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Good Day Sunshine: Stock Returns and the Weather

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ABSTRACT

Psychological evidence and casual intuition predict that sunny weather is associated with upbeat mood. This paper examines the relationship between morning sunshine in the city of a country's leading stock exchange and daily market index returns across 26 countries from 1982 to 1997. Sunshine is strongly significantly correlated with stock returns. After controlling for sunshine, rain and snow are unrelated to returns. Substantial use of weather-based strategies was optimal for a trader with very low transactions costs. However, because these strategies involve frequent trades, fairly modest costs eliminate the gains. These findings are difficult to reconcile with fully rational price setting.

SUNSHINE AFFECTS MOOD, as evidenced by song and verse, daily experience, and formal psychological studies. But does sunlight affect the stock market?

The traditional efficient markets view says no, with minor qualifications. If sunlight affects the weather, it can affect agricultural and perhaps other weather-related firms. But in modern economies in which agriculture plays a modest role, it seems unlikely that whether it is cloudy outside the stock exchange today should affect the rational price of the nation's stock market index. (Even in countries where agriculture plays a large role, it is not clear that one day of sunshine versus cloud cover at the stock exchange should be very informative about harvest yield.)

An alternative view is that sunlight affects mood, and that people tend to evaluate future prospects more optimistically when they are in a good mood than when they are in a bad mood. A literature in psychology has found that mood affects judgment and behavior. The psychological literature on sunlight, mood, and misattribution of mood is discussed in the next section. An important strand of this literature has provided evidence that mood contains valuable information

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about the environment. The inferences drawn from mood can go astray however; people sometimes attribute their mood to the wrong feature of the environment. For example, someone who is in a good mood because of sunshine may unconsciously attribute this feeling to generally favorable life prospects. If such misattribution extends to investments, then stock prices will fluctuate in response to the mood of investors. Furthermore, people in good moods find positive material more salient and psychologically available than negative material. This evidence suggests that on dim, dull, dreary, depressing days stocks will decline, whereas cheery bright days will boost stocks.

For three reasons, examining the effects of sunlight on the stock market provides an attractive means of testing whether psychological biases can affect stock returns. First, any such relationship 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. Second, 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. Third, sunshine is an easily measured exogenous influence.[1] Some previous work emphasizes the dynamics of the social transmission of popular sentiments and theories (see, e.g., the overview of Shiller (2000a)). Some empirical headway along these lines has been made through survey methods (see, e.g., Shiller (1990, 2000b) and Hong, Kubik, and Stein (2003)). Here, we sidestep the complexities of the process of social influence by focusing on an exogenous external influence.

The first test of the hypothesis that sunshine affects returns involves examining individually for each city the relationship between daily cloudiness and daily nominal return on the nation's stock index using univariate regression at 26 stock exchanges internationally from 1982 to 1997. To ensure that the effects we identify do not derive from well-known seasonal stock return effects, we examine the deviation between the day's cloudiness and the ordinary expected degree of cloudiness for that day of the year. We examine the relationship of cloudiness both to continuous returns, and (in logit regressions) to the probability that the return will be positive. Depending on the specification, in either 18 or 25 of the 26 cities, the relationship between returns and cloudiness is negative (in most cases not significantly). Based on a simple nonparametric joint test, it is unlikely that these results would arise by sheer chance.

These city-by-city results strongly suggest that there is a genuine relationship between stock returns and cloudiness. To examine this issue in a more structured way, we provide several joint (cross-city) parametric tests using the entire data set. In pooled regressions where the intercept and slope are constrained to be the same across cities, we find a highly statistically significant relationship between

[1] As Roll (1992) put it, "Weather is a genuinely exogenous economic factor. … It was a favourite example of an exogenous identifying variable in the early econometrics literature… Because weather is both exogenous and unambiguously observable … weather data should be useful in assessing the information processing ability of financial markets."

cloud cover and returns ($t = -4.49$), or ($\chi^2 = 43.6$), for the logit. However, these tests assume independent errors, which is implausible.

To address this issue, we estimate a city-specific fixed effects model with panel corrected standard errors (PCSE). Our PCSE specification allows errors to be contemporaneously correlated, heteroskedastic across cities and autocorrelated within each city's time series. Once again there is a highly significant negative relationship between cloud cover and returns (asymptotic z-statistic $= -3.96$). To examine the relationship of weather to the probability of a positive return, we estimate a fixed effects linear probability model with PCSE using an indicator variable that is one when returns are positive. This again yields a strongly significant relationship ($t = -6.07$). In all cases, adjusting for contemporaneous correlation and heteroskedasticity across panels and autocorrelation within panels has little effect on the inference.

The magnitude of the sunshine effect is substantial. For example, for New York City, the annualized nominal market return on perfectly sunny days is approximately 24.8 percent per year versus 8.7 percent per year on perfectly cloudy days. However, from an investor's perspective, the value of these return differentials depends on whether it is possible to diversify the risk of a sunshine-based trading strategy. We find that for very low levels of transaction costs, trading strategies based on the weather generate statistically significant but economically modest improvements in portfolio Sharpe ratios. However, some countries' stock indices cannot be traded cheaply, and weather strategies involve frequent trading, so for most investors, trading on the sunshine effect does not appear to be profitable net of costs.[2]

We also explore by means of multiple regression whether the effect derives from sunshine versus cloudiness, or from other associated weather conditions such as rain or snow. We find that sunshine remains significant, and that after controlling for sunshine, rain and snow are essentially unrelated to returns.

The remainder of the paper is structured as follows. Section I discusses misattribution of mood, sunshine, and stock returns. Section II describes the data we use for our analyses, while Section III reports our evidence in detail. Section IV concludes.

I. Misattribution of Mood, Sunshine, and Stock Returns

A. Mood, Judgment, and Decisions

A literature in psychology considers how emotions and moods influence human decision making. Individuals who are in good moods make more optimistic choices. A highly robust effect is that individuals in good moods have more positive evaluations of many sorts, such as life satisfaction, past events, people, and consumer products (see, e.g., Wright and Bower (1992), and the survey of Bagozzi, Gopinath, and Nyer (1999)). There is a mood congruency effect, wherein

[2] Our findings do not rule out the possibility that weekly or more complex weather-based strategies can retain high returns while further economizing on transaction costs; no doubt practitioners will explore these possibilities.

people who are in bad moods (good moods) tend to find negative (positive) material more available or salient (see, e.g., Isen et al. (1978) and Forgas and Bower (1987)). Mood most strongly affects relatively abstract judgments about which people lack concrete information (Clore, Schwarz, and Conway (1994) and Forgas (1995)).

Several studies have found that individuals who are in good moods engage in more use of simplifying heuristics to aid decisions (see the reviews of Bless, Schwarz, and Kemmelmeier (1996) and Isen (2000)). However, there is debate as to whether this use of heuristics reflects cognitive deficiencies associated with good moods, or more efficient use of means of simplifying complex data.

Several studies have reported that bad moods tend to stimulate people to engage in detailed analytical activity, whereas good moods are associated with less critical modes of information processing (Schwarz (1990), Petty, Gleicher, and Baker (1991), and Sinclair and Mark (1995)), so that people in good moods are more receptive to weak as well as strong arguments (see Mackie and Worth (1991)). One review describes the evidence as indicating that good moods cause greater reliance on category information, and therefore more simplistic stereotyping (see Bless et al. (1996)). However, Isen (2000) points out several complexities in the interpretation of such studies owing to interacting psychological effects. Bless et al. provide evidence that good moods cause people to rely more heavily on "pre-existing knowledge structures," but do not necessarily create a general decrease in the motivation or capacity to think effectively.

