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# Reassessment of the Weather Effect: Stock Prices and Wall Street Weather

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## Introduction

Sunshine affects mood and mood can shape behavior. It is then plausible to test if weather is related to economic outcomes, such as market return. The 'weather effect' is documented by some, Saunders (1993) and Hirshleifer and Shumway (2003), and claimed an exercise in data mining by others, Kramer and Runde (1997). In the paper that follows, I study the relationship between weather and equity prices over time using various measures of the change in weather and market return.

To test the hypothesis that sunshine affects stock returns, I use simple regressions to examine the relationship between daily cloudiness, the inverse of sunshine, of New York City and the return on the Dow Jones Industrial Average index. For the time period of 1948 to 2010, there is a negative relationship between average cloudiness and DJI gross simple return. After controlling for market anomalies, such as the January and the weekend effects, a change in weather from sunny to overcast skies is associated with an additional .79 percentage point decline in gross return ($t$-statistic = -2.81). So the weather effect seems to exist for this time period in New York City. On sunny days, investors feel more optimistic and more willing to invest in risky assets; this change in behavior leads to higher stock prices. However, if the same simple regression is used to study 30 year sub-samples at a time, although the estimated coefficient on average cloudiness is negative for all periods, the relationship between cloudiness and market return is statistically insignificant for some sub-samples. To analyze whether the sunshine effect is robust over time, I measure the return difference between good and bad weather days for each year and study its evolution over time. Once the volatility of this difference in returns variable is reduced by computing its moving average, it is positive for almost all years and slightly increasing over the past 50 years. So the market return is higher on

good weather days, defined as exceptionally sunny days, than on bad weather days, defined as exceptionally cloudy days. This difference in returns is strongly persistent and increasing for periods such as 1975 to 1980 or the late 1990s; for other sub-samples, namely 2000 to 2008, the difference in returns of sunny vs. cloudy days is sharply decreasing.

One possible explanation for the rise and fall of the sunshine effect over time is the entry of small investors into the market during periods in which equity investment attracts popular attention. These non-professionals' misattribution of good mood on sunny days extends to their investment decision-making process more so than professional investors allow for such a psychological bias. Hence the weather effect is more pronounced for certain years, specifically those periods for which the market is not dominated by perfectly rational investors. This finding supports the theoretical argument of Mehra and Sah (2002) that investors' feelings have a significant effect on equity prices. Furthermore, the increase of the weather effect for certain time periods provides empirical evidence for the 'limits to arbitrage' argument made by Barberis and Thaler (2002): equities can remain mispriced, due to the actions of a small subset of investors, even if arbitrageurs suspect mispricing.

The overall implication of these results is that there is a significant relationship between weather and stock prices; this relationship exhibits a cyclical pattern over the past half-century. Thus, depending on the years under study, a researcher may find a significant relationship between weather and stock prices or may find insignificant results and label the weather effect "an exercise in data mining." However, I conclude that extreme and intermediate weather changes in New York City are strongly correlated with within day DJI return.

## 1. Related Literature

Recent research in behavioral economics, for instance Loewenstein (2000, p. 426), argues that emotions 'propel behavior in directions that are different from that dictated by a weighing of the long-term costs and benefits of disparate actions.' One area of decision-making where emotions and feelings are relevant is in equity pricing. Behavioral finance researchers have recently begun to investigate whether investors' emotions influence their decision-making and if such an impact on behavior has significant economic outcomes. One area of research, pertinent to the topic of this paper, is mood misattribution. This area considers the effect of environmental factors, such as weather and social settings, on equity pricing. This literature suggests that supposedly rational investors are affected by feelings, which are at times induced by unrelated events in their surroundings, and the effect of feelings on behavior influences investment decisions and market outcomes.

In traditional models of decision-making that involve risk and uncertainty, the decision-maker is assumed to quantitatively weigh the costs and benefits of possible outcomes and choose the one with the best risk-benefit trade-off. This 'consequentialist perspective' ignores the fact that the decision-maker is affected by feelings. Lucey and Dowling (2005) cite extensive literature that documents the influence of feelings on decisions, especially risky ones. In light of such studies, improvements have been made to the traditional model to account for the impact of anticipated emotions, or emotions experienced by the decision-maker conditional on the perceived outcome. However, even this advancement to the model ignores the impact of the current emotional state of the decision-maker. Therefore, Loewenstein *et al.* (2001) developed the 'risk-as-feelings' model to incorporate peoples' current emotions and feelings into the decision-making process. They establish the relevance of feelings to the decision-making process

by making three basic assumptions. They argue that cognitive evaluations induce emotional reactions: emotions are 'considered by most contemporary theories to be postcognitive, that is, to occur only after considerable cognitive operations have been accomplished' (Zajonc, 1980, p. 151). Conversely, emotions inform cognitive evaluations: people in positive moods make more optimistic choices and people in negative moods make more pessimistic choices (Johnson and Tversky, 1983). Finally, Loewenstein *et al.* (2001) argue that feelings can affect behavior. Through these assumptions, they arrive at their model. The three decision-making models are illustrated in Figure 1: the traditional consequentialist model, the anticipated emotions model, and the risk-as-feelings model.

