# Dew Point Effect on Financial Market Volatility

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**Abstract**

In this paper we investigate the weather effect on the U.S. stock market based on a new thermal variable, dew point temperature, which has been verified as one of the most important weather-related measures of human comfort. We test the impacts of the weather in New York City on the intraday volatilities and returns of three indices of the U.S. stock market, including the Dow Jones Industrial Average Index, the NASDAQ index and the Standard & Poor 500 Index. The results suggest that (1) both high and low dew point levels are significantly associated with high volatility at market open as well as lunch time; (2) dew point has the least effect on NASDAQ compared with that of the other two indices. Moreover, we leverage on the empirical findings of the dew point effects to develop a volatility-based high-frequency trading strategy. Our back-test results demonstrate that the new strategy outperforms several baselines under frictionless market setting.

***Keywords:*** Weather effect, dew point, NYSE, financial market volatility, behavioral finance.
**JEL Classification:** G02, G14, G17

## 1. Introduction

Recent studies have shown evidence that reality always comes into conflict with traditional finance theory, which assumes that the market is dominated by rational and risk-averse investors. In the extensive literature on market irrationality, people found that emotional traders may dominate the price setting in certain conditions when they are overconfident (Kule and Wang, 1997; Daniel and Hirshleifer, 2015) or pessimistic (Miller, 1977). Different sources of irrationality are found in existing research, and the

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explanations vary. For instance, based on the study of disposition effect (Sheferin and Statman, 1985), investors tend to be less willing to sell shares with decreasing prices than those prices have increased. One explanation comes from the studies of loss aversion (Kahneman and Tversky, 1984; 1992) that believe losses are twice as powerful as gains psychologically. January effect (Thaler 1987) suggests that investors' stock prices increase more in January than in other months. This phenomenon is commonly explained by the yearly bonuses paid in January, which are generally invested in the stock market, and in turn inflate the market. Additional evidence about market irrationality can also be found in Barber and Odean (2001) and Hirshleifer (1998; 2001).

Much research has been conducted to locate exogenous factors, such as weather, that have significant effects on investors' emotion and their trading behaviors. In the initial work about the weather effect, Saunders (1993) found significant evidence to support the effect of cloud-cover in New York City on New York Stock Exchange (NYSE) stock returns. After that, Hirshileifer and Shumway (2003) tested the significant relationship between the total sky cover (SKC) and daily market index returns across 26 countries from 1982 to 1997, and the results were consistent with previous findings. Goetzmann and Zhu (2005) discovered that the average stock spreads widen on cloudy days and the weather effect was found insignificant if the spread effect is controlled in the models. Based on the findings, they claimed that there is little link between individual investor behaviors and local weather but market makers may be responsible for the relation between weather and returns. This explanation was further confirmed in Goetzmann (2014).

In this paper, we focus on investigating intraday weather effects on the New York stock market. To better represent the link between human comfort and the weather in the tests, we employ dew point temperature ($T_{DP}$), the temperature where the water vapor contained in air starts to condense and dew forms, as a key measure of weather instead of cloud-cover, relative humidity, temperature or wind speed. We technically improve the test mechanism by conducting robust regression and Monte Carlo method. Based on related findings, we propose and apply a dew-point and volatility based high-frequency trading strategy, which finally validates the practical value of the work.

The dew point temperature we employed is an effective measure of atmospheric moisture and human comfort. Both high and low dew points are associated with discomfort. We use the local weather recorded in central park as a weather proxy in New York, the Dow Jones Industrial Average Index (DJIA) as a New York financial market proxy and the NASDQ Index, the Standard and Poor 500 Index (S&P 500) as contrasts. Hourly weather records and intraday trading intervals are applied. Our findings suggest that both high and low dew points are associated with high volatility at market open. The dew point seems to have the least impact on NASDAQ, which has a pre-market session and differs from NYSE. Interestingly, a similar effect is also found during lunch time. We also optimize a volatility-based trading strategy, the Dual Thrust, with the dew point factor that yields a better back-test performance, assuming no market frictions exist.

The paper starts with literature review, states the proxies, the data and methodology applied, analyzes the empirical findings and tests the robustness after that, optimizes the Dual Thrust trading strategy with empirical findings, concludes and discusses at last.

# 2. Literature Review

*2.1 Dew Point and Human Comfort*

Dew point has been considered an effective measure of the atmospheric moisture and indicator of human comfort. Clayton H. Reitan (1963) figured out that mean monthly values of surface dew point and mean monthly values of precipitable water were well related, which suggests dew point is an indicator of the moisture content in the air. Consistently, S. J. Bolsenga (1964, 1965) found a similar relationship at a daily and hourly frequency. Auliciems and Szokolay (1997) discussed effects of several environmental factors of human comfort including air temperature, air movement, humidity and radiation. The humidity factor could be either expressed in the relative humidity way or the dew point temperature way.

The widely used method to calculate dew point is the Magnus Formula. And the Arden Buck equation could be used to promote the accuracy of calculation with a more precise saturated water vapor pressure (Mark G. Lawrence, 2005). Dew point temperature, $T_{DP}$(°C), can be calculated as a function of the dry bulb temperature, $T$(°C), and the relative humidity, $RH$(%), as follows:

$$T_{DP} = \frac{c\gamma(T, RH)}{b-\gamma(T, RH)}$$

*where*

$$\gamma(T,\ RH) = \ ln\left(\frac{RH}{100} exp\left[\left(b\ -\frac{T}{d}\right) * \left(\frac{T}{c+T}\right)\right]\right)$$

and a=6.1121 hPa; b= 18.678; c=257.14 °C; d=234.5 °C.

Wind speed, air temperature, relative humidity and solar radiation have been investigated as some of the major weather factors that affect human comfort in an urban area (Stathopoulos, Wu, Zackarias 2004). Nonetheless, dew point is a more effective measure of human comfort since it's a derived thermal factor based on relative humidity and air temperature. High dew point usually comes with high air temperature and high relative humidity in which case people tend to sweat but dew forms more easily on human's skin and prevents sweat evaporating, while lower dew point usually comes with lower temperature and lower relative humidity, in which case people feel dry and cold. Also high dew point makes human breath harder and low dew point takes more water content from human body. Thus, both high and low dew points make people feel uncomfortable. To most people, a relative humidity of 70% might be quite comfortable at 20°C but considerably uncomfortable at 30°C (Wallace & Hobbs, 2006). Therefore, relative humidity is a less effective indicator of human comfort solely without considering the temperature factor.

OSHA (Occupation Safety & Health Administration, United States Department of Labor) recommends indoor temperature maintained at 20 to 24.5 °C and relative humidity at 20-60% (accordingly the recommended indoor dew point at -4.5 to 15.5 °C). This recommended thermal condition interval allows people to keep a fresh mind and working efficiency. The dew point temperature below 0 °C is called frost point temperature. We simply set the dew point around 0 °C the comfort zone and take the absolute value of dew point into study. We'll show later with subinterval checks whether this treatment is appropriate.

