Impact of temperature on clean energy stock returns

Relative to the market and oil/gas index

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Abstract

This study examines the effect temperature has on stock returns, and whether clean energy stocks respond differently to temperature than the general stock market. The paper focuses on three different indices; a clean energy index, a market index, and an oil/gas index, with the majority of stocks trading at the New York Stock Exchange (NYSE). Psychological studies suggest that temperature affects people's mood, in turn leading to behavioural changes. Further on, the feeling of apathy and aggressiveness has been linked to warm and cold temperatures, respectively. With aggressiveness related to increased risk-taking and apathy linked with a reduced appetite for risk, we expect to see a general negative correlation between temperature and stock market returns. With climate change poising a growing threat, it has become a major reason for concern, both globally and locally. Studies on temperature and perceived climate change have shown that temperature anomalies have a significant influence on global warming attitudes. In light of this, we expect sufficiently high and low temperatures to have a positive impact on clean energy returns. After examining and comparing three different US stock indices, we find convincing evidence to support our primary hypotheses. Apathy seemingly dominates aggressiveness when temperatures rise, resulting in generally lower returns. For colder temperatures aggressiveness seem to be the dominating factor, leading to overall greater returns. However, the impact on clean energy returns is positive for both warm and cold temperatures, relative to the market. In addition, clean energy -and oil/gas companies have a completely opposite response pattern to warm weather, with a very positive reaction on clean energy stocks and an equally negative reaction on oil/gas stocks. This suggests that abnormally warm temperatures increase people's beliefs and awareness of climate change, resulting in excess returns for clean energy stocks. The observed results are statistically significant and robust to alternative tests, both before and after controlling for seasonal effects.

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1. Introduction

Traditionally markets are said to be efficient, but particularly in more recent years this view has been challenged by theory of behavioural finance. Psychology plays an important role in investing. The field of behavioral finance proposes that psychological influences and biases affect financial behaviors and decision making of investors and other market-participants.

Research in psychology has shown that temperature affects mood, and mood may cause behavioural changes. Evidence shows that lower temperatures can lead to aggression, while higher temperatures may lead to both apathy and aggression, with apathy as the dominating factor. The former could entail risk-taking, while the latter could impede investors' appetite for risk (Cao and Wei, 2004).

Previous research linking temperature to stock market returns, suggest there might be a negative correlation between the two, although not all studies have led to the same conclusion. Studies have also shown that temperature plays an important role in the way people perceive the threat of climate change, and their attitude toward global warming (Zeval et al, 2014). With growing climate change concerns and increased focus on clean energy sources, we are interested in whether temperature has an effect on stock returns for clean energy companies, and whether this effect is different from the rest of the market.

The effects of global warming and climate changes poise a very serious threat, with potentially huge environmental and economical repercussions. This has resulted in an increasing consciousness worldwide regarding the challenges with global warming. Fossil based energy production, such as oil, coal and gas, is the primary contributor of CO2 emissions (wwf.no). A change from fossil based energy towards clean energy is necessary in order to reduce emissions. In light of this, we find it interesting to compare the performance of clean energy stocks against oil/gas stocks for different temperature ranges.

Based on theory and research as summarized above, we ask the question: Can we find evidence of a temperature effect on stock market returns? And furthermore: If temperature indeed has an effect on stock market returns, will the impact on clean energy companies be different than the rest of the market?

The aim of our study is two-sided. First we want to examine whether stock market returns are indeed related to temperature. This is a study that has been conducted quite a few times over the years, for several different stock markets, with quite different results. Secondly, and what will be the main focus of our study, is to examine if and how temperature affects stock returns on clean energy companies, relative to the market. This part of the study has, to the best of our knowledge, not been conducted before.

In order to answer these questions we collect temperature data for New York City, and stock return data for selected stock indices. Three different indices are chosen: A clean energy index, a general market index, and an oil/gas index. We design alternative tests to uncover a potential relationship in temperature related returns, with tests conducted comparatively for the three stock indices.

As mentioned above, few, if any studies have looked at the effect of temperature on clean energy returns. This is an interesting point of study, for several reasons. Firstly, from a theoretic point of view, it could work to shed more light on the (ir)rationality of the stock market. Any evidence of a temperature anomaly in stock returns would be further evidence against EMH. Secondly, from a financial point of view, a possible pattern in temperature related returns could be exploited and used in trading strategies for different market participants. Or perhaps, work as a gentle remainder of the irrationality that sometimes is present in investment decisions.

