The Weather Effect: Examining Sky Cloud Cover and Stock Returns in New York City, 1990-2018

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Abstract

Psychological evidence supports that individuals' optimistic opinions are postiviely associated with the number of hours of sunshine. Recent scholarship on behavioral finance has investigated the occurrence of mispricing in financial markets due to weather variables such as sunshine and sky cloud cover. While some concluded that significant negative relationships exist between sky cloud cover and the stock returns, others found no evidence to claim the existence of such weather effects. This paper studies the effect of sky cloud cover in New York City on the daily changes in stock returns at the New York Stock Exchange (NYSE) and Dow Jones Industrial Average (DJIA) from 1990 to 2018.

Keywords: *Psychology, The Weather Effect, Financial Market, New York City, Stock Returns*

1. Introduction

Traditional financial theory argues that the stock market is fundamentally rational and efficient, and that it only reflects economic information relevant to asset pricing (Chang and Lin 2008). The *portfolio theory* by Markowitz (2001) and the *capital-asset pricing model* (CAPM) by Sharpe (1964) conclude that when making investment decisions, investors will act rationally and will select the optimal portfolio weight by evaluating the risk-return trade-off in a mean-variance efficient framework. However, an increasing number of economists argue that this 'consequentialist' perspective is inconsistent with reality (Loewenstein and Welch 2001; Stecklow 1993). This is because such a perspective ignores the fact that decision-makers are affected by feelings (Lucey and Dowling 2005).

Psychological research has amply documented the effects of mood on judgement and decision-making and suggests that mood is an influential factor in preferences (Loewenstein 1996), cognitive process (Isen 2001), and in the integration of information (Estrada and Young 1997). Some scholars claim that certain weather variables affect individuals' mood (Baron and Bell 1976; Cunningham 1979; Schneider 1980). In particular, sunshine has been associated as a driver for positive mood. Loewenstein and Welch (2001) describe the traditional perspective of how people make decisions involving conditions of risk and uncertainty as a "consequentialist perspective." An advance in the traditional perspective has been to include the impact of anticipated emotions on decision-making. Anticipated emotions are emotions that are expected to be experienced by the decision-maker given a certain outcome. For example, it might be assumed that the decision-maker is influenced by the effect of emotions such as regret and disappointment if they experience a negative outcome—this can be seen in the model of regret developed by Loomes and Sugden (2005).

Among other things, sunshine has been linked to tipping (Rind and Strohmetz 2001), and lack of sunshine to depression (Eagles 1994) and suicide (Tietjen and Kripke 1994). Being in a good mood is also associated with holding optimistic opinions about future prospects (Hirshleifer 2001) Since stock markets are driven by future expectations, it is then plausible to examine whether various weather conditions influence equity returns. An interesting ongoing debate is whether investors are inclined to buy more stocks on a sunny day as opposed to cloudy. In fact, a relatively early study by Stecklow (1993) discovered a relationship between weather and stock returns (Bagozzi, Mahesh, and Prashanth 1999).

Stecklow (1993) estimated that by affecting an individual's mood, weather influences stock returns. He found a strong negative correlation between daily percentage change in stock returns at the New York Stock Exchange (NYSE) and the sky-cloud cover in Manhattan. This finding sparked immediate attention on Wall

*I am grateful to Dr. John C. Ham for excellent advice, supervision, and mentorship, as well as to Dr. Maximilian Mihm and the participants in my capstone seminar for helpful questions and comments.

Street. In fact, Stecklow (1993) commented in the Wall Street Journal: "Forget the January effect. A professor at the University of Massachusetts has come up with what he believes is a better indicator of when the stock market will rise or fall. Check the weather on Wall Street". Additionally, recent and rapidly expanding literature supports Stecklow's view that equity returns are associated with behavioral factors as a result of weather effect. These include Hirshleifer and Shumway (2003) and Symeonidis and Markellos (2010). While some have found no clear association between weather and stock returns (Goetzmann and Zhu 2005), others have rejected Stecklow's claims (Trombley 1997; Krämer and Runde 1997). This literature has been discussed in the next section in detail. Clearly, the question as to whether investors' mood and weather variables such as sky cloud cover affect the stock market return is an ongoing debate. In this paper, we study the relationship between weather and equity prices over time using recent available data from 1990 to 2018. By comparing multiple regressions, we examine if the weather effect persists or if it is, rather, a one-time phenomenon.

