The Effect of Weather on Stock Trading

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Abstract

Many studies find that weather has a close relationship with human's mood and behavior. In this paper, I examine the effect of weather on stock return and trading volume. By using data of weather in New York and Chicago as well as data of price and trading volume of SPY and conducting two OLS regressions, I find that: (1) temperature, relative humidity, sea level pressure, and precipitation have a significant relationship with return of SPY; (2) humidity, wind speed, sea level pressure, and precipitation have a significant relationship with hourly trading volume of SPY. Visibility does not have any effect on either return or trading volume of SPY. Despite a significant linear relationship of weather factors on stock return and trading volume, a nonlinear relationship tends to explain the weather effect better than a linear relationship.

KEY WORDS: Weather effect, Stock trading, Extreme weather, Bidirectional effect

Introduction

Research on the correlation between weather and stock market has been done for many years. There have been many studies on the effect of sunny days versus cloudy days on the stock market, starting with Saunders' research in Stock Prices and Wall Street Weather (Saunders, 1993). Hirshleifer & Shumway also study the correlation between sunshine and stock return by using morning sunshine and daily market index returns in twenty six countries, from 1972 to 1997. They find a significant relationship between sunshine and daily stock return but say rain and snow do not have a significant correlation with stock return (Hirshleifer & Shumway, 2003). On the other hand, many studies suggest that there is no significant relationship between weather and stock return (Pardo & Valor, 2003, Wang & Kuang-Hsunshih & Jang, 2017). Thus, previous studies have used different datasets and have reached contradictory conclusions. In recent years, the role of ETFs has grown substantially. Since 2007, its inflow is steadily increasing, and "ETFs now account for about 30 percent of all US trading by value, and 23 per cent by share volume" (Wigglesworth, 2017).

In keeping with this trend, I examine the relationship between weather and trading volume and return of SPY, the SPDR S&P 500 trust ETF (Exchange Traded Fund). The fact that weather affects people's mood has been found in so many studies that it is now common sense. J A Denissen & Butalid & Penke & Aken (2008) suggest that temperature, wind, and sunlight affect people's mood. Howarth & Hoffman (1984) suggest that high humidity tends to decrease concentration and potency by increasing fatigue and sleepiness, while very cold weather tends to increase aggressive feelings. There have also been many studies on the effect of weather on human decision-making, which is also related to individual economic activities and business decisions. Huang & Zhang & Hui & Wyer (2014) suggest that warm temperatures tend to make consumers feel close to other decision makers, therefore, give more validity to opinion of those decision makers regarding product preference and stock forecasts.

I find that there is a significant relationship between SPY and weather. Temperature, humidity, sea level pressure, and precipitation have a significant effect on the return of SPY, while visibility and speed of wind do not have a significant relationship with return of SPY. Different results are suggested about the correlation between trading volume of SPY and weather. Humidity, wind speed, sea level pressure, and precipitation have a significant relationship with the trading volume of SPY, but visibility and temperature do not.

Many previous studies have been done using different data. Unlike these previous researches, I examine the correlation between weather and stock trading by using SPY which is one of the largest ETFs and a proxy for the market factor. Also, by using hourly data that summarizes all transactions made in seconds, my findings show how continuously changing weather affects stock trading. These provide important information to many investors, especially, to contemporary investors who want to make more rational and trendy decisions by actively utilizing weather information in their stock trading.

Literature Review

Many similar topics have been extensively covered in many research papers.

Wang & C. Lin & J. Lin (2011) find that precipitation, sunshine hours, and temperature do not have a significant relationship with stock return. However, they say that weather effect exists in stock market because sunshine hours and temperature has a significant correlation with stock risk. They apply GJR-GARCH model and use data in Taiwan from 2001 to 2007.

Narayanamoorthy & Dharani & Muruganandan (2015) find that temperature has a significant correlation with the stock return and stock return volatility. They apply GARCH (1, 1) model and use daily closing values of S&P CNX Nifty index and daily weather data in India from January 2008 to December 2013. By choosing four cities, Chennai, Kolkata, Mumbai, and Delhi, they indicate that: (1) temperature in Mumbai affects the stock returns as per mean equation; (2) temperature in Mumbai, Delhi, and Chennai affects the stock returns as per variance equation, which suggests that temperature has a significant correlation with the stock return volatility in India.

Loughran & Schultz (2004) examine the relationship between weather and stock returns by considering cloud cover in the city of a Nasdaq company's listing and using OLS and logit model regressions. They suggest that cloudy weather in the city where the stock market is located in does not affect the stock returns. In their paper, they discuss about localized trading.

They say that trading volume of stock differs based on where stock traders live. The trading volume of East Coast stock trades is high at 10 am (Eastern time) when many people start working, while the trading volume of West Coast stock trades is low at that time since it is before work time or while people are commuting to work. They also discuss about the impact of blizzards and religious holiday on local trading volume, which shows relationship between them. With these empirical tests, they conclude that "the weather in the city where a company is located is a good proxy for the weather facing the investors who trade the stock".

They indicate a limitation of research that examine the effect of weather on U.S. stocks by saying that investors can submit the order from anywhere around the world which have all different weather. As a result, they use Nasdaq, that has strong local components. Yet, no significant correlation is found between cloud cover near a company headquarters and its stock's return.

Sariannidis & Giannarakis & Partalidou (2016) find that changes in humidity and wind levels as well as changes in returns oil and gold prices seem to have a positive effect on the European stock market. They use daily data of market indices of DJSI Europe, Gold Bullion LBM US$/Troy Ounce, Crude oil BRNP$/B, US bond, US dollar/Yen exchange rate, and environmental data. They include gold because gold is considered as a safe asset for investment in risky circumstance and can be used as an investment hedge against US dollar. They say that oil can represent the performance of overall economy and US dollar/Yen exchange rate can represent the effects of exchange rate on the European stock returns.

By applying GARCH model, they suggest that aggressive behavior stem from high level of humidity that negatively affects the human comfort leads to the increase in stock market return. They also say that higher wind speed tends to give investors a safe feeling by preventing air pollution; therefore, it leads to decline in stock return volatility by removing risk factors in the economy.

Worthington (2009) indicates that "there is no statistically significant relationship between the weather and market returns in Australia". In his paper, daily weather data at Sydney's observatory Hill and Airport meteorological stations from 1958 to 2005 are collected, and a regression-based approach is used. He suggests, for further research, testing the direct correlation between mood and investor's decision-making instead of indirect relationship between stock market and weather.

Previous researches contribute to establishing the awareness of people on how important weather influences the economy. My thesis will add contribution more to previous researches by touching different areas because I use weather data in the United States and stock data of SPY. Unlike the Nasdaq which has a limitation to be used as a dependent variable due to its small size, SPY is the second most popular fund in the world (Egan, 2015) and the largest ETF in the world (Authers & Rennison, 2018).

Therefore, using SPY will give more reasonable results that represent large part of stock market's movement along with the weather data. Also, using six weather factors, such as visibility, temperature, humidity, wind speed, sea level pressure, and precipitation, will provide more various information to investors when they consider the weather to decide their stock trading behavior rather than just looking at one or two factors, such as temperature and humidity or sunshine and cloudiness.