Based on previous research and theory summarized above, we have two main hypotheses:
1. “There is a general negative correlation between temperature and stock market returns.”
2. “Clean energy companies will have a positive impact from both warm and cold temperatures, relative to the market.” Additionally, we expect clean energy stocks to outperform oil/gas stocks when the weather gets warm. Our thought is that if higher temperatures, consciously or unconsciously, has an impact on people’s perception of climate change, more money is invested in clean energy companies on those days, possibly resulting in a opposite effect on fossil fuel companies.

The remainder of the paper is organized as follows; section 2 takes a look at some of the theory in question and summarizes previous research on related topics. Section 3 contains our predictions, while section 4 presents the data material: Where it is contained, how it is processed and so on. Section 5 goes trough the methodology, the construction and execution of empirical tests, and the main results of the study. Section 6 discusses some of the results, issues and potential for further research. A brief summary and concluding remarks are found in section 7.

2. Theory & Literature Review

2.1 Behavioral Finance

Traditional finance theory states that all markets, including the stock market, are fundamentally rational, and that available information are reflected in asset prices. By other words, all stocks trade at their fair value. However, many have argued that this perspective is inconsistent with reality. The reasons are many, but the efficient market hypothesis is particularly challenged on the fact that it ignores the impact of investor sentiment on stock analyzes, valuation, and decision-making processes (Dhir, 2019). In more recent times a lot of research on the field have led to attention on different types of market inefficiencies, or anomalies, that have further challenged the theory of efficient markets. Evidence seems to point at psychological factors having quite an influence on market outcome and returns, which stands in stark contrast to the proposed rationality of efficient markets. These newfound outlooks on investor behavior and financial markets have brought forward behavioral finance as a counterweight to the efficient market hypothesis (EMH), and an important field of research trying to explain abnormal observations in financial markets.

The theory of behavioral finance challenges the well-known and widely accepted theory of EMH. It proposes that psychological influences and biases affect the behavior and decision making of investors and other market participants in the financial markets. Many different types of heuristics help explain investor behavior observed in behavioral finance. A particularly relevant bias to this research paper is perhaps the Availability heuristic. Availability is a heuristic where people make judgments on the likelihood of an event, based on how “close to mind” an occasion – or a particular occurrence is. When people can imagine an event, they judge the event to be more reasonable. (Tversky & Kahneman, 1974).

In relation to this paper, the availability heuristic may play a part in that investors judge warm or cold weather as evidence of global warming tendencies, when in reality periodic fluctuations in temperature has always been present. In turn, possibly influencing investment decisions.

2.2 Weather effects on mood and stock returns

It is well established in psychological theory and literature that mood, feelings and emotions have an impact on people's decision making. And these feelings may be caused by environmental factors, such as weather conditions. People who are in a good mood make more optimistic judgments and choices than people in a bad mood (Wright and Bower, 1992). In recent times, a sub-field of behavioral finance, studying the effect of weather conditions on investor behavior and stock market returns, have emerged. Studies have shown that different weather variables may affect mood or cause mood misattribution. It is reasonable to think that weather could potentially lead to implications in decision making and investment behavior. As mood may affect investors' willingness to assume risk, emotional or moody reactions may take decision-making off track from rational thinking, and ultimately affect their investment behavior.

One of the first research papers that linked investment behavior to weather conditions was that of Saunders (1993). He examined the relationship between weather and stock returns in New York City, and discovered that sunny days were associated with greater returns. The differences in returns between the cloudiest days and the least cloudy days, were statistically significant. Kramer and Runde (1997) tried to replicate the findings in Saunders (1993), but their study suggested that no systematic relationship exists. However, the research conducted by Saunders (1993) was later supported by Hirshleifer and Shumway (2003), who examined 26 indices around the world for the period 1982-1997. They found that sunshine was strongly correlated with stock returns, while rain and snow were unrelated to returns.
Other studies suggest that the weather effect on stock returns, that is highlighted in many cases, is merely a data-driven inference and an exercise in data-mining (Jacobsen and Marquering, 2004; Kramer and Runde, 1997).

Even though there is a commonly held belief that weather affects mood, and most research seems to suggest so, the belief is not undisputed. Huibers et al. (2010); Denissen et al. (2008) all suggest that the effects of weather on mood were only small or non-existent. The extent to which weather affects mood, as well as which weather variables has the most influence on mood is also disputed. Denissen et al. (2008) research indicates that the average effect of weather on mood was only small; temperature, wind power, and sunlight had a significantly increased effect on a person's negative mood. Higher temperatures increased the negative feelings, while less amounts of wind and higher degree of sunlight decreased these negative feelings. No significant main effects of daily weather on positive affect were found.

