Are Earnings Surprises Interpreted More Optimistically on Very Sunny Days? Behavioral Bias in Interpreting Accounting Information

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Using bootstrap randomization procedures, we find that market reactions to earnings surprises are higher when earnings are announced on very sunny days in New York City. The effect exists for firms traded in New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) (i.e., New York–based exchanges), but does not exist for firms traded on NASDAQ (National Association of Securities Dealers Automated Quotation). Moreover, this sunshine effect is most (least) prominent for firms that are more likely to be followed by naïve (sophisticated) investors. The sunshine effect is most prevalent on unambiguously sunny days, however, and is weaker on moderately sunny days. Average bid-ask spreads are lower on sunny days relative to cloudy days, suggesting that market-makers may contribute to the effect. Lastly, we find evidence of a short-term reversal of the sunshine-induced overreaction and underreaction.

Keywords: *Weather; earnings surprises; behavioral bias; trading anomalies; sunshine*

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1. Introduction

Several studies in the economics and finance literature have documented a positive relation between sunshine and stock returns. For instance, Saunders (1993) examines the correlation between New York City sunshine and the contemporaneous daily returns of three New York–based indexes and finds that sunshine is positively related to index returns. Hirshleifer and Shumway (2003) document a similar relation for the daily weather patterns of twenty-five other international cities with each city's respective stock exchange. Motivated by a rich body of evidence in the psychology literature, they conclude: "[S]unlight affects mood, and . . . people tend to evaluate future prospects more optimistically when they are in a good mood than when they are in a bad mood . . . cheery days will [therefore] boost stocks." Alternatively, sunshine may also reduce investors' risk aversion, causing them to exhibit a higher tolerance for risk; this in turn would reduce the required rate of return, and therefore lead to higher stock returns.

Documenting a "sunshine effect" in stock returns, these studies contribute to a growing body of evidence suggesting that factors unrelated to fundamental value can affect stock prices. However, at least three questions are left unanswered. First, it is unclear whether the sunshine effect arises from the market's interpretation of value-relevant economic news events, or whether it arises from value-irrelevant noise (e.g., news about a pop-culture celebrity scandal). Second, because prior studies consider only index returns, it is unclear whether the sunshine effect can exist at a firm-specific level. Lastly, if the sunshine effect exists at the firm level, a natural question that arises is whether certain firms are more susceptible to the effect than other firms—and if so, can systematic differences in the sunshine effect be ex ante predicted?

To investigate these questions, we examine the market reactions to firms' earnings announcements. Overall, our empirical results suggest that firm-specific earnings surprises exhibit a sunshine effect—and that this sunshine effect is systematically related to proxies for investor sophistication: firm size and analyst following. Specifically, for firms trading on New York–based stock exchanges (i.e., New York Stock Exchange [NYSE] or American Stock Exchange [AMEX]) during 1982–2004, we use bootstrap randomization procedures and find that market reactions to earnings surprises are incrementally more positive (or less negative) when conditioned on very sunny weather in New York City surrounding the earnings announcement dates. Moreover, this sunshine effect is most prominent for small-size firms and firms that are followed by a relatively small number of analysts. Results are robust to several alternative research designs and alternative specifications. Not surprisingly, the documented sunshine effect is most prevalent on unambiguously sunny days and is much weaker on moderately sunny days. In subsequent tests, we find that average bid-ask spreads are lower on sunny days relative to cloudy days, suggesting that market-makers may be contributing to this sunshine effect. Lastly, when examining post–earnings announcement returns, we find evidence of a short-term reversal of the sunshine-induced overreaction (underreaction) to good (bad) earnings news.

The remainder of the paper is organized as follows. Section 2 briefly discusses the related literature. Section 3 describes the sample and presents descriptive statistics. Section 4 describes our research design, our bootstrap randomization procedures, and main empirical results. Section 5 presents robustness results. Section 6 presents results from examining bid-ask spreads. Section 7 presents results from examining post–earnings announcement returns. Section 8 concludes.

2. Related Literature

2.1 Sunshine, Mood, and Information Processing

A long line of empirical studies in the psychology literature documents a positive relation between sunshine and individuals' moods and emotions. Persinger (1975) finds that weather variables account for 35 percent of the variance in self-reported moods on the day of evaluation; "higher moods" are associated with more hours of sunshine. Similarly, Howarth and Hoffman (1984) find that objectively measured mood increases as individuals are exposed to more hours of sunshine, showing that optimism increases, while anxiety and skepticism decrease. These studies draw an explicit link between sunshine and mood. Other studies find that mood can in turn affect the efficiency and bias of how individuals process information. For instance, Isen, Shalker, Clark, and Karp (1978) find that individuals in good moods make more favorable evaluations of the performance and service records of the products they own. Johnson and Tversky (1983) and Nygren et al. (1996) find that individuals in good moods tend to have more favorable assessments of future prospects and lower assessments of risk compared with those in bad moods (also see Arkes, Herren, and Isen [1988]).

2.2 Sunshine and Stock Returns

Could stock markets exhibit a sunshine effect? Under standard assumptions of market efficiency, only factors that affect expected future cash flows or the discount rate can have predictable effects on market prices. Under such efficiency assumptions, there is no room for value-irrelevant factors like the day's sunshine to influence a firm's stock price. Yet, evidence from the psychology literature discussed above documents clear, causal links between sunshine and mood, and between mood and the interpretation of information. This implies that sunshine may affect the moods of market participants, and in turn, their interpretation of value-relevant information, and thereby, the stock price of publicly traded firms. This is consistent with the well-documented mood congruency effect, in which individuals in good moods find positive information more salient, while those in bad moods find negative information more salient; individuals are also quicker to make mood-consistent judgments (e.g., Forgas and Bower [1987]). More formally, sunshine may induce correlated shifts in beliefs (and utility functions) in cases in which individual perceptions shift uniformly toward higher probabilities for positive cash flows and lower probabilities for negative cash flows (or greater risk-tolerance). If markets have some imperfections, such utility or belief changes may lead to predictable effects on stock prices.

Indeed, extant evidence suggests that stock markets can exhibit a sunshine effect. Saunders (1993) examines the correlation between New York City sunshine and the contemporaneous daily returns of three New York–based indexes (the Dow Jones Industrial Average, and equal- and value-weighted NYSE/AMEX indexes) during 1927–1989. He finds that sunshine is positively related to index returns; this finding is confirmed by several later studies (e.g., Goetzmann and Zhu [2003]; Loughran and Schultz [2004]). Hirshleifer and Shumway (2003) extend Saunders' original work by examining the relation between market returns and sunshine for twenty-five additional cities around the world during the 1982–1997 period. Specifically, they identify twenty-six international cities that host stock exchanges and correlate the index returns from each of these exchanges with each respective city's level of sunshine. Overall, they find that the sunshine effect is evident in several other cities/countries as well as pooled across all twenty-six countries; their results are robust to several other specifications.

2.3 Which Market Participants?

If market participants geographically located in New York are optimistically biased by New York sunshine, one natural question arises: Which market participants? Two potential candidates are investors and market makers. One interpretation is that investors located in New York are the cause of the sunshine effect. Here, we adopt the view of Hirshleifer and Teoh (2003) in viewing asset prices to be determined as an equilibrium representing the aggregate of all demands and supply in the market, not solely determined by the demands of some marginal group of (geographically dispersed) investors. That is, it is not necessary for the unidentifiable "marginal investor" to be located in New York, but merely *some* subset of investors to be located there. A second potential explanation for the sunshine effect is that it is driven by the moods of market-makers physically located in New York. Consistent with this explanation, Goetzmann and Zhu (2003) find that bid-ask spreads narrow (widen) on sunny (cloudy) days. They argue that such inefficiencies are possible because market-makers do not operate in a fully competitive environment, and thus (weather-influenced) bid-ask spreads are not subject to a short-term competitive mechanism. We explicitly consider this potential explanation in our empirical tests.