If decision-making processes which involve risk and uncertainty are affected by feelings, then it is certainly true that investors, who are constantly engaged in assessing risky opportunities, are influenced by feelings. One may ask, however, whether the effect of feelings equates to changes in equity pricing. It could be possible that individual investors make suboptimal decisions due to mood misattribution, but rational market forces, such as arbitrage, ensure that fundamentals are accurately priced. Mehra and Sah (2002), however, provide support for significant economic outcomes as a result of decisions that are affected by feelings. According to Mehra and Sah (2002), investors' feelings affect equity prices if:

1. Investors' 'subjective parameters' (level of risk aversion, judgment of appropriate discount factors, etc) fluctuate over time due to changes in mood;
2. The effects of these changes in mood are widely and uniformly experienced by market players;
3. Investors do not realize that their decisions are being influenced by such mood fluctuations.

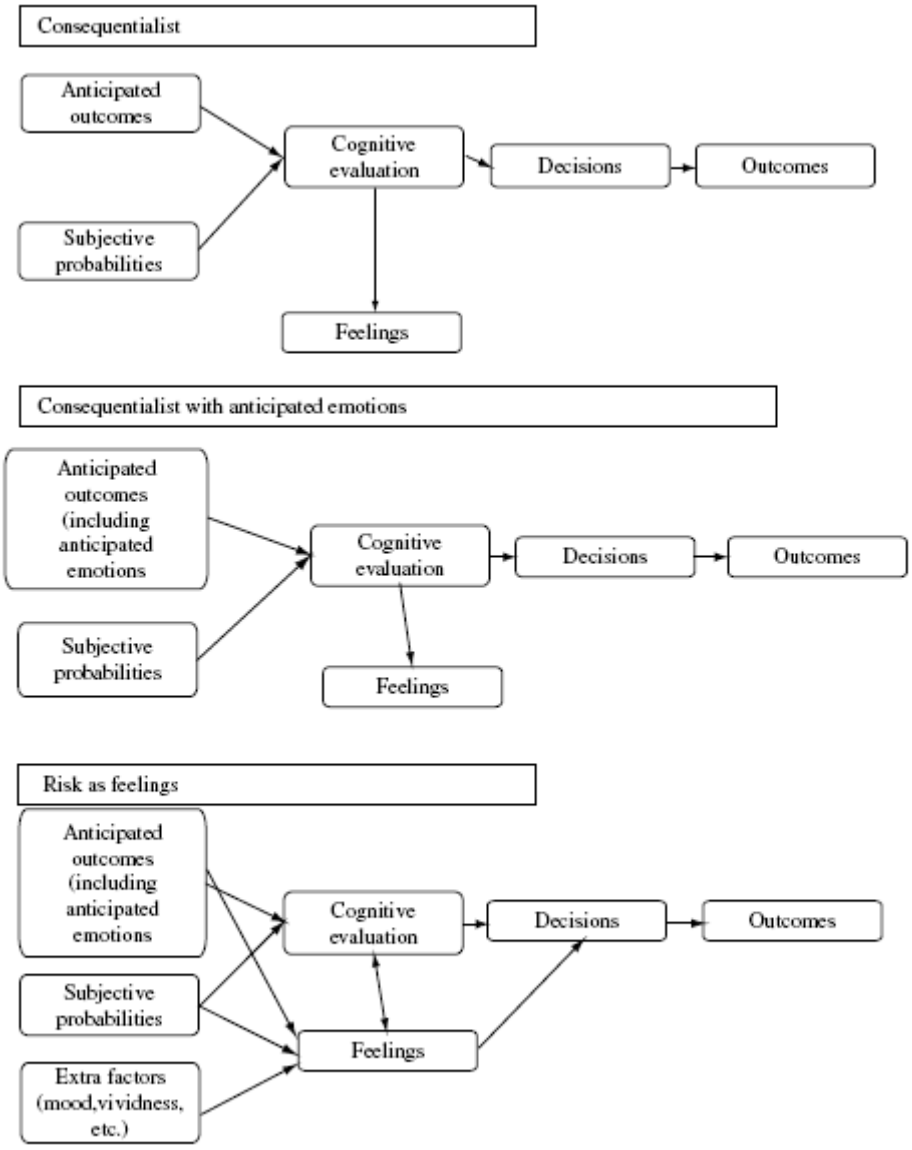



**Figure 1.** Adapted from Loewenstein *et al.* (2001)

This gives rise to the question: if the above conditions hold only for a subset of investors, are equity prices still affected by mood fluctuations? The traditional view has been that even if some investors misprice equity, informed and rational market participants will arbitrage the mispricing away. However, Barberis and Thaler (2002) point to the 'limits of arbitrage' and argue that equities can remain mispriced even if arbitrageurs suspect mispricing' and this mispricing can occur as a result of the actions of only a small subset of investors.

Based on the above discussion, fluctuations in mood influence the decision-making of investors which can affect the equilibrium stock prices. Furthermore, Schwarz and Clore (1983) document how mood can inform decisions even when the cause of the mood change is unrelated to the decision being made. This 'mood misattribution' has encouraged behavioral finance researchers to investigate whether factors that determine mood but are irrelevant to the pricing of fundamentals affect equity investment decisions.