We hypothesize that the weather effect as proposed by Stecklow (1993) should not exist or should decrease over time. This paper tests the null hypothesis that stock prices from exchanges from New York City have not been systematically affected by local weather against the alternative hypothesis that stock prices from exchanges from New York City have been systematically affected by local weather. Stecklow (ibid.) studied the effects of weather on stock returns for the time period 1927-1989. Since 1989, the stock market in the US has seen several technological advancements with the use of algorithmic and computerized trading (Hendershott and Menkveld 2011). Furthermore, the market participant has also included more investors across countries i.e. NYSE trading orders come from across the US as well as around the world. Hence, the weather in Manhattan should not at best predict the stock market returns in the present time.

To test our hypothesis that the weather effect must be decreasing over time, we use simple linear regressions in order to examine the relationship between the daily cloudiness of New York City and the return on New York Stock Exchange (NYSE), and Dow Jones Industrial Average (DJIA). We regress daily stock return on the sky cloud cover for varying time-periods and compare the coefficient of multiple regressions.

To contribute to the existing literature, we extend our time period until November 2018. The rest of the paper is organized as follows: Section 2 provides a review of the literature, followed by the description of data and the research methodology adapted for this study in Section 3. The results have been reported in Section 4. Section 5 discusses these findings and our conclusions.

2. Literature Review

Many scholars support the association of weather variables with investors sentiments thereby dictating trading behaviors. Stecklow (1993) studied whether the daily cloudiness in New York City affects the market returns in NYSE. He tested the null hypothesis that stock prices from exchanges in New York City have not been systematically affected by local weather against the alternative hypothesis that stock prices have been systematically affected by local weather. By examining correlations among different weather variables, he identified cloud cover as the primary explanatory variable. By matching the cloud-cover variable to the daily return for the Dow Jones Industrial Average from 1927-1989 and value-weighted and equal-weighted NYSE/AMEX indices for 1962-1989, he found a significant negative correlation between the daily cloudiness in Manhattan and equity returns. The findings are robust with market anomalies such as the January and weekend effects.

Similarly, Hirshleifer and Shumway (2003) found supporting evidence of a negative correlation between cloud cover and stock return by extending the research on a more global scale. Using panel data, they examined 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. Their study de-seasonalized cloud-cover to avoid any results driven by seasonal effects. Using sophisticated methodology other than simple regressions, they conclude that 18 of the 26 cities have a negative correlation between cloud cover and the stock returns, out of which four cities were found to have a significant negative relationship.

Likewise, a study on weather effects on the returns and volatility of the Shanghai stock market conducted by Kang and Yoon (2010) found that the weather effect exists in the A-class share returns but does not exist in the B-class share returns over the period January 1996 to December 2007. Furthermore, they also found that the weather effect has a strong influence on the volatility of both classes' share returns.

The research mentioned above confirm the weather effect in one way or the other. However, some researchers tend to disagree with the findings mentioned above. They have asserted that either there is no cloud effect, or that the effect is negligible and can be ignored. For instance, Goetzmann and Zhu (2005) did not identify any weather effect. They used a database of trading accounts of approximately 80,000 investors from 1991 to 1996 to comprehend if the individual investor's propensity to buy-sell differs as a result of weather effect for a particular group of agents in the market. Their study finds no difference in individual's propensity to buy or sell equities on cloudy days as opposed to sunny days. This suggests that the weather effect is primarily a result of the market-participants such as market-makers, news providers or other agents physically located in the city of exchange rather than individual investors.

Similarly, Trombley (1997) re-assessed Stecklow's work by using the multiple range test developed by Duncan (1975) for each of the three stock indices over three separate time periods. He concluded that there is no difference between NYSE stock returns on clear sunny days, full-cloudy days, or rainy days.

The Shanghai Stock Exchange (SHSE) divides its stock market into a domestic board (A-class share) and a foreign board (B-class share). Most of the ownership of A-class share is restricted to residents of domestic investors, while that of B-class share is restricted to foreign investors. Stecklow (1993) observations appear in only one of the three periods examined, and the effect is limited to only few months of the year.