3. Sample and Descriptive Statistics

Our sample and data definitions closely mimic the work of Hirshleifer and Shumway (2003). In Section 5, we also examine several alternative definitions for each of our variables.

3.1 Sample

We obtain financial information from the quarterly *Compustat* files (full, industrial, and research), stock return data from the daily Center for Research in Security Prices (CRSP) files, and analyst following and earnings forecast data from Institutional Brokerage Estimate System (I/B/E/S). The original Hirshleifer and Shumway (2003) data set examines the sunshine effect for the 1982–1997 period; we also include the more recent 1998–2004 period. Our main sample spans from 1982 to 2004 and includes the universe of 171,749 firm-quarter observations trading on the NYSE or AMEX, with necessary data on earnings, earnings announcement dates, and stock returns. We do not include firms traded on NASDAQ because NASDAQ is not a New York–based exchange.

3.2 Sunshine Variable

The National Climactic Data Center (NCDC) collects weather data and publishes it in their International Surface Weather Observations data set. In this data set, the variable *Total Sky Coverage* measures the extent to which the sky is covered by clouds. Data are collected hourly (i.e., twenty-four observations per day). The NCDC codes *Total Sky Coverage* to take one of four values: (1) *Clear*, (2) *Scattered*, (3) *Broken*, or (4) *Overcast*.[1] Thus, *Total Sky Coverage* is perfectly negatively correlated with the level of sunshine—*Clear* days are sunny, while *Overcast* days are not sunny. To construct a measure of each day's sunshine, we consider each hourly observation of *Total Sky Coverage* between the hours of 6 a.m. to 4 p.m. This ten-hour time frame mimics the definition used by Hirshleifer and Shumway (2003), and closely coincides with the hours that the exchanges are open for trading. For each trading day, if 100 percent of the ten hours that make up the trading day are *Clear*, then the day is coded as equal to one; otherwise, the day is coded as equal to zero. Though this definition is quite restrictive in requiring 100 percent of the day's hours to be *Clear*, it is the least susceptible to researcher-induced bias in identifying a sunny day. Next, because we examine the three-day returns around earnings announcements, we define our main sunshine variable, *SUNNY*, as the average of the three days' indicator variables. For instance, if the average *Total Sky Coverage* for the three days surrounding an earnings announcement is *Clear*, then *SUNNY* is equal to one. On the other hand, if only one (two) of the days surrounding an earnings announcement is *Clear*, then *SUNNY* is equal to 0.33 (0.67). In Section 5, we consider several alternative definitions and alternative windows for our *SUNNY* metric. For instance, we also consider less-restrictive definitions of *SUNNY* (e.g., 75% of the day's hours to be *Clear*).

1. Prior to 1998, the NCDC coded the variable on a scale from 0 (*Clear*) to 8 (*Overcast*). Our data set includes observations from both periods, so we convert the old 0–8 scaling to the newer four-point scale using accepted conversion procedures in the literature.

TABLE 1

Descriptive Statistics and Correlations

Panel A: Descriptive statistics

Variable	Mean	Std. Dev.	5%	25%	50%	75%	95%
SUNNY	0.021	0.086	0.000	0.000	0.000	0.000	0.333
NEG_DNI	−0.016	0.059	−0.073	−0.006	0.000	0.000	0.000
POS_DNI	0.015	0.053	0.000	0.000	0.002	0.008	0.062
AR	0.003	0.069	−0.094	−0.026	0.001	0.029	0.103
ANALYST	0.845	2.120	0.000	0.000	0.000	1.000	5.000
SIZE	2,743.0	12,068.5	13.6	84.3	376.0	1,463.0	10,254.7

Panel B: Pearson and Spearman correlations (above and below diagonal)

	SUNNY	*NEG_DNI*	*POS_DNI*	*AR*	*ANALYST*	*SIZE*
SUNNY		−0.004	0.001	0.001	−0.023	−0.038
p-value		0.124	0.723	0.768	0.000	0.000
NEG_DNI	−0.006		0.076	0.084	0.041	0.187
p-value	0.009		0.000	0.000	0.000	0.000
POS_DNI	−0.002	0.837		0.088	−0.043	−0.157
p-value	0.489	0.000		0.000	0.000	0.000
AR	−0.002	0.166	0.182		0.005	−0.008
p-value	0.463	0.000	0.000		0.031	0.001
ANALYST	−0.032	0.045	−0.025	0.024		0.412
p-value	0.000	0.000	0.000	0.000		0.000
SIZE	−0.043	0.171	−0.015	0.030	0.479	
p-value	0.000	0.000	0.000	0.000	0.000	

Note: The sample is comprised of 171,749 firm-quarter observations trading on the NYSE and AMEX from 1982 to 2004. *SUNNY* is the three-day average of a daily indicator variable equal to one when *Total Sky Coverage* is *Clear* for 100 percent of the day's ten hours between 6am-4pm, equal to zero otherwise. By definition, *SUNNY* = [0, 0.33, 0.67, 1]. *DNI* is the seasonally-adjusted quarterly change in net income, scaled by prior-quarter market value of equity. *POS_DNI* is equal to *DNI* when *DNI* is positive, and is equal to zero otherwise. *NEG_DNI* is equal to *DNI* when *DNI* is negative, and is equal to zero otherwise. *AR* is the three-day firm-specific raw returns on earnings announcement date minus the value-weight market returns over the same period. *ANALYST* is the number of analysts that make quarterly earnings forecasts during the quarter, where the quarter is defined as the period between the day after prior-quarter earnings announcement to the day of the current-quarter earnings announcement. *SIZE* is prior-quarter market value of equity. The top and bottom 0.5 percent of observations for *DNI* are winsorized.

Pearson and Spearman correlations are presented above and below the diagonal, respectively.

3.3 Returns and Earnings

Returns data are from the daily CRSP files. Abnormal returns, *AR*, is defined as the three-day firm-specific raw returns surrounding earnings announcement date minus the value-weight market returns over the same period. We consider equal-weight market adjustments, as well as decile-size adjusted returns; we also consider one-day and two-day windows to mimic similar windows for our alternative definitions of *SUNNY*.

Earnings surprises, *DNI*, are defined as the seasonally adjusted quarterly change in net income, scaled by prior-quarter market value of equity. To mitigate the influence of outliers, the top and bottom 0.5 percent of *DNI* observations are winsorized. We also consider the change in "core" earnings (i.e., excluding special items, income from discontinued operations, extraordinary items), as well as using prior-quarter total assets as a scalar. (Using analysts' earnings forecast errors as a proxy for earnings surprise merits a lengthier discussion and is discussed in Section 5.) Because the prediction for the interaction of earnings surprise with sunshine is dependent on the direction of the earnings surprise, we bifurcate *DNI* into positive and negative surprises, *POS_DNI* and *NEG_DNI*, respectively. We define *POS_DNI* (*NEG_DNI*) as equal to *DNI* when *DNI* is positive (negative), and equal to zero otherwise.