*2.2 Human Comfort, Rationality and Financial Activities*

Environmental conditions influence human comfort level both physiologically and psychologically. Most people do not feel good on a hot humid or freezing arid day as a common sense. On such a day, the atmosphere of a place where people gather is also considered uncomfortable, such as public transport or workplace, since interpersonal interactions always exist and spread the discomfort, stress and anxiety among them. And the interpersonal interactions allow the environmental atmosphere to remain affecting human's psychology for a period of time, which is one of the major reasons that lead human behavior (Bell & Sundstrom 2001). Schwarz (1990) proposed that people could deal with feelings as if they were information. Keller (2004) claimed that during spring, high temperature or barometric pressure was considered pleasant weather and increased the levels of mood, memory as well as cognition. The time people spent outside increased the effect's significance. Thus, human discomfort is associated with not only physiological status but also fluctuations of emotion, perception, cognition and decision.

Such fluctuations increase noise in a certain place no matter if it's a virtual market or entity and the percentage of noise trading in financial markets. Black (1986) argued that noise always drives a certain part of investors' decisions in not only finance, but also economy. He then categorized traders into information traders and noise traders. Information traders are those investors that trade rationally based on fundamental analyses while noise traders are the so-called liquidity traders that trade on noise and chase trends in the market. Noise trading leads to larger financial market dynamic equilibrium stochasticity thereby increasing the market volatility. Financial market volatility is positively related to the percentage of noise trading behavior since one of the significant features of noise trading is trend chasing. The positive feedback will make the price movement proceed in the same direction (De Long, 1990; Shleifer & Summers, 1990). Hong and Stein (1999) named the two groups of investors "news-watchers" and "momentum traders". The news-watchers usually under-react to information while the momentum traders based on historical trends eliminate the under-reaction and even diverge prices further away from values, moreover, bring overreaction into the market, which increases the market volatility.

*2.3 Weather Effects on Financial Markets*

Saunders (1993) investigated how the cloud cover on New York City could affect daily stock returns on NYSE. He presumed that floor traders might be influenced by the cloud cover and thereby influence the market with their own trading interest. He employed morning weather before market open recorded in Central Park and LaGuardia field in New York City to do analyses. Mean test results indicated that returns on those sunny days were significantly higher than cloudy days. The regression result also suggested that return and cloudiness were negatively correlated. The robustness was checked with Monte Carlo method, subinterval data and outlier-removed data.

Hirshleifer and Shumway (2003) reviewed a basket of psychology papers that would support weather effects on financial markets. Consistent findings were reported among 26 financial centers all over the world using Ordinary Least Squares Regression (OLS) and Logistic Regression. He deseasonalized the daily cloudiness (subtracting weekly average) and included raininess and snowiness as control variables. He also proposed some weather-based trading strategies, which were profitable for low-cost traders. They also applied a fixed effects linear probability model to allow the violation of the assumption of error independent identical distribution.

Goetzmann and Zhu (2005) also employed the sky cover, consistent with former studies. He used individual investor account data to examine the buy-sell activity differences between sunny and cloudy days. Little relationship between local weather and individual propensity was found. He then proposed that the weather effect could be realized through specialists/market makers in the New York financial center and significant association was found between liquidity/bid-ask spread and New York weather. The morning effect was even more significant.

Chang (2008) especially investigated the short term weather effect on the New York financial market. Significant results were found at market open and volatility was influenced by cloudiness. The volatility was represented by price range and standard deviation. A bunch of other market activities were reported associated with the instant weather of New York City.

Lu and Chou (2012) studied the weather effect on an order-driven market, the Shanghai Stock Exchange. They found that weather significantly affects financial market activities rather than returns. Interestingly, such an effect was found at lunch time.

Goetzmann (2014) used disaggregated data to argue that the weather effect on the financial market was accomplished through institutional investors.

Our hypothesis is that a high or low local dew point is an indicator of higher financial market volatility. The presumption is that human discomfort leads to physiological and psychological fluctuations. In the meantime, human's irrationality enhances the noise trading behavior which is one of the major reasons for market volatility.

The dew point effect is supposed to be a short-term effect at market open. We employ intraday 15 minute trading intervals and use hourly dew point data to investigate the effect. The morning period is the most possible time that financial participants in Manhattan get influenced by the dew point outside since it's when they are usually on the way to work and the dew point works.

Compared to DJIA and S&P 500, the NASDAQ is supposed to have the least dew point effect or no such kind of effect, due to the pre-market session, where investors can trade before the formal open at 9:30 AM. Both S&P 500 and DJIA are indices based on publicly traded stocks on NYSE. About 90% of S&P 500 components are listed on NYSE while DJIA consists of 30 of the most influential "blue-cheap" stocks, 26 of which listed on NYSE. It results in DJIA getting more involvement from institutional investors, floor traders or specialist traders, who are mostly distributed in Manhattan and directly impact the market.

## 3. Proxy, Data and Methodology

The weather recorded in Central Park, which is located in the heart of Manhattan and geographically close to the financial center of New York City, is used as a proxy of the weather in Manhattan. The dew point is calculated based on the dry bulb temperature and relative humidity provided by the database. The absolute value of the dew point temperature is taken to plausibly measure human comfort.

The Dow Jones Industrial Average Index, the S&P 500 Index and the NASDAQ index are used as proxies of the financial market in Manhattan. We use price range, *RANGE*, as a proxy of volatility, which is the difference between the highest price in a trading period ($P_H$), and the lowest price in the same trading period ($P_L$).

$$RANGE = P_H - P_L$$

The weather data recorded in Central Park is obtained from the National Oceanic and Atmospheric Administration (NOAA) online database covering a time period from January 1, 2013 to April 30, 2016 with an hourly frequency. The DJIA, S&P 500 and NASDAQ indices data is obtained from Bloomberg Terminal at Stony Brook University covering the same time period with a frequency of 15 minute. The data from year 2013 to year 2015 is used as the testing dataset and the data of year 2016 is used as the validating dataset for the trading strategy optimization.