Similar empirical results were found by Krämer and Runde (1997) for the German DAX stock index. They used daily returns for the German stock returns from 1960 - 1990 and the local Frankfurt weather to examine if the weather effect dictates the market returns. By using a similar methodology as Stecklow (1993), they concluded that there exists no relationship between the local cloudiness in Frankfurt and the DAX returns. Similarly, Pardo and Valor (2001) and Tufan and Hamarat (2004) find similar results for the Madrid stock index, and the Istanbul stock exchange respectively. This suggests that the weather effect might not be universal as suggested by Hirshleifer and Shumway (2003). This paper tries to establish if stock market returns in Wall Street can be explained by the local cloudiness in Manhattan by using similar methodology as Stecklow (1993), but with recent data from 1990 to 2018. The paper studies if the weather effect still persists in the modern era of algorithmic trading and a diverse pool of global investors and examines the 'efficient market hypothesis' in the financial market.

3. Data and Methodology

We collect weather data from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (www.ncdc.noaa.gov) Precisely, we use the Integrated Surface Data recorded from the Laguardia, New York City (Station number 14732) because this station is physically closest to Wall Street. This dataset contains information on various meteorological variables, such as temperature, humidity, precipitation, the sky cloud-cover etc. from 1990-2018. The observations about the meteorological variables are collected hourly. As expected, high precipitation, and rain is strongly correlated with fully obscured sky. Hours of sunshine are strongly correlated with the absence of cloud cover. Humidity and cloud cover are almost perfectly correlated to each other.

Since our paper is a direct extension to that of Stecklow, the variable of interest is total sky cover. We collect the ISD variable that measures the total sky cover (SKC). The amount of sky cloud cover is measured in terms of oktas ranging from 0 oktas to 8 oktas i.e. sky conditions are estimated in terms of how many eighths of the sky is covered in cloud. A zero okta represents a completely clear sky whereas an eight okta signifies that the sky is overcast. The dataset does not explicitly record the measure of sky cloud cover. Rather ISD categorizes the sky conditions based on oktas. The categorical variables collected were: CLR (0 oktas), FEW (1-2 oktas), SCT (3-4 oktas), BKN (5-7 oktas), OVC (8 oktas). CLR refers to a clear sky while OVC refers to a completely obscured sky. FEW, SCT and BKN denotes intermediate states of the sky cloud cover labelled few clouds, scattered clouds and broken clouds respectively. There were also entries labelled OBS and POB referring to obscured and partially obscured sky conditions due to poor visibility. We drop all such 123 such observations to improve the quality of the data.

We calculate the average cloud cover for each day from 9 AM to 5 PM in New York City to account for the trading hours. To do so, we assign numeric values to the hourly categorical variables obtained from the ISD. We assign CLR = 0, FEW = 1, SCT = 2, BKN = 3, and OVC = 4. Then, we find the average for each day using these values. Finally, to distinguish the cloudiness we use dummy variables for each category. There was a total of 10,531 intra-day periods. However, to account for the days corresponding to the trading days, we omit the weekends and any other days when trading did not occur on Wall Street. After the omission, the number of observations was reduced to 7268.

To measure the market performance, we collect the daily index return of the New York Stock Exchange (NYSE), and Dow Jones Industrial Average (DJIA) from yahoo finance. We, then, compute the daily percentage changes in gross returns from January 1st 1990, to November 1st 2018 for each stock index using the closing price.

3.1. Empirical Specification

To proceed with testing the hypothesis that local weather and stock returns are correlated, first we estimate a simple regression model similar to that used by Stecklow (1993) of the following form:

$$R_t = \beta_0 + \beta_{Cloud} * Cloud + \sum_{2}^{6} \beta_{day} * D_{day} + \sum_{2}^{12} \beta_{month} * D_{month} + u \quad (1)$$

R_t is defined as the percentage daily change in gross returns of the NYSE and DJIA on each trading day t; Dday is the day dummy with Monday omitted,and D_{month} is the month dummy with January omitted from the regression. The variable Cloud takes three values -1, 0 and 1 where -1 denotes completely clear sky, 1 denotes a completely obscured sky while 0 denotes intermediate states. Stecklow's model assumes the effect of cloud cover to be linear across the three states in cloud cover variable. The model assumes that a change from any level of partial cloudiness to overcast generates the same effect on investors' mood.