One such determinant of feelings is sunlight. Psychology literature has long established sunshine to affect mood and feelings. From the traditional efficient market perspective, since sunlight affects the weather, it may also affect agricultural and construction industries. The market will then adjust to this 'exogenous variation' accordingly. However, in modern capitalistic economies, agriculture plays a small role and should not affect the price of a stock index, especially if such an index is not composed primarily of weather-related industries. Also, sunshine that occurs in one particular location is not representative of the weather in the entire economy. On the contrary, the risk-as-feelings model predicts that when the sun shines, people are more optimistic and, hence, more inclined to buy stocks. They incorrectly attribute their good mood to positive economic prospects rather than good weather. The effect of hours of sunlight on investors' feelings meets the three requirements proposed by Mehra and Sah (2002): unknown uniform mood fluctuations over time experienced by a large group of people. Hence investors' mood fluctuations induced by sunshine can in turn affect equity pricing; this suggests that sunshine is positively correlated with stock returns.

Saunders (1993) examines whether there is a relationship between local New York City weather and daily changes in New York-based equities. Specifically, Saunders' hypothesis is that negative mood effects of bad weather, which he defines as cloudy days, result in lower stock

prices and the positive mood effects of good weather, or clear days, result in higher stock prices. Based on the matching of a cloud-cover variable to daily data for the Dow Jones Industrial Average from 1927 to 1989 and value-weighted and equal-weighted NYSE/AMEX indices for 1962 to 1989, Saunders (1993) finds a significant relationship between the level of cloud-cover in New York City and stock prices. This estimated effect of local weather on stock prices is robust with respect to market anomalies such as the January, weekend, and small-firm effects.

Hirshleifer and Shumway (2003) study whether psychological biases affect stock returns on a more global scale. They study 26 international financial centers from 1982 to 1997. Using panel data rather than a long time series, they test for the sunshine effect throughout the entire world. The research deseasonlizes cloud-cover to avoid identifying a relationship between the market return and cloud-cover that may be due to other seasonal affects. Using more sophisticated methodology than simple regressions, their results show that 18 of the 26 cities have a negative sign on the coefficient measuring the relationship between cloud-cover and the equity index return, and four of the cities have a significant negative relationship. Thus Hirshleifer and Shumway (2003) conclude that days with high cloud-cover are associated with lower return, even once adverse weather conditions, such as rain and snow, are controlled for.

Other studies have been done to further understand the weather effect. Goetzmann and Zhu (2002) investigate the weather effect for a particular group of agents in the market. These researchers use a database of trading accounts of approximately 80,000 investors from 1991 to 1996 to understand whether investors trade differently based on the weather. Their analysis of trading activity in five major U.S. cities finds no difference in individuals' propensity to buy or sell equities on cloudy days as opposed to sunny days. This suggests that the weather effect is caused by market participants other than individual traders, such as market-makers, news

providers, or other agents physically located in the city of the exchange. Specifically, they find NYSE spreads widen on cloudy days, suggesting that the behavior of market makers is related to the weather with greater bid-ask spreads (greater risk aversion) for cloudy days.

The most recent work on this topic is a paper by Symeonidis *et al.* (2008) which investigates the impact of weather on stock market volatility. This research uses the same data set as Hirshleifer and Shumway (2003), for which the weather effect is empirically evident, and finds historical volatility estimates to have a negative relationship with sunshine. The researchers argue that weather may affect volatility by increasing the diversity of opinions amongst traders regarding the true value of assets. They conjecture that investors belong to one of two groups: Investors are either 'rational,' as assumed in the Efficient Market Hypothesis, or 'behavioral,' as assumed in the risk-as-feelings model. To the extent that weather affects the mood of behavioral investors, excess volatility will result from a divergence of opinions among the two groups of investors.

In converse to the studies mentioned above which all, in one way or another, confirm the weather effect, the relationship between market return and the weather is not confirmed in two studies by Kramer and Runde (1997) and Trombley (1997). Kramer and Runde (1997) analyze the return on a German stock index which was traded exclusively on the Frankfurt stock exchange from 1960 to 1990. They find any weather effects to be nonrobust with respect to the way that data is classified; both a positive and a negative weather effect can be established depending on the test procedure used. Trombley (1997) uses the same data as Saunders (1993) to illustrate that the conclusions drawn by Saunders (1993) are not robust to alternative definitions of the cloud-cover variable and the choice of which return to compare.

This paper reassesses the weather effect in an attempt to consolidate the current findings on whether environmental factors, such as hours of sunshine, which influence investor mood, can systematically affect stock prices.