Data description

To test the hypothesis that weather is significantly correlated with stock trading, data of trading volume and price of SPY from 2001 to 2012 are collected from Wharton Research Data Services. Also, weather data of New York and Chicago from 2001 to 2012 are collected from National Centers for Environmental Information.

From the originally collected data of trading volume and price of SPY that are from all trading transactions made in irregular seconds, I calculated the hourly average price and sum of trading volume. I sum up prices of all transactions that are made for an hour and divide them by number of transactions for an hour to get the hourly average price. Then, I calculate the hourly stock return. I simply add up the trading volumes that are made for each hour to get the sum of trading volume. Since weather data is available hourly, I only use data from whole hours. I exclude premarket trading from 4am to 9:30am and after-hours trading from 4pm to 8pm, because trade outside the regular market session is thin, as indicated in Table 1. Accordingly, I use the whole hours between 10am and 4pm.

Table 1. Number of Transaction by Hour

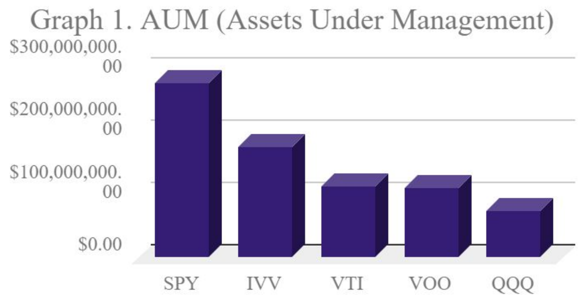
Hour	4	5	6	7	8	9	10	11	12
Count	2,672	2,725	3,237	3,677	5,000	5,822	5,821	5,823	5,822
Hour	13	14	15	16	17	18	19	20	
Count	5,821	5,813	5,803	5,791	5,657	5,412	4,659	104	

There are quite similar numbers of transaction right before and after the normal trading hours. However, I still eliminate transaction data out of trading hours because those have a higher possibility to be made out of the United States or outside the East Coast and Midwest because traders in different places have different activity hours due to the time difference (Loughran & Schultz, 2004). Therefore, using data only from 10 am to 4 pm will give more accurate results by matching to data of weather in New York and Chicago. Hourly return and sum of trading volume of SPY are the two dependent variables.

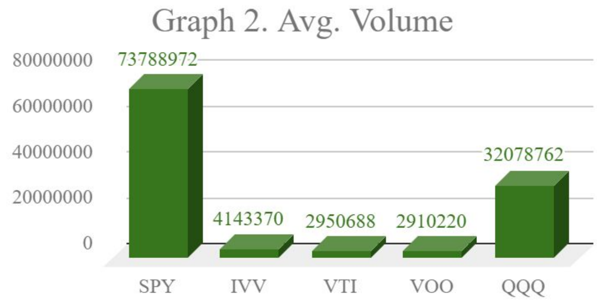
As previously mentioned, we choose to use SPY data because SPY is the largest ETF in the world and represents the movement of the overall stock market more accurately than individual stocks. In addition, ETFs use electronic systems and have the ease accessibility to all investors, regardless of the size of their assets and professionality in stock trading, due to significantly lower trading costs than other types of stocks. Weather is also an equal resource given to everyone, regardless of their socio-economic status. Thus, using SPY, an easily accessible ETF for all investors in various socioeconomic status, is more appropriate for examining the correlation between weather and stock trading than using other stocks or types of stock.

The AUM (Assets Under Management) of SPY is $279,409,163.25 which is the largest among the five top largest ETFs in the world ("Largest ETFs: Top…"). As of April 18, 2019, according to Yahoo!Finance, SPY's net assets is 264.06 billion, year to date return is 16.53 percent, yield is 1.85 percent, and average daily trading volume is 73,788,972. The comparison of 5 top largest ETFs are shown in Graph 1, Graph 2, Graph 3, Graph 4, Graph 5, and Graph 6. Graph 1 and 2 show that SPY is the largest and the most actively traded ETF. Graph 3, 4, 5 and 6 are to provide summary about five top largest ETFs. SPY contains eleven sectors, which are basic materials, consumer cyclical, financial services, real estate, consumer defensive, healthcare, utilities, communication services, energy, industrials, and technology (Yahoo!Finance). Sector Weightings are shown in Graph 7.

The sector that takes the biggest portion in SPY is technology, taking 22.93 percent, followed by healthcare, taking 14.49 percent, and financial services, taking 13.75 percent. Insurance, agriculture, energy, beverage industry, commercial fishing, skiing, and wineries are seven industries that have the greatest risk from climate change.



Source: ETFdb.com



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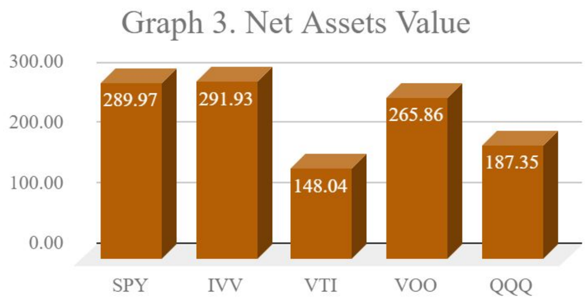

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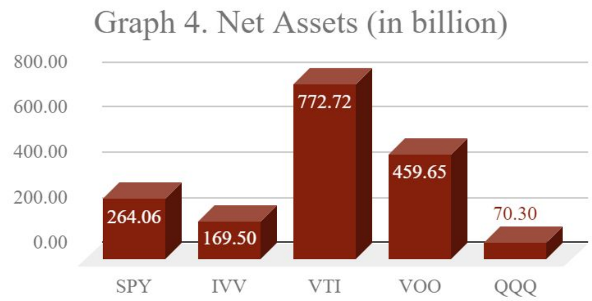

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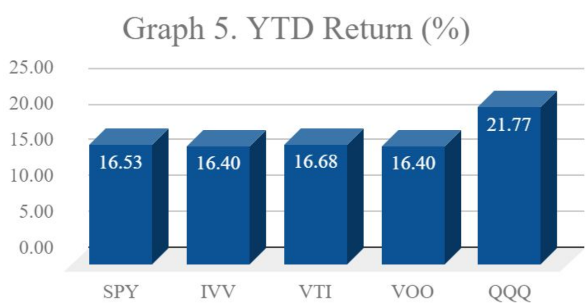