It is worth pointing out that while the effects of seasons on mood are well documented (e.g., Rosenthal et al., 1984), comparatively few studies have assessed the relationship between daily variation in weather, human mood and cognition (Keller et al., 2005). Thus the area in which research seems to differ is in the effects of day-to-day variations in weather and mood. However, most research seems to support the commonly held belief that weather is an important explanatory variable and influence on mood.

2.3 Temperature effects on mood and stock returns

Studies show that temperature affects mood, and mood may cause behavioural changes. In fact, temperature seems to be one of the most significant variables affecting people's mood (Howarth and Hoffman, 1984;). Low temperatures may lead to aggressiveness, while high temperature may result in apathy or aggressiveness. Evidence from previous studies suggests that the temperature anomaly is characterized by a negative relationship between stock market returns and temperature.

Researchers Baron and Ransberger, (1978); Palamerek and Rule, (1980); Bell, (1981); Howarth and Hoffman, (1984) discovered that high temperature leads to aggression. Schneider et al (1980) concluded that cold temperature can also lead to aggression. Thus previous studies imply that very low or very high temperature can lead to aggression, while high temperature may also lead to apathy and hysteria.

Cao and Wei (2004) discovered a significant negative correlation between temperature and stock market returns after examining more than 20 international markets[1]. Their findings proved to be valid, also after controlling for several known anomalies, such as the tax loss effect, the seasonal affective disorder (SAD) effect, the Monday effect, and the cloud cover effect. Keef and Roush (2002) discovered that temperature had a small effect on stock returns in New Zealand. Using daily data from five European countries, Floros (2008) found a negative link between temperature and stock market returns for only three of the countries[2]. A positive relationship between temperature and returns was shown for Greece and UK, although these results were not significant. Keef and Roush (2007) also discovered a negative correlation between temperature and stock market returns for two stock indices in Sydney, Australia. Further on, they found evidence that suggested "deseasonalized" temperatures have a stronger negative influence than the level of temperature.
In a different type of study Hou et al. (2019) measured the impact of high temperatures on stock returns on NYSE in the years prior to, and after the installation of air-cooling systems on the floor of Wall Street. Their findings suggest a significant correlation between high temperatures and low returns before the installation of air-cooling, and a ”largely weakened” correlation in the following years.

2.4 Temperature effects on perceived climate change

Weather and climate play a vital role in individuals' perceptions and interpretations of the world they live in (Akerlof et al., 2013). Global warming is a highly complex matter, and signs of it are sometimes difficult to visualize, and this leads to a high degree of uncertainty among the public regarding the existence of global warming. Thus, in an attempt to determine the extent to which global warming is occurring, individuals are likely to be influenced by temporary variations in their environment (Joireman et al., 2010).

[1] Only eight of these markets were examined in depth

[2] Austria, Belgium, and France

A study by Zeval et al. (2014) shows evidence of local warming effects, a term referring to the observation that climate change judgments can depend on whether today seems warmer or colder than usual. They show that recent temperature abnormalities are given unwarranted weight, leading to an overestimation of the frequency of similar past events. Further resulting in increased belief and concern for global warming. The findings also indicate that respondents who perceived any given day as warmer than usual, not only developed a stronger belief and concern for global climate change, but where also willing to donate more money to climate change charities. The authors also control for some well-known sources of biases and heuristics of behavioral finance, such as framing[3] and attribute substitution[4], and suggest that an attempt to de-bias the robust effect of perceived temperature abnormalities would be difficult.

The idea that changes in local weather may affect perceptions of changes in climate, is supported by several other studies. For example, media coverage regarding climate change tend to increase during warmer weather (Shanahan & Good, 2000), and the unusually hot summer of 1988 have been argued to be responsible for the rise of concern for global warming during the time (Read et al., 1994; Ungar, 1992; cf. Bostrom & Lashof, 2007). Further to this, Fownes & Allred (2018) conducted a study on New York State residents' perception of climate change in relation to recent weather conditions. They found that perception of personally experienced climate change, significantly increased with warmer minimum temperatures. Maximum temperatures and total precipitation levels were not significant predictors in their study.
Generally, a number of studies have suggested that public belief and concern about climate change varies in line with local temperature and temperature changes (Akerlof et al. 2013; Lorenzoni and Pidgeon 2006; Joireman et al. 2010; Li et al. 2011; Howe et al. 2013).