Table 1

Hourly Weather Data in Central Park Statistics

| Time | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| | **Tdp** | | | | | |
| **04:51** | -28.17 | -3.056 | 7.174 | 5.572 | 15.06 | 25.02 |
| **05:51** | -28.25 | -2.994 | 7.141 | 5.62 | 15.16 | 24.84 |
| **06:51** | -28.25 | -3.251 | 7.279 | 5.656 | 15.43 | 25.87 |
| **07:51** | -28.25 | -3.408 | 6.953 | 5.647 | 15.52 | 25.92 |
| **08:51** | -27.67 | -2.721 | 7.674 | 5.991 | 16.04 | 25.21 |
| **09:51** | -26.18 | -3.222 | 6.888 | 5.671 | 15.91 | 26.17 |
| **10:51** | -25.13 | -3.069 | 7.004 | 5.816 | 15.53 | 26.05 |
| **11:51** | -25.89 | -3.33 | 6.776 | 5.649 | 15.53 | 25.87 |
| **12:51** | -25.21 | -3.402 | 7.077 | 5.74 | 15.5 | 27.48 |
| **13:51** | -24.62 | -3.688 | 6.85 | 5.531 | 15.26 | 26.17 |
| **14:51** | -25.09 | -3.476 | 7.145 | 5.733 | 15.53 | 26.92 |
| **15:51** | -24.62 | -3.713 | 6.876 | 5.607 | 15.5 | 26.28 |
| | **T** | | | | | |
| **04:51** | -16.1 | 3.3 | 11.7 | 10.73 | 18.9 | 28.3 |
| **05:51** | -16.7 | 3.3 | 11.7 | 10.68 | 18.9 | 28.3 |
| **06:51** | -16.7 | 2.8 | 12.2 | 10.95 | 19.4 | 28.9 |
| **07:51** | -16.7 | 3.3 | 12.8 | 11.5 | 20.6 | 30.6 |
| **08:51** | -15.6 | 3.9 | 13.9 | 12.53 | 21.7 | 31.1 |
| **09:51** | -14.4 | 4.4 | 14.7 | 13.29 | 22.8 | 33.3 |
| **10:51** | -12.8 | 5.6 | 16.1 | 14.45 | 23.9 | 34.4 |
| **11:51** | -10.6 | 6.1 | 16.1 | 15.03 | 24.4 | 35.6 |
| **12:51** | -8.9 | 6.25 | 16.7 | 15.59 | 25.6 | 36.1 |
| **13:51** | -8.3 | 6.1 | 16.7 | 15.44 | 24.4 | 36.1 |
| **14:51** | -8.9 | 6.7 | 17.2 | 15.62 | 25 | 35.6 |
| **15:51** | -8.9 | 6.7 | 16.7 | 15.21 | 24.4 | 35 |
| | **RH** | | | | | |
| **04:51** | 24 | 55 | 67 | 67.07 | 79 | 100 |
| **05:51** | 25 | 56 | 67 | 67.46 | 79 | 100 |
| **06:51** | 26 | 55 | 65 | 66.33 | 78 | 100 |
| **07:51** | 20 | 53 | 62 | 63.99 | 75 | 97 |
| **08:51** | 20 | 49 | 59 | 61.28 | 73 | 97 |
| **09:51** | 17 | 45 | 54 | 57.27 | 69 | 97 |
| **10:51** | 14 | 41 | 50 | 53.88 | 64 | 97 |
| **11:51** | 13 | 38 | 47 | 51.68 | 63 | 97 |
| **12:51** | 13 | 36 | 46 | 50.32 | 62 | 97 |
| **13:51** | 14 | 35.5 | 46 | 50.27 | 62 | 97 |
| **14:51** | 11 | 36 | 46 | 50.32 | 62 | 100 |
| **15:51** | 12 | 36 | 47 | 51.27 | 65 | 97 |

Going through the weather dataset, we notice that both intraday temperature and relative humidity vary with time a lot while dew point is relatively stable. The air temperature reaches its lowest in the early morning and highest in the early afternoon in contrast with the relative humidity. The relative stability of intraday dew point provides us another approach to study the relationship between human comfort and financial activities. We also find that there was a financial market collapse on August 24 (the dew point on that day was above 20°C) and some holidays on which the NYSE and NASDAQ closed at different times. We remove these trading days to do analyses.

Table 2
Indices Volatility Statistics (in points)

| **9:30-9:45** | **Min.** | **1st Qu.** | **Median** | **Mean** | **3rd Qu.** | **Max.** |
|---|---|---|---|---|---|---|
| **DJIA** | 13.97 | 42.2 | 60.73 | 77.94 | 97.62 | 423.9 |
| **S&P 500** | 1.32 | 4.03 | 5.98 | 7.547 | 9.315 | 42.17 |
| **NASDAQ** | 2.665 | 8.33 | 11.3 | 13.22 | 16.06 | 55.21 |

Table 3
Indices Volatility Correlation Matrix

| **9:30-9:45** | **DJIA** | **S&P 500** | **NASDAQ** |
|---|---|---|---|
| **DJIA** | | | |
| **S&P 500** | 0.942578 | | |
| **NASDAQ** | 0.46818 | 0.533033 | |

Table 4
Indices Open Price Correlation Matrix

| **9:30** | **DJIA** | **S&P 500** | **NASDAQ** |
|---|---|---|---|
| **DJIA** | | | |
| **S&P 500** | 0.987252 | | |
| **NASDAQ** | 0.956402 | 0.983881 | |

The DJIA, S&P 500 and NASDAQ Indices open prices are highly correlated to each other, with correlation coefficients over 0.95. The volatilities of DJIA and S&P 500 in the first 15 minute trading interval are also highly correlated, with a correlation coefficient of over 0.9 while NASDAQ index has a considerably smaller correlation coefficient with the other two indices, which are around 0.5. One of the most significant differences between NYSE and NASDAQ is that NASDAQ has a pre-market session. The dew point effect at market open, if there is any, could have been already erased due to the pre-market session on NASDAQ.

Ordinary Least Squared (OLS) regression is applied to find out the potential relationship between dew point and market volatility. The reason multivariate linear regression is carefully used is the concern of multicollinearity among different weather factors. Using *V* to represent volatility which is measure by *RANGE*, $F_i$(s) to represent the other factor(s) that might impact volatility, the dew point-volatility relationship could be described as the following model:

$$V = \beta_0 + \sum_{i=1}^{n} \beta_i * F_i + \beta * \left|T_{DP}\right|$$

where β is the coefficient of absolute Dew Point Temperature's impact on volatility, $\beta_0$ is the intercept, $\beta_i$(s) is (are) the coefficient(s) of other factor(s) that might impact volatility.

We employ robust regression with M-estimator, Iteratively Reweighted Least Squares to check whether there is any outlier influence (Venables & Ripley 2002). We employ Monte Carlo method, permutation test in specific, to check on the regression residuals' non-normality (Anderson & Robinson, 2001). We shuffle the dew point data so that each day's dew points get matched onto another day's volatility. This is the method that Saunders employed in his 1993 paper. We run OLS regression with the shuffled data and repeat for 10,000 times. If the result given by OLS is robust, then the frequency that the coefficients given by permutation regressions that are larger than OLS coefficient should be small. The smaller the frequency is, the more robust the result should be.

We examine the subinterval dew point effect, the real dew point and the frost point respectively. We include control variables, the wind speed (*WIND*), the sky cover (*SKC*) and the calendar effects (*MONDAY*, *FRIDAY*), into regression model to check the robustness of the dew point effect on financial market volatility.

$$V = \beta_0 + \sum_{i=3}^{n} \beta_i * F_i + \beta * \left|T_{DP}\right| + \beta_1 * WIND + \beta_2 * SKC + \beta_3 * MONDAY + \beta_4 * FRIDAY$$

where $\beta$ is the coefficient of absolute Dew Point Temperature's impact on volatility, $\beta_0$ is the intercept, $\beta_i$(s) is (are) the coefficient(s) of other factor(s) that might impact volatility, $\beta_1$, $\beta_2$, $\beta_3$ and $\beta_4$ are respectively the coefficients of *WIND*, *SKC*, *MONDAY* and *FRIDAY*.