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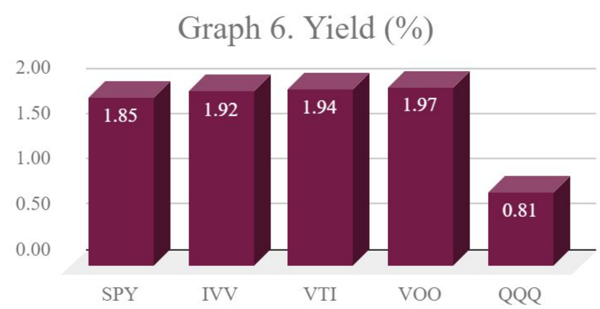
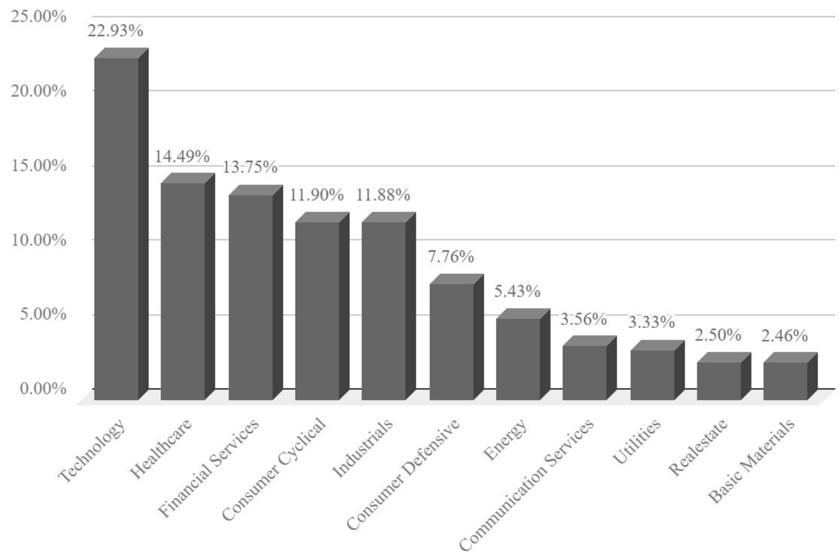


Source: Yahoo!Finance

Graph 7. Sector Weightings of SPY (%)



Source: Yahoo!Finance

Among these seven industries, insurance and energy are included in financial services and energy sector, respectively. The rest of industries are all included in industry sector. This suggests that the trading volume and price of SPY might not only depend on people's mood or behavior affected by the weather, but it also could be affected by each industry's different prospect in response to its productivity or outcome that is influenced by changing weather.

The weather data of New York and Chicago are collected at a particular weather station in Central Park in New York City and a particular weather station at Chicago Midway Airport in Chicago. Panel weather data are collected for the period from 2001 to 2012. The reason that I choose these particular weather stations is that the physical locations of these weather stations are the closest to each stock exchange market in New York and Chicago (the New York Stock exchange is about seven miles away from the weather station, and the Chicago stock exchange is about eleven miles away from the weather station). We collected hourly observation data of sky conditions, visibility, weather type, dry bulb temperature in Fahrenheit and Celsius, wet bulb temperature in Fahrenheit and Celsius, dew point temperature in Fahrenheit and Celsius, relative humidity, wind speed, wind direction, wind gusts, station pressure, pressure tendency, sea level pressure, precipitation total, altimeter setting. From these data set, we dropped hourly wind gust speed, wet bulb temperature in Fahrenheit and Celsius, and dew point temperature in Fahrenheit and Celsius because of multicollinearity, and sky condition and station pressure are dropped because of missing observations. Weather type, station pressure, pressure tendency, and altimeter setting are also not used because their data are covered bu other weather factors. Wind direction is dropped to increase relevance to the hypothesis. Since the scale of Fahrenheit is almost twice the scale of Celsius, bulb temperature in Fahrenheit is used because of its greater precision.

After organizing the ideal dataset for the hypothesis testing to prevent any bias on results, the hourly data, from 10 am to 4 pm, which is normal trading hours of SPY, of visibility, dry bulb temperature, relative humidity, wind speed, sea level pressure, and precipitation are used as independent variables.

Table 2 shows data description of each variable. Summary statistics of each variable are shown in Table 3. From Table 3, it is possible that each variable has some outliers. Since weather is sometimes extreme, it is unavoidable to have outliers in data. Outliers are also observed in stock data. Table 4 shows outliers of return. This could result in biased results by making return too high or too low.

Table 2. Definitions of Variables, (from 2001 to 2012)	
Variable	Definition
Return	Hourly return of SPY
Volume	Hourly sum of trading volume of SPY made in seconds
Visibility	The horizontal distance an object can be seen and identified given in whole miles. Note visibilities less than 3 miles are usually given in smaller increments (e.g. 2.5)
Temperature	The dry-bulb temperature that is commonly used as the standard air temperature reported. It is given here in whole degrees Fahrenheit
Humidity	The relative humidity given to the nearest whole percentage
WindSpeed	Speed of the wind at the time of observation given in miles per hour (mph)
Pressure	Sea level pressure given in inches of Mercury (in Hg)
Precipitation	Amount of precipitation in inches to hundredths over the past hour. For certain automated stations, precipitation will be reported at sub-hourly intervals (e.g. every 15 or 20 minutes) as an accumulated amount of all precipitation within the preceding hour.
Month	
Jan	= 1 if January, 0 otherwise
Feb	= 1 if February, 0 otherwise
Mar	= 1 if March, 0 otherwise
Apr	= 1 if April, 0 otherwise
May	= 1 if May, 0 otherwise
Jun	= 1 if June, 0 otherwise
Jul	= 1 if July, 0 otherwise
Aug	= 1 if August, 0 otherwise
Sep	= 1 if September, 0 otherwise
Oct	= 1 if October, 0 otherwise
Nov	= 1 if November, 0 otherwise
State	= 1 if New York, 0 if Chicago
Recession	= 1 if from December 2007 to June 2009, 0 otherwise
Hour	
11	= 1 if Hour=11, 0 otherwise
12	= 1 if Hour=12, 0 otherwise
13	= 1 if Hour=13, 0 otherwise
14	= 1 if Hour=14, 0 otherwise
15	= 1 if Hour=15, 0 otherwise
16	= 1 if Hour=16, 0 otherwise

Source: National Centers for Environmental Information.

Table 3. Summary Statistics								
Variable	Return	Volume	Visibility	Temperature	Humidity	WindSpeed	Pressure	Precipitation
Obs	40,693	40,694	38,149	38,369	38,299	38,384	34,819	32,142
Mean	.000029	1.59E+07	9.006	57.745	57.679	9.595	30.014	0.003
Std. Dev.	.007459	1.76E+07	2.256	19.568	19.137	5.145	0.226	0.022
Min	-.367021	100	0	-10	6	0	28.77	0
Max	.572136	2.14E+08	20	103	101	46	30.81	0.85
Skewness	17.52123	2.587	-2.324	-0.223	0.348	0.638	-0.105	13.478
Kurtosis	2102.636	13.950	7.301	2.137	2.361	3.976	3.557	272.649

Table 4. Outliers on Price of SPY								
Date	Hour	Price	Date	Hour	Price	Date	Hour	Price
12/06/04	13	119	02/06/04	13	114	07/03/02	9	95
	14	120		14	114		10	95
	15	188		15	142		11	117
	16	119		16	115		12	94
	17	119		17	114		13	94

Methodology

The OLS (Ordinary Least Squares) is used to test the hypothesis that there is any relationship between factors of weather and trading volume and return of SPY. To use the OLS method, the following assumptions should be met: (1) the relation between each independent variable and dependent variable is linear; (2) each independent variable is uncorrelated with error term for all regressors; (3) the error term has zero expected value; (4) the error term has a constant variance for all observations; (5) the error terms are statistically independent, and hence the covariance between error terms are zero; (6) there is no exact linear relationship among the independent variables; and (7) the error terms are normally distributed.