In a report conducted by the Yale Program on Climate Change Communication and George Mason University Center for Climate Change, Leiserowitz et al. (2017) document an upward trend in concern about global warming in the American population. Amongst the things they observe are:

[3] The study showed that the framing of the questions had no significant effect on participants overall belief in and concern for global climate change

[4] The study find that attribute substitution is an important cause of the effect, however it is dominated by other biases and heuristics that lead to local warming effects

1. 71% of Americans think global warming is happening, an increase of 8% since 2015
2. 54% understand that global warming is mostly human-caused
3. 64% think global warming is affecting weather in the US
4. 44% say they have personally experienced global warming effects, an increase of 13% since 2015

This indicates a growing belief in global warming and an increased feeling of “realness” amongst US residents. There is also a strong belief in weather changes due to global warming, which may suggest that when individuals experience abnormal weather, they have a tendency to link the experience to global warming.

Interestingly, in a different survey, as much as 81% of New York State respondents’ believed that climate change was happening and 69% reported having personally experienced the effects of climate change. This may point to a unique strength of climate perception for New York residents (Fownes & Allred, 2018).

Although studies somewhat differ, consensus seems to be that there is a positive correlation between high –or higher than normal temperatures and peoples’ perception of climate change. The connection between cold –or colder than usual temperatures and perception of climate change is more ambiguous. While some may interpret cold weather as evidence against global warming, the tendency seems to be the opposite. Laypersons more often tend to judge exceptionally cold weather as confirmation of climate change (Capstick & Pidgeon, 2014). Perhaps because respondents associate abnormal cold, with weather that is extreme, bizarre, strange, or different than expected, words that are often used when specialists talk about the effects of climate change. The study further showed that skeptics tended to assign the cold weather as evidence against climate change, while non-skeptics were willing to accept the alternative.

Exposure to local TV weather stations may be an important source of information on climate change, particularly for people who don’t spend a lot of time outdoors. Local weather forecasts may increase perception of extreme weather events, and therefore climate change in general (Bloodhart et al., 2015).

3. Predictions

Clean energy stocks are generally riskier compared to the market and most other sectors. Previous studies suggest that cold temperatures lead to aggressiveness and increased risk taking. This would suggest an increased willingness to invest in riskier assets, perhaps leading to excess returns for clean energy stocks. Similarly, previous research suggests that apathy dominates aggressiveness in hot temperatures, resulting in less risk taking. This effect may result in lower returns for the riskier stocks compared to the general market. Thus, a potential positive effect of increased climate change perception when temperature increases, could be offset by the competing effect of apathy. Depending on which effect dominates the other, the total impact could be both positive and negative.

In light of the aforementioned research literature and expectations of how underlying psychology will affect behavioral outcomes, our first hypothesis is an overall negative correlation between temperature and stock market returns. Since returns are generally highly correlated, we expect this relationship to be present for all indices. Our second hypothesis is that both high and low temperatures will have a positive impact on clean energy returns, relative to the market. The idea is that extreme temperatures may lead to an increase in peoples' perceived risk of climate change. Potentially causing short-term positive effects in clean energy stock returns. Cold temperatures might not influence peoples' perception of climate change as strongly as warm weather, making the impact more difficult to predict. However, provided that lower temperatures increase investors' appetite for risk, we might expect a positive impact on clean energy stock returns, relative to the market, on this basis alone.

While increased awareness regarding global and local climate change could lead to a greater willingness to invest in clean energy companies, the opposite might be the case for oil/gas companies. Investors could possibly be moving capital from one sector to the other, resulting in a negative impact from extreme temperatures on oil/gas returns.

4. Data

The scope of our study is to look at the effect of temperature on clean energy stock returns, relative to the market and an oil/gas index. Our empirical research is based on return data from three US stock indices and temperature data from New York City, with a sample period ranging from August 16, 2004 to December 31, 2019. The indices cover a clean energy sector, a broad-based market sector and an oil/gas sector. Data on stock indices are retrieved from Wildershares and Yahoo Finance, while temperature data is acquired from NOAA's National Climatic Data Center (NCDC). After correcting for weekends and holidays, we have 3871 matching observations in our full sample.

The choice of the American stock market was primarily because we needed a clean energy index with a sufficiently long history, preferably in a mature market. With the WilderHill Clean Energy Index (ECO) being the first most important of its kind, New York became the natural choice (WilderShares, 2020). A possible issue with the US market is that the country is large and widespread, with climatic differences throughout. Thus a few assumptions have to be made, as is the case in any study of this kind. We have to make the assumption that temperature is sufficiently correlated across the country, or that trading in New York is representative of the market fluctuations. Later in the study we will compute simple tests on temperature impacts across regions in the US. Doing this enables to compare results and see whether the assumptions seem to hold.