Good moods have significant positives as well. People in good moods tend to generate more unusual associations, perform better in creative problem-solving tasks, and show greater mental flexibility. In addition, people in good moods tend to elaborate more on tasks involving neutral or positive (but not negative) stimulus material (see, e.g., the review of Isen (2000)).

Emotions influence assessments both of how favorable future prospects are (see, e.g., Johnson and Tversky (1983) and Arkes, Herren, and Isen (1988)), and assessments of risk (see, e.g., the reviews of Loewenstein et al. (2001) and Slovic et al. (2002)). The direction of the influence of mood on risk assessment is complex, and depends on the task and situation (see, e.g., the discussion of Isen (2000)).

An important strand of the theory of affective states (emotions or moods) holds that such states provide information to individuals about the environment (see, e.g., Frijda (1988) and Schwarz (1990)).[3] A substantial body of evidence supports an informational role of affect (see, e.g., Schwarz (1990), Clore and Parrott (1991), Wilson and Schooler (1991), and Clore et al. (1994)). Indeed, a procedure of decision making based upon feelings has been called "the affect heuristic" by Slovic et al. (2002).[4]

[3] Consistent with this view, people often talk approvingly about making decisions based on "gut feelings," good or bad "vibes," or doing "what your heart tells you." However, ordinary conversation also includes criticism of bad judgments based on feelings ("Marry in haste, repent at leisure.").

[4] Decisions are influenced not just by immediate feelings, but by the anticipation of future feelings; see, for example, the reviews of Mellers (2000), Loewenstein et al. (2001), and Slovic et al. (2002).

People often attribute their feelings to the wrong source, leading to incorrect judgments. As an example of this problem of *misattribution*, people feel happier on sunny days than on cloudy days. The effect of sunlight on their judgments about happiness is reduced if they are primed by asking them about the weather (Schwarz and Clore (1983)). Presumably this reminds them to attribute their good mood to sunshine rather than to long-term considerations.

B. Mood, Sunlight, and Behavior

Psychologists have been documenting correlation between sunshine and behavior for decades. Among other things, sunshine has been linked to tipping (Rind (1996)), and lack of sunshine to depression (Eagles (1994)) and suicide (Tietjen and Kripke (1994)). Most evidence suggests that people feel better when they are exposed to more sunshine. If people are more optimistic when the sun shines, they may be more inclined to buy stocks on sunny days. Specifically, they may incorrectly attribute their good mood to positive economic prospects rather than good weather. This suggests that sunshine is positively correlated with stock returns. Furthermore, the prediction is not that the news (as in a weather forecast) that the day will be sunny causes an immediate and complete positive stock price reaction. Rather, it is the occurrence of the sunshine itself that should cause prices to move.

An alternative to the informational perspective on affect is to view feelings as influencing preferences. Loewenstein (1996) reviews literature on, and models how, "visceral factors" such as hunger, fatigue, sexual desire, moods, emotions, pain, and drug cravings affect preferences between different goods. Mehra and Sah (2000) provide an analysis of the determination of stock prices when mood affects preferences. They show that small random fluctuations in preference parameters can cause significant volatility in prices.

In contrast, if people are rational maximizers, there is little reason to conjecture that sunshine is correlated with stock returns. It is certainly likely that weather affects economic output, particularly in industries like agriculture and construction. However, the sunshine that occurs in one particular location is not generally representative of the weather in an entire economy. Moreover, sunshine is a transitory variable. The amount of unexpected sunshine occurring today is not highly correlated with the amount that will prevail one week or one month from today. Finally, the occurrence of rain or snow should be more strongly correlated with output than cloudiness versus sunshine. Severe weather could hamper markets, communications, or other commercial activities. We therefore jointly test for the incremental effects on stock returns of rain, snow, and sunshine.[5]

[5] If people derive utility from both consumption and sunshine, some slight correlation between daily stock returns and sunshine may be rationally induced. However, most rational models do not attempt to capture stocks' sunshine risk.

C. Mood, Sunlight, and Stock Prices

There is already some evidence that sunshine influences markets. Saunders (1993) shows that when it is cloudy in New York City, New York Stock Exchange index returns tend to be negative. He shows that the cloudiness/returns correlation is robust to various choices of stock index and regression specification. Although this finding is noteworthy, it has received little attention, possibly because of concerns about unintentional data mining. Studies that identify significant relationships are more likely to be published than those that find nothing, so there will always be well-executed, published papers describing significant, but meaningless results. Our paper helps remedy this potential concern with respect to sunshine effects by examining data from many exchanges and a more recent time period.

Kamstra, Kramer, and Levi (2000a) use data from several countries to show that the Friday to Monday return is significantly lower on daylight-savings-time weekends than on other weekends. However, such changes can affect sleep patterns, not just waking hours of sunlight. Furthermore, examining weather data allows us to exploit the full sample of daily returns instead of a sample restricted to the dates of daylight-saving-time changes.

Kamstra, Kramer, and Levi (2000b) examine the effects of seasonal shifts in length of day in five stock markets (including markets in both the Northern and Southern Hemispheres). They find that stock market returns are significantly related to season, and argue that this relationship arises because of the deterministic shifts in the length of day through the seasons. They therefore suggest that deterministic variations in length of day help explain the January effect.[6]

We examine here the relationship of stock returns to a stochastic variable, the realization of the weather. We test the hypothesis that cloudy weather is correlated with poor stock returns. We do this with a sample of 26 stock exchanges. Using a panel rather than a long time series has three advantages.

First, it helps identify whether the hypothesized phenomenon is pervasive. The psychological argument for the effect of sunshine should apply globally.

Second, our recent sample allows us to examine whether this phenomenon is still present in the years subsequent to Saunders (1993). If financial markets have become more efficient over time, it is possible that the sunshine effect found by Saunders is no longer relevant. Consistent with this notion, Saunders found that his regression does not work well in the last subperiod of his sample (1983 to 1989). However, our study finds that sunshine effects are still present internationally and in the United States.

Third, the panel increases our power to detect an effect. Even if sunshine affects returns, we know there are many other important influences on any given day. Most variation in returns will be driven by economic events and news. Given

[6] Kramer (2000) examines another possible effect of mood on stock prices. She describes psychological evidence of predictable swings in mood over the course of the day. In a meta-analysis of three previous empirical studies on intraday returns, Kramer argues that the evidence on intraday patterns in expected stock returns is consistent with psychological patterns of diurnal mood swings.

the high variability of returns, it is useful to maximize power by using a large number of markets.

II. Data

Since we want to examine whether stock returns are correlated with cloudiness, we need both stock return and weather data. We collect weather data from the *International Surface Weather Observations* (ISWO) data set sold by the National Climactic Data Center (http://lwf.ncdc.noaa.gov/oa/ncdc.html). The ISWO data set contains detailed descriptions of the weather at 3,000 locations worldwide from 1982 to 1997. In most ISWO locations, observations about the wind, cloud cover, and barometric pressure are collected hourly. Since the hypothesis that we examine relates stock returns to the amount of sunshine on a particular day, we collect the ISWO variable that measures total sky cover (SKC). SKC ranges from zero (clear) to eight (overcast). We calculate the average cloud cover for each day from 6 a.m. to 4 p.m. local time for cities with stock exchanges. While the ISWO data appear to be of very high quality, a complete record of sky cover observations is not available for all of the cities with major stock exchanges. In particular, SKC data for Tokyo, Hong Kong, Seoul, Lisbon, Mexico City, Toronto, Jakarta, Frankfurt, and Wellington are not sufficiently complete to make data from these cities usable.

Of course, the daily cloud cover in any particular city is highly seasonal. For example, winter months are associated with cloudier weather in New York City. Many seasonal patterns have been identified in stock return data as well (e.g., Keim (1983)), and numerous possible causal forces exhibit annual seasonality. To be certain that our results are driven by cloudiness rather than other seasonal effects, we therefore deseasonalize the cloud data. This provides a conservative measure of the effect of cloud cover, in the sense that we exclude any contribution that cloud cover may make to seasonal return patterns.