From the Scatter Plot 1 that shows scatter plots between each variable, the data seems to be heteroskedastic. In the presence of Heteroskedasticity, the t-statistic and the confidence interval tend to be biased because of bigger standard errors. This violates the assumption (4) and leads to less precise conclusion. I conduct the Breusch-Pagan test to see if data is indeed heteroscedastic.

H_0 : Absence of heteroskedasticity, H_1 : Presence of heteroskedasticity.

By running regression on *Return*, the value of χ^2 is 51283.94, and the p-value of χ^2 is 0.0000. So, I reject the null hypothesis, H_0, which indicates that heteroskedasticity problem is present. By running the regression on *Volume*, the value of χ^2 is 9669.15, and the p-value of χ^2 is 0.0000. I also reject the null hypothesis, which indicates that heteroskedasticity problem is also present. This heteroskedasticity problem is often observed when dataset is big. By using a panel data and the robust standard error, I expect to improve preciseness of results.

Scatter Plot 1. Scatter Plot Matrix

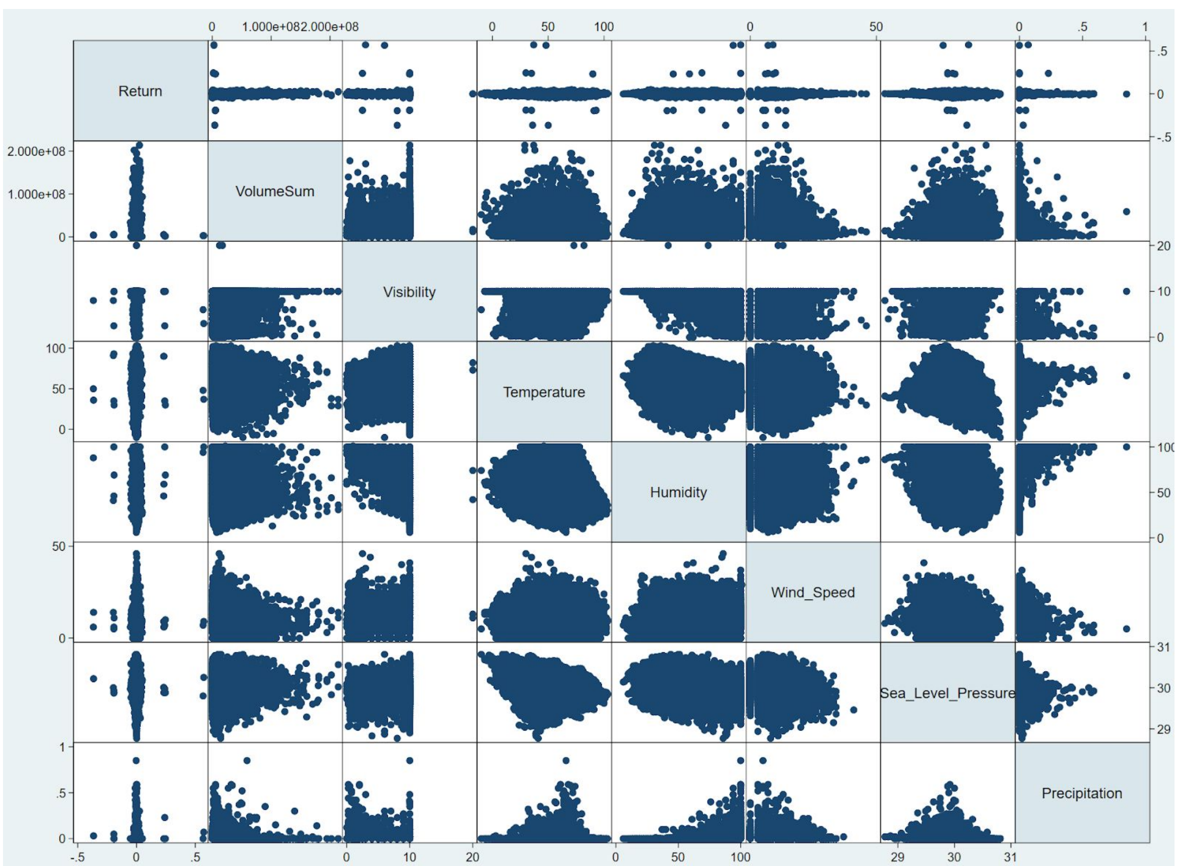


Table 5 shows the correlation between each variable. Correlation close to 0 is preferred in OLS method because it tells that there is no exact linear relationship among the independent variables. Correlations in Table 4 appear to be very close to 0. Visibility and humidity seem to have a high collinearity, corr = -0.5732. However, they are not perfectly correlated; therefore, the OLS assumption (6) is not violated.

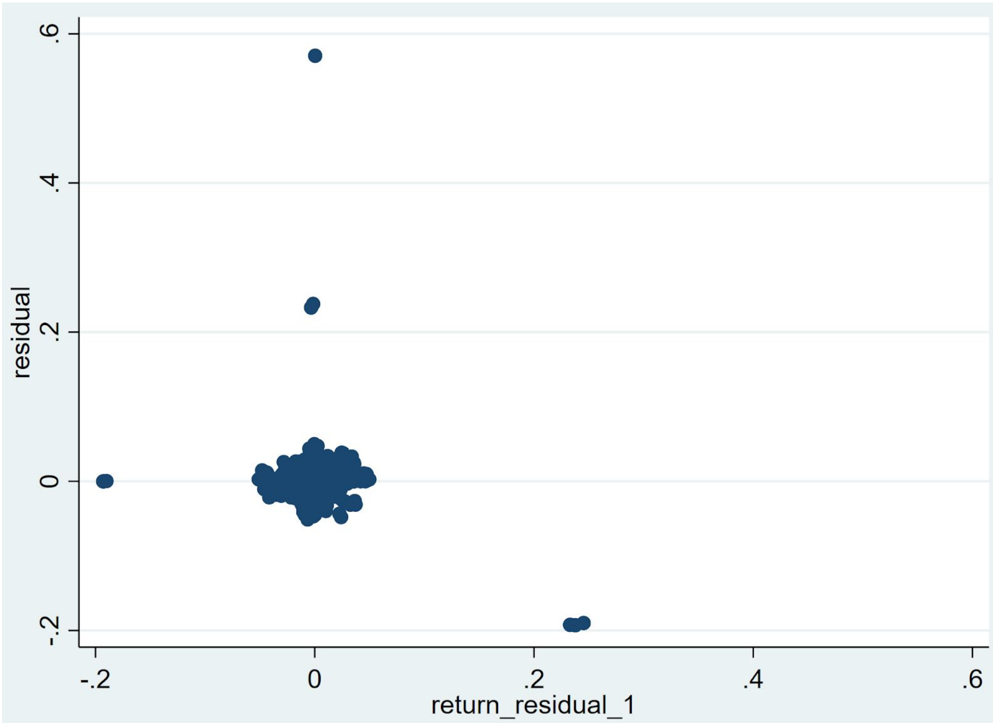
Scatter Plot 2 shows the scatter plot between residual and lagged residual after running the regression (1-a). The correlation between residual and lagged residual, r_1, is -0.1349. The DW statistic (d $\approx 2(1 - r_1)$) is 2.2698. Since the DW statistic is between 1.5 and 2.5, we are free from the autocorrelation, and the regression on *Return* does not violate the assumption (5).