3.4 Descriptive Statistics

Panel A of Table 1 provides descriptive statistics. As discussed in Section 3.2, *SUNNY* is defined as the average of the three days' indicator variables, and therefore takes on one of four values (0, 0.33, 0.67, or 1) depending on what proportion of the three days are perfectly *Clear*. Panel A reveals that the mean *SUNNY* is 0.021; however, this statistic does not mean that 2.1 percent of the sample is perfectly sunny. The ninety-fifth percentile observation for *SUNNY* is 0.33, which means that, for at least 5 percent of the sample, at least one of the three days (1/3=0.33) surrounding the earnings announcement date exhibits perfectly *Clear* skies. For most of the three-day announcement windows, New York City skies are rarely perfectly sunny. For earnings surprises, the mean *POS_DNI* (*NEG_DNI*) is 0.015 (−0.016). Mean abnormal returns, *AR*, is 0.003. Panel B of Table 1 provides Pearson and Spearman correlations between *SUNNY* and other relevant variables. *SUNNY* is not highly correlated with any of the firm characteristics.

4. Main Empirical Results

4.1 Bootstrap Randomization Procedure

To mitigate the potential clustering of observations on *SUNNY* days, we use a bootstrap randomization procedure to estimate the statistical significance of our estimated coefficients. Therefore, the *t*-statistics that we report in all of our empirical tests (except bid-ask spread and post–announcement return tests) are bootstrap *t*-statistics.

The randomization procedure is performed as follows. (1) For the main, original sample, we estimate our model using standard ordinary least squares (OLS) procedures to obtain "original" parameter estimates. (2) We recreate a random sample with the same number of observations as the original sample by randomly selecting observations (with replacement) from the original sample. (3) For this random sample, we estimate our model using OLS procedures; save the parameter estimates. (4) We repeat steps (2) and (3) 1,000 times, creating 1,000 random samples and estimating our model 1,000 times. This yields a distribution of 1,000 estimated coefficients for each of the independent variables of the model. (5) Finally, we compute the bootstrap *t*-statistic for each coefficient as the "original" parameter estimate (from step (1) above) divided by the standard deviation of the 1,000 estimated coefficients. This bootstrap *t*-statistic is reported throughout our tables.

4.2 Pooled Specification

Our main empirical test is a simple modification of the regressions used in Saunders (1993) and Hirshleifer and Shumway (2003) to include earnings surprises and their interactions with sunshine. Alternatively, the regressions can be viewed as a modification of the returns-on-earnings regressions used in the accounting literature (e.g., Kothari [2001]) to include sunshine's interaction with earnings surprises.

The significant difference between the current study and prior studies that examine the sunshine effect is that they consider daily market index returns for all trading days, while we consider firm-specific returns for only days on which earnings are announced. Because earnings announcements are regularly occurring economic events that receive widespread attention, they are arguably least vulnerable to investor irrationality, and hence, least likely to exhibit a sunshine effect.[2] In this respect, we view our research as a conservative litmus test of whether sunshine affects the interpretation of value-relevant information in general. The model is as follows:

$$\begin{aligned} AR = \beta_0 &+ \beta_1 SUNNY + \beta_2 POS\_DNI + \beta_3 NEG\_DNI \\ &+ \beta_4 SUNNY * POS\_DNI + \beta_5 SUNNY * NEG\_DNI + \varepsilon \end{aligned} \tag{1}$$

Definitions for each of the variables are provided in Sections 3.2 and 3.3. As discussed in Section 4.1, the estimated parameters we report in our tables are from standard OLS procedures. However, the reported *t*-statistics are calculated from bootstrap randomization procedures.

2. Also, earnings announcements are not clustered in calendar time (e.g. Kothari [2001]) and are less susceptible to incorrectly specified models of expected returns (e.g., Brown and Warner [1985]).

Our main focus is on the coefficients for the two interaction terms, *SUNNY *POS_DNI* and *SUNNY *NEG_DNI*. Specifically, if market reactions to earnings surprises exhibit a sunshine effect, then the coefficient for the *SUNNY *POS_DNI* interaction will be positive, suggesting that positive earnings changes exhibit incrementally more positive market returns on sunny days. Similarly, the coefficient for the *SUNNY *NEG_DNI* interaction will be negative, suggesting that negative earnings changes exhibit incrementally less negative returns on sunny days. The sunshine effect may be asymmetric (i.e., exists for positive earnings changes, but not negative ones, or vice versa); but absent sufficient ex ante reasons for expecting such asymmetries, we leave this possibility as an empirical question.

4.3 Pooled Results

We report our main, pooled results in Table 2. Both the dependent variable, *AR*, and the independent variable, *SUNNY*, are defined over three-day windows

TABLE 2

OLS Estimates of Regressing Abnormal Returns on Earnings Surprises, *SUNNY*, and Interaction Terms for Pooled Sample (Bootstrap *t*-statistics)

Event Window	Intercept	*SUNNY*	*NEG_DNI*	*POS_DNI*	*SUNNY* NEG_DNI*	*SUNNY* POS_DNI*	Adj. R^2
(−1,+1)	0.002	−0.003	0.093	0.103	−0.110	0.130	0.014
	(13.58)	(−1.65)	(15.51)	(18.45)	(−1.94)	(2.14)	
(0,+1)	0.001	0.000	0.070	0.072	−0.071	0.135	0.010
	(9.36)	(−0.28)	(13.11)	(13.37)	(−0.95)	(2.04)	
(−1,0)	0.002	−0.002	0.060	0.083	−0.035	0.123	0.012
	(13.01)	(−1.47)	(12.52)	(18.93)	(−0.74)	(1.32)	
(0)	0.001	−0.001	0.037	0.053	−0.016	0.100	0.007
	(8.26)	(−0.71)	(9.63)	(14.13)	(−1.01)	(1.13)	

Note: This table presents results from OLS regressions of abnormal returns (*AR*) on *SUNNY*, *NEG_DNI*, *POS_DNI*, and interaction terms for the sample of 171,699 firm-quarter observations. Four event windows are presented (where 0 is the day of the earnings announcement): (−1,+1) is a three-day window, (0,+1) and (−1,0) are both two-day windows, and (0) is a one-day window. For the three-day window, *SUNNY* is the three-day average of a daily indicator variable equal to one when *Total Sky Coverage* is *Clear* for 100 percent of the day's ten hours between 6 a.m. to 4 p.m., equal to zero otherwise. By definition, *SUNNY* = [0, 0.33, 0.67, 1]. *DNI* is the seasonally-adjusted quarterly change in net income, scaled by prior-quarter market value of equity. *POS_DNI* is equal to *DNI* when *DNI* is positive, and is equal to zero otherwise. *NEG_DNI* is equal to *DNI* when *DNI* is negative, and is equal to zero otherwise. Abnormal returns are the three-day firm-specific raw returns on earnings announcement date minus the value-weight market returns over the same period. Definitions for *SUNNY* and abnormal returns are adjusted accordingly for two-day and one-day windows.

t-Statistics (provided in parentheses) are calculated from a bootstrap randomization procedure on 1,000 randomly generated samples. Refer to Section 4.1 for details.