We also take seasonality into consideration. The de-seasonalized dew point temperature ($T_{DP}D$) is calculated with de-seasonalized dry bulb temperature and de-seasonalized relative humidity. We use the difference between each day's *SKC* and weekly *SKC* average (3 days before and 3 days after each day) as the de-seasonalized sky condition (*SKCD*), the difference between each day's *WIND* and weekly *WIND* average as the de-seasonalized wind speed (*WINDD*), the difference between each day's dry bulb temperature and weekly average as the de-seasonalized dry bulb temperature (*TD*), the difference between each day's *RH* and weekly average as the de-seasonalized relative humidity (*RHD*), and calculate the de-seasonalized dew point with *TD* and *RHD*. We repeat the control variable regression.

$$T_{DP}D = \frac{c\gamma(TD, RHD)}{b-\gamma(TD, RHD)}$$

## 4. Empirical Findings

Table 5
Dew Point and Index Volatility OLS Regression Result

| | Dew Point Time Point | | | | | | |
|---|---|---|---|---|---|---|---|
| | 04:51 | 05:51 | 06:51 | 07:51 | 08:51 | 09:51 | 10:51 |
| Interval | | | | | | | |
| | DJIA | | | | | | |
| 9:30-9:45 | 0.8019 *** | 0.8259 *** | 0.8096 *** | 0.8359 *** | 0.8248 *** | | |
| 11:00-11:15 | 0.1437 * | 0.1556 ** | 0.1467 * | 0.1408 * | 0.1337 * | 0.1294 * | 0.111 |
| 13:15-13:30 | 0.115 | 0.1294 * | 0.1299 * | 0.1414 ** | 0.137 * | 0.1362 * | 0.1207 |
| 14:30-14:45 | 0.1547 ** | 0.149 * | 0.1332 * | 0.1271 * | 0.1119 | 0.1055 | 0.0826 |
| | S&P 500 | | | | | | |
| 9:30-9:45 | 0.0735 ** | 0.0776 *** | 0.0748 *** | 0.0759 *** | 0.0755 *** | | |
| 11:00-11:15 | 0.0178 ** | 0.0186 ** | 0.0174 * | 0.0171 * | 0.0165 * | 0.0164 * | 0.0144 |
| 13:15-13:30 | 0.0112 | 0.0128 | 0.013 | 0.0145 * | 0.0143 * | 0.0142 | 0.0128 |
| 14:30-14:45 | 0.0211 ** | 0.02 ** | 0.0187 ** | 0.0185 ** | 0.0167 * | 0.0159 * | 0.013 |
| | NASDAQ | | | | | | |
| 9:30-9:45 | 0.0214 | 0.0301 | 0.0271 | 0.0286 | 0.0287 | | |
| 11:00-11:15 | 0.037 | 0.0366 | 0.0311 | 0.0305 | 0.0288 | 0.0292 | 0.0254 |
| 13:15-13:30 | 0.029 | 0.0332 | 0.033 | 0.0362 | 0.0364 | 0.0368 * | 0.0347 |
| 14:30-14:45 | 0.0565 ** | 0.0527 ** | 0.0496 ** | 0.0507 ** | 0.0477 ** | 0.0449 * | 0.0398 * |

*The first row marks the time points of dew point applied. The first column marks the trading interval applied. Each result consists of the dew point-volatility regression coefficient and the p-value in parentheses. Significance level: "*" 10%, "**" 5%, "***" 1%.*

The regression results suggest that the morning dew points have significant influence on market volatility in several trading intervals with a concentration in

9:30-9:45 AM, 11:00-11:15 AM, 1:00-1:15 PM and 2:30-2:45 PM. The market volatilities in these trading intervals are enlarged on those mornings with high absolute dew points, which means both high dew point and low frost point are positively related to market volatility. The DJIA and S&P 500 have the most significant results in 9:30-9:45 AM right after market open (1% significance level). On the contrary there is no significance on NASDAQ in 9:30-9:45 AM. As we discussed before, NASDAQ has a pre-market session which might have already erased the dew point effect before formal market open. To our best knowledge, former studies on weather effects and financial markets didn't mention NASDAQ. We present our humble findings on NASDAQ here and this could be evidence of behavioral finance.

Interestingly, a similar but less significant (5% or 10% significance levels) effect is also found around 11:00 AM, 1:00 PM and 2:30 PM, which are usually right before or after lunch time. Since the intraday dew point is relatively more stable, this finding is no big surprise. Lunch time for the financial participants is not as concentrated as morning time. It makes sense that the lunch time effect is less significant than the morning effect. And our conservative inference is that the financial participants could be influenced by dew point in either physical or psychological way that is they might physically feel the dew point when going out for lunch or just simply associate and misattribute their current feelings around lunch time with morning feelings or working environment. Then their financial decisions get affected by cognitive biases.

Robust regression and permutation methods give consistent results with OLS. The coefficients given by robust regression have the same magnitudes as those given by OLS, which suggests that the outliers are not a problem and the results are reliable in terms of statistics. Also, the frequency that permutation regression coefficients are larger than the actual coefficient is smaller than 0.5% (using dew point at 7:51 AM and DJIA 9:30-9:45 AM trading interval).

We include control variables, wind speed, cloud cover and calendar effects as well as another dependent variable, rate of return (RR). The dew point effect on market volatility is still significant. And the de-seasonalized data shows similar results (using dew point at 7:51 AM and DJIA 9:30-9:45 AM trading interval).

Table 6
OLS Regression Result with Control Variables

| Variables | $T_{DP}$ | *SKC* | *WIND* | *MONDAY* | *FRIDAY* |
|---|---|---|---|---|---|
| *RANGE* | 0.8156*** | 0.8435 | 0.1946 | 2.774 | 1.082 |
| *RR* | -0.346 | -2.368 | 0.5204 | -6.326 | -6.96 |

*where RANGE is the price range in the trading interval 09:30-09:45, RR is the rate of return of the same trading interval, $T_{DP}$ is the Dew Point Temperature at 07:51. Significance level: "*" 10%, "**" 5%, "***" 1%.*

Table 7
OLS Regression Result with Deseasonalization

| Variables | $T_{DP}D$ | *SKCD* | *WINDD* | *MONDAY* | *FRIDAY* |
|---|---|---|---|---|---|
| *RANGE* | 0.8663*** | 1.052 | 0.9056 | 5.428 | -4.491 |
| *RR* | -0.3828 | -2.054 | 1.217 | -5.147 | -9.176 |

*where RANGE is the price range in the trading interval 09:30-09:45, RR is the rate of return of the same trading interval, $T_{DP}D$ is the de-seasonalized Dew Point Temperature at 07:51. Significance level: "*" 10%, "**" 5%, "***" 1%.*

We separate dew point data into 2 subintervals, ( , 0] and (0, ), which represent dew point and frost point respectively. The results remain (using dew point at 7:51 AM and DJIA 9:30-9:45 AM trading interval). And low frost point is associated with low rate of return. Moreover, when dew point is below zero, deseasonalized sky cover is negatively related to rate of return, which is consistent with former studies.