Scatter Plot 3 shows the scatter plot between residual and lagged residual after running the regression (2-a). The correlation between residual and lagged residual, r_2, is 0.5944. The DW statistic (d $\approx 2(1 - r_2)$) is 0.8112. Since the DW statistic is not between 1.5 and 2.5, we are not free from the autocorrelation, and the regression (2-a) violates the assumption (5). To avoid the omitted variable bias due to the autocorrelation, I include a time lag variable of *Volume* as a regressor in the regression (2-a) to get a better regression model (2-b).

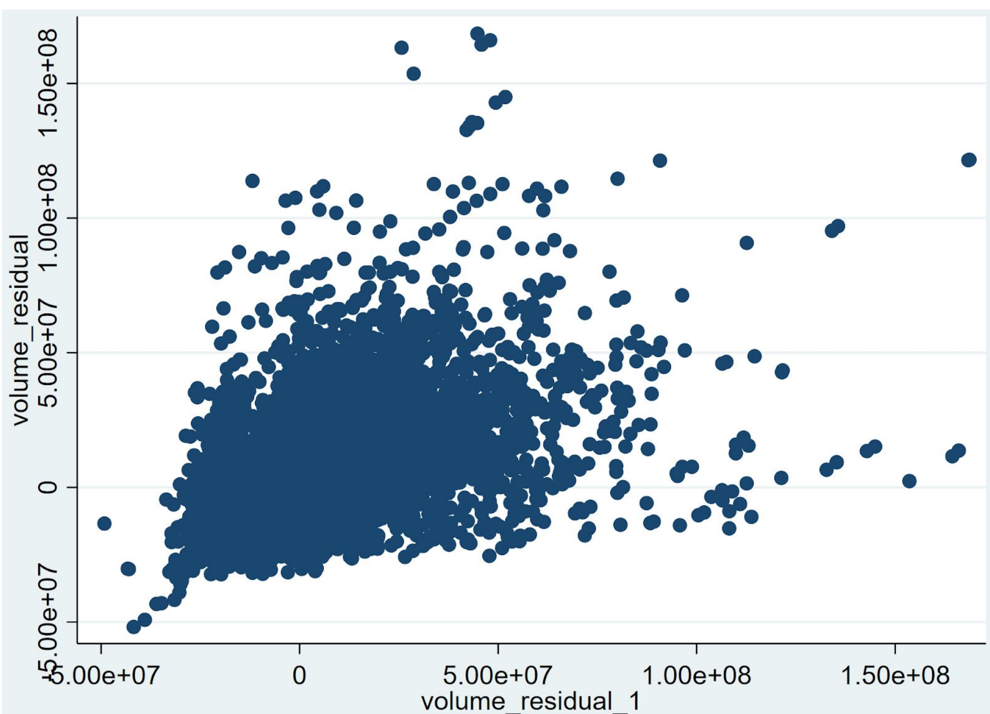
Table 5. Correlation Matrix

	Return	VolumeSum	Visibility	Temperature	Humidity	WindSpeed	Pressure	Precipitation
Return	1	0.0063	-0.0138	-0.0076	0.0094	0.0013	0.0072	0.0202
VolumeSum	-	1	0.0693	0.0032	-0.0613	-0.0194	0.0283	-0.0290
Visibility	-	-	1	0.0588	-0.5732	0.0959	0.1403	-0.3925
Temperature	-	-		1	-0.1466	-0.1294	-0.2917	-0.0305
Humidity	-	-	-	-	1	-0.0569	-0.1753	0.2749
WindSpeed	-	-	-	-	-	1	-0.1753	0.0135
Pressure	-	-	-	-	-	-	1	-0.0957
Precipitation	-	-	-	-	-	-	-	1

Scatter Plot 2. $Residual_t$ vs $Residual_{t-1}$, Regression (1-a)



Scatter Plot 3. $Residual_t$ vs $Residual_{t-1}$, Regression (2-a)



To see whether non-linear terms are needed in the regression model, I conduct RESET test for regression (1-a). I predict a fitted value and generate a squared and cubic term of it. Then, I test the hypothesis below.

H_0 : The coefficient of $\widehat{y^2}$ and $\widehat{y^3}$ equal to 0, H_1 : The coefficient of $\widehat{y^2}$ and $\widehat{y^3}$ do not equal to 0.

The value of χ^2 is 24.50, and the p-value of χ^2 is 0.000. Therefore, I reject the null hypothesis. Non-linear specification is needed in the regression (1-a). To find which non-linear term is needed, I check the t-statistic for the coefficient of a squared term and log term of each variable. All coefficients of them are insignificant at the 5% significance level except a squared term of *Humidity* (t-statistic: 2.49, p-value: 0.013) and a natural logarithm of *Temperature* (t-statistic: 2.01, p-value: 0.044). Therefore, a squared term of *Humidity,* $Humidity^2$*,* and a natural logarithm of *Temperature*, *lnTemperature*, are included in the regression (1-a) to get a better regression (1-b). After including *lnTemperature*, variable *Temperature* is not significant, and so is dropped.

I also conduct RESET test for regression (2-b).

H_0 : The coefficient of $\widehat{y^2}$ and $\widehat{y^3}$ equal to 0, H_1 : The coefficient of $\widehat{y^2}$ and $\widehat{y^3}$ do not equal to 0.

The value of χ^2 is 125.38, and the p-value of χ^2 is 0.000. Therefore, I reject the null hypothesis. Non-linear specification is needed in the regression (2-b) as well. To find which non-linear term is needed in the regression, I again check the t-statistic for the coefficient of a squared term and log term of each variable. A squared term of *Humidity* (t-statistic: -4.70, p-value: 0.000) and a natural logarithm of *WindSpeed* (t-statistic: -8.57, p-value: 0.000) are significant at the 5% significance level. Therefore, a squared term of *Humidity,* $Humidity^2$*,* and a natural logarithm of *WindSpeed, lnWindSpeed,* are included in the regression (2-b) to get a better regression (2-c). After including *lnWindSpeed*, variable *WindSpeed* is not significant and so is dropped.

We assume that the other OLS assumptions are met, and used the following two multiple regressions.

- $Return = \beta_0 + \beta_1 * Visibility + \beta_2 * lnTemperature + \beta_3 * Humidity + \beta_4 * Humidity^2 + \beta_5 * Windspeed$

  $+ \beta_6 * Pressure + \beta_7 * Precipitation + \sum_{i=8}^{18} \beta_i * Month + \beta_{19} * State + \beta_{20} * Recession + \sum_{j=21}^{26} \beta_j * Hour + \varepsilon_i$

- $Volume = \beta_0 + \beta_1 * Visibility + \beta_2 * Temperature + \beta_3 * Humidity + \beta_4 * Humidity^2 + \beta_5 * lnWindspeed$

  $+ \beta_6 * Pressure + \beta_7 * Precipitation + \sum_{i=8}^{18} \beta_i * Month + \beta_{19} * State + \beta_{20} * Recession + \sum_{j=21}^{26} \beta_j * Hour$

  $+ \beta_{27} * Volume_{t-1} + \varepsilon_i$

The independent variables are defined in Table 2. *Month*, *State*, and *Recession* are dummy variables that take value of 0 or 1. In *Month* and *Hour* dummies, December and 10 am are omitted to avoid the dummy variable trap that causes multicollinearity. *Hour* dummy variable is included to prevent omitted variable bias because trading volume exhibits a diurnal pattern (high near the beginning and end of trading, and lower at mid-day).