around the earnings announcement date. We also present results for two-day and one-day windows. For the three-day window specification, we find that the coefficient on *SUNNY *POS_DNI* is significantly positive (0.130, $t = 2.14$) and the coefficient on *SUNNY *NEG_DNI* is significantly negative (-0.110, $t = -1.94$). This suggests that positive (negative) earnings surprises on *SUNNY* days are incrementally more positive (less negative). To gauge the economic significance of these coefficients, consider the 0.130 coefficient for the *SUNNY *POS_DNI* interaction term with the 0.103 coefficient for the unconditional *POS_DNI* term. Comparing these two coefficients suggests that the average market reaction to one unit of positive earnings surprise is more than doubled when conditioned on a *SUNNY* = 1 observation (0.130/0.103 = 126%). However, *SUNNY* = 1 observations—three days surrounding earnings announcements, where each day has 100 percent of its ten consecutive trading hours as perfectly *Clear*—are rare. Indeed, the most common non-zero *SUNNY* observation is *SUNNY* = 0.33, where only one of the three days is 100 percent *Clear*. Using this more-common value of *SUNNY*, the average market reaction to one unit of positive earnings surprise is still more than 40 percent higher when conditioned on *SUNNY* (0.130*0.33/0.103 = 42%). Thus, the sunshine effect appears to exhibit some economic significance. However, results for the other windows are weaker, so results should be interpreted with caution. Hereafter, as is standard practice in the literature, we use the three-day window because it is mostly likely to fully capture the market's reaction to earnings surprises. Untabulated results for the other windows are qualitatively similar throughout all of our tests. In later sections, we consider several alternative research designs.

4.4 Cross-Sectional Specification

The second goal of our study is to test whether the sunshine effect systematically varies with levels of investor sophistication. This investigation contributes to the existing literature by documenting whether there is predictable cross-sectional variation in the sunshine effect. These cross-sectional tests also buttress our main pooled results because, if the sunshine effect is a result of random chance, we would not expect the effect to systematically vary.

Kim and Verrecchia (1994) argue that sophisticated investors are able to earn higher returns from trading on earnings news because they have a superior ability to interpret the implications of public disclosures. Sophisticated investors exhibit superior information-processing capabilities and, in the context of our study, are therefore less susceptible to allowing sunshine to creep into their assessment of earnings surprises. Conversely, naïve investors are more susceptible to the whim of their sunshine-induced emotions and moods. Put simply, less (more) sophisticated investors rely less (more) on value-relevant information and more (less) on sunshine-induced moods. Following Hong, Lim, and Stein (2000), we use firm size and analyst following as proxies for investor sophistication. Firms that are larger (smaller) in size or have a higher (lower) analyst following are more (less) likely to be heavily followed by sophisticated investors (e.g., Atiase [1985]; Hand [1990]; Walther [1997]). *SIZE* is defined as prior-quarter market value of equity. *ANALYST* is defined as the number of analysts that make quarterly earnings forecasts during the quarter. We create ranked portfolios based on *SIZE* and *ANALYST*, then estimate our main model separately for each rank portfolio. For *SIZE*, we create three portfolios: *S_SIZE*, *M_SIZE*, and *B_SIZE*. The *S_SIZE* portfolio contains firms with firm size less than $100 million, *M_SIZE* contains firms with firm size between $100 million and $1 billion, and *B_SIZE* contains firms with firm size greater than $1 billion.[3] For *ANALYST*, we create four portfolios: *0_ANALYST* contains firms with zero analyst following, *L_ANALYST* contains firms with one or two analyst following(s), *M_ANALYST* contains firms with three to five analyst followings, and *H_ANALYST* contains firms with six or more analyst followings.[4]

4.5 Cross-Sectional Results

We report results from cross-sectional tests in Table 3. Because our goal is to examine whether the sunshine effect is more prominent among firms that are more likely to be followed by naïve investors, we pay particular attention to whether the coefficients for the interaction terms are statistically significant for the smaller size and lower analyst following portfolios. In Panel A of Table 3, we find the coefficients on the interaction terms are statistically significant for the *0_ANALYST* portfolio, but statistically insignificant for the other *ANALYST* portfolios. Specifically, for the *0_ANALYST* portfolio, the coefficient on *SUNNY *POS_DNI* is significantly positive (0.113, $t = 2.00$) and the coefficient on *SUNNY *NEG_DNI* is significantly negative (-0.109, $t = -1.98$). In Panel B of Table 3, for the *S_SIZE* portfolio, the coefficient on *SUNNY*POS_DNI* is significantly positive (0.118, $t = 1.82$) and the coefficient on *SUNNY *NEG_DNI* is significantly negative (-0.127, $t = -1.94$). All other interaction terms in the other *SIZE* portfolios are statistically insignificant. Assuming that *ANALYST* and *SIZE* are adequate proxies for investor sophistication, the results in Table 3 suggest that less (more) sophisticated investors rely relatively more (less) on sunshine-induced moods.

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3. These portfolios closely mimic three equal-weighted *SIZE* portfolios of 52,846 observations each. The cutoffs for the equal-weighted portfolios are *S_SIZE* = ($0–$144), *M_SIZE* = ($144–$903), and *B_SIZE* = $903+. Results are qualitatively similar using the equal-weighted portfolios.

4. The distribution of *ANALYST* is substantially non-normal: 72 percent of the observations have zero *ANALYST*. Of the remaining 28 percent with non-zero *ANALYST*, the distribution is as follows: 39 percent with one analyst, 21 percent with two analysts, 13 percent with three analysts, 13 percent with four to five analysts, and 14 percent with more than six analysts.

TABLE 3

OLS Estimates of Regressing Abnormal Returns on Earnings Surprises, *SUNNY*, and Interaction Terms for Cross-sectional Samples (Bootstrap *t*-statistics)

Portfolio	Intercept	*SUNNY*	*NEG_DNI*	*POS_DNI*	*SUNNY** *NEG_DNI*	*SUNNY** *POS_DNI*	Adj. R^2 *n*
Panel A: Analyst following portfolios							
0_ANALYST	0.002	−0.002	0.096	0.108	−0.109	0.113	0.017
	(9.66)	(−0.94)	(16.01)	(17.81)	(−1.98)	(2.00)	124,111
L_ANALYST	0.003	−0.005	0.060	0.084	−0.133	0.214	0.004
	(7.05)	(−1.33)	(1.66)	(4.69)	(−0.75)	(1.06)	28,775
M_ANALYST	0.003	−0.005	0.070	0.069	0.297	0.297	0.004
	(5.51)	(−1.01)	(1.97)	(1.99)	(0.37)	(0.78)	12,259
H_ANALYST	0.004	−0.008	0.098	0.052	−0.234	0.314	0.005
	(3.74)	(−0.52)	(1.63)	(1.18)	(−0.26)	(1.46)	6,536
Panel B: Firm size portfolios							
L_SIZE	0.003	−0.001	0.095	0.114	−0.127	0.118	0.022
	(9.43)	(−0.64)	(12.15)	(15.21)	(−1.94)	(1.82)	57,464
M_SIZE	0.002	−0.005	0.121	0.071	−0.102	0.082	0.009
	(7.17)	(−1.26)	(9.93)	(7.87)	(−1.53)	(0.79)	62,129
H_SIZE	0.002	−0.004	0.033	0.038	0.102	0.232	0.001
	(9.58)	(−1.50)	(2.26)	(4.02)	(0.83)	(1.37)	52,094