Likewise, the model also assumes that the effect is same on investor when a state in sky cloud cover condition changes from sunny to any level of partial cloudiness. These assumptions are not plausible because intermediate or partial cloudiness in the sky could actually have no effect on investor's moods when compared to the overcast days. Hence, to improve the model, we create a dummy variable to denote each intermediate cloud cover state from the others. We do this in two steps:

First, we use three dummy variables to denote each clear, intermediate and obscured sky conditions. I group all the intermediate states into one single group:

$$R_t = \beta_0 + \beta_{C_{minus1}} * C_{minus1} + \beta_{C_{zero}} * C_{zero} + \beta_{C_{one}} * C_{one} + \sum_{2}^{6} \beta_{day} * D_{day} + \sum_{2}^{12} \beta_{month} * D_{month} + u \quad (2)$$

C_{minus1}, C_{zero} and C_{one} are the cloud cover measure denoting each of the three dummies. C_{minus1} equals 1 for clear sky condition, and 0 otherwise. Similarly, C_{one} equals 1 for obscured sky condition, 0 otherwise. Finally, C_{zero} equals 1 for intermediate sky condition, and 0 otherwise.

To improve the model 2, we further distinguish each of the intermediate states in sky conditions using two more dummies. We use the following model:

$$R_t = \beta_0 + \beta_{CLR} * D_{CLR} + \beta_{FEW} * D_{FEW} + \beta_{SCT} * D_{SCT} + \beta_{BKN} * D_{BKN} + \beta_{OVC} * D_{OVC} + \sum_{2}^{6} \beta_{day} * D_{day} + \sum_{2}^{12} \beta_{month} * D_{month} + u \quad (3)$$

- R_t is daily percentage change in stock returns for NYSE and DJIA respectively;
- D_{CLR} = 1, if *avg_skycondition* = 0, and D_{CLR}= 0, if otherwise;
- D_{FEW} = 1, if 0 < *avg_skycondition* <= 1.5, and D_{FEW} = 0, if otherwise;
- D_{SCT} = 1, if 1.5 < *avg_skycondition* <= 2.5, and D_{SCT} = 0, if otherwise;
- D_{BKN} = 1, if 2.5 < *avg_skycondition* <= 3.5, and D_{BKN} = 0, if otherwise;
- D_{OVC} = 1, if *avg_skycondition* >= 3.5, and D_{OVC} = 0, if otherwise;
- D_{day} is a day-of-the week dummy variable with Monday omitted;
- D_{month} is a month dummy variable with January omitted.

Even if the weather effect is prevalent, it is plausible that these effects were prominent in some year while less prominent in others. Hence, to test this, we run regression models (1), (2) and (3) in four stages for both NYSE and DJIA stock indices respectively. First, we run above regressions for the entire time period from 1990 to 2018 to note the effect of certain cloud cover measures when compared against the overcast days. We then remove the observations during the era of financial crisis of 2007-2008. We do this mainly to get rid of any abnormal stock returns that occurred as a result of crisis. We perform the regression analysis for pre-crisis period as well as post-crisis period.

4. Findings

4.1. Baseline Results

Table 1 presents the summary statistics. After dropping for the weekends and holidays, we have a total of 7,268 observations. The *avg_skycondition* is a continuous variable obtained by averaging the categorical variable for different states of sky condition with a mean of 2.281 and a standard deviation of 1.284.

The dot com bubble did not affect NYSE and DJIA as much as it did on NASDAQ. Hence, I do not exclude period of dot com bubble during my study. Gross returns on NYSE and DJIA are multiplied by a scalar 100 for convenience. This does not alter any findings. On a total intraday trading period between 1990 – 2018, NYSE dropped the most by 9.7% while DJIA decreased by 7.8%. Similarly, NYSE and DJIA gained most by 12.22% and 11.08% during this period.

From the summary statistics table, it can be observed that 10% of the time, the sky is fully clear while 22% of the time the sky is completely covered with clouds. It highlights the flaw of the model that assumes the cloud cover to be linear.

4.2. Regression model 1

In table 2, we explore the relationship between NYSE stock returns and the cloud cover measure (C) for different time periods. Table 3 follows the regression from the same model for DJIA stock returns.