We calculate the average cloudiness value for each week of the year in each city, and deseasonalize by subtracting each week's mean cloudiness from each daily mean. For example, we calculate the average value of $\mathrm{SKC}_{i,t}$ for the first full calendar week of the year for a particular city, taking an average of 80 values (16 years times five days in the week). Then we subtract this mean from the city's daily $\mathrm{SKC}_{i,t}$ values in the first week of each year. We denote the deseasonalized value of SKC for city i on day t as SKC^*_{it}. The mean of SKC^*_{it} is close to zero, and its global standard deviation is 2.19.

To check whether our results are driven by adverse weather conditions, we include measures of raininess and snowiness in some of our regression specifications. The ISWO data set contains a number of variables that describe the current and recently passed weather at each station. We use these variables to determine whether it is raining or has rained within the last observation period at each station. We then average the number of observation periods for which rain is reported per day. We perform similar calculations for snowy weather. Finally, we deseasonalize our raininess and snowiness variables by week in the same way that we deseasonalize the SKC variable. We denote the deseasonalized raininess in location i on day t $RAIN^*_{it}$ and we denote our deseasonalized snow variable $SNOW^*_{it}$.

We collect daily index returns from Datastream. All cities that have data from at least 1988 to 1997 are included in the analysis. For most cities, we use the market index calculated by Datastream (Datastream Global Index). However, for several cities, other indices exist with longer time series. Thus, we collect the following indices for the corresponding locations: Bovespa for Rio de Janeiro, IGPA for Santiago, Hex for Helsinki, Kuala Lumpur Composite for Kuala Lumpur, PSE Composite for Manila, Madrid SE General for Madrid, Taiwan SE Weighted for Taipei, and the Bangkok Composite for Bangkok.

Some summary statistics for the sample appear in Table I. The cloudiness measure used to calculate the means in column 3 of Table I is the original SKC_{it},

Table I

Summary Statistics

Table I displays a number of summary statistics that describe the sample. The time series for each city listed in column 1 begins in the year listed in column 2 and ends on December 31, 1997. The variable described as Cover is total sky cover, taken from the ISWO data set. Cloud cover ranges from zero to eight in any particular city at any particular time. Columns 3 and 4 report the mean and standard deviation of cloud cover in each city listed in column 1. Columns 5 and 6 report the mean and standard deviation of percentage returns in the local currency for each city.

Location (1)	Begin Date (2)	Mean Cover (3)	STD Cover (4)	Mean Ret (5)	STD Ret (6)
Amsterdam	1982	5.39	2.28	0.057	0.89
Athens	1988	3.23	2.55	0.097	1.81
Bangkok	1982	5.51	1.59	0.056	1.46
Brussels	1982	5.09	2.32	0.057	0.79
Buenos Aires	1988	4.35	2.71	0.496	4.13
Copenhagen	1982	5.35	2.31	0.059	0.88
Dublin	1982	5.84	1.85	0.069	1.06
Helsinki	1987	5.47	2.39	0.044	1.12
Istanbul	1988	3.85	2.58	0.269	2.63
Johannesburg	1982	3.00	2.52	0.075	1.25
Kuala Lumpur	1982	6.80	0.43	0.019	1.44
London	1982	5.74	2.00	0.054	0.86
Madrid	1982	3.42	2.74	0.067	1.06
Manila	1986	5.31	1.92	0.108	1.95
Milan	1982	4.29	2.95	0.052	1.24
New York	1982	4.95	2.72	0.058	0.92
Oslo	1982	5.40	2.37	0.068	1.39
Paris	1982	5.25	2.41	0.054	1.03
Rio de Janeiro	1982	5.17	2.46	0.806	3.79
Santiago	1987	3.28	3.07	0.112	1.00
Singapore	1982	6.70	0.91	0.025	1.16
Stockholm	1982	5.49	2.25	0.074	1.23
Sydney	1982	4.15	2.40	0.048	1.09
Taipei	1982	5.55	2.12	0.088	2.08
Vienna	1982	5.03	2.59	0.056	0.95
Zurich	1982	5.33	2.57	0.067	0.82

complete with its seasonal variability. It is evident from the sample statistics that some cities consistently experience more sunshine than other cities. Moreover, some cities appear to have substantially higher expected returns than other cities. This can be understood by noting that all returns are nominal returns expressed in local currencies. Some currencies, like that of Brazil, experience substantial inflation, so high nominal returns are not surprising.

A correlation matrix of both deseasonalized cloudiness, SKC^*_{it}, and of daily returns appears in Table II. The cross-city correlation of returns appear below the diagonal in the table, while the cloudiness correlations are above the diagonal. While no measure of statistical significance is reported in the table, almost all correlations greater in absolute value than 0.04 are significant at the five percent level. Not surprisingly, most of the returns correlations are positive, large, and significant. Only two estimated correlations are negative, and none are larger than 0.65. Thus, while the global component of daily international returns is

Table II

Correlation Matrix

Table II displays estimated cross-city correlation coefficients for the principal variables in the analysis. Correlations of deseasonalized cloudiness appear above the diagonal, while returns correlations appear below the diagonal. Almost all correlations with an absolute value greater than 0.04 are statistically significant.

	Ams	Ath	Ban	Bru	Bue	Cop	Dub	Hel	Ist	Joh	Kua	Lon	Mad
Ams	■	−0.06	−0.01	−0.74	−0.01	0.29	0.12	0.12	−0.08	0.02	0.01	0.43	−0.07
Ath	0.12	■	−0.05	−0.07	0.02	−0.02	0.04	−0.03	0.41	0.00	−0.02	−0.01	−0.00
Ban	0.07	0.10	■	−0.02	0.01	−0.00	−0.02	−0.02	−0.04	−0.01	0.02	−0.03	0.01
Bru	0.46	0.16	0.12	■	−0.01	0.25	0.10	0.09	−0.09	0.02	0.00	0.40	−0.09
Bue	0.08	0.03	0.05	0.07	■	0.01	−0.01	0.00	0.02	0.02	0.02	−0.01	−0.01
Cop	0.29	0.15	0.11	0.28	0.05	■	0.04	0.19	−0.04	0.02	−0.01	0.12	−0.05
Dub	0.39	0.17	0.12	0.29	0.05	0.29	■	−0.02	0.00	0.00	0.00	0.37	−0.03
Hel	0.32	0.07	0.10	0.26	0.05	0.33	0.25	■	−0.04	−0.00	−0.04	0.03	−0.06
Ist	0.03	0.09	0.05	0.02	0.01	0.06	0.08	0.05	■	−0.01	−0.00	−0.03	0.01
Joh	0.19	0.11	0.08	0.14	0.00	0.17	0.19	0.27	0.06	■	0.02	−0.01	−0.01
Kua	0.20	0.16	0.22	0.22	0.03	0.21	0.21	0.19	0.04	0.19	■	−0.00	0.02
Lon	0.63	0.10	0.08	0.35	0.09	0.24	0.40	0.28	0.05	0.21	0.21	■	−0.01
Mad	0.32	0.17	0.15	0.36	0.09	0.24	0.28	0.28	0.03	0.18	0.20	0.29	■
Man	0.08	0.09	0.16	0.06	0.03	0.14	0.11	0.12	0.03	0.13	0.20	0.08	0.12
Mil	0.30	0.11	0.16	0.25	0.04	0.30	0.30	0.32	0.06	0.34	0.29	0.29	0.32
New	0.27	0.10	0.13	0.28	0.06	0.22	0.21	0.27	0.03	0.13	0.15	0.24	0.30
Osl	0.34	0.05	0.03	0.23	0.11	0.08	0.12	0.10	0.01	0.02	0.11	0.35	0.13
Par	0.46	0.13	0.11	0.36	0.07	0.28	0.34	0.30	0.02	0.22	0.24	0.39	0.30
Rio	0.55	0.14	0.08	0.47	0.09	0.26	0.33	0.27	0.04	0.18	0.19	0.47	0.37
San	0.08	0.03	0.02	0.08	0.08	0.08	0.05	0.11	0.03	0.04	0.08	0.08	0.06
Sin	0.16	0.06	0.08	0.19	0.13	0.12	0.13	0.08	0.03	0.09	0.13	0.15	0.17
Sto	0.25	0.17	0.22	0.26	0.06	0.26	0.27	0.24	0.06	0.22	0.65	0.26	0.28
Syd	0.43	0.18	0.13	0.38	0.08	0.28	0.31	0.39	0.06	0.16	0.21	0.36	0.37
Tai	0.05	0.12	0.10	0.08	0.01	0.06	0.10	0.07	0.07	0.06	0.11	0.05	0.12
Vie	0.24	0.17	0.17	0.28	0.06	0.22	0.24	0.24	0.11	0.16	0.22	0.18	0.32
Zur	0.61	0.19	0.13	0.51	0.07	0.34	0.40	0.33	0.03	0.24	0.28	0.48	0.42