Note: This table presents results from OLS regressions of abnormal returns (*AR*) on *SUNNY*, *NEG_DNI*, *POS_DNI*, and interaction terms. Portfolios are created based upon proxies for investor sophistication and the main model is estimated separately for each portfolio. *SUNNY* is the three-day average of a daily indicator variable equal to one when *Total Sky Coverage* is *Clear* for 100 percent of the day's ten hours between 6am-4pm, equal to zero otherwise. By definition, *SUNNY* = [0, 0.33, 0.67, 1]. *DNI* is the seasonally-adjusted quarterly change in net income, scaled by prior-quarter market value of equity. *POS_DNI* is equal to *DNI* when *DNI* is positive, and is equal to zero otherwise. *NEG_DNI* is equal to *DNI* when *DNI* is negative, and is equal to zero otherwise. Abnormal returns are the three-day firm-specific raw returns on earnings announcement date minus the value-weight market returns over the same period. *ANALYST* is the number of analysts that make quarterly earnings forecasts during the quarter, where the quarter is defined as the period between the day after prior-quarter earnings announcement to the day of the current-quarter earnings announcement. *0_ANALYST* contains all firms with zero *ANALYST*, *L_ANALYST* contains all firms with one or two *ANALYST*, *M_ANALYST* contains all firms with three or five *ANALYST*, and *H_ANALYST* contains all firms with more than five *ANALYST*. *SIZE* is prior-quarter market value of equity. *S_SIZE* contains all firms with *SIZE* less than $100 million, *M_SIZE* contains all firms with *SIZE* between $100 million and $1 billion, and *B_SIZE* contains all firms with *SIZE* greater than $1 billion.

t-Statistics (provided in parentheses) are calculated from a bootstrap randomization procedure on 1,000 randomly generated samples. Refer to Section 4.1 for details.

5. Robustness Tests

In this section, we consider alternative research designs and empirical specifications. Appendix A summarizes these additional tests.

5.1 Sunny Days versus Cloudy Days Matched Sample

We consider a matched sample of observations that include earnings announcements on only non-zero *SUNNY* days or days that are similarly defined as non-zero *Cloudy* (i.e., where 100% of the day's hours are *Overcast*). This essentially purges the sample of any ambiguous, mixed sunny/cloudy days and therefore considers only extremely sunny and extremely cloudy days. Trombley (1997) states that:

> This is an intuitive choice and, without prior analysis of the data, might be expected to give the greatest power in detecting a weather effect if such an effect exists. If there is concern about measurement error produced by the subjective nature of weather observation, a comparison based on two points on each end of the range ... may be reasonable.

In Table 4, we present results for this matched sample; all reported *t*-statistics are bootstrapped. Overall, the results further corroborate our main findings. For instance, for the full sample in Panel A, the coefficient on *SUNNY *POS_DNI* is significantly positive (0.161, $t = 2.34$) and the coefficient on *SUNNY *NEG_DNI* is significantly negative (-0.125, $t = -1.71$). Results are qualitatively similar for the *ANALYST* and *SIZE* portfolios; however, the *SUNNY*NEG_DNI* coefficients in these portfolios are less statistically significant.

5.2 Firm and Earnings Matched Sample

To control for potential correlated omitted variables and other documented cross-sectional differences in earnings-related market reactions (e.g., differences in earnings persistence), we create a matched sample where we use each firm as its own control. Here, our goal is to isolate the effect of sunshine as a treatment by considering a firm-matched control sample not exposed to the treatment. For each earnings announcement made on a non-zero *SUNNY* day, we randomly select a matching earnings announcement made by the same firm on a zero *SUNNY* day; we also match on the direction of the earnings surprise (i.e., positive versus negative). We present results in Table 5; all reported *t*-statistics are bootstrapped. We find that the coefficients on the interaction terms are statistically significant for the full sample as well as for the *0_ANALYST* and *S_SIZE* portfolios. For instance, for the full sample in Panel A, we find that the coefficient on *SUNNY *POS_DNI* is significantly positive (0.262, $t = 3.11$) and that the coefficient on *SUNNY *NEG_DNI* is significantly negative (-0.206, $t = -2.56$).

TABLE 4

OLS Estimates of Regressing Abnormal Returns on Earnings Surprises, *SUNNY*, and Interaction Terms for *SUNNY* versus CLOUDY Matched Sample (Bootstrap *t*-statistics)

	Intercept	*SUNNY*	*NEG_DNI*	*POS_DNI*	*SUNNY* NEG_DNI*	*SUNNY* POS_DNI*	Adj. R^2 / *n*
Panel A: Pooled sample							
	0.002	−0.003	0.099	0.091	−0.125	0.161	0.015
	(7.72)	(−1.57)	(9.64)	(9.20)	(−1.71)	(2.34)	64,166
Panel B: Analyst following portfolios							
0_ANALYST	0.002	−0.002	0.105	0.092	−0.132	0.153	0.018
	(6.50)	(−1.09)	(10.59)	(8.70)	(−1.84)	(2.21)	47,241
L_ANALYST	0.003	−0.003	0.050	0.129	−0.105	0.083	0.005
	(2.72)	(−0.81)	(0.49)	(3.17)	(−0.35)	(0.50)	10,355
M_ANALYST	0.004	−0.008	0.078	0.024	0.278	0.429	0.004
	(3.48)	(−0.98)	(1.18)	(0.74)	(0.37)	(1.02)	4,359
H_ANALYST	0.003	−0.003	−0.029	0.019	0.142	0.413	−0.002
	(1.48)	(−0.29)	(−0.77)	(0.08)	(0.73)	(1.60)	2,193
Panel C: Firm size portfolios							
L_SIZE	0.004	−0.002	0.103	0.095	−0.148	0.168	0.022
	(5.37)	(−0.63)	(8.14)	(7.35)	(−1.50)	(2.03)	22,682
M_SIZE	0.002	−0.004	0.121	0.078	−0.103	0.064	0.010
	(3.40)	(−0.85)	(5.71)	(4.90)	(−1.33)	(0.65)	22,971
H_SIZE	0.003	−0.004	0.025	0.047	0.122	0.209	0.001
	(5.44)	(−1.45)	(1.16)	(2.64)	(0.88)	(1.36)	18,501

Note: This table presents results from OLS regressions of abnormal returns (*AR*) on *SUNNY*, *NEG_DNI*, *POS_DNI*, and interaction terms for a matched sample of observations that include earnings announcements on only non-zero *SUNNY* days or days that are similarly defined as non-zero *CLOUDY* (i.e., where 100% of the day's hours are *Overcast*). Portfolios are created based on proxies for investor sophistication and the main model is estimated separately for each portfolio.

t-Statistics (provided in parentheses) are calculated from a bootstrap randomization procedure on 1,000 randomly generated samples. Refer to Section 4.1 for details. See Table 3 for variable definitions and portfolio construction details.