Table 6 shows the results of the regressions on *Return*. Regression (1-b) is the ideal regression to be used. Table 7 shows the results of the regressions on *Volume*. Regression (2-c) is the ideal regression to be used.

Results, Correlation Between Weather And Return

To test the hypothesis that the weather affects the stock return, I regress the hourly return on the hourly data of weather every hour on the hour (For example, I regress the hourly return between 10 am and 11 am on the houlry data of weather at 10 am). After running the regression (1-b), *Temperature, Humidity, Pressure, and Precipitation* appear to have a significant correlation with the return of SPY, while *Visibility and WindSpeed* do not have a significant correlation with the return of SPY. *Temperature*, *Pressure*, and *Precipitation* have a positive effect on the return of SPY. *Humidity* has both negative and positive effect on the return of SPY. It first has a negative effect on the return of SPY, but after a certain point, it starts having a positive effect on the return of SPY.

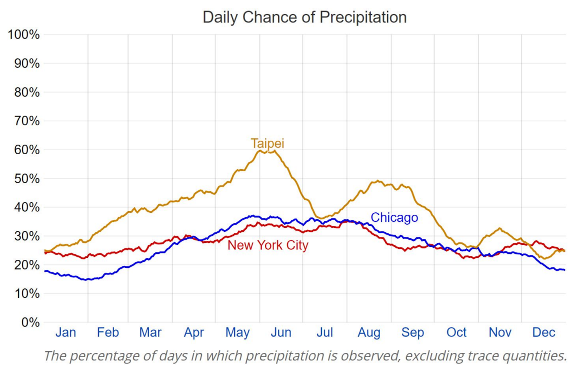
Table 6. Regression Result, Dependent Variable: *Return*								
	(1-a)		**(1-b)**		**(1-c)**		**(1-d)**	
	Coefficient (Std. Error)	*t-statistic (p-value)*	*Coefficient (Std. Error)*	*t-statistic (p-value)*	*Coefficient (Std. Error)*	*t-statistic (p-value)*	*Coefficient (Std. Error)*	*t-statistic (p-value)*
Regressor:								
Visibility	**-.0000204 (8.84e-06)**	-2.31 (0.021)**	**.0000222 (.0000144)**	1.54 (0.123)	**.0000151 (.0000136)**	1.11 (0.266)	**.0000203 (.0000151)**	1.34 (0.179)
Temperature	**6.39e-06 (3.13e-06)**	2.05 (0.041)**						
lnTemperature			**.000422 (.0001881)**	2.24 (0.025)**	**.0000108 (.0001788)**	0.06 (0.952)	**.0004349 (.0001895)**	2.30 (0.022)**
Humidity	**2.78e-06 (2.41e-07)**	11.51 (0.000)***	**-.0000349 (3.99e-06)**	-8.74 (0.000)***	**-.000036 (1.83e-06)**	-19.62 (0.000)***	**-.0000358 (3.75e-06)**	-9.54 (0.000)***
Humidity^2			**3.42e-07 (4.31e-08)**	7.94 (0.000)***	**3.44e-07 (2.28e-08)**	15.12 (0.000)***	**3.45e-07 (4.27e-08)**	8.08 (0.000)***
WindSpeed	**9.97e-07 (1.83e-06)**	0.55 (0.586)	**9.10e-07 (2.26e-06)**	0.40 (0.687)	**4.42e-06 (2.40e-06)**	1.84 (0.066)*	**1.66e-06 (2.30e-06)**	0.72 (0.470)
Pressure	**.0004321 (.0000108)**	40.10 (0.000)***	**.0004937 (.0000318)**	15.53 (0.000)***	**.0004065 (.0000158)**	25.71 (0.000)***	**.0004886 (.0000283)**	17.26 (0.000)***
Precipitation	**.0083465 (.0012435)**	6.71 (0.000)***	**.0070494 (.0009662)**	7.30 (0.000)***	**.0067199 (.0010859)**	6.19 (0.000)***	**.0070969 (.0009681)**	7.33 (0.000)***
Month	**Included**		**Included**		**Not Included**		**Included**	
State	**Included**		**Included**		**Included**		**Included**	
Recession	**Included**		**Included**		**Included**		**Included**	
Hour	**Included**		**Included**		**Included**		**Not Included**	
Intercept	**-.0129379 (.0006968)**	-18.57 (0.000)***	**-.0154458 (.0018989)**	-8.13 (0.000)***	**-.0115527 (.0011796)**	-9.79 (0.000)***	**-.0152783 (.0017227)**	-8.87 (0.000)***
Robust	**Yes**		**Yes**		**Yes**			
Regression summary statistics								
R^2	**0.0018**		**0.0021**		**0.0016**		**0.0014**	
Within R^{22}	**0.0019**		**0.0022**		**0.0016**		**0.0015**	
Sigma_e	**.00737489**		**.00737387**		**.00737518**		**.00737554**	
n	**30,442**		**30,424**		**30,424**		**30,424**	
*** p<0.01, ** p<0.05, * p<0.1								