## 2. Data

To examine whether stock returns and the weather are correlated, I use two data sets: one contains weather information for New York City and the other pertains to the market return. I gather weather data from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (www.ncdc.noaa.gov). Specifically, I use the *Integrated Surface Data* recorded from LaGuardia, New York City, since this station is the one physically closest to Wall Street. This data set contains information on various meteorological variables, such as temperature, precipitation, wind, and cloud-cover, from 1948 to 2010. Previous research done on influential weather variables has established 'hours of sunshine' as the most significant predictor of mood[1]. Since hours of sunshine are inversely related to the presence of clouds, and also to be consistent with previous research, I use cloud-cover measures in constructing a variable that approximates daily sunshine levels. Cloud-cover ranges from 0 for clear skies to 8 for overcast. Prior to 1972, all observations were recorded on the hour or every 3 hours; the recent data includes many more observations for overcast days. Thus, to avoid over sampling of days with worse weather, only observations that are recorded 9 minutes before the hour or on the hour are used. This greatly improves the quality of the data by eliminating clustered and redundant observations. I measure cloudiness in two ways: I calculate the simple average of cloud-cover for each day and I define an extreme weather variable to distinguish completely clear days from

[1] Persinger (1975) and Cunningham (1979) find that number of hours of sunshine is inversely correlated to negative mood. Howarth and Hoffman (1984) find "cynical, doubting outlook," or skepticism, is inversely related to hours of sunshine: Across eight weather variables, hours of sunshine was the one significant variable for predicting optimism scores.

days with severe weather. This variable is equal to -1 for clear days, 1 for overcast days, and 0 for days with intermediate weather. This extreme weather variable is meant to capture the possibility that differences in returns for intermediate weather changes are rather small. Saunders (1993) contributes almost all of the lower return on cloudy days to the two extreme cloud-cover groups by pointing out that partially cloudy days are not particularly depressing.

To measure market performance, I collect the daily index return of the Dow Jones Industrial Average (DJI) using Yahoo! Finance (www.finance.yahoo.com). From July 1, 1948 to March 31, 2010, I compute the daily gross simple return to keep consistent with earlier studies. I also calculate the 24-hour return, in natural logarithm, as the difference between today's closing price and the previous day's closing price. Additionally, I compute within day and overnight return: within day return is the difference, in natural logarithm, between today's closing price and today's opening price and overnight return is the difference between today's opening price and the previous day's closing price, again in natural logarithm. The sum of these two measures gives the 24-hour return, defined earlier as the difference in closing prices, or the close-to-close return.

Furthermore, I measure the return difference between good and bad weather days as follows. To deseasonalize the weather data, I calculate the average weather for each month throughout all years and measure the residual weather for each day relative to this average. Then for each year, I calculate two measures of return using the close-to-close return: one for days with unusually cloudy weather, or days in the $90^{th}$ percentile of extremely cloudy days, and one for days with unusually sunny weather, or days in the $90^{th}$ percentile of extremely sunny days. Finally, for each year, I compute the difference of these two returns, or the residual-difference, to

measure how much higher the return is on exceptionally sunny days as opposed to the return on exceptionally cloudy days.

## 3. Evidence and Discussion

To proceed with testing the hypothesis that local weather and stock returns are correlated, I first replicate the results of earlier studies that find such a relationship. I then proceed to consider the evolution of this effect over time. Additionally, I study the robustness of the weather effect using various measures of return. Finally, I examine whether the driving force behind this relationship is extreme weather or daily weather changes.

### A. Replication of Earlier Results

I estimate a simple regression, similar to Saunders (1993), of the following form:

$$R_t = \beta_0 + \beta_1 C_t + \beta_2 R_{t-1} + \sum_{t=1}^{t=11} \tau_i M_{it} + \sum_{t=2}^{t=5} \delta_i D_{it} + \varepsilon_t$$

in which $R_t$ is defined as the gross return of the DJI on day $t$, $M$ is a month dummy, with December omitted, $D$ is a day-of-the-week dummy, with Friday omitted, $C$ is the average cloud cover variable, and $\varepsilon$ is the error term. The lagged return variable $R_{t-1}$ is included to control price movement persistence. Day and month dummies are included in the regression to control for seasonal and day-of-the week anomalies. The results in Table 1 report the ordinary least squares estimates of some of the coefficients in the above regression. The second column of Table 1 reports estimates for the entire time period; the third column reports the estimates for a smaller window of time, specifically for the years 1962 to 1989. I find that New York City cloud cover is significantly correlated with the DJI return even after seasonal effects are controlled for. These results mirror the findings of Saunders (1993), especially for the sub-sample of 1962 to 1989, which Saunders also analyzes. The coefficient estimates, standard errors, and $t$-statistics are almost identical to the ones found by Saunders (1993).

**Table 1 - Significant Parameter Estimates for Regressions on Daily Gross Return of DJI: NYC, 1948-2010**

| | 07/1/1948 - 03/31/2010 | 01/01/1962 - 12/31/1989 |
|---|---|---|
| Explanatory variable | DJI | DJI |
| Lagged return | 0.026980*** | 0.097700*** |
| | (3.36) | (8.23) |
| May | -0.00077** | -0.001168** |
| | (-2.18) | (-2.30) |
| Monday | -0.000928*** | -0.001623 |
| | (-4.10) | (-4.89) |
| Cloud cover | -0.000087*** | -0.000092** |
| | (-2.81) | (-2.10) |
| Number of observations: | 15531 | 7041 |
| Adjusted R-squared: | 0.003 | 0.02 |

*Notes*: Cloud-cover data are from National Climatic Data Center, DJI data are from Yahoo! Finance. The dependent variable is daily percentage change in the index; *t* statistics are given in parentheses.