TABLE 5

OLS Estimates of Regressing Abnormal Returns on Earnings Surprises, *SUNNY*, and Interaction Terms for Firm- and Earnings-Matched Sample (Bootstrap *t*-statistics)

	Intercept	*SUNNY*	*NEG_DNI*	*POS_DNI*	*SUNNY* NEG_DNI*	*SUNNY* POS_DNI*	Adj. R^2 / *n*
Panel A: Pooled sample							
	0.003	−0.003	0.130	0.052	−0.206	0.262	0.020
	(3.55)	(−1.42)	(6.08)	(3.58)	(−2.56)	(3.11)	20,214
Panel B: Analyst following portfolios							
0_ANALYST	0.002	−0.001	0.138	0.056	−0.219	0.249	0.024
	(1.79)	(−0.34)	(6.42)	(3.82)	(−2.55)	(2.85)	14,385
L_ANALYST	0.005	−0.010	0.018	−0.016	−0.007	0.501	0.001
	(3.26)	(−2.00)	(0.21)	(−0.76)	(−0.21)	(2.50)	3,235
M_ANALYST	0.002	−0.003	0.105	0.105	0.191	0.192	0.010
	(1.64)	(−0.83)	(2.61)	(1.98)	(0.61)	(0.55)	1,558
H_ANALYST	0.002	−0.001	0.154	0.089	−0.406	0.217	0.014
	(0.66)	(−0.10)	(1.24)	(0.66)	(−0.76)	(1.05)	1,018
Panel C: Firm size portfolios							
L_SIZE	−0.001	0.011	0.121	0.064	−0.194	0.248	0.029
	(−0.14)	(1.20)	(4.73)	(3.39)	(−1.89)	(2.40)	7,078
M_SIZE	0.004	−0.011	0.188	0.064	−0.285	0.103	0.017
	(3.08)	(−1.99)	(2.64)	(2.22)	(−1.51)	(0.88)	6,814
H_SIZE	0.003	−0.005	−0.060	0.013	−0.331	0.300	0.001
	(3.47)	(−1.76)	(−0.24)	(0.56)	(−1.13)	(1.36)	6,310

Note: This table presents results from OLS regressions of abnormal returns (*AR*) on *SUNNY*, *NEG_DNI*, *POS_DNI*, and interaction terms for a matched sample where each firm is used as its own control. For each earnings announcement made on a non-zero *SUNNY* day, we randomly select a matching earnings announcement made by the same firm on *SUNNY*=0 day; we also match on the direction of the earnings surprise (i.e., positive vs. negative). Portfolios are created based on proxies for investor sophistication and the main model is estimated separately for each portfolio.

t-Statistics (provided in parentheses) are calculated from a bootstrap randomization procedure on 1,000 randomly generated samples. Refer to Section 4.1 for details. See Table 3 for variable definitions and portfolio construction details.

5.3 Deseasonalized *SUNNY*

Sunshine is highly seasonal. For instance, in New York City, October, February, and March are the three calendar months with the greatest number of 100 percent *Clear* days. Many seasonal patterns have been identified in stock return data (e.g., Keim [1983]). To remove any potential seasonal effects, we deseasonalize our *SUNNY* variable. Following Hirshleifer and Shumway (2003), we first compute the mean daily *SUNNY* of the six days surrounding the event date from all sample years; we then subtract this mean *SUNNY* from the event day's *SUNNY*.[5] This mean-adjusted, deseasonalized sunshine metric attempts to measure the day's "weather surprise." Untabulated results reveal that results for this deseasonalized sunshine variable further corroborate our main findings. For instance, for the full sample, the coefficient on *SUNNY *POS_DNI* is significantly positive (0.131, $t = 1.90$) and the coefficient on *SUNNY *NEG_DNI* is significantly negative (-0.106, $t = -1.88$). Results are similarly significant for the coefficients on both the interaction terms for the *0_ANALYST* portfolio and the *S_SIZE* portfolio.

5.4 Less Restrictive Definitions of *SUNNY*

In the tests thus far, we require *Total Sky Coverage* to be *Clear* for 100 percent of the trading day's hours for the day's indicator variable to be equal to one. As Trombley (1997) states, this definition is an "intuitive choice" that creates the most unambiguous case of a sunny day and is arguably least susceptible to "measurement error produced by the subjective nature of weather observation" (i.e., researcher-induced bias).[6] However, since only 5.55 percent of our sample exhibits non-zero values of *SUNNY*, this definition may be viewed as overly restrictive. We reexamine our main model using two less-restrictive definitions: where 75 percent or 50 percent of the trading day's hours are required to be *Clear*. Untabulated results reveal that the relaxed 75 percent (50%) requirement increases the number of observations that have non-zero *SUNNY* to 12.4 percent (21%) of the sample. However, these relaxed definitions inevitably introduce more noise into the definition of sunshine and therefore reduce the power of our empirical tests. Indeed, untabulated results reveal that the sunshine effect is weaker under these relaxed conditions; although the direction of the coefficients is consistent with predictions, rarely is statistical significance better than the 20 percent level.

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5. For example, the deseasonalized *SUNNY* for April 27, 2004, equals the *SUNNY* of April 27, 2004, minus the average *SUNNY* of April 24, 25, 26, 28, 29, and 30 from all sample years (1982–2004). Although this method increases comparability with Hirshleifer and Shumway, it suffers from a look-ahead bias.

6. Trombley states that "[t]his is an intuitive choice and, without prior analysis of the data, might be expected to give the greatest power in detecting a weather effect if such an effect exists. If there is concern about measurement error produced by the subjective nature of weather observation, a comparison based on two points on each end of the range . . . may be reasonable" (1997).

Next, we reexamine our main model using the continuous *Total Sky Coverage* variable. As discussed in Section 3.2, *Total Sky Coverage* can take one of four values. We define a new variable *TSC* on a 0–3 scale, where *TSC* = 0 if *Overcast*, *TSC* = 1 if *Broken*, *TSC* = 2 if *Scattered*, and *TSC* = 3 if *Clear*. We then use *TSC* in lieu of *SUNNY* as our main weather variable. Untabulated results reveal that the sunshine effect is weaker when using this alternative definition. Specifically, the coefficient on *TSC*POS_DNI* is significantly positive (0.008, $t = 2.26$), but the coefficient on *TSC*NEG_DNI* is statistically insignificant (0.001, $t = 0.15$). In the cross-sectional tests, for the *0_ANALYST* portfolio, the coefficient on *TSC*POS_DNI* is significantly positive (0.008, $t = 2.28$) and the coefficient on *TSC*NEG_DNI* is insignificant (-0.001, $t = -0.10$). For the *S_SIZE* portfolio, the coefficient on *TSC*POS_DNI* is significantly positive (0.007, $t = 1.82$) and the coefficient on *TSC*NEG_DNI* is insignificant.

5.5 Alternative Definition of Earnings Surprise: Analyst Forecast Errors

Analysts' forecast errors of earnings are largely considered to be more accurate proxies of earnings surprises than time-series earnings changes (e.g., Brown and Rozeff [1978]; Kothari [2001]). We therefore reexamine our results using analysts' forecast errors as our proxy for earnings surprise. However, these forecast errors can be computed only for the subsample of firms that have an analyst following. The catch-22 is that our cross-sectional predictions suggest that firms with analyst following (i.e., those more likely to be followed by sophisticated investors) are precisely the firms that should not exhibit a strong sunshine effect. Consistent with this discussion, untabulated results reveal that the sunshine effect does not exist when we define earnings surprise using analysts' forecast errors. We interpret these results to be evidence consistent with our cross-sectional predictions.

5.6 Other Robustness Tests

We perform several other untabulated robustness tests to ensure that our results are not sensitive to our research design choices. We originally value-weight market-adjusted returns; we reexamine our results using equal-weight adjustments, as well as decile-size adjustments. We reexamine our results using winsorized abnormal returns to ensure that influential observations are not driving our results. We originally scale earnings changes by prior-period market value of equity; we reexamine our results scaling by prior-period total assets. We originally define earnings changes using net income; we reexamine our results using "core" earnings changes (i.e., excluding special items, income from discontinued operations, extraordinary items). We include fixed season effects (spring, summer, fall, winter), fixed month effects, and day of week effects. We also control for *ANALYST* and *SIZE* (in the full as well as investor sophistication portfolios). None of these alternative specifications affect the tenor of our results.