Table II—*continued*

	Man	Mil	New	Osl	Par	Rio	San	Sin	Sto	Syd	Tai	Vie	Zur
Ams	– 0.03	0.01	0.01	0.00	0.14	0.46	0.03	– 0.01	0.01	0.15	– 0.02	0.13	0.15
Ath	– 0.01	0.02	– 0.09	– 0.02	0.01	– 0.09	– 0.00	0.01	– 0.02	– 0.02	– 0.02	– 0.05	– 0.03
Ban	0.07	– 0.01	– 0.00	0.01	– 0.04	– 0.00	– 0.03	– 0.00	0.02	– 0.02	0.03	– 0.02	– 0.01
Bru	– 0.02	– 0.01	0.05	– 0.01	0.10	0.64	0.01	– 0.01	– 0.01	0.14	– 0.03	0.16	0.24
Bue	– 0.03	– 0.03	– 0.00	0.00	0.01	– 0.01	– 0.19	0.22	– 0.01	0.01	0.03	0.01	– 0.00
Cop	0.00	– 0.00	0.03	0.00	0.34	0.16	0.02	– 0.02	0.03	0.36	– 0.01	0.10	0.10
Dub	– 0.01	– 0.00	– 0.03	– 0.02	0.00	0.10	– 0.02	0.01	– 0.00	0.00	– 0.00	0.02	0.05
Hel	0.03	0.03	0.00	0.00	0.12	0.07	0.03	0.00	0.01	0.40	0.02	0.06	0.04
Ist	– 0.00	0.02	– 0.12	– 0.00	0.01	– 0.12	0.00	– 0.00	– 0.02	– 0.04	– 0.00	– 0.13	– 0.09
Joh	0.00	– 0.00	0.02	0.01	0.01	0.03	0.03	0.02	– 0.01	0.03	– 0.01	0.03	0.03
Kua	0.03	0.01	0.01	– 0.00	– 0.04	0.01	– 0.02	0.01	0.19	– 0.03	0.04	– 0.00	0.00
Lon	– 0.02	0.01	0.00	– 0.02	0.08	0.41	0.01	0.00	– 0.00	0.04	– 0.01	0.05	0.09
Mad	– 0.01	– 0.01	0.21	0.00	– 0.01	– 0.04	– 0.00	– 0.02	– 0.02	– 0.06	– 0.01	– 0.07	– 0.02
Man	■	– 0.04	– 0.02	– 0.01	– 0.01	– 0.02	0.02	– 0.03	0.05	– 0.01	– 0.01	– 0.01	– 0.02
Mel	0.21	■	0.00	0.00	0.01	– 0.01	0.02	– 0.03	0.03	0.00	– 0.01	– 0.00	0.02
Mil	0.06	0.19	■	– 0.01	0.07	0.13	– 0.01	– 0.00	– 0.01	0.03	0.03	0.07	0.31
New	– 0.01	0.05	0.12	■	– 0.03	– 0.01	0.02	0.00	– 0.00	– 0.02	0.01	0.01	– 0.01
Osl	0.11	0.35	0.23	0.13	■	0.11	0.02	0.01	0.00	0.40	0.02	0.01	0.06
Par	0.05	0.22	0.29	0.27	0.37	■	0.03	0.00	0.02	0.10	– 0.01	0.11	0.29
Rio	0.03	0.09	0.05	0.09	0.09	0.10	■	– 0.09	– 0.04	0.00	– 0.02	– 0.01	0.01
San	0.04	0.13	0.12	0.17	0.17	0.18	0.13	■	– 0.04	– 0.01	0.03	– 0.01	– 0.01
Sin	0.25	0.41	0.19	0.11	0.29	0.22	0.06	0.13	■	– 0.02	– 0.01	– 0.00	– 0.00
Sto	0.10	0.31	0.27	0.18	0.39	0.41	0.10	0.17	0.27	■	– 0.00	0.07	0.07
Tai	0.08	0.11	0.08	– 0.00	0.05	0.06	0.01	0.05	0.13	0.08	■	– 0.01	– 0.02
Vie	0.16	0.22	0.24	0.08	0.23	0.26	0.07	0.08	0.24	0.27	0.13	■	0.29
Zur	0.11	0.35	0.34	0.29	0.47	0.56	0.11	0.21	0.34	0.50	0.09	0.33	■

fairly large, there is also a large local component to each national index return. We expect that cloudiness affects the local component of an index return.

Even after deseasonalizing cloudiness, there are many significant cross-city correlations. The cloudiness correlations appear to be determined largely by geography, with proximate cities exhibiting large correlations. The correlations in returns and cloudiness present econometric problems that our test specifications will have to overcome.

III. Evidence

This section describes the statistical results of testing the hypothesis that cloudy weather is associated with low stock market returns. Our first set of results concerns some very simple specifications estimated city by city. Simple city-by-city specifications give us an idea of the significance of cloudiness in explaining returns. However, given the relatively short time series in our sample, we cannot expect many individual city results to be statistically significant.

Because there is a tremendous amount of variation in individual index stock returns, to increase power we perform joint tests that employ the entire panel of

26 exchanges. We also check whether raininess or snowiness are correlated with returns, and whether any correlation between sunshine and returns can be explained by raininess and snowiness. Finally, we examine the economic significance of the sunshine effect with traditional measures similar to R^2 and with a simple trading strategy.

A. City-by-City Tests

We first estimate simple regressions that are similar to those in Saunders (1993). Specifically, we estimate the parameters of the regression equation

$$r_{it} = \alpha_t + \beta_{iC}\mathrm{SKC}^*_{it} + e_{it} \quad (1)$$

Ordinary least squares estimates of the β_{iC} coefficient of this regression are reported in the third column of Table III, and the associated t-statistics are reported in the fourth column of Table III. The results are quite robust. Estimates that use the original cloudiness measure (SKC_{it}) are quite similar to those reported. Regressions that replace the cloudiness measure with a variable that is set to one when SKC_{it} is less than one, to zero when SKC_{it} is between one and seven, and to minus one when SKC_{it} is greater than seven also produce very similar results.

It might be conjectured that it is not just cloudiness per se, but also the change in cloudiness from the previous day that influences moods. While regressions of returns on changes in cloudiness produce results that are similar to the levels results in Table III, the levels results are slightly stronger. When both levels and changes are included in the regression, the levels remain significant but the changes coefficient becomes insignificant.