From Table 2, without controlling for sample period, we observe that on average, a unit change in sky cloud cover (C) is associated with -0.0073 percentage points change in gross returns in NYSE. A unit change in sky cloud cover denotes the change in state of sky condition from clear sky to intermediate state to the obscured sky. When the sky condition is clear, C equals -1, so days with clear skies are associated with positive returns on average. Similarly, when C is 1, days with obscured skies is associated with negative returns. However, the effect is not significant. Since the stock returns during the financial crisis of 2007-2009 was largely affected by economic shocks in housing market, we run a regression after controlling for the time-period. We exclude the data on stock returns relating to financial crisis era. To study if the effect follows a trend, we also control for pre-financial crisis and post-financial crisis. Table 2 shows that the weather effect declines when years with financial crisis are controlled. The column 2 suggests that the coefficient of cloud cover measure (C) increases to -0.0212 percentage points after controlling for data from financial crisis. The effect is bigger during the pre-crisis era rather than during post-crisis era by 0.0149 percentage points. However, we fail to reject null hypothesis that the stock returns are systematically affected by local weather.

We see similar results for the DJIA. From table 3, column 1, we observe that a unit change in sky cloud cover is associated with -0.0127 percentage points change in DJIA stock returns. The result confirms the association of positive stock returns with days with clear skies and negative stock returns with days with cloudy skies. We observe that the coefficient of cloud cover variable decreases during post financial crisis period from pre-crisis period for both stock indices. This result highlights that the weather effect is decreasing for the recent years. One possible explanation for this could be the integration of global investors in the financial markets, and the use of automated computerized trading.

4.3. Regression model 2

We perform similar regression using 3 dummy variables in cloud cover variable. From table 4, column 1, we can observe that on average NYSE stock returns decreases by 0.014 percentage on completely obscured days compared to the completely clear days. Similarly, the intermediate states of sky condition are associated with decline in the index returns as observed from table 4 column 1. Precisely, the coefficient for C_{zero} or cloud cover variable for intermediate sky conditions is -0.0007 which indicates that on average the stocks returns decline by -0.0007 percentage points on partially cloudy days, compared to the sunny days. However, no significant results are obtained.

When the financial crisis period is excluded from the data, the effects are more profound with larger coefficients for the sky cloud cover variables. Following the table 1, the effects are more profound for pre-crisis era compared to the post crisis era. The coefficient for C_{zero} decreases from 0.0711 to 0.0001 from pre-crisis era on Column 3 to post crisis era on Column 4. Interestingly, we can observe that the coefficient for C_{one}, obscured skies, is 0.008 or positive for the pre-crisis era. Our findings suggest that on average, stock returns were higher on cloudier days than on sunnier days by 0.008 percentage points. This result is contradictory to Stecklow (ibid.) and suggests that the weather effect do not follow a similar pattern but rather is a period-specific phenomenon.

Similar observations are made for DJIA returns on Table 5. From column 1, we find that on average daily stock returns decline by 0.0236 percentage points on completely obscured days compared to clear days. The effect is larger by 0.0174 percentage points when data from financial crisis is excluded. Similar to the observations on Table 4, the coefficient of C_{one} declines for DJIA on Table 5 during post-crisis period compared to the pre-crisis period. This result reconfirms our finding that weather effect is abnormal and time-specific phenomenon. The results are not statistically significant, and hence the results are inconclusive.

4.4. Regression model 3

Since the intermediate sky cloud conditions could also have effects on stock returns, we assign dummy variables to each of the intermediate sky conditions including the complete clear sky and the obscured sky.

Column 1 of table 6 suggests that the upon the inclusion of five dummy variables for all the sky cloud cover conditions, on average stock returns decline the most on days with completely overcast sky condition than the intermediate sky conditions with reference to the days with clear sky. On average NYSE stock returns decline by 0.021 percentage points on overcast days while on days labelled as having few clouds (FEW), and scattered clouds (SCT), stock returns decline by 0.007 percentage points and by 0.018 percentage respectively. Interestingly, from column 1, the state of the intermediate sky condition that is labelled as having broken (BKN) clouds (which is defined as the sky condition with *average_skycondition* value between 2.5 oktas and 3.5 oktas), is associated with positive returns on NYSE. The stock returns are expected to rise by 0.0324 percentage points more than the clear sky condition. When the data for financial crisis is excluded, the coefficient for BKN is significant with a magnitude of 0.0744 percentage point. The result suggests that it could be in fact the expectation that the sky will be fully covered with clouds rather than the occurrence of the overcast sky that give rise to the to the weather effect. However, the results are insignificant when regression is carried out for sample period for pre-financial-crisis and post-financial-crisis eras.