4.1 Data Sources and Processing

As mentioned above, the sample consists of temperature data from New York City and return data for three different stock indices, one of which is a broad market index, and two narrower sector indices. The clean energy index is the main focus of the study, while the other two are included for comparison purposes, as well as trying to establish a general relationship between temperature and stock market returns. The ECO Index consists of clean energy stocks listed on the New York Stock Exchange (NYSE) and NASDAQ. NYSE Composite Index (NYA) is a broad market index that reflects the performance of all the stocks listed on the exchange. NYSE ARCA Oil & Gas Index (XOI) is a sector index measuring the performance of oil/gas companies listed on NYSE. The ECO Index has a significantly higher correlation towards NYSE than NASDAQ. Therefore, NYSE makes the most relevant benchmark.

Throughout this paper, we define returns for each index in the following way; ordinary returns for the market index, and abnormal returns for the clean energy –and oil/gas indices[5]. We use the broad market index as a benchmark, and calculate abnormal returns for the two sector indices, relative to the market, using CAPM[6]:

$$E(r) = r_f + \beta(R_m - r_f) ,$$

The expected returns are subtracted from the observed returns to create an abnormal return variable for both indices. This approach is intuitive as it enables us to study the effect of temperature on clean energy returns relative to the market, and compare directly against the oil/gas index. A very beneficial part of using abnormal returns as a performance measure for the two sector indices is that everything is measured relative to the market. Thus a possible seasonal effect on stock market returns, wouldn't impact the relative results of the indices.

[5] Abnormal returns for the two sector indices may be referred to as just "returns" later in the paper.

[6] The risk-free rate of return is obtained from Kenneth R. French, data library. Beta values for the clean energy –and oil/gas indices are 1.35, and 1.19, respectively.

There are fundamentally two different measures of temperature that can be used to study the impact on stock returns. You can either use the observed temperature on a given day, or the abnormal temperature, relative to a time-defined average. The former could lead to biased results, impacted by seasonal effects, and not by temperature itself. As for the latter, the challenge is to find the best possible measure of what is a “normal” temperature for a particular day. In this paper, we will take use of both sets of temperature measures.

Temperature data for New York City is obtained from National Climatic Data Center (NCDC) covering the period from August 16, 2004 to December 31, 2019. The meteorological convention is used to create the average daily temperature as the average of daily maximum and minimum temperature, which will simply be referred to as the “daily temperature” or “temperature” later in the paper. We compute abnormal, or “deseasonalized” temperature impacts based on the moving average temperature over a 5-day period of t-2, t-1,…, t+1, t+2. For each day j of the year y, we calculate the “normal temperature” as an average of the 5 days moving period over the last 10 years. I.e., we calculate the “moving average” at day j of years y-1, y-2, …, y-10. Thus for our sample period (2004 - 2019) we take use of temperature data all the way back to 1994. In this way, we are able to efficiently calculate a historical average temperature on any given day of a month, while at the same time capturing any changes in average temperatures throughout the sample period. The moving average is then subtracted from the observed temperature to create abnormal temperature data.

Due to the fact that returns can only be observed for trading days, we originally end up with more observations on temperatures than regarding returns. Thus, we remove temperature data for weekends and holidays, so the data are matched for each index. After cleaning the data we end up with 3871 matching observations[7]. A summary statistics is included in table 1 and 2:

[7] The final sample size is bit smaller for the deseasonalized set of observations, due to winsorizing of the top and bottom 1% of returns. The process and reasoning is explained in section 5.4.

Table 1: Summary Statistics – Full Sample with Seasonality

		Summary Statistics	
City		New York	
Period		17.08.2004 - 31.12.2019	
Index	Clean Energy	Market	Oil&Gas
		Panel A: Daily Return (%), Full Sample	
# of obs	3871	3871	3871
% Positive Returns	48,26 %	53,71 %	49,52 %
Mean	-0,0310 %	0,0274 %	0,0003 %
St. Dev	1,14 %	1,19 %	0,89 %
Min	-8,53 %	-9,73 %	-6,28 %
Max	8,61 %	12,22 %	5,34 %
Skewness	0,05	-0,22	-0,03
Kurtosis	3,73	12,49	2,96
		Panel B: Daily Temperature (°C)	
	Full sample		Trading sample
# of obs	5615		3871
Mean	13,33		13,50
St. Dev	9,56		9,53
Min	-13,75		-12,7
Max	34,45		34,45
Skewness	-0,22		-0,24
Kurtosis	-0,93		-0,91

Note:

1. As previously stated, mean returns (frequency of positive returns) for the clean energy –and oil/gas indices are abnormal, relative to the market index. Obtained using CAPM: $E(r) = r_f + \beta(R_m - r_f)$. *Please be referred to the text in section 4 for more details.*

Table 2: Summary Statistics – Winsorized Sample without Seasonality

		Summary Statistics	
City		New York	
Period		17.08.2004 - 31.12.2019	
Index	Clean Energy	Market	Oil&Gas
	Panel C: Daily Return (%), Winsorized sample		
# of obs	3748	3748	3748
% Positive Returns	48,24 %	53,80 %	49,47 %
Mean	-0,0352 %	0,0347 %	-0,0012 %
St. Dev	1,06 %	0,89 %	0,84 %
Min	-4,75 %	-3,56 %	-4,62 %
Max	4,54 %	3,23 %	3,96 %
Skewness	0,03	-0,32	-0,13
Kurtosis	1,21	1,52	1,67
	Panel D: Abnormal Temperature (°C)		
	Trading sample		Winsorized sample
# of obs	3871		3748
Mean	0,27		0,29
St. Dev	4,24		4,25
Min	-14,66		-14,66
Max	16,40		16,40
Skewness	0,10		0,10
Kurtosis	0,38		0,39

Note:

1. As previously stated, mean returns (frequency of positive returns) for the clean energy –and oil/gas indices are abnormal, relative to the market index. Obtained using CAPM: $E(r) = r_f + \beta(R_m - r_f)$. *Please be referred to the text in section 4 for more details.*

5. Methodology, Empirical Tests and Results

In order to answer the research questions, we utilize two different types of tests, in form of a semi-parametric and a parametric approach. Following Saunders (1993) and later Cao and Wei (2004), we sort returns for each stock index according to the collected temperature data and calculate a z-score to estimate the statistical difference in return groups for each of the indices. This makes for our semi-parametric test, which we will refer to as a "bin test". Further on we perform regression analysis' to measure the correlation between temperature and clean energy stock returns. Through the empirical tests we will be able to study the relationship between temperature and stock returns, both for the specific case of the clean energy sector, and for the market in general.

5.1 Bin Tests – Uncovering the effects of temperature related returns

For each stock market index we match returns with the corresponding temperature data, from the highest to the lowest temperature (descending order). We then divide the temperature series into sub-groups or bins, and calculate the mean return and frequency of positive returns for each bin. The mean return of the "high" bin (i.e., the sub-group covering the higher spectrum of the temperature range) is then compared with the mean return of the "low" bin (i.e., the sub-group covering the lower spectrum of the temperature range), and similar analysis is done for the frequency of positive returns. The purpose of this exercise is to determine whether the difference in mean returns is seemingly significant. Based on previous research we would expect to see higher returns in the low temperature bins for the general stock market. As for the clean energy index, we expect to see positive abnormal returns in both ends of the temperature range, due to increased perceived climate change, particularly for higher temperature ranges.

The frequency of positive returns in each temperature bin could be a good indicator of whether there is a trend, or pattern in temperature related returns. For example, if lower temperatures yield higher returns, we would probably expect to see a higher frequency of positive returns in the lower temperature bins, and vice versa. Similarly we would expect the frequency of positive abnormal returns to be higher in the high and low temperature bins for the clean energy index.

The detailed procedure is as follows: We compute the difference between the highest (maximum) and lowest (minimum) daily temperature in our sample data. We then divide the difference by number of bins, k, to obtain the temperature range of each sub-group[8].

$$\Delta = \frac{Temp_{max} - Temp_{min}}{k}$$

Thus, the first bin contains temperatures in the range [$Temp_{max}$, $Temp_{max}$ - Δ]; for the second bin we get [$Temp_{max}$ - Δ, $Temp_{max}$ - 2Δ], and so on. Constructing temperature intervals in this way enables us to observe the effect of the extreme and more rare observations. We argue that this is the most appropriate way with regards to our research questions, and the method that is best suited to show the effect of temperature on clean energy returns. Another option would be to construct bins equal in size, however this could potentially dilute the data. This would most certainly be an issue for the abnormal temperature sample, and in all likelihood have a negative impact on results. For our sampled data from New York we have a (max, min) daily temperature range of (34,5, -12,7) degrees Celsius. Given a number of 4 bins, the first bin (high bin) would contain temperatures ranging from 34,5 to 22,7 and the fourth bin (low bin) ranging from -0,9 to -12,7.