The simple regression coefficients in Table III already give an idea of the global significance of cloudiness for returns. Four of the negative estimated coefficients are significantly different from zero using a two-tailed, five percent test. However, Saunders (1993) argues that a one-tailed test is appropriate, since the alternative hypothesis being examined concerns only the left tail. Using a one-tailed, five percent test, 7 of the 26 coefficients are statistically significantly negative. In contrast, the largest positive t-statistic is 0.83.

We can examine the joint significance of these results with some simple nonparametric calculations. The coefficient on SKC^*_{it}, reported in column 3, is positive for 8 out of 26 cities. If the sign of each regression is an independent draw from the binomial distribution, and if the probability of drawing a negative coefficient is 0.5, then the probability of finding only 8 positive coefficients out of 26 possible is 0.038. This is within the five percent level of significance for a one-tailed test. The simple regression coefficients reported in Table III suggest that cloudiness and returns are correlated.

However, the simple regressions may not be the most powerful way to examine our hypothesis. The simple regressions relate the level of returns on any given day to the percentage of cloud cover on that particular day. Thus, while a fairly cloudy day ($\mathrm{SKC}_{it} = 6$) may be associated with negative index returns, a very cloudy day ($\mathrm{SKC}_{it} = 8$) should be associated with very negative returns according to the sim-

Table III

Sunshine Regression and Logit Model Results

This table displays city-by-city and pooled results of estimating a regression of daily stock returns on cloudiness and a logit model that relates the probability of a positive daily stock return to cloudiness. The regression results appear in columns 3 and 4, while the logit results appear in columns 5 to 7. An asterisk indicates statistical significance at the five percent level or greater.

	OLS Regression			Logit Model		
Location	Observations (2)	β_{iC} (3)	t-Statistic (4)	γ_{iC} (5)	$\chi 2$ (6)	P-Value (7)
Amsterdam	3984	– 0.007	– 1.07	– 0.024	2.76	0.0963
Athens	2436	0.012	0.71	– 0.014	0.53	0.4649
Bangkok	3617	0.009	0.45	– 0.014	0.24	0.6259
Brussels	3997	– 0.018*	– 3.25	– 0.036*	6.75	0.0094
Buenos Aires	2565	– 0.030	– 0.98	– 0.019	1.60	0.2054
Copenhagen	4042	– 0.002	– 0.30	– 0.002	0.02	0.8999
Dublin	3963	– 0.000	– 0.02	– 0.025	2.13	0.1445
Helsinki	2725	– 0.016	– 1.67	– 0.034*	4.01	0.0452
Istanbul	2500	0.007	0.32	– 0.001	0.00	0.9488
Johannesburg	3999	0.004	0.47	– 0.012	0.67	0.4124
Kuala Lumpur	3863	0.014	0.26	– 0.109	1.99	0.1586
London	4003	– 0.010	– 1.52	– 0.019	1.41	0.2355
Madrid	3760	– 0.011	– 1.60	– 0.015	1.41	0.2353
Manila	2878	0.018	0.83	0.003	0.02	0.9023
Milan	3961	– 0.014*	– 2.03	– 0.021	3.69	0.0549
New York	4013	– 0.007	– 1.28	– 0.035*	8.64	0.0033
Oslo	3877	– 0.018	– 1.92	– 0.025	3.31	0.0688
Paris	3879	– 0.009	– 1.27	– 0.027*	3.93	0.0474
Rio de Janeiro	2988	– 0.057	– 1.93	– 0.016	0.96	0.3267
Santiago	2636	0.000	0.05	– 0.012	0.73	0.3935
Singapore	3890	0.008	0.37	– 0.002	0.00	0.9588
Stockholm	3653	– 0.014	– 1.54	– 0.025	2.89	0.0889
Sydney	4037	– 0.014*	– 1.96	– 0.020	2.16	0.1417
Taipei	3784	– 0.016	– 0.97	– 0.013	0.66	0.4164
Vienna	3907	– 0.013*	– 2.14	– 0.026*	4.11	0.0425
Zurich	3851	– 0.007	– 1.28	– 0.012	0.89	0.3465
All cities (naive)	92808	– 0.011*	– 4.49	– 0.020*	43.62	0.0001
All cities (PCSE)	92808	– 0.010*	– 3.96	—	—	—

ple regression. Saunders (1993) finds that returns are negative more often on cloudy days than on sunny days. It is possible that while the sign of an index return on a particular day is related to the exchange city's cloudiness that day, the magnitude of the index return is not strongly related to cloudiness.

To examine this alternative specification, we estimate logit models of the form

$$P(r_{it} > 0) = \frac{e^{\gamma_{iC}\mathrm{SKC}^*_{it}}}{1 + e^{\gamma_{iC}\mathrm{SKC}^*_{it}}} \tag{2}$$

by maximum likelihood. The fifth column of Table III reports the estimates of γ_{iC}. The sixth and seventh columns of Table III report each coefficient's chi-square test of statistical significance and its associated p-value.

While only four of the simple regression coefficients are statistically significant in the five percent, two-tailed test, five of the logit coefficients are significant at this level. Furthermore, nine of the coefficients are significant at the 10 percent level, or equivalently, in a one-tailed test. Again, no positive estimate of γ_{iC} is even close to significant.

In fact, 25 out of 26 estimated γ_{iC} coefficients are negative. Performing the same calculation as before, if each of the signs of the γ_{iC} was independently binomial ($p = 0.5$), the probability of this occuring would be 4×10^{-7}. This is quite strong evidence that cloudiness is correlated with returns.

Moreover, the chi-share test statistic for the New York logit regression is highly statistically significant, with an associated p-value of 0.0033. This is a notable contrast with the finding of Saunders (1993) that the sunshine effect is insignificant in the last subperiod of his sample (1983 to 1989). Saunders concluded that the sunshine effect may be of purely historical interest. Splitting the New York logit regression into similar subperiods, the logit coefficient estimate calculated with our data for the eight-year period from 1982 to 1989 is -0.0136 with an associated chi-square statistic of 0.68 (p-value = 0.4081). However, the logit coefficient estimate for the eight-year period from 1990 to 1997 is -0.0578 with an associated chi-square statistic of 11.38 (p-value = 0.0007). Thus, although we replicate Saunders' finding that the weather effect was weak in the 1980s, the sunshine effect appears most strongly in New York during the 1990s. Because of sampling noise, eight years is a short period of time to measure these effects. Thus, the results are not inconsistent with a stable sunshine effect through the entire period.

B. Joint Tests

While the city-by-city results reported above strongly suggest that stock returns are correlated with cloudiness, we can use the entire data set to make more definitive statements about the statistical significance of the cloudiness effect. We report the results of several joint (across cities/indices) tests of significance in this section.

The first joint tests can be considered simple generalizations of the regressions described above. We estimate one regression with the simple specification of equation (1) with all of the data from each city. We refer to this as a pooled regression. In particular, we estimate a pooled regression of the form

$$r_{it} = \alpha + \beta_C \mathrm{SKC}^*_{it} + e_{it}, \tag{3}$$

where now the parameters α and β_C are constrained to be the same across markets. In this simple pooled specification, we assume that the error terms, e_{it}, are i.i.d. This specification does not adjust for any contemporaneous correlations across the error terms of different indices, nor does it adjust for any autocorrelation among a particular index's errors. Contemporaneous correlation across index-specific error terms almost certainly exists, given the correlations in Table II.

The results of the simple pooled regression appear in the penultimate line of Table III. The β_C coefficient estimate is -0.011, which is approximately the mean of the city-by-city estimates. The associated t-statistic is -4.49, which is highly statistically significant.

We also perform a pooled test with the logit model described by equation (2). Again, we simply concatenate the data from each city, resulting in one sample of 92,808 observations, 53.2 percent of which are positive. The estimate of γ_c is -0.02, approximately the mean of the city-by-city results. Moreover, the chi-square test of statistical significance is 43.62, which is very statistically significant. However, these test statistics are also based on the dubious assumption that each observation is i.i.d.