Similar result is obtained for DJIA index when five dummies for sky cloud cover variable is introduced in the model. From table 7, overcast skies are associated with negative stock returns for column 1, column 2 and column 4. On average, DJIA stock declines by 0.039 percentage points on average on overcast days compared to clear skies for the total sample period. The effect increases to -0.0438 percentage points when data from financial crisis is excluded. For the sample with pre-crisis era, the coefficient for overcast sky (D_{OVC}) is 0.0086 while it decreases to -0.054 percentage points during post-crisis period.

Table 7 also provides a significant result for broken sky (BKN) for the sample period that excludes financial crisis. On average, DJIA stock index declines by 0.079 percentage points on sky with broken clouds than sky with no clouds. The effect is greater for the both pre-crisis period in column 3, and post crisis period in column 4. This effect is not significant for pre-crisis period, but significant for post crisis period.

5. Discussion and Conclusion

The results in this paper do not support the claim that the stock returns in New York City are significantly affected by the local weather even though a weak correlation exists between the cloudy days and decline in stock returns. Our results are consistent with the Efficient Market Hypothesis (Malkiel 1989) that market reflects all relevant information in determining security prices.

Even though psychological studies claim that individuals' moods are related to the certain weather variables such as hours of sunshine, a rational financial market would not respond to such influence as shown in our results. It could be plausible that a bank manager would feel optimistic on a sunny day and give out loans to borrowers. It is also plausible for stock traders to trade more as a result of a good weather. However, a rational financial market would not suffer from this bias because the stock prices reflect all available information. Therefore, the market automatically adjusts to any mispricing, if any, as a result of the weathers' influence on an investor.

A potential future research work could be to study if any relationship exists between the weather forecast and the stock returns. The weather forecasts have become more accurate recently, with the use of advanced supercomputers. Hence, since stock markets are largely driven by future expectations, a future weather forecast could actually affect stock returns. We failed to locate the data on weather forecasts for each day from 1990 to 2018. While we examined the possibility of using auto-regressive model to forecast the weather variable, the observed sky cover variable was categorical, and not continuous. This largely limited the potential of forecasting the weather. Furthermore, we do not find significant weather effect.

We could also test the hourly effects of weather on stock returns. It is plausible that investors could behave differently in the morning when the investors and stock brokers have to commute to their offices, compared to during afternoon when investors are at the convenience of their homes and offices as a result of the weather conditions. Therefore, we could compare the stock returns at different times of the day.

Furthermore, we could also test the prevalence of the weather effect on different stock indices around the world replicating Hirshleifer and Shumway (2003). Because Hirshleifer and Shumway used data from 1982 to 1997, we could test how the weather effect has flourished in different cities over time, using recent data.

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Appendix

Correlation between cloud cover and stock returns:

Prior to the analysis, we correlated the cloud cover measure with stock returns. We observed a weak and positive correlation between the change in gross returns at NYSE and the days when the sky is completely clear.

The positive correlation also exists for DJIA on clear days. Similarly, gross returns on the two stock indices have a weak and negative correlation on obscured days. This result confirms that weather variables such as sky cloud cover are associated with the stock returns. We then performed the regression analysis.

Table 1: *Summary Statistics*

Variables	N	Mean	S.D.	Min	Max
Average Sky Condition	7268	2.281	1.284	0	4
Median Sky Condition	7268	2.318	1.401	0	4
Change in NYSE (%)	7267	0.0302	1.074	-9.726	12.22
Change in DJIA (%)	7267	0.0359	1.055	-7.873	11.08
Sky Conditions (C)	7268	0.0171	0.471	-1	1
Clear Sky Conditions	7268	0.103	0.303	0	1
Intermediate Sky Conditions	7268	0.778	0.416	0	1
Obscured Sky Conditions	7268	0.120	0.324	0	1
Clear Sky	7268	0.103	0.303	0	1
Few Clouds	7268	0.156	0.363	0	1
Scattered Clouds	7268	0.263	0.440	0	1
Broken Clouds	7268	0.255	0.436	0	1
Overcast Weather	7268	0.223	0.417	0	1

Table 2: *Regression Statistics: The Cloud Cover Measure (C) and NYSE Stock Returns*