6. Bid-Ask Spreads: Moods of Market-Makers

Goetzmann and Zhu (2003) argue that the sunshine effect is driven by the moods of market-makers physically located in New York. Consistent with their predictions, they find that bid-ask spreads narrow (widen) on sunny (cloudy) days. To consider this possibility, we first compute each day's bid-ask spread, scaled by the average of the closing bid and ask prices. We define *SPREAD* as the mean bid-ask spread for the three-day window around the earnings announcement date. We assign each observation into one of the four *SUNNY* portfolios (*SUNNY* = [0, 0.33, 0.67, 1]), and compute the mean *SPREAD* for each *SUNNY* portfolio. Results are reported in Table 6. We find that the mean *SPREAD* monotonically decreases across sunnier portfolios. For instance, the *SUNNY* = 0 portfolio exhibits a *SPREAD* of 0.0371, while the *SUNNY* = 0.33 portfolio exhibits a *SPREAD* of 0.00351; the difference in means is statistically significant ($t = 8.88$). The difference in *SPREAD* between the *SUNNY* = 0 and *SUNNY* = 1 portfolios is −0.0042 ($t = 2.99$). This suggests that mean bid-ask spreads are lower on sunnier days and that the sunshine effect may partially be driven by the moods of market-makers physically located in New York.

In Section 3.1, we described the sample selection process to include NYSE and AMEX firms, but not NASDAQ firms. The NYSE and AMEX are exchanges that are both physically (geographically) located in New York City, while NASDAQ is not. In untabulated results, we estimate our tests for NASDAQ firms and find that the sunshine effect does not exist for these firms. Because NASDAQ does not necessarily have market-makers located in New

TABLE 6

Mean Bid-ask Spreads of Each *SUNNY* Portfolio

Portfolio	*SPREAD*	Difference	*t*-Stat.
SUNNY = 0	0.0371		
		−0.0020	(8.88)
SUNNY = 0.33	0.0351		
		−0.0004	(0.54)
SUNNY = 0.67	0.0347		
		−0.0018	(1.15)
SUNNY = 1	0.0329		
Difference between *SUNNY* = 0 and *SUNNY* = 1		−0.0042	(2.99)

Note: This table presents the mean bid-ask spreads for each *SUNNY* portfolio. Each day's bid-ask spread is scaled by the average of the closing bid and ask prices. *SPREAD* is defined as the mean bid-ask spread for the three-day window around earnings announcement. Each observation is then assigned to a *SUNNY* portfolio. Differences between the mean *SPREAD* of each adjacent *SUNNY* portfolio are provided in the column labeled *Difference*. The *t*-statistic for the difference in means is provided in the column labeled *t*-Stat.

York City, this finding further supports the notion that the mood of market makers may be contributing to the sunshine effect.

7. Post–Earnings Announcement Abnormal Returns

Our evidence suggests that, when firms announce earnings on *SUNNY* days, market participants overreact to positive earnings news and underreact to negative earnings news. In Table 7, we present the post–earnings announcement abnormal returns for each *SUNNY* portfolio. Here, our goal is to examine whether we can observe a reversal in returns over a subsequent short-term window. We define *CAR* as the cumulative value-weight market-adjusted returns for the three-day window immediately after earnings announcements (i.e., +2 to +4). We separately report the results for positive and negative earnings surprises. We find that the average post–earnings announcement returns generally decrease in each successive *SUNNY* portfolio—that is, post–earnings announcement returns tend to be negative and lower in the *SUNNY* = 1 portfolios than in the *SUNNY* = 0 portfolios. This pattern is particularly true for the *POSDNI* portfolio. For instance, the average post–earnings announcement *CAR* for firms that report *POSDNI* on

TABLE 7

Mean Post Earnings Announcement Abnormal Returns of Each *SUNNY* Portfolio

		NEGDNI			*POSDNI*	
Portfolio	*CAR*	Diff	*t*-Stat.	*CAR*	Diff	*t*-Stat.
SUNNY = 0	0.00020			0.00070		
		−0.00060	(−0.84)		0.00030	(0.58)
SUNNY = 0.33	0.00080			0.00040		
		0.00280	(1.27)		0.00240	(1.23)
SUNNY = 0.67	−0.00200			−0.00200		
		0.01000	(1.41)		0.01500	(3.68)
SUNNY = 1	−0.01200			−0.01700		
Difference between *SUNNY* = 0 and *SUNNY* = 1		0.01220	(1.91)		0.01770	(5.29)

Note: This table presents the post–earnings announcement abnormal returns for each firm-quarter earnings announcement. *CAR* is defined as the cumulative value-weight market-adjusted returns for the three days after the earnings announcement window; that is, (+2,+4) window. Each observation is first assigned into a *NEGDNI* or *POSDNI* portfolio, where *DNI* is the seasonally-adjusted quarterly change in net income, scaled by prior-quarter market value of equity. Observations are then assigned to one of four *SUNNY* portfolios, where *SUNNY* = [0, 0.33, 0.67, 1]. The mean *CAR* is computed for each *DNI-SUNNY* portfolio. Mean *CAR*s are presented in the columns labeled *CAR*. The differences between the mean *CAR*s of each adjacent *SUNNY* portfolio are provided in the column labeled *Diff.* The *t*-statistic for the difference in means is provided in the column labeled *t*-Stat.

SUNNY = 0 days is 0.00070, while it is −0.01700 for similar firms that report on *SUNNY* = 1 days; this difference is statistically significant ($t = 5.29$). Moreover, the differences are economically meaningful: over the three-day period, a 1.22 percent difference for *NEGDNI* firms, and a 1.77 percent difference for *POSDNI* firms.

We caution, however, that such informational inefficiencies do not necessarily yield implementable arbitrage opportunities. Indeed, Hirshleifer and Shumway (2003) are careful to point out that even fairly modest transaction costs could do away with any likely profits from sunshine-based trading (e.g., Rubinstein [2001]).[7] The contribution of our study does not rely on documenting profitable trading strategies per se. Rather, regardless of the existence of arbitrage opportunities, our main goal is to provide further evidence that psychological factors may play a role in the efficiency with which prices reflect publicly available, value-relevant information.

8. Conclusion

For firms traded in New York–based exchanges, market reactions to earnings surprises are higher when earnings are announced on perfectly sunny days in New York City. Moreover, this sunshine effect is more prominent for firms that are small in size or have low analyst following. Not surprisingly, however, the documented sunshine effect is most prevalent on unambiguously sunny days and is much weaker on moderately sunny days. Average bid-ask spreads are lower on sunny days relative to cloudy days, suggesting that market-makers may be contributing to the sunshine effect. Lastly, there is some evidence of a short-term reversal of the sunshine-induced overreaction and underreaction.

We contribute to the literature in a number of ways. First, we are the first to provide evidence that the sunshine effect can exist for economic news events rather than value-irrelevant noise (e.g., news about a pop-culture celebrity scandal). This suggests that other economic events could be susceptible to a sunshine effect. Second, we provide evidence that the sunshine effect can exist at the firm level. This suggests that the phenomenon is not merely a market-level, macroeconomic phenomenon. Third, we identify cross-sectional variation in the sunshine effect. This suggests that future researchers may be able to uncover other types of characteristics that make a firm more susceptible to a sunshine effect. Conceivably, such work could lead to further fine-tuning and, ultimately, profitable trading strategies based on weather patterns.