** Significant at the 5% level.

*** Significant at the 1% level.

Additionally, results from Hirshleifer and Shumway (2001) can be replicated by considering data from 1982 to 1997. In simple regressions of their city-by-city tests, although statistically insignificant, they find a negative estimated coefficient on cloud-cover for New York City. For this sub-sample, I estimate the parameter on cloud-cover to be -.00010 with *t*-statistic (-1.60). A discussion of why the weather effect is statistically insignificant for this period follows below.

## B. Weather Effect Over Time

Although the weather effect seems to influence the market return, it is worthwhile to study its persistence over time. Local New York City weather is an insignificant predictor of DJI

close-to-close return in the more recent years, 2000-2010.[2] One prediction might be that the weather effect has been declining over time. To test for the linear decrease of the weather effect, I estimate the following simple regression:

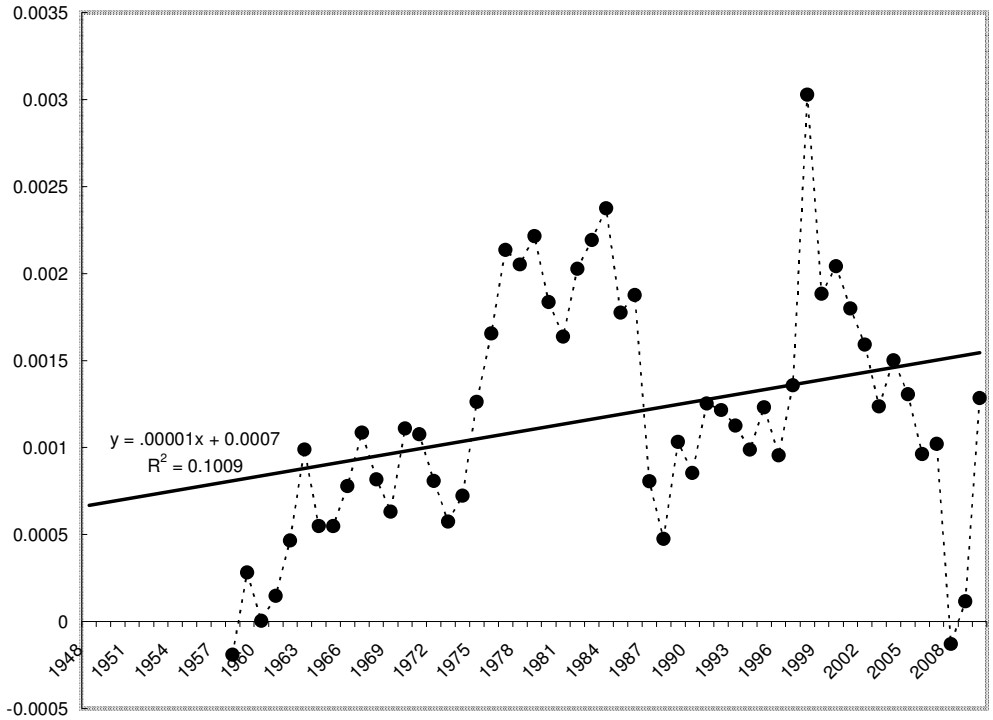
$$R_t = \beta_0 + \beta_1 C_t + \beta_2 (C_t * T) + \sum_{t=1}^{t=11} \tau_i M_{it} + \sum_{t=2}^{t=5} \delta_i D_{it} + \varepsilon_t$$

in which $R_t$ refers to close-to-close return and a positive coefficient on the interaction of time and cloud-cover, $C_t*T$, allows for $\beta_1$ to approach 0 as time passes. The estimated coefficient on the interaction term is, however, very close to zero with *t*-statistic of (-.14) and, thus, insignificant. So it is not the case that the weather effect has disappeared in a linear way over time. If the main regression from Section 3A is studied separately for 30 year windows, it seems that the coefficient on the average cloud-cover variable is sometimes significant and sometimes not significant. This suggests that the weather effect is present only during particular periods.

To analyze the evolution of the weather effect over time, I use the residual-difference return variable to detect the possible patterns in the data. As described in Section 2, I deseasonalize the cloud-cover variable so that the computed weather effect excludes any contributions that cloud-cover makes to seasonal return patterns. Unusually sunny days, those in the 90$^{th}$ percentile of sunny days when compared to the monthly average, are separated from unusually overcast days, those days in the 90$^{th}$ percentile of cloudy days as compared to the monthly average. Then the respective return for each of these weather types is computed on a yearly basis. I compute the residual-difference return as the close-to-close return on good weather days minus the close-to-close return on bad weather days. To reduce the volatility of the residual-difference return, I calculate, for each year, the average of the past ten years' residual-difference return. Figure 2 shows the plot of this moving average over all years for which such

[2] A discussion for why close-to-close return is an appropriate measure of return will follow in Section 3C.