To allow for violations of the assumption that each error term is i.i.d., we estimate a city-specific fixed effects model of the form

$$r_{it} = \alpha_i + \beta_C \mathrm{SKC}^*_{it} + e_{it}, \tag{4}$$

with panel corrected standard errors (PCSE). Our PCSE specification allows e_{it} to be contemporaneously correlated and heteroskedastic across cities, and autocorrelated within each city's time series. We estimate β_C to be -0.010 with an associated asymptotic z-statistic of -3.96. These estimates are quite close to the naive pooled estimates discussed above, so adjusting for the correlations in the panel data does not reduce the power of the inference very much. Adjusting the logit model for panel correlations is significantly more complicated than adjusting the simple regression. Therefore, we estimate a fixed effects linear probability model with PCSE of the form

$$I(r_{it} > 0) = \alpha_{P,i} + \beta_P \mathrm{SKC}^*_{it} + e_{it}, \tag{5}$$

where $I(r_{it} > 0)$ is an indicator variable that is one when returns are positive. Estimating this regression yields an estimate of β_P of -0.005 with an associated t-statistic of -6.07. Again, adjusting for contemporaneous correlation and heteroskedasticity across panels and autocorrelation within panels has little effect on the inference.

The sunshine effect has been criticized by Trombley (1997) on the grounds that the results documented for New York weather and returns in Saunders (1993) are not statistically significant in each month of the year and subperiod of the data (a criterion which we regard as inappropriate). Trombley also finds that average returns do not appear to be a monotonic function of cloudiness in Saunders' data. In unreported tests that employ our entire panel of data, we find that average returns are almost monotonically decreasing in cloudiness and that the effect of cloudiness on returns is negative in all 12 months of the year and significantly negative in one-sided tests in 6 of the 12 months. Overall, our finding that sunshine is statistically significantly correlated with daily returns appears quite robust.

C. Controlling for Adverse Weather

As discussed above, it is possible that sunshine is just a proxy variable for other weather conditions, such as lack of rain or snow, that may be correlated with stock returns. We examine this hypothesis by measuring raininess and snowiness and including adverse weather conditions in the regressions. The regressions that we estimate and report in Table IV take the form

$$r_{it} = \alpha_i + \beta_{iC}\mathrm{SKC}^*_{it} + \beta_{iR}\mathrm{RAIN}^*_{it} + \beta_{iS}\mathrm{SNOW}^*_{it} + e_{it}, \tag{6}$$

where the variables are measured as defined in Section II. Table V reports estimates of logit models analogous to those described in the previous subsection.

The results in Tables IV and V indicate that the sunshine effect is not explained by other weather conditions. In Table IV, only 9 of the 26 sky cover coefficients reported in column 2 are positive. In the regressions without raininess and snowiness (in Table III), 8 of the coefficients are positive. Similar to the regressions

Table IV

Sunshine Regressions Controlling for Other Weather Conditions

This table displays city-by-city and pooled results of estimating a regression of daily stock returns on cloudiness, raininess, and snowiness. Column 2 contains the coefficient estimate for cloudiness, and column 3 contains the associated t-statistic. Columns 4 and 5 contain coefficient estimates for raininess and snowiness. An asterisk indicates statistical significance at the five percent level or greater.

Location (1)	β_{iC}	t-Statistic	β_{iR}	β_{iS}
Amsterdam	− 0.005	− 0.69	− 0.064	− 0.075
Athens	0.014	0.77	− 0.295	− 0.393
Bangkok	0.014	0.63	− 0.566	0.392
Brussels	− 0.011	− 1.76	− 0.219*	0.123
Buenos Aires	− 0.022	− 0.64	− 0.580	2.226
Copenhagen	− 0.001	− 0.10	− 0.193	0.264
Dublin	0.001	0.08	− 0.018	0.111
Helsinki	− 0.016	− 1.51	0.319	− 0.397
Istanbul	0.008	0.33	− 0.340	2.575
Johannesburg	0.003	0.28	0.090	0.044
Kuala Lumpur	0.021	0.38	− 0.206	− 0.023
London	− 0.009	− 1.14	− 0.052	− 0.019
Madrid	− 0.011	− 1.42	0.031	− 0.411
Manila	0.015	0.63	0.234	− 2.318
Milan	− 0.015*	− 1.99	0.342	− 1.026
New York	− 0.002	− 0.31	− 1.929*	− 1.555
Oslo	− 0.019	− 1.76	0.035	0.078
Paris	− 0.012	− 1.53	0.279	0.378
Rio de Janeiro	− 0.067*	− 2.16	1.135	2.805
Santiago	0.001	0.17	− 0.409	− 1.154
Singapore	0.007	0.32	0.095	− 0.377
Stockholm	− 0.012	− 1.22	0.094	− 0.594
Sydney	− 0.013	− 1.51	− 0.073	0.459
Taipei	− 0.020	− 1.13	0.212	3.378
Vienna	− 0.013*	− 2.00	0.005	0.009
Zurich	− 0.002	− 0.31	− 0.101	− 0.015
All cities (naive)	− 0.010*	− 3.94	− 0.058	0.076
All cities (PCSE)	− 0.009*	− 3.47	− 0.065	0.067

Table V

Sunshine Logit Models Controlling for Other Weather Conditions

This table displays city-by-city and pooled results of estimating a logit model that relates the probability of a positive daily stock return to cloudiness, raininess, and snowiness. Column 2 contains the coefficient estimate for cloudiness, and column 3 contains the associated χ^2-statistic. Columns 4 and 5 contain coefficient estimates for raininess and snowiness. An asterisk indicates statistical significance at the five percent level or greater.

Location (1)	γ_{iC} (2)	$\chi2$ (3)	γ_{iR} (4)	γ_{iS} (5)
Amsterdam	– 0.028	3.04	0.133	0.023
Athens	– 0.014	0.51	0.357	– 2.819
Bangkok	– 0.007	0.05	– 0.810	– 0.207
Brussels	– 0.019	1.42	– 0.565*	0.474
Buenos Aires	– 0.012	0.51	– 0.254	– 0.272
Copenhagen	0.002	0.01	– 0.435	0.103
Dublin	– 0.012	0.40	– 0.225	0.739
Helsinki	– 0.038*	4.07	0.606	– 0.130
Istanbul	0.003	0.02	– 0.557	1.441
Johannesburg	– 0.016	1.05	0.166	0.298
Kuala Lumpur	– 0.103	1.74	– 0.277	0.310
London	– 0.007	0.16	– 0.330	– 0.034
Madrid	– 0.018	1.59	0.300	0.989
Manila	0.005	0.04	– 0.151	0.605
Milan	– 0.021	2.94	0.180	– 1.742
New York	– 0.025*	4.14	– 4.943*	2.636
Oslo	– 0.024	2.45	0.021	– 0.120
Paris	– 0.031*	4.46	0.242	2.060
Rio de Janeiro	– 0.022	1.83	0.945	0.472
Santiago	– 0.009	0.34	– 1.074	– 1.615
Singapore	– 0.008	0.05	0.417	– 0.467
Stockholm	– 0.015	0.85	– 0.988	– 1.010
Sydney	– 0.019	1.48	– 0.053	0.386
Taipei	– 0.015	0.77	0.103	2.542
Vienna	– 0.030*	4.51	0.229	0.776
Zurich	0.001	0.00	– 0.289*	0.112
All cities (naive)	– 0.017*	28.86	– 0.190*	0.128

without raininess and snowiness, 3 of the coefficients are significantly negative at the five percent level, but none of the coefficients is close to significantly positive. By comparison, raininess and snowiness have 12 and 13 positive estimated coefficients in columns 4 and 5, respectively. Two of the raininess and 1 of the snowiness coefficients are statistically significant.