Because earnings announcements are regularly occurring economic events that receive widespread attention, we view our work as a contribution to the growing body of evidence that documents complex associations between accounting information and stock prices. For instance, evidence from Schrand and Walther (2000) suggests that managers may engage in selective emphasis of more-favorable prior-period benchmarks—factors that have no direct impact on the fundamental

7. Markets are *minimally rational* if prices are not necessarily set as if investors are rational, but transaction costs are sufficiently high, preventing rational investors from exploiting such opportunities (e.g., Rubinstein [2001]).

APPENDIX A

Summary of Alternative Tests Performed

Alternative definitions	Section	Table
Alternative windows for sunshine/ returns	Section 4.1.1	Table 2
Less restrictive definitions of sunshine	Section 5.4	Available from authors
Continuous measure of sunshine (*TSC*)	Section 5.4	Available from authors
Analysts' earnings forecast errors	Section 5.5	Available from authors
Core earnings changes	Section 5.6	Available from authors
Equal-weight market-adjust returns	Section 5.6	Available from authors
Decile-size-adjust returns	Section 5.6	Available from authors
Winsorize returns for outliers	Section 5.6	Available from authors
Prior-quarter total assets scaling	Section 5.6	Available from authors
Alternative research designs		
Sunny-day-versus-cloudy-day matched sample	Section 5.1	Table 4
Firm- and earnings-matched sample	Section 5.2	Table 5
Alternative explanations		
Seasonal adjustment for *SUNNY*	Section 5.3	Available from authors
Fixed season effect	Section 5.6	Available from authors
Fixed month effects	Section 5.6	Available from authors
Fixed day of week effects	Section 5.6	Available from authors
Controls for *ANALYST* and *SIZE*	Section 5.6	Available from authors
Other tests		
Bid-ask spreads	Section 6.1	Table 6
NASDAQ firms	Section 6.2	Available from authors
Post–earnings announcement returns	Section 6.3	Table 7

value of a firm—and that such selective emphasis can affect investors' reactions to earnings surprises (similarly, Hirst and Hopkins [1998]; Bowen, Davis, and Matsumoto [2005]).[8] In the same vein, we show that the level of sunshine may have a discernible effect on market prices. In documenting this sunshine effect, our hope is to open up new and creative avenues of future research.[9]

8. Similarly, it is possible that managers suspect the existence of a sunshine effect and attempt to strategically time the release of their earnings announcements to occur on *SUNNY* days.

9. We are not suggesting that researchers start data-mining expeditions on other weather patterns. Hirshleifer and Shumway argue that the sunshine effect "is not subject to the criticism of data snooping. Exploration of whether this pattern exists was specifically stimulated by the psychological hypothesis—the hypothesis was not selected to match a known pattern. . . . Such a pattern, if it exists, has a psychological explanation but no plausible rational explanation. This contrasts with many well-known patterns of stock returns for which psychological and rational explanations are currently competing" (2003, 1010).

REFERENCES

Arkes, H., L. Herren, and A. Isen. 1988. "The Role of Potential Loss In the Influence of Affect on Risk-Taking Behavior." *Organizational Behavior and Human Decision Making Processes* 42 (October): 181–193.

Atiase, R. 1985. "Predisclosure Information, Firm Capitalization, and Security Price Behavior Around Earnings Announcements." *Journal of Accounting Research* 23 (Spring): 21–36.

Bless, H., N. Schwarz, and M. Kemmlmeier. 1996. "Mood and Stereotyping: The Impact of Moods on the Use of General Knowledge Structure." *European Review of Social Psychology* 7 (January): 63–93.

Bowen, R., A. Davis, and D. Matsumoto. 2005. "Emphasis on Pro Forma versus GAAP Earnings in Quarterly Press Releases: Determinants, SEC Intervention, and Market Reactions." *The Accounting Review* 80 (October): 1011–1038.

Brown, L., and M. Rozeff. 1978. "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings." *Journal of Finance* 33 (March): 1–16.

Brown, S., and J. Warner. 1985. "Using Daily Stock Returns in Event Studies." *Journal of Financial Economics* 14 (March): 3–31.

Forgas, J., and G. Bower. 1987. "Mood Effects on Person-Perception Judgments." *Journal of Personality and Social Psychology* 53 (March): 53–70.

Goetzmann, W., and N. Zhu. 2003. "Rain or Shine: Where Is the Weather Effect?" Working paper, National Bureau of Economic Research.

Hand, J. 1990. "A Test of the Extended Functional Fixation Hypothesis." *The Accounting Review* 65 (October): 764–780.

Hirshleifer, D., and S. Teoh. 2003. "Limited Attention, Information Disclosure, and Financial Reporting." *Journal of Accounting and Economics* 36 (December): 337–386.

Hirshleifer, D., and T. Shumway. 2003. "Good Day Sunshine: Stock Returns and the Weather." *Journal of Finance* 58 (June): 1009–1032.

Hirst, D., and P. Hopkins. 1998. "Comprehensive Income Reporting and Analysts' Valuation Judgments." *Journal of Accounting Research* 36 (Supplement): 47–75.

Hong, H., T. Lim, and J. Stein. 2000. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *Journal of Finance* 55 (February): 265–295.

Howarth, E., and M. Hoffman. 1984. "A Multidimensional Approach to the Relationship between Mood and Weather." *British Journal of Psychology* 75 (February): 15–23.

Isen, A. 2001. "An Influence of Positive Affect on Decision Making in Complex Situations: Theoretical Issues with Practical Implications." *Journal of Consumer Psychology* 11: 75–85.

Isen, A., T. Shalker, M. Clark, and L. Karp. 1978. "Affect, Accessibility of Material in Memory and Behavior: A Cognitive Loop?" *Journal of Personality and Social Psychology* 36 (January): 1–12.

Johnson, E., and A. Tversky. 1983. "Affect, Generalization, and the Perception of Risk." *Journal of Personality and Social Psychology* 45 (January): 20–31.

Keim, D. 1983. "Size Related Anomalies and Stock Return Seasonality: Further Evidence." *Journal of Financial Economics* 12 (June): 13–32.

Kim, O., and R. Verrecchia. 1994. "Market Liquidity and Volume around Earnings Announcements." *Journal of Accounting and Economics* 17 (January): 41–67.

Kothari, S. P. 2001. "Capital Markets Research in Accounting." *Journal of Accounting and Economics* 31 (September): 105–231.

Loughran, T., and P. Schultz. 2004. "Weather, Stock Returns, and the Impact of Localized Trading Behavior." *Journal of Financial and Quantitative Analysis* 39 (June): 343–364.

Persinger, M. 1975. "Lag Responses in Mood Reports to Changes in the Weather Matrix." *International Journal of Biometerology* 19 (June): 108–114.

Rind, B. 1996. "Effects of Beliefs about Weather Conditions on Tipping." *Journal of Applied Social Psychology* 26 (January): 137–147.

Rubinstein, M. 2001. "Rational Markets: Yes or No? The Affirmative Case." *Financial Analysts Journal* 57 (May/June): 15–29.

Saunders, E., Jr. 1993. "Stock Prices and Wall Street Weather." *American Economic Review* 83 (December): 1337–1345.

Schrand, C., and B. Walther. 2000. "Strategic Benchmarks in Earnings Announcements: The Selective Disclosure of Prior-Period Earnings Components." *The Accounting Review* 75 (April): 151–177.

Trombley, M. 1997. "Stock Prices and Wall Street Weather: Additional Evidence." *Quarterly Journal of Business and Economics* 36 (Summer): 11–21.

Walther, B. 1997. "Investor Sophistication and Market Earnings Expectations." *Journal of Accounting Research* 35 (Autumn): 157–179.