**Figure 2 - Moving Average of Residual-Difference Return of DJI: NYC, 1958-2010**




an average could be computed. The linear line which best fits the data has a slope of .000014 and *t*-statistic of (2.39), and is, thus, significant at the 5% level. It is clear from Figure 2 that the DJI return is higher on very sunny days: almost all residual-difference return averages are above zero. This result confirms the existence of a correlation between sunshine and stock returns. It is also clear from Figure 2 that there are periods of time in which the weather effect is strong and increasing and periods in which the weather effect is declining. It is interesting to point out that that the rise and fall in the weather effect over even a short span of time can have a large impact on parameter estimates. Using the close-to-close return in a simple regression, the analysis of the time periods 1975 to 1985 and 1975 to1987 result in very different estimates of the coefficient on cloud-cover. Table 2 summarizes these results. As Figure 2 shows, the weather effect is sharply declining in 1986 and 1987. As these years are added to the analysis, the estimated parameter on

**Table 2 - Parameter Estimates for Regressions on Close-to-Close Return of DJI for 2 Periods: NYC**

| Explanatory variable | DJI |
|---|---|
| Period 1: 01/01/1975 - 12/31/1985 | |
| Cloud cover | -0.000165** |
| | (-2.35) |
| Number of observations: | 2780 |
| Adjusted R-squared: | 0.004 |
| Period 2: 01/01/1975 - 12/31/1987 | |
| Cloud cover | -0.000018 |
| | (-0.23) |
| Number of observations: | 3286 |
| Adjusted R-squared: | 0.002 |

*Notes*: Cloud-cover data are from National Climatic Data Center, DJI data are from Yahoo! Finance. The dependent variable is close-to-close return of DJI; *t* statistics are given in parentheses.

** Significant at the 5% level.

cloud-cover, reported in the Period 2 panel of Table 2, becomes statistically insignificant. So in establishing a correlation between local New York City weather and the DJI return, the time period of the analysis must be given careful consideration.

The weather effect has been slightly increasing over the past half-century and there are definite patterns present in the weather effect. Saunders (1993) acknowledges that the relationship between stock price changes and weather decreases significantly for the last sub-period of his sample, form January 1, 1983 through December, 31, 1989, and this is clear from Figure 2 as well. He claims that these results may reflect the evolution of more global influences on security prices, particularly the increased importance of index futures trading in Chicago since 1982. However, this claim may be incorrect because global influences have been on the rise for the past two decades and yet there is still an upward trend seen in the weather effect throughout

the 1990s. The presence of the sunshine effect in New York City in the 1990s is also confirmed by Hirshleifer and Shumway (2003) when they estimate a significant logit coefficient on cloud-cover for the eight-year period from 1990 to 1997. Thus they reject Saunders' conclusion that the weather effect may be of purely historical interest. Figure 2 clearly illustrates that the weather effect is present even after the publication of Saunders' paper in 1993 and confirms the finding by Hirshleifer and Shumway (2003).

One possible explanation for the rise and fall in the weather effect may simply be that market trends and cyclical weather patterns match up in certain periods. Alternatively, by observing that the weather effect peaks during the 'dot-com bubble' and falls significantly during the recent financial crisis, it can be argued that the weather effect is stronger when the stock market is popular with non-professional investors who are presumably less rational than investment professionals.

**C. Various Measures of Return**

The dependent variable in Section 3A, which is used to ensure consistency with previous studies, measures the gross return within a day. I further investigate the weather effect using the overnight as well as the 24-hour return.

I estimate a similar regression to the specification in 3A:

$$R_t = \beta_0 + \beta_1 C_t + \sum_{t=1}^{t=11} \tau_i M_{it} + \sum_{t=2}^{t=5} \delta_i D_{it} + \varepsilon_t$$

in which $R_t$ is defined as either the within day return, the overnight return, or the close-to-close return defined in Section 2. Monthly and day-of-the week indicators are defined similar to the model represented by Table1. The estimates of the coefficients on the average cloud-cover variable are reported in Table 3 for all three definitions of the dependent variable. As expected, by natural log properties, the parameter estimate of the overnight return and the within day return

**Table 3 - Parameter Estimates for Regressions on Alternative Measures of Return of DJI: NYC, 1948-2010**

| Explanatory variable | DJI |
|---|---|
| Model 1 - overnight return: | |
| Cloud cover | -0.000003 |
| | (-0.48) |
| Adjusted R-squared: | 0.002 |
| Model 2 - within day return: | |
| Cloud cover | -0.000089*** |
| | (-2.87) |
| Adjusted R-squared: | 0.003 |
| Model 3 - close-to-close return: | |
| Cloud cover | -0.000092*** |
| | (-2.80) |
| Adjusted R-squared: | 0.003 |
| Number of observations: | 15531 |

*Notes*: Cloud-cover data are from National Climatic Data Center, DJI data are from Yahoo! Finance. The dependent variable varies for each model; *t* statistics are given in parentheses.
*** Significant at the 1% level.

add to give the parameter estimate of the close-to-close return. Also, since for small changes, the logarithmic function approximately calculates percentage change, it is expected that the estimates of the regression which uses the within day return, Table 3, is close to the estimates of the regression which uses percentage change of DJI, Table 1. The results of the second column indicate that New York City weather does not predict the overnight return of the DJI; on the other hand, local cloud cover is significantly correlated with within day return. Thus the correlation between local weather and close-to-close return of the DJI can be completely attributed to how weather is related to within day return as opposed to overnight return.