Table 7. Regression Result, Dependent Variable: *Volume*										
	(2-a)		**(2-b)**		**(2-c)**		**(2-d)**		**(2-e)**	
	Coefficient (Std. Err.)	*t-statistic (p-value)*	*Coefficient (Std. Err.)*	*t-statistic p-value*	*Coefficient (Std. Err.)*	*t-statistic p-value*	*Coefficient (Std. Err.)*	*t-statistic p-value*	*Coefficient (Std. Err.)*	*t-statistic p-value*
Regressor:										
Visibility	**351321.4 (153766.7)**	2.28 (0.022)**	**131956.1 (52617.93)**	2.51 (0.012)**	**48345.55 (57856.17)**	0.84 (0.403)	**71079.95 (57433.62)**	1.24 (0.216)	**43312.3 (41805.08)**	1.04 (0.300)
Temperature	**-5370.798 (21370.06)**	-0.25 (0.802)	**-3922.589 (7730.812)**	-0.51 (0.612)	**-3482.337 (6031.054)**	-0.58 (0.564)	**12026 (2563.765)**	4.69 (0.000)***	**-24193.78 (6688.503)**	-3.62 (0.000)***
Humidity	**-46574.35 (12403.59)**	-3.75 (0.000)***	**-18506.56 (3722.411)**	-4.97 (0.000)***	**52228.69 (1735.226)**	30.10 (0.000)***	**89504.47 (1892.07)**	47.31 (0.000)***	**104933.3 (6060.686)**	17.31 (0.000)***
Humidity^2					**-645.0551 (39.68587)**	-16.25 (0.000)***	**-892.447 (24.66254)**	-36.19 (0.000)***	**-1040.792 (35.85821)**	-29.03 (0.000)***
WindSpeed	**-198974.9 (2120.97)**	-93.81 (0.000)***	**-72899.02 (875.8049)**	-83.24 (0.000)***						
lnWindSpeed					**-728457.4 (60998.45)**	-11.94 (0.000)***	**-201026.5 (37763.54)**	-5.32 (0.000)***	**-1076068 (83629.48)**	-12.87 (0.000)***
Pressure	**-1936637 (34814.77)**	-55.63 (0.000)***	**-808165.1 (34679.47)**	-23.30 (0.000)***	**-848428.6 (21328.25)**	-39.78 (0.000)***	**-111482.9 (149407.5)**	-0.75 (0.456)	**-627776.4 (75608.56)**	-8.30 (0.000)***
Precipitation	**5450539 (5314622)**	1.03 (0.305)	**1078735 (1728314)**	0.62 (0.533)	**4047063 (1933644)**	2.09 (0.036)**	**5371735 (2060284)**	2.61 (0.009)***	**4842382 (2225380)**	2.18 (0.030)**
Volume_1			**.6037575 (.0063804)**	94.63 (0.000)***	**.6046173 (.0071212)**	84.90 (0.000)***	**.6160644 (.0075288)**	81.83 (0.000)***	**.4980139 (.0061438)**	81.06 (0.000)***
Month	**Included**		**Included**		**Included**		**Not Included**		**Included**	
State	**Included**		**Included**		**Included**		**Included**		**Included**	
Recession	**Included**		**Included**		**Included**		**Included**		**Included**	
Hour	**Included**		**Included**		**Included**		**Included**		**Not Included**	
Intercept	**7.65e+07 (4228455)**	18.09 (0.000)***	**3.82e+07 (108101.7)**	353.65 (0.000)***	**3.93e+07 (112941.8)**	347.70 (0.000)***	**1.39e+07 (4542272)**	3.07 (0.002)***	**2.49e+07 (3196830)**	7.78 (0.000)***
Robust	**Yes**		**Yes**		**Yes**		**Yes**		**Yes**	
Regression summary statistics										
R^2	**0.3533**		**0.5919**		**0.5941**		**0.5915**		**0.4714**	
Within R^{22}	**0.3534**		**0.5918**		**0.5941**		**0.5914**		**0.4713**	
Sigma_e	**14276273**		**11343622**		**11301052**		**11335457**		**12895003**	
n	**30,443**		**30,443**		**28,747**		**28,747**		**28,747**	
*** p<0.01, ** p<0.05, * p<0.1										

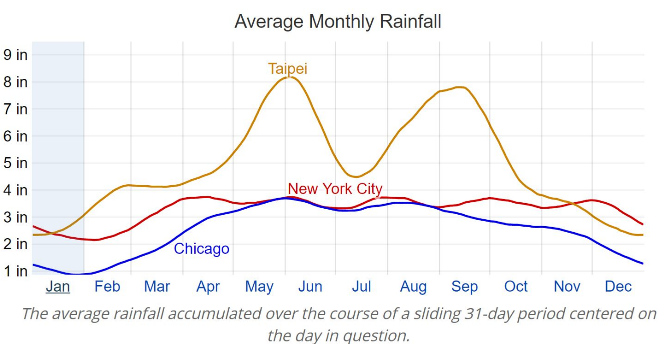
According to the coefficients in Table 6, per one percent increase in the dry-bulb temperature in Fahrenheit, the hourly return of SPY is expected to increase by 0.000422 percent on average, holding other variables constant. When the relative humidity increases by one percent, the hourly return of SPY changes by - 0.0000349 + 0.000000684**Humidity* on average, holding other variables constant. If the relative humidity is less than 51.02 percent, it has a negative effect on the return of SPY. However, once it gets greater than 51.02 percent, it starts having a positive effect on the return of SPY (Since the coefficient of $Humidity^2$ is positive, the marginal effect of the relative humidity on the hourly return of SPY is increasing as the relative humidity increases). Since the mean of humidity is about 57.68 percent, most of time, humidity has a positive effect on the hourly return of SPY. Per one inch increase of Mercury in sea level pressure, the hourly return of SPY is expected to increase by 0.0004937 (0.04937 percent) on average, holding other variables constant. Per one inch increase in the amount of precipitation, the hourly return of SPY is expected to increase by 0.0070494 (0.70494 percent) on average, holding other variables constant.

Among factors of weather which have a significant relationship with the return of SPY, precipitation is the most effective factor on the return of SPY. This result does not agree with studies of Hirshleifer & Shumway (2003) and Wang & C. Lin & J. Lin (2011) . Hirshleifer & Shumway (2003) say that there is no significant correlation between rain and stock return. They use daily stock return of market index, while I use hourly stock return of SPY. This could give us different results because I focus more on short-term effect of weather on stock trading. Thus, it can be said that change in precipitation can result in the immediate and short-term effect on the return of SPY which do not last for a day. Wang & C. Lin & J. Lin (2011) also use different data which is from Taiwan, while U.S. weather data is collected in my study. It is not surprising to have different results because of the climatic characteristics of Chicago and New York. There are on average 113 rainy days per year in New York and 124 in Chicago (BestPlaces). On the other hand, according to World Weather & Climate Information, Taipei, Taiwan, has an average of 165 rainy days a year (“Average monthly rainy days...”). In Taiwan, it rains half of the year. Taiwan also has significantly higher daily chance of precipitation and higher amount of average monthly rainfall than New York and Chicago (“Comparison of the Average…”). Thus, Taiwan is more familiar with the rain, so precipitation might not significantly affect people's mood or decision making. New York and Chicago, on the other hand, have a significantly lower daily chance of precipitation, the amount of average monthly rainfall, and average annual rainy days, which can have a greater impact on people's stock trading decisions when it actually rains. Graph 8 and 9 show the daily chance of precipitation and average monthly rainfall in New York, Chicago, and Taipei, respectively.

Graph 8. Daily Chance of Precipitation In New York, Chicago, and Taipei



Graph 9. Average Monthly Rainfall In New York, Chicago, and Taipei



Source: Weather Spark

Humidity has a bidirectional impact. When the humidity is low, it has a negative effect on the stock return, but if it goes beyond a certain level, it affects the stock return positively. This partly agrees with the suggestions of Howarth & Hoffman (1984) and Sariannidis & Giannarakis & Partalidou (2016). They say that high humidity has a positive effect on stock return, as it causes fatigue and lethargy, causing people to lose their concentration and energy (Howarth & Hoffman, 1984), and takes away comfort, making people behave more aggressively (Sariannidis & Giannarakis & Partalidou, 2016). Although the finding that there is a significant correlation between temperature and the return of SPY does not agree with what Wang & C. Lin & J. Lin (2012) find, it agrees with what Narayanamoorthy & Dharani & Muruganandan (2015) find. Also, The suggestion of Huang & Zhang & Hui & Wyer (2014) also supports this finding. They argue that warm temperatures make people more trust decision makers' opinions on product preference and stock outlook. Because SPY consists of shares of 500 companies, SPY reflects more investors' opinions than a stock of one company does. New York and Chicago are relatively cold cities where temperature drops below zero in winter. Therefore, Huang & Zhang & Hui & Wyer's argument supports that high temperatures have a positive effect on the return of SPY. This also explains the positive effect of sea level pressure on the return of SPY because when the pressure is high, it is usually sunny; therefore, temperature tends to be higher.