	(1)	(2)	(3)	(4)
Variables	1990-2018	1990-2018 (excl. 2007- 2009)	Pre-crisis	Post-crisis
Cloud Cover Measure (C)	-0.0073	-0.0212	-0.0329	-0.0180
	(0.0269)	(0.0236)	(0.0333)	(0.0385)
May	0.0527	0.0054	0.0616	-0.1013
	(0.0618)	(0.0553)	(0.0663)	(0.0996)
December	0.1091*	0.0859	0.0985	0.0583
	(0.0624)	(0.0559)	(0.0663)	(0.1027)
Friday	0.0130	-0.0040	-0.0286	0.0451
	(0.0405)	(0.0363)	(0.0434)	(0.0656)
Constant	-0.0270	0.0116	0.0430	-0.0467
	(0.0516)	(0.0462)	(0.0553)	(0.0843)
Observations	7267	6511	4286	2225
R^2	0.0018	0.0026	0.0036	0.0052
Adjusted R^2	-0.000389	0.000131	-0.000172	-0.00204

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: *Regression Statistics: Cloud Cover Measure (C) and Dow Jones Industrial Average*

Variables	(1) 1990-2018	(2) 1990-2018 (excl. 07-09)	(3) Pre-Crisis	(4) Post-Crisis
Cloud Cover Measure (C)	-0.0127	-0.0208	-0.0367	0.0030
	(0.0264)	(0.0246)	(0.0369)	(0.0353)
April	0.1035*	0.0597	0.0614	0.0582
	(0.0611)	(0.0579)	(0.0740)	(0.0919)
May	0.0473	0.0164	0.0550	-0.0569
	(0.0607)	(0.0164)	(0.0735)	(0.0912)
November	0.1020*	0.0935	0.0895	0.0991
	(0.0617)	(0.0586)	(0.0741)	(0.0947)
Wednesday	-0.0509	-0.0539	-0.0803*	0.0011
	(0.0395)	(0.0375)	(0.0480)	(0.0597)
Thursday	-0.0621	-0.0742**	-0.1237***	0.0233
	(0.0397)	(0.0376)	(0.0480)	(0.0599)
Friday	-0.0740*	-0.0859**	-0.1282**	-0.0026
	(0.0397)	(0.0377)	(0.0481)	(0.0600)
Constant	0.0362	0.0688	0.1154*	-0.0150
	(0.0507)	(0.0480)	(0.0613)	(0.0772)
Observations	7267	6511	4286	2225
R^2	0.0032	0.0045	0.0065	0.0053
Adjusted R^2	0.000977	0.00205	0.00279	-0.00187

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: *Regression Statistics: Obscured and Intermediate Sky Conditions and New York Stock Exchange*

Variables	(1) 1990-2018	(2) 1990-2018 (excl. 07-09)	(3) Pre-Crisis	(4) Post-Crisis
Intermediate Sky Conditions	-0.0007	0.0214	0.0711	0.0001
	(0.0330)	(0.0305)	(0.0677)	(0.0402)
Obscured Sky Conditions	-0.0140	-0.0419	-0.0080	-0.0724
	(0.0468)	(0.0412)	(0.0731)	(0.0966)
April	0.0990*	0.0429	0.0401	0.0479
	(0.0568)	(0.0540)	(0.0687)	(0.0873)
May	0.0526	0.0039	0.0591	-0.0991
	(0.0557)	(0.0532)	(0.0635)	(0.0960)
December	0.1089*	0.0841*	0.0955	0.0588
	(0.0570)	(0.0503)	(0.0603)	(0.0912)
Tuesday	0.0379	0.0153	-0.0260	0.0947
	(0.0431)	(0.0373)	(0.0452)	(0.0662)
Constant	-0.0247	0.0020	-0.0174	-0.0388
	(0.0579)	(0.0525)	(0.0838)	(0.0852)
Observations	7267	6511	4286	2225
R^2	0.0018	0.0030	0.0041	0.0054
Adjusted R^2	-0.000521	0.000355	000145	-0.00229

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: *Regression Statistics: Obscured and Intermediate Sky Conditions and Dow Jones Industrial Average*