This finding confirms the prediction made by Hirshleifer and Shumway (2003) that it is not the news (as in weather forecasts) that the day will be sunny which causes an immediate and complete positive stock price reaction. Rather it is the occurrence of sunshine that causes prices to move. The fact that the weather effect is completely driven by the within day return, and not overnight return, suggests that it is the current weather that affects peoples' psychological state. If overnight return and stock returns were significantly correlated, a possible explanation could be that the prediction of tomorrow's weather, which is most accurate the night before, affects investor mood, and therefore their risk-taking behavior. However, it is unlikely that weather forecasts, or *predictions,* are a determinant of people's mood. Since weather and overnight return are unrelated to one another, one can conclude that it is today's occurrence of sunshine that drives the weather effect, not people's predictions about hours of sunshine.

Since within day return and close-to-close return parameter estimates are very close to one another in magnitude and overnight return is irrelevant to the study of the weather effect, I will proceed to use close-to close return in my analysis.

**D. Extreme Weather Effect**

Saunders (1993) claims that although the relationship between the weather and the market return is monotonic across all cloud-cover groups, extreme weather days affect returns considerably more. He proceeds to use only a cloud-cover variable that distinguishes 0-20 percent cloudy days from 100 percent cloudy days in his analysis; he argues that there would be little expected variation in mood on days with cloud cover between 20 and 90 percent. To test the hypothesis that it is extreme weather changes that drive the result, I define the extreme-weather variable as described in Section 2. This variable uses an ordinal scale and is designed to permit a

linear estimate of the nonlinear relationship between cloud cover and stock prices as driven by the two extreme cloud cover groups. First, I estimate the model:

$$R_t = \beta_0 + \beta_1 EW_t + \sum_{t=1}^{t=11} \tau_i M_{it} + \sum_{t=2}^{t=5} \delta_i D_{it} + \varepsilon_t$$

in which $R_t$ refers to close-to-close return, *EW* is the extreme-weather variable, and monthly and day-of-the-week indicators are included to control for seasonal anomalies. I also restrict my analysis to the period from 1962 to 1985: according to the patterns found in Section 3B, the weather effect is strongly present in this period. Thus estimates of the extreme-weather effect will not be tainted by the patterns in the weather effect over time. Table 4 reports the result of this regression in the panel for Model 1. Extreme weather changes are significantly related to the DJI close-to-close return. The Model 2 panel in this table uses the exact same regression as above with the average cloud-cover variable as the explanatory variable. The estimate on cloud-cover is higher than those estimated in previous sections. This is to be expected since the time period considered in this regression is a period with strong, and increasing, weather effects, as seen in Figure 2. The last model in Table 4, Model 3, reports estimates for the following specification:

$$R_t = \beta_0 + \beta_1 C_t + \beta_2 EW_t + \sum_{t=1}^{t=11} \tau_i M_{it} + \sum_{t=2}^{t=5} \delta_i D_{it} + \varepsilon_t$$

in which extreme-weather and cloud-cover are both used as explanatory variables. The parameter estimate on extreme-weather is not significant once daily cloudiness is controlled for: inclusion of variables that proxy extreme weather changes and intermediate weather changes in the regression results in significant estimates of intermediate weather changes and statistically insignificant estimates for extreme weather changes.

**Table 4 - Parameter Estimates for Extreme Weather Regressions on Close-to-Close Return of DJI: NYC, 1962 – 1985**

| | 01/01/1962 - 12/31/1985 |
|---|---|
| Explanatory variable | DJI |
| Model 1: extreme weather | |
| Extreme weather | -0.00059*** |
| | (-2.93) |
| Adjusted R-squared: | 0.01 |
| Model 2: average cloud cover | |
| Cloud cover | -0.00018*** |
| | (-3.83) |
| Adjusted R-squared: | 0.01 |
| Model 3: extreme weather & average cloud cover | |
| Extreme weather | 0.00008 |
| | 0.25 |
| Cloud cover | -0.00019** |
| | (-2.47) |
| Adjusted R-squared: | 0.01 |
| Number of observations | 6030 |

Notes: Cloud-cover data are from National Climatic Data Center, DJI data are from Yahoo! Finance. The dependent variable is close-to-close return of DJI; *t* statistics are given in parentheses.
** Significant at the 5% level.
*** Significant at the 1% level.

Consistent with the findings of Trombley (1997) and Kramer and Runde (1997), the estimates of the above specifications imply that careful consideration must be given to how cloudiness measures are defined in studying the weather effect. Hirshleifer and Shumway (2003) confirm that regressions of return on changes in cloudiness and regressions that replace the cloudiness variable with a variable which measures extreme weather produce similar results. Table 4 verifies that the two predictions are in fact similar: Model 1 estimates that a change from clear to overcast results in an additional .12 percentage point fall in DJI close-to-close return (.059 percent fall for a change from sunny to intermediate and .059 percent fall for a change

from intermediate to overcast) and Model 2 estimates that a change from clear to overcast will result in an additional .14 percentage point decrease in the DJI return. However, it is not evident that the weather effect is predominantly and exclusively driven by the two extreme groups of cloudiness, as Saunders (1993) has previously attributed. Inherent in using an ordinal scale of {-1, 0, 1} to categorize and distinguish the two extreme cloud-cover groups is the assumption that a change from *any level* of partial cloudiness to overcast induces the same mood change in investors as a change from sunny to *any level* of partial cloudiness. This assumption may be incorrect if one kind of change in weather, for example the change from very little clouds to overcast, has a deeper impact on investor mood than a change from very cloudy to overcast skies. So extreme weather does explain changes in stock returns; however, intermediate weather changes are also important.