Table 8
OLS Regression Result with Subinterval Check

| Variables | $T_{DP}D$ | *SKCD* | *WINDD* | *MONDAY* | *FRIDAY* |
|---|---|---|---|---|---|
| | Dew Point | | | | |
| *RANGE* | 0.6966* | 1.7665 | 0.7712 | 11.2151 | 0.3657 |
| *RR* | -0.1819 | 2.8716 | 1.2650 | -13.0356 | -14.1182 |
| | Frost Point | | | | |
| *RANGE* | 1.0537* | 3.0162 | 1.3807 | -2.5324 | -16.8196 |
| *RR* | -1.3705* | -12.0849** | 1.4604 | 14.0773 | -0.4996 |

*Significance level: "*" 10%, "**" 5%, "***" 1%.*

## 5. Using Dew Point Factor to Optimize A Trading Strategy

In accordance with the discussion in former sections, there seems to be a positive relationship between the absolute value of the morning dew point temperature in Central Park and opening volatility of the DJIA, which is a short term effect. We propose an optimization based on the Dual Thrust trading strategy.

### *5.1 Dual Thrust Trading Strategy*

A well-known trading strategy based on volatility is called Dual Thrust. Trading signals would be generated once the price crosses either the upper line/ceiling or the lower line/floor. Both of the lines depend on the price movements in the past several days.

There are four commonly used prices to describe a financial instrument, the open price in a trading period ($P_O$ $or$ $OPEN$), the highest price in a trading period ( $P_H$ $or$ $HIGH$), the lowest price in a trading period ($P_L$ $or$ $LOW$) and the close price in a trading period ($P_C$ $or$ $CLOSE$). Traders employ the highest of *HIGH*s in n days (*HH*), the lowest of *CLOSE*s in n days (*HC*), the lowest of *CLOSE*s in n days (*LC*) and the lowest of *LOW*s in n days (*LL*) to define two ranges as follow:

$$HH = max(HIGH_t, HIGH_{t-1}, ..., HIGH_{t-n})$$
$$HC = \left(CLOSE_t, CLOSE_{t-1}, ..., CLOSE_{t-n}\right)$$
$$LC = \left(CLOSE_t, CLOSE_{t-1}, ..., CLOSE_{t-n}\right)$$
$$LL = min(LOW_t, LOW_{t-1}, ..., LOW_{t-n})$$

$$Range_1 = HH - LC$$
$$Range_2 = HC - LL$$

*where t is the current time point and n is the number of the past trading days.*

They then pick the bigger one of the two ranges as *Range* and combine two parameters, $k_1$ and $k_2$ as well as *OPEN* price to construct the *ceiling* and *floor*. Larger *k* values make the strategy generate signals more strictly.

$$Range = max(Range_1, Range_2)$$

$$ceiling = OPEN + k_1 * Range$$
$$floor = OPEN - k_2 * Range$$

Once the price crosses over *ceiling*, traders choose to set long positions, while crosses over *floor*, they choose to set short positions.

*5.2 Optimization with Dew Point Factor*

Generally, uncomfortable dew points, either too high or too low, could lead to relatively irrational financial decisions and thereby increase the short-term market volatility (price range). In this case, there is a larger probability that “fake” breakthroughs appear as if the noise were new information into the market and less reliable signals are given by the strategy. While a relatively comfortable dew point enhances the reliability of the trading signals.

The calibration is (1) to adjust each day’s $OPEN_t$ to the previous day’s $CLOSE_{t-1}$ as well as $HIGH_t$, $LOW_t$ and $CLOSE_t$ accordingly. Let $OPEN_t^{'}$, $HIGH_t^{'}$, $LOW_t^{'}$ and $CLOSE_t^{'}$ represent the adjusted prices. They are defined as follow:

$$OPEN_t^{'} = CLOSE_{t-1}$$
$$HIGH_t^{'} = HIGH_t + OPEN_t^{'} - CLOSE_{t-1}$$
$$LOW_t^{'} = LOW_t + OPEN_t^{'} - CLOSE_{t-1}$$
$$CLOSE_t^{'} = CLOSE_t + OPEN_t^{'} - CLOSE_{t-1}$$

(2) to construct a new interval series with opening 15-minute trading intervals of past n days, as if they were continuous thereby generate signals (3) to double the positions given comfortable dew points and cut the positions into half given uncomfortable dew points. The back-test period is January-April 2016. The trades in the first 15 minutes

every trading day were used to generate trading signals. The dew point at 07:51 AM in Central Park was used to reallocate weights for positions. Suppose there are no market frictions, including but not limited to tax, commission, slippage; no opponents in the market trading against the calibrated strategy; the DJIA is perfectly reproduced and tradable; and no financial leverage used, employing k values of 0.6, 0.4 and 0.2 to represent strict, fair and easy signal generating models, the performance back-test results are shown below:

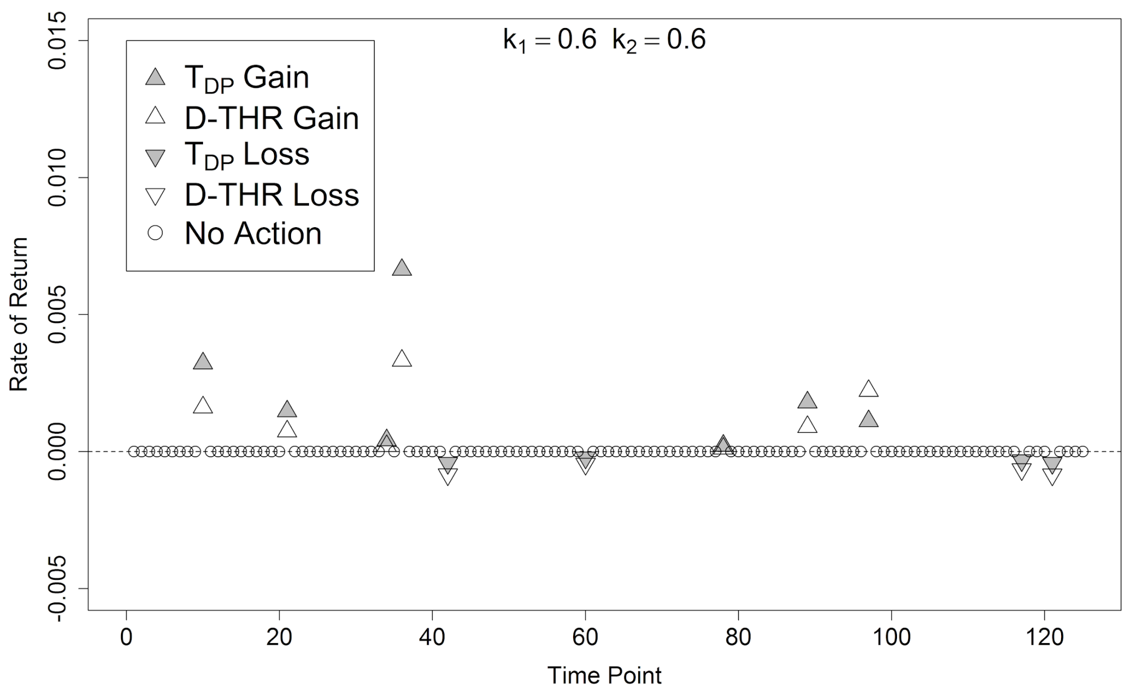


Fig.1. Strict model back-test trade

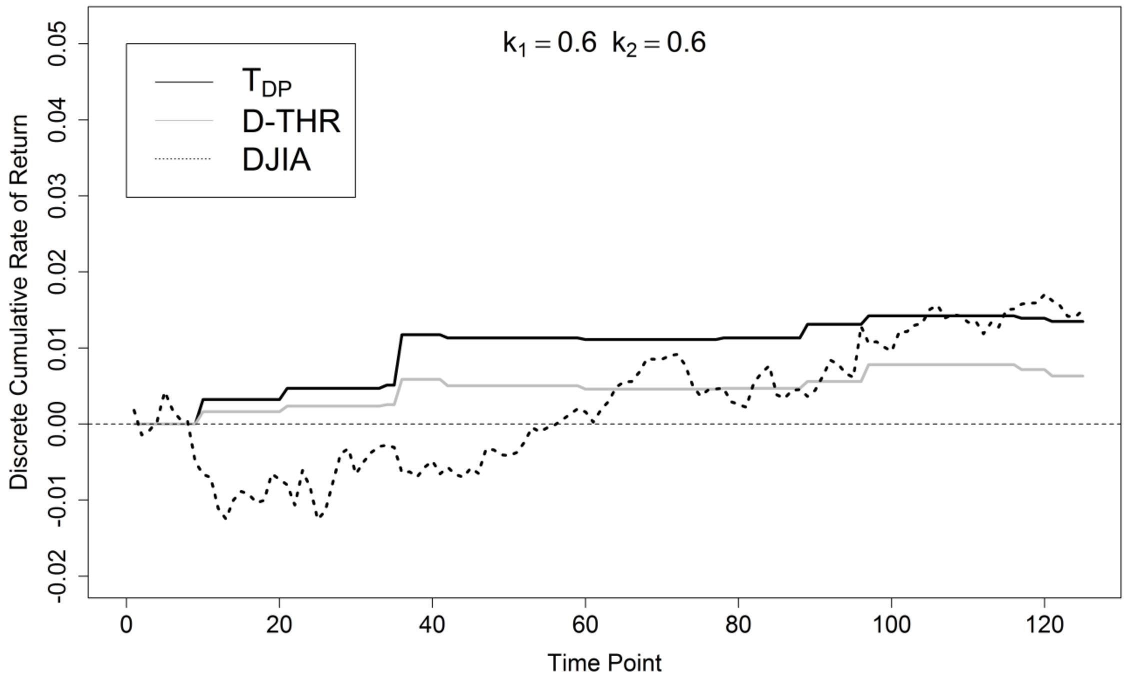


Fig.2. Strict model discrete cumulative rate of return

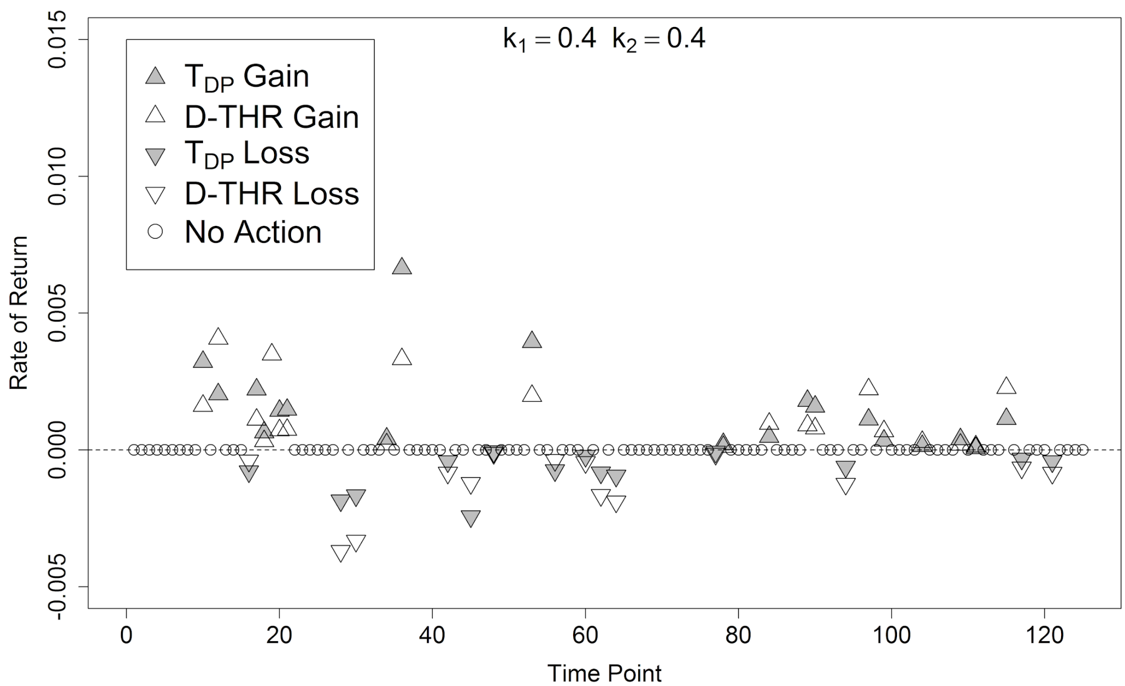


Fig.3. Fair model back-test trade

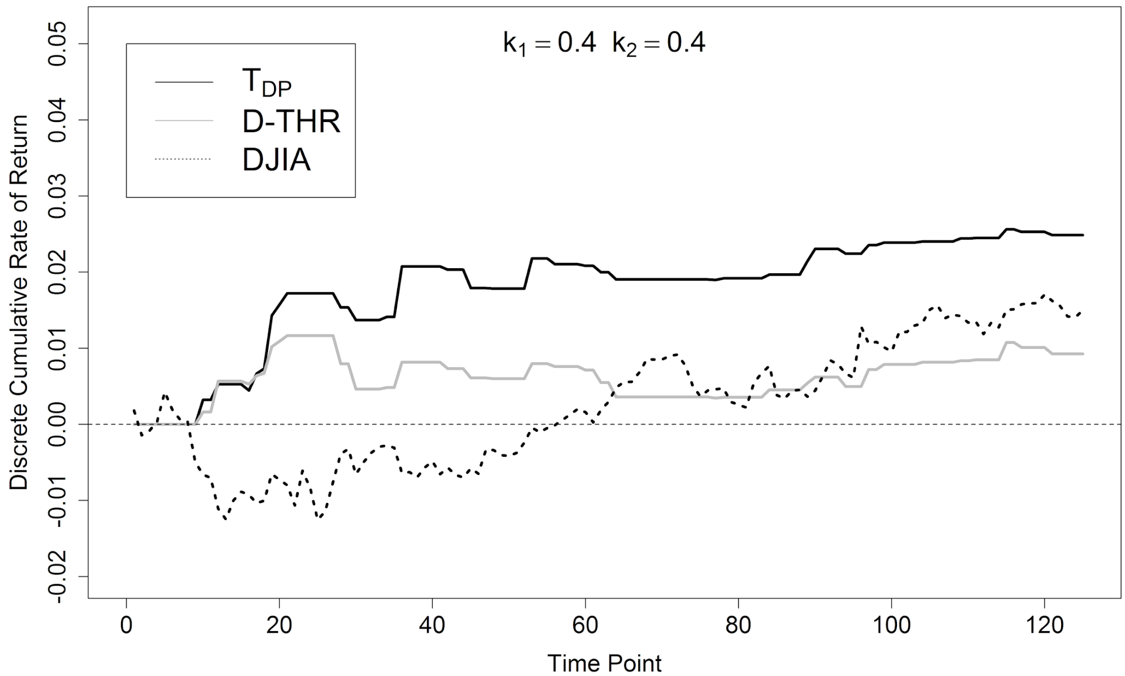


Fig.4. Fair model discrete cumulative rate of return

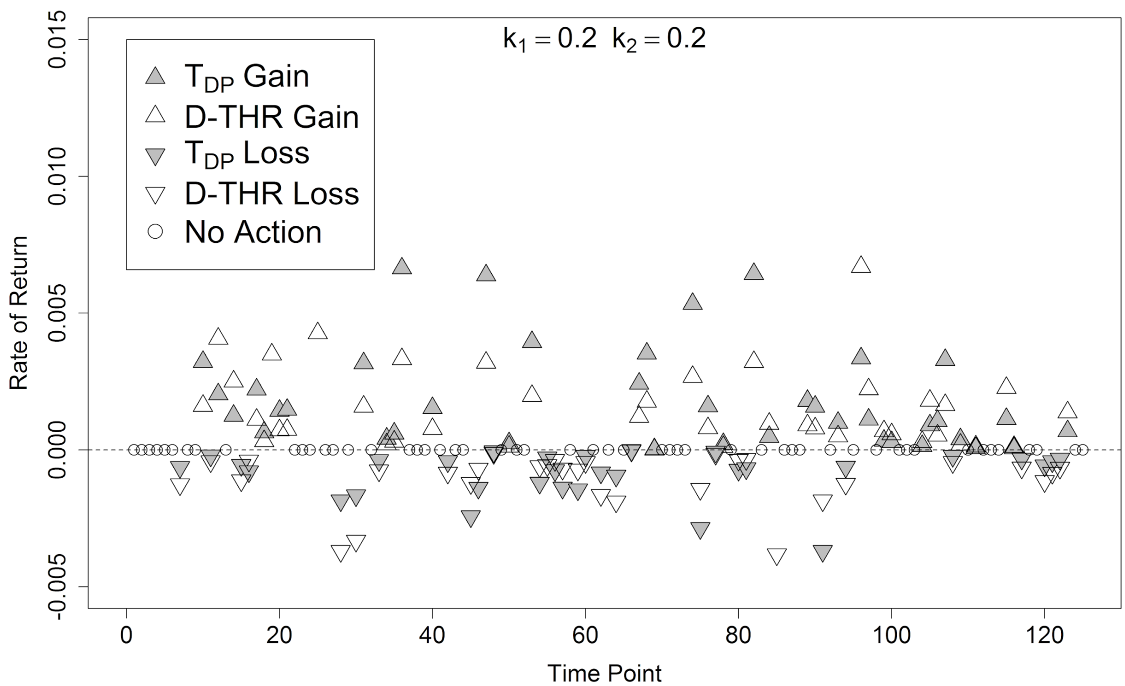


Fig.5. Easy model back-test trade

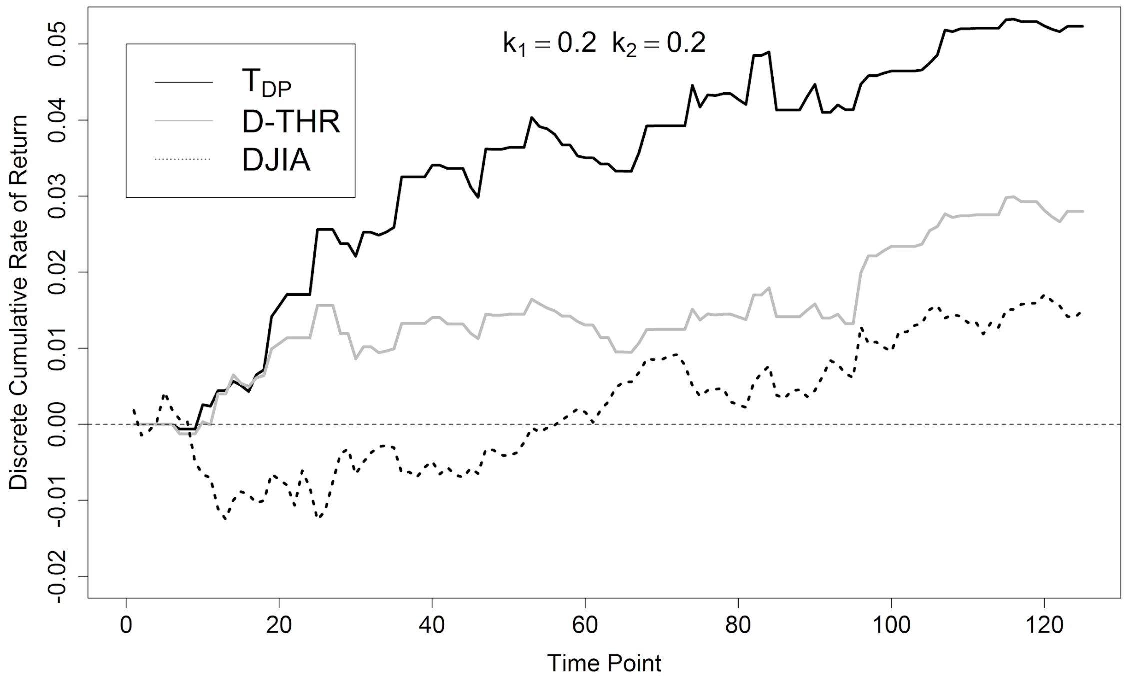


Fig.6. Easy model discrete cumulative rate of return

*where in back-test trade figures, filled point-up triangles stand for gaining trades introduced by dew point strategy, hollow point-up triangles stand for gaining trades introduced by dual thrust strategy, filled point-down triangles stand for losing trades introduced by dew point strategy, hollow point-down triangles stand for losing trades introduced by dual thrust strategy; in cumulative rate of return figures, black solid curves stand for discrete cumulative rate of return introduced by dew point strategy, gray solid curves stand for