While the city-by-city results in Table IV suggest that the sunshine effect is independent of raininess and snowiness, we can design more powerful tests of the adverse weather explanation by considering all cities' returns jointly. The last two lines of Table IV report the results of an all city pooled regression and a fixed-effects PCSE regression analogous to those regressions described in the previous subsection. In both regressions, the coefficient on sky cover is significantly negative, with t-statistics of -3.94 and -3.47. However, raininess and snowiness are economically and statistically insignificant in both specifications. Overall, the results of Table IV do not support the other-weather-condition explanation of our results.

The binary results in Table V are not favorable to the adverse weather hypothesis either. As in the previous section, the logit model estimates reported in Table V relate the sign of the return in city i on day t to the weather in that city on that day. Specifically, the models we estimate are of the form

$$P(r_{it} > 0) = \frac{e^{\gamma_{iC}\mathrm{SKC}^*_{it} + \gamma_{iR}\mathrm{RAIN}^*_{it} + \gamma_{iS}\mathrm{SNOW}^*_{it}}}{1 + e^{\gamma_{iC}\mathrm{SKC}^*_{it} + \gamma_{iR}\mathrm{RAIN}^*_{it} + \gamma_{iS}\mathrm{SNOW}^*_{it}}}. \tag{7}$$

Looking at the city-by-city results, only 4 of the sky cover coefficient estimates reported in column 2 are positive, while 4 of the estimates are significantly negative. While 3 of the raininess coefficients reported in column 4 are significantly negative, 12 of the raininess coefficients are positive. None of the snowiness coefficients in column 5 is significant, and 16 of them are positive. The city-by-city logit results confirm that sunny days tend to coincide with positive returns.

To assess the joint significance of the city-by-city logit estimates, we again estimate a naive pooled logit model and a fixed-effects PCSE linear probability model. The results of the pooled logit model appear in the final row of Table V. The pooled estimate of the logit coefficient on sky cover is -0.017, which is close to the mean of the city-by-city estimates. The associated chi-square statistics is 28.86, which indicates that the coefficient estimate is very statistically significant. The coefficient estimate for raininess is -0.190, and it is statistically significant. The estimate for snowiness is positive and insignificant.

As in the case without adverse weather controls, the fixed-effects PCSE linear probability model is consistent with the pooled logit model. The coefficient estimate for $\mathrm{SKC}^*_{i,t}$ is -0.0043, with an asymptotic z-statistic of -5.01. The coefficient estimate for $\mathrm{RAIN}^*_{i,t}$ is -0.049, with a z-statistic of -3.06, and the coefficient estimate for $\mathrm{SNOW}^*_{i,t}$ is positive and insignificant. Again, even after controlling for other weather conditions, sunshine is strongly significantly correlated with both the sign and the magnitude of returns.

D. Ability of Sunlight to Predict Returns

With the parameter estimates reported in Table III, we now consider the profitability of trading strategies based upon the sunshine effect, and whether morning sunlight can predict returns for the day. We use the coefficient of the simple pooled regression, -0.011, as our estimate of the sunshine effect. The mean daily return across all countries is 0.103, with a standard deviation of 1.58. We know that the cloudiness variable ranges from zero to eight, so the difference in expected return between a completely overcast day and a sunny day is 0.088 or about nine basis points. While nine basis points is approximately how much the markets go up on an average day, it is only about five percent of the standard deviation of daily returns. Consistent with this calculation, the R^2 of the naive pooled regression reported in Table III is 0.02 percent, a very low number.

It is, of course, not reasonable to expect the explanatory power of sunshine to be large. Many shocks affect daily stock returns, such as real news about global, national, and local fundamentals. Unless the market is grotesquely inefficient, fundamental news must have a large effect on returns.

Rather than focusing on R^2, we consider whether a portfolio strategy based on weather trading can significantly increase the Sharpe ratio of a hypothetical investor. We employ a Britten-Jones (1999) test of the mean-variance efficiency of a simple global market portfolio, and the global portfolio combined with a weather-based strategy. The Britten-Jones test regresses a vector of ones on portfolio returns. When more than one set of portfolio returns are used as dependent variables, a mean-variance efficient portfolio will be significantly related to the vector of ones and all other portfolios will be unrelated to the vector of ones. The intuition behind the test is that a vector of ones represents the ideal asset return—the returns are positive with no variability. Put differently, the vector of ones represents the returns of an asset with an infinite Sharpe ratio, having a mean of one and a variance of zero. The regression finds the combination of potentially mean-variance efficient portfolios that most closely approximates this ideal asset return.

Our global market portfolio is the equal-weighted portfolio of all cities' returns in local currencies. To construct our trading strategy returns, we average $\mathrm{SKC}_{i,t}$ for each city from 5 a.m. to 8 a.m. each morning. We then deseasonalize the morning SKC variable in the same way that we deseasonalize the previous measure of SKC (as described in Section II). Finally, we calculate the equal-weighted average return of cities with positive deseasonalized morning SKC and the equal-weighted average return of cities with negative deseasonalized morning SKC. We consider strategies that are long indices with sunny cities, short indices with cloudy cities, and both long the sunny indices and short the cloudy indices. The results of our test appear in Table VI.

Table VI shows that in the absence of transaction costs investors can improve their Sharpe ratios by trading on the weather. In the first model, the returns of the sunny strategy are given almost the same weight in the mean-variance efficient portfolio as the returns of the global market portfolio. The weight on the sunny strategy returns is statistically significant, with a t-statistic of 3.39. In the second model, the mean-variance efficient portfolio is clearly short the cloudy portfolio. The t-statistics of the weight of the cloudy portfolio is -3.22. The results of the third model are somewhat ambiguous, presumably because of a high degree of multicollinearity in the regression. However, the fourth model again implies that trading on the weather can increase a Sharpe ratio. The strategy of buying the sunny portfolio and selling the cloudy portfolio is clearly a substantial part of the global mean-variance efficient portfolio.

E. Accounting for Transaction Costs

To determine whether exploiting the sunshine effect can increase a Sharpe ratio after accounting for reasonable transaction costs, we propose a strategy that requires fewer trades than the strategy described above, and we calculate the

Table VI

Tests of Weather-based Trading Strategies

This table displays results of tests of the mean-variance efficiency of a global equity portfolio. The global equity portfolio return is the equal-weighted average of local currency returns of the 26 stock exchanges in the sample. Tests are performed within the framework of Britten-Jones (1999). We estimate regressions of the form

$$1 = \beta_m r_{mt} + \beta_s r_{st} + u_t$$

where r_{mt} is the return on the global equity portfolio and r_{st} is the return to a weather-based strategy on day t. The weather-based strategies that we consider are: the sunny strategy, in which we invest an equal amount in each exchange for which morning total sky cover SKC^*_{it} is negative on day t; the cloudy strategy, in which we invest an equal amount in each exchange for which morning SKC^*_{it} is positive on day t; and the sunny–cloudy strategy, in which we go long the sunny strategy and short the cloudy strategy. Morning SKC^*_{it} is measured from 5 a.m. to 8 a.m. local time in each city on each day. A statistically significant coefficient for a return series in one of our models implies that the return series is an important component of a mean-variance portfolio. The t-statistics are in parentheses.