We follow the methodology used by Saunders (1993) and calculate a z-score to determine whether the mean returns associated with the highest and lowest temperature bins are statistically different for each of the indices:

$$\boldsymbol{z - score_{1,k}^{mean}} = \frac{\boldsymbol{r_1 - r_k}}{\sqrt{\frac{\boldsymbol{\sigma_1^2}}{\boldsymbol{n_1}} + \frac{\boldsymbol{\sigma_k^2}}{\boldsymbol{n_k}}}} \quad ,$$

where r_i, σ_i^2 and n_i represent the mean return, the variance of return and number of observations in bin i, where i equals (1,2,3,…,k) number of bins. We compute a similar z-statistic for the frequency of positive returns, to determine whether there is significant difference between extreme bins:

[8] Unless otherwise stated, all bins throughout this paper will be constructed in this way

$$z - score_{1,k}^{frequency} = \frac{p_1 - p_k}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_k(1-p_k)}{n_k}}} \quad ,$$

where p_i is the percentage of positive returns in bin *i* (*i = 1,2,3,…,k*).

Based on similar reasoning by Saunders (1993) and later Cao and Wei (2004), we argue that potential heteroskedasticity in variance estimators shouldn't be a problem. For the frequency of positive returns, heteroskedasticity in the variance estimator can be ruled out, as the variable measures a binomial outcome. It is also unlikely to be present in the variance for daily returns, due to observations being grouped by temperature, a random exogenous factor. As seen in Table 3, the standard deviation of returns are quite close in each test and for all bins in our study.

The above calculations and test are conducted for all three indices, with the market index working as a benchmark for abnormal clean energy –and oil/gas returns.
We set the number of bins equal to two, three, four, and five. With an increasing number of bins, the amount of data within each bin naturally decreases. In the extreme temperature bins, the amount of data decreases at an increasing rate due to the rarity of the most abnormal observations.

First, we want to test whether returns in the warm and cold bins are statistically different from zero[9]. The null and alternative hypothesis are stated as:

$$H_0: r_1 = r_k$$
$$H_1: H_0 \text{ not true } (r_1 \neq r_k)$$

The results are presented in table 3[10].

[9] Unless otherwise stated, all tests are conducted against the two-sided alternative throughout the paper. However, please note that, for one-tailed tests at the 10% significance level, the critical z-score or t-value for a large enough sample is 1.282.

[10] For brevity and reliability we only present the results of the 4 and 5 bin tests. These bin sizes gives narrower temperature intervals, yet contains enough observations to give reliable results.

Table 3: Relationship Between Temperature and Stock Returns – Overall Correlation with Seasonality

		# of bins = 4					# of bins = 5					
		Bin 1	Bin 2	Bin 3	Bin 4	Z-score (1,4)	Bin 1	Bin 2	Bin 3	Bin 4	Bin 5	Z-score(1,5)
# of Observations		875	1439	1270	287		499	1249	1112	860	151	
Temperature Interval (°C)		(34.45, 22.7)	(22.6 , 10.9)	(10.8 , -0.9)	(-1.0 , -12.7)		(34.45 , 25.0)	(24.9 , 15.6)	(15.5 , 6.2)	(6.1 , -3.2)	(-3.3 , -12.7)	
Market	Return Mean	-0,0193 %	0,0272 %	0,0497 %	0,0718 %	-1,1605	-0,0265 %	0,0175 %	0,0329 %	0,0670 %	0,0203 %	-0,4094
	Std. Dev. of Return	1,05 %	1,20 %	1,26 %	1,19 %		1,06 %	1,17 %	1,21 %	1,24 %	1,28 %	
	% of Positive Returns	51,89 %	53,37 %	54,57 %	57,14 %	-1,5580	49,50 %	54,04 %	54,59 %	54,30 %	54,97 %	-1,1819
Clean Energy Abnormal	Return Mean	-0,0163 %	-0,0827 %	0,0033 %	0,0316 %	-0,6422	0,0170 %	-0,0383 %	-0,1074 %	0,0276 %	0,0996 %	-0,8211
	Std. Dev. of Return	1,02 %	1,15 %	1,19 %	1,12 %		1,04 %	1,10 %	1,19 %	1,17 %	1,10 %	
	% of Positive Abn Returns	48,91 %	47,05 %	48,82 %	49,83 %	-0,2680	49,30 %	48,76 %	45,23 %	50,35 %	50,99 %	-0,3650
Oil/Gas Abnormal	Return Mean	-0,0207 %	-0,0020 %	0,0049 %	0,0560 %	-1,4699	-0,0530 %	-0,0074 %	0,0124 %	0,0115 %	0,0875 %	-1,9189 *
	Std. Dev. of Return	0,88 %	0,88 %	0,94 %	0,72 %		0,89 %	0,86 %	0,93 %	0,91 %	0,75 %	
	% of Positive Abn Returns	48,00 %	49,27 %	50,00 %	53,31 %	-1,5642	45,29 %	49,16 %	50,18 %	50,47 %	56,29 %	-2,3859 **