discrete cumulative rate of return introduced by dual thrust strategy and black dotted curves stand for discrete rate of return introduce by DJIA (or market) in the same time period.*

Table 9
Performance Back-test

| Strategies | D-THR | $T_{DP}$ | D-THR | $T_{DP}$ | D-THR | $T_{DP}$ |
|---|---|---|---|---|---|---|
| | **k1=k2=0.6** | | **k1=k2=0.4** | | **k1=k2=0.2** | |
| **Returns** | 0.0063 | 0.0135 | 0.0093 | 0.0249 | 0.0280 | 0.0523 |
| **AveReturn** | 0.00057 | 0.00123 | 0.00027 | 0.00073 | 0.00038 | 0.0007 |
| **SumWin** | 0.0090 | 0.0149 | 0.0261 | 0.0363 | 0.0617 | 0.0879 |
| **SumLoss** | -0.00278 | -0.00139 | -0.0168 | -0.0114 | -0.0337 | -0.0356 |
| **Trades** | 11 | 11 | 34 | 34 | 73 | 73 |
| **Wins** | 7 | 7 | 20 | 20 | 41 | 41 |
| **Losses** | 4 | 4 | 14 | 14 | 32 | 32 |
| **Wins%** | 63.6% | 63.6% | 58.8% | 58.8% | 56.2% | 56.2% |
| **Losses%** | 36.4% | 36.4% | 41.2% | 41.2% | 43.8% | 43.8% |
| **AveWin** | 0.0013 | 0.0021 | 0.0013 | 0.0018 | 0.0015 | 0.0021 |
| **AveLoss** | -0.0007 | -0.0003 | -0.0012 | -0.0008 | -0.0011 | -0.0011 |

