minutes)	Month	Maximum Daily Temperature (°F)	Time Spent Outdoors (Minutes)	Month	Maximum Daily Temperature (°F)	Time Spent Outdoors (Minutes)
July	75.3	40.8	July	79.3	41.4	August	85.5	45.9
August	72.5	39.4	August	76.4	40.5	June	85.6	45.2
June	70.5	37.7	June	79.5	40.2	July	85.3	45.1
September	67.1	34.8	September	73.9	38.9	September	84.4	44.8
May	62.9	29.2	May	70.0	37.0	May	84.4	44.3
October	55.6	22.8	April	65.3	32.6	October	82.9	44.0
April	54.5	21.7	October	63.1	30.3	April	83.1	43.3
November	45.9	16.0	November	56.5	23.3	November	79.8	42.6
March	43.7	14.7	March	55.3	21.9	March	79.8	40.9
December	39.2	12.1	December	49.2	18.5	December	76.3	39.3
February	35.6	10.6	February	48.4	16.9	February	77.1	39.1
January	34.4	10.1	January	46.6	16.2	January	75.2	38.4