Variables	(1) 1990-2018	(2) 1990-2018 (excl. 07-09)	(3) Pre-Crisis	(4) Post-Crisis
Intermediate Sky Conditions	0.0050	0.0282	0.0812	0.0144
	(0.0335)	(0.0317)	(0.0777)	(0.0385)
Obscured Sky Conditions	-0.0236	-0.0410	0.0102	-0.0408
	(0.0467)	(0.0429)	(0.0835)	(0.0817)
April	0.1033*	0.0586	0.0578	0.0603
	(0.0569)	(0.0573)	(0.0761)	(0.0820)
May	0.0469	0.0146	0.0522	-0.0548
	(0.0547)	(0.0551)	(0.0707)	(0.0870)
Wednesday	-0.0508	-0.0533	-0.0805*	-0.0006
	(0.0405)	(0.0380)	(0.0485)	(0.0601)
Thursday	-0.0621	-0.0738*	-0.1234**	0.0225
	(0.0420)	(0.0393)	(0.0501)	(0.0592)
Friday	-0.0739*	-0.0856**	-0.1274**	-0.0039
	(0.0406)	(0.0388)	(0.0503)	(0.0592)
Constant	0.0357	0.0541	0.0463	-0.0217
	(0.0575)	(0.0548)	(0.0952)	(0.0793)
Observations	7267	6511	4286	2225
R^2	0.00032	0.0050	0.0071	0.0056
Adjusted R^2	0.000882	0.00236	0.00313	-0.00210

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: *Regression Statistics: Gradations of Sky Conditions and New York Stock Exchange*

Variables	(1) 1990-2018	(2) 1990-2018 (excl. 07-09)	(3) Pre-Crisis	(4) Post-Crisis
Few Clouds	-0.0065	0.0025	0.0608	-0.0178
	(0.0398)	(0.0377)	(0.0758)	(0.0470)
Scattered Clouds	-0.0181	-0.0015	0.0552	-0.0421
	(0.0396)	(0.360)	(0.0713)	(0.0806)
Broken Clouds	0.0324	0.0744**	0.1051	0.1295
	(0.0395)	(0.0371)	(0.0708)	(0.0806)
Overcast	-0.0209	-0.0325	0.0183	-0.0712
	(0.0410)	(0.0361)	(0.0702)	(0.0744)
April	0.0979*	0.0420	0.0427	0.0316
	(0.0568)	(0.0540)	(0.0686)	(0.0870)
December	0.1076*	0.0827*	0.0961	0.0479
	(0.0571)	(0.0502)	(0.0602)	(0.0911)
Tuesday	0.0374	0.0138	-0.0278	0.0956
	(0.0432)	(0.0373)	(0.0452)	(0.0662)
Constant	-0.231	0.0038	-0.0163	-0.0343
	(0.0579)	(0.0523)	(0.0836)	(0.0850)
Observations	7267	6511	4286	2225
R^2	0.0022	0.0042	0.0049	0.0086
Adjusted R^2	-0.000421	0.00131	0.000441	4.71e-05

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: *Regression Statistics: Gradations of Sky Conditions and Dow Jones Industrial Average*

Variables	(1) 1990-2018	(2) 1990-2018 (excl. 07-09)	(3) Pre-Crisis	(4) Post-Crisis
Few Clouds	0.0104	0.0197	0.0736	0.0043
	(0.0404)	(0.0388)	(0.0858)	(0.0461)
Scattered Clouds	-0.0039	0.0129	0.0744	-0.0228
	(0.0398)	(0.0378)	(0.0817)	(0.0520)
Broken Clouds	0.0367	0.0792**	0.1196	0.1256*
	(0.0397)	(0.0385)	(0.0810)	(0.0690)
Overcast	-0.0367	-0.0438	0.0086	-0.0540
	(0.0409)	(0.0375)	(0.0803)	(0.0644)
April	0.1017*	0.0569	0.0593	0.0464
	(0.0569)	(0.0573)	(0.0761)	(0.0819)
Wednesday	-0.0511	-0.0549	-0.0826*	-0.0004
	(0.0405)	(0.0380)	(0.0485)	(0.0601)
Thursday	-0.0623	-0.0746*	-0.1250**	0.0239
	(0.0420)	(0.0393)	(0.0501)	(0.0590)
Friday	-0.0725*	-0.0840**	-0.1258**	0.0006
	(0.0406)	(0.0387)	(0.0502)	(0.0590)
Constant	0.0385	0.0572	0.0492	-0.0173
	(0.0575)	(0.0547)	(0.0951)	(0.0792)
Observations	7267	6511	4286	2225
R^2	0.0038	0.0064	0.0083	0.0086
Adjusted R^2	0.00117	0.00346	0.00384	1.50e-05

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$