*where D-THR is the strategy Dual Thrust, $T_{DP}$ is the optimized strategy with dew point factor, "Returns" is the discrete cumulative rate of return, "AveReturn" is the average rate of return per trade, "SumWin" is the discrete cumulative rate of return of all the winning trades, "SumLoss" is the discrete cumulative rate of return of all the losing trades, "Trades" is the time of all trades, "Wins" is the time of winning trades, "Losses" is the time of all losing trades, "Wins%" is the percentage of winning trades out of all trades, "Losses%" is the percentage of all losing trades out of all trades, "AveWin" is the average rate of return per winning trade, "AveLoss" is the average rate of return per losing trade.*

The performance back-test tells us that the dew point-market volatility relationship is effective in optimizing the Dual Thrust strategy in the validating period. This also once again demonstrates that the dew point-market volatility relationship does exist.

## 6. Conclusions

In this study, we investigate the weather effect on the New York financial market with a new thermal variable, dew point temperature, based on existing environmental and psychological studies. High dew point and low frost point are found significantly associated with increased market volatility. The short-term effect is found at both market open and lunch time on New York Stock Exchange in contrast with only lunch time on NASDAQ. Such an effect is validated in constructing a trading strategy using a volatility-based strategy. The effect might also be employed to better assess financial market risk.

## References


Anderson, M. J., & Robinson, J. (2001). Permutation Tests for Linear Models. *Australian & New Zealand Journal of Statistics*, *43*(1), 75-88. https://drive.google.com/open?id=0BwExEhPuhGljMXo3c1VUTDBoeDA

Auliciems, A., & Szokolay, S. V. (1997). *Thermal Comfort*. https://drive.google.com/open?id=0BwExEhPuhGljX09ueWtkci1oU00

Bell, P. A., Greene, T. C., Fisher, J. D., & Baum, A. (2001). *Environmental psychology*. 5th ed.. Belmont, CA: Thomson Wadsworth. https://books.google.com/books?id=3Iqu_0OC8d0C&lpg=PA373&ots=v_jnyPRBra&dq=Bell%20P%20A%2C%20Green%20T%2C%20Fisher%20J%20D%2C%20et%20al.%20Environmental%20Psychology&lr&hl=zh-CN&pg=PA373#v=onepage&q&f=false

Black, F. (1986). Noise. *The Journal of Finance*, *41*(3), 528-543. https://drive.google.com/open?id=0BwExEhPuhGljM3huUWI4Z09MNjQ

Bolsenga, S. J. (1965). The relationship between total atmospheric water vapor and surface dew point on a mean daily and hourly basis. *Journal of Applied Meteorology*, *4*(3), 430-432. https://drive.google.com/open?id=0BwExEhPuhGljQVdVblJDXzNDa1k

Chang, S. C., Chen, S. S., Chou, R. K., & Lin, Y. H. (2008). Weather and intraday patterns in stock returns and trading activity. *Journal of Banking & Finance*, *32*(9), 1754-1766. https://drive.google.com/open?id=0BwExEhPuhGljbFQ3VW5QdEZEODg

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 703-738. https://drive.google.com/open?id=0BwExEhPuhGljTVhfc2I2SkdVV1k

Fairfax, R. E. (2003). OSHA policy on indoor air quality: office temperature/humidity and environmental tobacco smoke. *Occupational Safety & Health Administration, Washington, DC*. https://www.osha.gov/dts/osta/otm/otm_iii/otm_iii_2.html#5

Goetzmann, W. N., & Zhu, N. (2005). Rain or shine: where is the weather effect?. *European Financial Management*, *11*(5), 559-578. https://drive.google.com/open?id=0BwExEhPuhGljUVE4bmJRak9lZlU

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2014). Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies*, hhu063.

https://drive.google.com/open?id=0BwExEhPuhGljSlZOcDZncEx6U1k

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, *58*(3), 1009-1032.
https://drive.google.com/open?id=0BwExEhPuhGljbjBTNkJPOVRlZEE

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, *54*(6), 2143-2184.
https://drive.google.com/open?id=0BwExEhPuhGljRGhyeUFkQVVNYTg

Lawrence, M. G. (2005). The relationship between relative humidity and the dewpoint temperature in moist air: A simple conversion and applications. *Bulletin of the American Meteorological Society*, *86*(2), 225-233.
https://drive.google.com/open?id=0BwExEhPuhGljOFpaWkxHVEc3NWs

Lu, J., & Chou, R. K. (2012). Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China. *Journal of Empirical Finance*, *19*(1), 79-93.
https://drive.google.com/open?id=0BwExEhPuhGljS0xWWk9QT0xtdkE

Keller, M. C., Fredrickson, B. L., Ybarra, O., Côté, S., Johnson, K., Mikels, J., ... & Wager, T. (2005). A warm heart and a clear head the contingent effects of weather on mood and cognition. *Psychological Science*, *16*(9), 724-731.
https://drive.google.com/open?id=0BwExEhPuhGljejJuX2VPeWlrVTQ

Reitan, C. H. (1963). Surface dew point and water vapor aloft. *Journal of Applied Meteorology*, *2*(6), 776-779.
https://drive.google.com/open?id=0BwExEhPuhGljZWstRXpFWXZ4Tms

Saunders, E. M. (1993). Stock prices and Wall Street weather. *The American Economic Review*, *83*(5), 1337-1345.
https://drive.google.com/open?id=0BwExEhPuhGljOC00cWwwVHBkVm8

Schwarz, N. (1989). *Feelings as information*. Mannheim.
https://drive.google.com/open?id=0BwExEhPuhGljMzFwVEwwZUhjYkE

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance.*The Journal of Economic Perspectives*, *4*(2), 19-33.
https://drive.google.com/open?id=0BwExEhPuhGljSVYtZ0xPaGxXYjQ

Stathopoulos, T., Wu, H., & Zacharias, J. (2004). Outdoor human comfort in an urban climate. *Building and Environment*, *39*(3), 297-305.
https://drive.google.com/open?id=0BwExEhPuhGljUHhZcUlGblM3V2c

Venables, W. N. & Ripley, B. D. (2002) *Modern Applied Statistics with S*. Fourth Edition.Springer, New York.
https://drive.google.com/open?id=0BwExEhPuhGljcU00S2hQUTBxbmc

Wallace, J. M., & Hobbs, P. V. (2006). *Atmospheric Science: an introductory survey* (Vol. 92). Academic press.
https://drive.google.com/open?id=0BwExEhPuhGljTGlpVkxiU2RkV3M