Model (1)	Market (2)	Sunny (3)	Cloudy (4)	Sunny–Cloudy (5)
Model 1	13.53	13.52		
	(2.92)	(3.39)		
Model 2	43.11		− 16.16	
	(7.59)		(− 3.22)	
Model 3	23.88	9.35	− 6.19	
	(1.45)	(1.24)	(− 0.66)	
Model 4	27.03			7.97
	(10.72)			(3.45)

returns to our strategy net of costs. In particular, we calculate the returns to a strategy that is long the market index of each city for which the average cloud cover variable between 5 a.m. and 8 a.m. is between zero and four, and short the city's index otherwise. Each city for which the strategy stipulates a long position receives a weight of $1/n$ (where n is the number of cities considered by the strategy) while each city for which the strategy stipulates a short position receives a weight of $-1/n$. Since the number of cloudy cities varies from day to day, this trading rule requires a positive net investment on some days and a negative net investment on other days. If the trading rule implies that the position in a particular city changes from a long to a short position or from a short to a long position, we subtract transaction costs from the return of the city on that day. After calculating the returns to this strategy for various levels of costs, we ask whether the strategy return should receive positive weight in a mean-variance efficient portfolio using the Britten-Jones test described above.

Performing the test with costs of one basis point per transaction (two points for changing a position from long to short or from short to long), the Britten-Jones test assigns a weight of 34.02 ($t = 11.20$) to the market portfolio and a weight of 20.21 ($t = 4.29$) to the weather strategy. For comparison, with no transaction costs the Britten-Jones test gives optimal weights of 36.11 ($t = 11.92$) and 26.07

($t = 5.56$) respectively. Increasing the costs to two basis points results in weights of 31.89 ($t = 10.46$) and 14.28 ($t = 4.72$), while increasing costs to three basis points results in weights of 29.73 ($t = 9.73$) and 8.32 ($t = 1.76$). Costs of four basis points are associated with optimal weights of 27.54 and 2.33, and costs of five basis points make trading on the sunshine effect unprofitable. Thus, trading on the sunshine effect could improve the Sharpe ratio of an investor's portfolio only if the costs of index trading were four basis points or less per transaction.

Although different types of investors may face different costs, we can approximate the costs involved in trading one S&P 500 index futures contract with some conservative back-of-the-envelope calculations. The transaction costs associated with trading in the U.S. market are modest, on the order of one basis point per transaction.[7] However, the costs associated with trading other market indices may be significantly higher.[8] Thus, trading on the sunshine effect may have been profitable for very low-cost traders, but it is not at all clear that it was profitable for most investors.

IV. Conclusion

Psychological evidence and casual intuition predict that sunny weather is associated with upbeat mood. This paper examines the relationship between whether a day is sunny and stock returns that day at 26 stock exchanges internationally from 1982 to 1997. We find that sunshine is highly significantly correlated with daily stock returns. After controlling for sunshine, other weather conditions such as rain and snow are unrelated to returns. An investor with very low transactions costs would have improved on the Sharpe ratio of the market portfolio, though somewhat modestly, by trading on the weather. However, because weather strategies involve frequent trading, fairly modest transaction costs eliminate this benefit. Nevertheless, the sunshine effect on stock returns is hard to reconcile with fully rational price setting.

Well-known patterns of return predictability, such as size and value effects, have been interpreted by some as indicating market inefficiency. However, others have attempted to rationalize stock price patterns as resulting from risk premia instead of psychological effects. This study offers some evidence that is tough to rationalize. The evidence is not a result of data snooping—the psychological hypothesis is the stimulus for exploring sunshine effects. There is no very appealing rational explanation for why a day of sunshine near a country's stock exchange should be associated with high returns on a national market index, nor why

[7] Huang and Stoll (1997) find that brokerage commissions for trading one S&P futures contract are generally less than \$25 per contract for institutional clients. Manaster and Mann (1996) find that the bid–ask spread that S&P 500 futures customers typically pay is \$4.33, so we estimate total costs of trading as \$30 per contract. Each contract's notional value is \$250 times the level of the index, which is currently close to 1,200. Thus, the notional value of one contract is approximately \$300,000 and the cost of trading one S&P 500 futures contract as a fraction of the contract's value appears to be approximately one basis point.

[8] However, Boudoukh et al. (2000) describe how individuals can trade between some international stock indices and money markets in open-end mutual fund families at essentially zero cost.

morning sunshine should predict subsequent returns. This evidence is, however, consistent with sunlight affecting mood, and mood affecting prices.

We think the main practical implication of our findings is somewhat less direct than the trading strategies discussed above. Our results suggest that investors can benefit from becoming *aware of their moods*, in order to avoid mood-based errors in their judgments and trades.[9] A useful direction for future experimental research will be to examine the effects of mood or weather on trading behavior, and the extent to which investors who are primed to attend to their moods can make better decisions.

Our findings, in conjunction with psychological literature, also suggest that it may be valuable to explore how weather or other mood proxies affect the stock market response to news events. Some of these effects can be subtle.[10] The simplest hypothesis is that good mood will make the reaction to news events more favorable. However, the evidence discussed earlier about differences in information-processing styles suggests a more mixed outcome. Individuals in bad moods, who process information more carefully, should react more strongly to truly relevant news, whether good or bad, and should be careful to avoid reacting to irrelevant pseudo-news. In contrast, individuals in good moods should be more prone to reacting to irrelevant announcements.

Recently evidence has been provided that security prices, including stock market prices, react to the salient publication of information that is irrelevant, or that is already publicly available, and that the reaction to information is affected by the form in which it is presented.[11] Psychological evidence on the effect of mood on information-processing style suggests that it would be interesting to examine whether stock market reactions to redundant or irrelevant news is greater when mood is good (e.g., weather is sunny) than when mood is bad.

Our findings also suggest some broader implications for asset pricing. Sunshine is just one of the many influences on mood. In confirming the effect of mood on asset prices, this study suggests that other mood effects may be important. For example, as discussed in Section I, negative moods tend to stimulate effort at careful analysis, whereas positive moods are associated with less critical and more receptive information processing. This suggests that after positive events have put people in a good mood, they will be more prone to accepting new theories of how the market works. The 1990s were certainly a period of positive mood in America, owing to the great success of the U.S. economy and stock market,

[9] Obviously weather is just one example of a mood-influencing factor that an investor may be able to discount for by paying attention to the sources of his mood. On a given day an individual who pauses to consider may be able to identify other influences, such as uncomfortable new shoes, a broken air conditioner, the triumph of a child in school or of a popular local sports team, news of a promotion at work, or of the nation's victory or defeat in war.

[10] We are grateful to Norbert Schwarz for insightful comments in this regard.

[11] See Ashton (1976), Ho and Michaely (1988), Hand (1990), Klibanoff, Lamont, and Wizman (1998), Andrade (1999), Avery and Chevalier (1999), Cooper, Dimitrov, and Rau (2001), Huberman and Regev (2001), and Rashes (2001). There is both experimental and capital markets evidence on accounting information in particular (see, e.g., Ashton (1976), Maines and McDaniel (2000), and Dietrich et al. (2001), and the review of experimental research of Libby, Bloomfield, and Nelson (2001)).

along with U.S. predominance as the sole world superpower. It is tempting to conclude that this positive mood made investors more receptive to "new economy" theories of the world, resulting in an Internet bubble.

A possible explanation for momentum in individual stock returns is that low returns on a stock put the investor clientele of that stock in a negative, critical mood. This bad mood in turn may cause skeptical and pessimistic interpretation of subsequently arriving information. There is evidence that people have trouble foreseeing their future moods and how this will affect their future behavior (a phenomenon known as projection bias; see, e.g., Loewenstein, O'Donoghue, and Rabin (2000) and the discussion in Mehra and Sah (2000)). This suggests that after bad news people will not fully foresee their negative interpretation of future information, causing a tendency toward continuation of the drop in price. These speculations about momentum and overreaction deserve further study. But there are other possible hypotheses that can be explored. The broadest message of this paper is that to understand security price movements, it is important to go beyond the behavior of prices and fundamentals to study what influences investor moods and emotions.

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