Although a significant relationship between some factors of weather and the return of SPY is suggested, the effect is very small. The maximum of precipitation is 0.85 inches which is not even one inch. The mean of precipitation is even less, which is 0.003. This means, although precipitation has a significant correlation with the return of SPY, the effect is too small to be economically meaningful. Therefore, despite the significant correlations between some factors of weather and the return of SPY, their effects are very slight. Moreover, some outliers on price are observed, which could result in biased results by making return too high or low. Therefore, the results might be less precise due to extreme outliers. Finally, *Humidity* seems to have a quadratic effect on SPY return. For instance, although it is found that the precipitation has a positive effect on the return of SPY, it does not make sense that flooding also makes a positive effect on the return of SPY. Therefore, there needs to be a certain point that offsets the particular effect of a weather factor on the stock return, which suggests that weather factors should have a bidirectional effect rather than a simple single effect on the stock return.

Results, Correlation Between Weather And Trading Volume

The second hypothesis is that the weather affects the trading volume of SPY. I sum up trading volumes of all transactions for an hour and regress the hourly total trading volume on the hourly weather data that is observed at the beginning of each hour. After running the regression (2-c), I find that *Humidity*, *WindSpeed*, *Pressure*, and *Precipitation* are significantly related to the trading volume of SPY at 5% significance level, while *Visibility* and *Temperature* have no significant relationship with the trading volume of SPY at 5% significance level.

According to the coefficients in Table 7, per one percent increase in the relative humidity, the hourly trading volume of SPY changes by 52228.69 - 1290.11**Humidity* on average, holding other variables constant. It has a positive effect on the hourly trading volume of SPY if the relative humidity is less than 40.48 percent and has a negative effect if the relative humidity is greater than 40.48 percent. Per one percent increase of mph in wind speed, the hourly trading volume of SPY is expected to decrease by 7284.57 on average, holding other variables constant. Per one inch increase of Mercury in sea level pressure, the hourly trading volume of SPY is expected to decrease by 848428.6 on average, holding other variables constant. Per one inch increase in the amount of precipitation, the hourly trading volume of SPY is expected to increase by 4047063 on average, holding other variables constant.

Unlike the results on the return of SPY, temperature has no significant correlation with the trading volume of SPY. However, wind speed comes out to have a significant negative correlation with the trading volume of SPY, which does not agree with what Sariannidis & Giannarakis & Partalidou (2016) suggest. They say that the stock return volatility and riskiness in the economy tend to decline when the wind speed is high because it prevents air pollution and gives investors a safe feeling. According what Sariannidis & Giannarakis & Partalidou (2016) say, trading volume is expected to increase when investors feel safer because safe feeling tends to lead to more investors' participation in stock trading. In addition, signs of two humidity terms are completely different from the ones on the return of SPY, resulting in totally different result. Pressure also has a negative effect on the trading volume of SPY unlike the positive effect on the return of SPY. These results do not agree with what Chandrapala (2011) and Tapa & Hussin (2016) find. They find that there is a significant positive correlation between stock return and trading volume. It is because when the trading volume is high, it provides a high liquidity of the stock; therefore, it increases the stock return.

The reason why I have different results on trading volume of SPY might be because trading volume is more related to changes in the stock outlook. As mentioned earlier, the industries that are the most sensitive to the weather are insurance, agriculture, energy, beverage industry, commercial fishing, skiing, and wineries (Duva, 2014). These seven industries are included in three sectors which are financial services, energy, and industry sectors. These three sectors account for 31.06 percent of the total SPY.

Duva (2014) says that insurance industry suffers when the sea level pressure is low) because low sea level pressure can cause a heavy rain, resulting in property damage. Llow sea level pressure also affects the commercial fishing industry negatively along with the high temperature. High temperature has a negative effect for agriculture industry and beverage industry because it can cause a huge loss due to drought, even though a warm temperature helps crops grow and water is the beverage industry's key raw material. Low temperature and more precipitation have positive effects on the skiing industry. High temperature again has a negative effect on wineries because grapes are sensitive to temperature. Financial Services industry is also affected by the weather. For example, Hurricane Sandy forced the New York Stock Exchange to close for two days, which resulted in a huge loss. To sum it all up, according to what Duva (2014) suggests, low or warm temperature, high sea level pressure, and high precipitation should have a positive effect on the outlook of SPY.

Unfortunately, the results do not agree with what Duva (2014) suggests. When I control for months and hours, temperature has no significant correlation with the trading volume of SPY. Also, as the sea level pressure goes up, the trading volume is expected to decrease, although precipitation appears to have a positive effect on the trading volume of SPY as suggested. The reason for this could be because seven industries that are included in three sectors of SPY only take up about 30 percent of SPY. Therefore, the other sectors that take up about 70 percent of SPY need to be considered as well to explain the coefficients better.

Although the some results differ from what I have for the return of SPY, precipitation again is the most effective factor on the trading volume of SPY as well as the return of SPY. This supports that precipitation does have a significant correlation with stock trading. In addition, bidirectional effect of humidity is found on the trading volume of SPY, which again suggests a nonlinear relationship between weather and trading volume of SPY. Table 8 shows the significance of each weather variable on the return and trading volume of SPY.

Table 8. Significance

	The return of SPY	The trading volume of SPY
	Significance	Significance
Visibility	No	No
Temperature	Positive	No
Humidity	Negative & Positive	Positive & Negative
Wind Speed	No	Negative
Pressure	Positive	Negative
Precipitation	Positive	Positive

Conclusion

In this paper, I examine whether there is a significant relationship between the weather and stock trading. I use the data of weather in New York and Chicago and the data of price and trading volume of SPY. I test two hypotheses. The first hypothesis is that there is a significant relationship between factors of weather and the hourly return of SPY. The second hypothesis is that there is a significant relationship between factors of weather and the hourly trading volume of SPY. These findings provide worthy information to trendy investors because the significant relationship between weather and stock return and trading volume of SPY can provide a good indicator that can be used to predict how overall stock market moves. Moreover, nonlinear relationship between humidity and both return and trading volume of SPY suggests that the effect of weather is not well captured by a linear model, perhaps because extreme weather has large effects on stock trading. Also, despite the significant relationships, their effects are very small on the return of SPY and findings could be less precise due to outliers in each variable. Finally, their effects on the trading volume of SPY still have some questions in spite of their significant statistics. Therefore, these are the questions that could be solved in further studies: (1) if a linear relationship can indeed explain all the weather effect on stock trading; (2) which nonlinear models can explain the best about bidirectional effect of weather on stock trading during the extreme weather as well as normal weather; (3) at which point each weather variable starts having a different effect on stock trading if a nonlinear relationship is actually found; (4) which relationship between the return and trading volume makes the signs of humidity completely opposite to each other. If these questions are answered, higher level of prediction on stock return and prospects would be possible to investors who take account of the weather.

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