## 4. Conclusion

The evidence discussed above supports previous literatures' finding that hours of sunshine in New York City has a significant correlation with stock prices. This supports the view that investor psychology does influence asset prices. If it is the case that people tend to evaluate future prospects more optimistically when they are in a good mood than when they are in a bad mood and sunshine results in better a mood, then sunnier days are associated with investors being more willing to take on risky investments, such as stocks, as opposed to less risky investments, or bonds.

The relationship between weather and market return has been slightly increasing over the past half-century. However, in long time-series analysis, since both periods of distinct growth as well as periods of decline are present, the estimates can either be significant or insignificant depending on the period which dominates. Hirshleifer and Shumway (2003) confirm the

sunshine effect using panel data. However, the analysis of panel data can be misleading since their period of study is from 1982 to 1997, a period which includes strong growth of the weather effect for New York City. The other 25 cities in their study may very well have variation over time in their respective sunshine effects; the period under study may be one characterized by a strong and increasing weather effect for those cities which they estimated to have a negative cloud-cover coefficient.

The 1990s were certainly a period of strong economic growth for America, partly due to the success of the stock market. During this period, many 'average Joes' entered the stock market to take advantage of hefty returns. These non-professional investors may be considered less rational players in the market and more likely the subject of psychological biases. This may help explain the sharp increase in the weather effect throughout the 1990s: the average investor misattributes his good mood due to sunny weather to generally favorable life prospects and is more inclined to buy stocks on sunny days. This explanation is inline with the argument made by Symeonidis *et al.* (2008) which categorizes investors as either rational or behavioral and attributes the relationship between weather and excess volatility to the differing opinions of these two groups of investors with respect to equity pricing. The 'average Joes' explanation can also help explain the conclusion made by Goetzmann and Zhu (2002) that there is no difference in individuals' propensity to trade equities on cloudy days as opposed to sunny days. Goetzmann and Zhu (2002) study investors' profiles from 1991 to 1996. During this period, many non-professionals entered the market and caused the significant increase of the weather effect. Overall Goetzmann and Zhu (2002) find no significant difference in trading patterns for sunny days as opposed to trading patterns for cloudy days because there are still many rational investors who do not misattribute their good mood to improved economic prospects. However,

the misattribution of behavioral investors, who were previously mostly absent from the market, has caused the weather effect to increase sharply in the 1990s from its previous level.

With careful consideration given to extreme, as well as intermediate, measures of daily cloudiness, it is confirmed that there is a relationship between local New York City weather and the within day return of the DJI index; for some periods this relationship is stronger than others. If exogenous measures, such as weather, that affect investor mood can predict returns in the market, an argument can be made for the inclusion of behavioral variables in asset pricing models. One direction for future research regarding the weather effect is to consider the channel, or agent, through which the weather effect operates. There should be further investigation of how the weather affects the attitudes of market makers, news providers, or other market agents that are physically located in the city of the exchange. Cloudy days are more depressing for everyone, not just investors!

## References

Barberis, N. and R. Thaler, 2002, A survey of behavioral finance, NBER Working Paper no. 9222.

Cunningham, M. R., 1979, Weather, mood and helping behavior, Quasi-experiments with the sunshine Samaritan, *Journal of Personality and Social Psychology* 37: 1947-1956.

Goetzmann, W. N. and N. Zhu, 2002, Rain or shine: Where is the weather effect? Yale ICF Working Paper no. 02-27 and SSRN.com

Hirshleifer, D. and T. Shumway, 2003, Good day sunshine: Stock returns and the weather, *Journal of Finance* 58(3): 1009-1032.

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

Johnson, E. J. and A. Tversky, 1983, Affect, generalization, and the perception of risk, *Journal of Personality and Social Psychology* 45: 20-31.

Kramer, W. and R. Runde, 1997, Stocks and the weather: An exercise in data mining or yet another capital market anomaly? *Empirical Economics* 22: 637-641.

Loewenstein, G., 2000, Emotions in economic theory and economic behavior, *American Economic Review* 65: 426-432.

Loewenstein, G., Weber, E. U., Hsee, C. K. and N. Welch, 2001, Risk as feelings, *Psychological Bulletin* 127: 267-286.

Lucey, B.M. and M. Dowling, 2005, The role of feelings in investor decision-making, *Journal of Economic Surveys* 19: 211-237.

Mehra, R. and R. Sah, 2002, Mood fluctuations, projection bias, and volatility of equity prices, *Journal of Economic Dynamics and Control* 26: 869-887.

Persinger, M. S., 1975, Lag responses in mood reports to changes in the weather matrix, *International Journal of Biometeorology* 19: 108-114.

Saunders, E. M., 1993, Stock prices and wall street weather, *American Economic Review* 83(5): 1337-1345.

Schwarz, N. and G. L. Clore, 1983, Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states, *Journal of Personality and Social Psychology* 45: 513-523.

Symeonidis, L., Daskalakis, G., and R. N. Markellos, 2008, Does the weather affect stock market

volatility? Working Paper, SSRN.com

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

Zajonc, R. B., 1980, Feeling and thinking: Preferences need no inferences, *American Psychologist* 35: 151-175.