Note:

1. $z - score_{1,k}^{mean} = \frac{r_1 - r_k}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_k^2}{n_k}}}$, and $z - score_{1,k}^{frequency} = \frac{\boldsymbol{p_1 - p_k}}{\sqrt{\frac{\boldsymbol{p_1(1-p_1)}}{\boldsymbol{n_1}} + \frac{\boldsymbol{p_k(1-p_k)}}{\boldsymbol{n_k}}}}$ *, where r_i and σ_i are the return mean and standard deviation for bin i, while n_i is the number of observations in bin i. p_i is the percentage of positive returns in bin i.*

2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.

*3. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

The results presented in table 3 suggest that there is a negative correlation between temperature and stock returns. For all indices, returns seem to be higher when temperatures are low. The market index has no significant z-scores, but exhibit a generally negative and monotonic pattern. Overall, z-scores are generally negative and very different from zero, for all indices. As for abnormal returns, both clean energy and oil/gas stocks seem to benefit from colder temperatures, with both indices outperforming the market in the low bins. Generally, this relationship seems to be stronger the colder the weather. That is, abnormal returns are increasing with decreasing temperatures. This could suggest that lower temperatures leads to aggressiveness, in turn resulting in excess returns for the riskier stocks.

Clean energy stocks seemingly benefits from both cold and warm temperatures, with cold temperatures having the greatest effect on returns. The clean energy index does not exhibit the same negative monotonic pattern that is observed in the other indices, instead having lower returns in the “middle” temperature range.

For the oil/gas index, abnormal returns are negative throughout for high temperatures, with returns seemingly getting increasingly low as the temperature rise. The statistically significant z-score confirms this relationship. A reasonable explanation could be that, even tough apathy seems to dominate when temperatures increases, investors' are also more concerned about the effects of climate change. The effect of increased perceived climate change seems to be positive on clean energy returns, and even dominate that of apathy, as weather gets warm. For oil and gas stocks however, this could possibly have an added negative effect on returns.

The frequencies of positive returns show the same tendency as the case of mean returns above, with a generally higher frequency of positive (abnormal) returns in the lower bins. The frequency is generally increasing as temperatures decreases, and this is the case for all indices. Generally, the lower the temperature, the higher the probability of a stock having a positive price change. The z-score for differences in frequency of positive –and abnormally positive returns is generally very different from zero, both for the market and oil/gas indices. However the clean energy index, once again, exhibit a far from monotonic pattern. This aligns well with our expectations, particularly when the observed tendency in mean returns above is considered.

The frequency is highest in warm and cold weather for the clean energy index, with a slightly greater percentage in the cold temperature intervals. However, the frequency isn't much higher than for the market in either end, but significantly lower in the middle temperature ranges. As for the oil/gas index, the pattern for frequency is much the same as that of returns, with the frequency decreasing in temperature. For both the 4 and 5 bin cases, the frequency of positive abnormal returns is significantly below (above) 50% when temperatures are warm (cold). A significant z-score (5%) for the 5-bin case confirms the negative temperature impact for the oil/gas stocks.

So far, the bin test results seem to reveal an overall negative correlation between temperature and stock market returns, even though results aren't conclusively significant. The results also seemingly confirm our hypothesis of clean energy stock returns having beneficial reactions to both warm and cold temperatures. However, cold temperatures have a stronger impact on returns than warm temperatures, which to some extent is a little surprising. From the results we can also infer that clean energy stocks outperform oil/gas stocks when temperatures rise, and that oil/gas sector have a very strong negative correlation in temperature related returns.

Although the presence of a negative correlation in temperature related returns seem to exist, the sample results do not offer sufficient evidence to conclude that stock market returns differ in temperature for the general market. The observed tendency could also be down to seasonal differences in stock market returns. However, results clearly indicate that temperature affect clean energy stocks differently than the general market, and that oil/gas stocks have a strong negative correlation in returns, relative to the market. These effects are more difficult to assign to a potential seasonal effect.

In the following section we will conduct further tests in the form of regression analysis.

5.2 Regression Analysis – Sample with Seasonality

Based on the results in bin tests above, the effect of temperature on clean energy returns seem to be stronger the higher and lower temperatures get. We also observe that the relationship does not exhibit monotonic behavior. Thus running a simple linear regression on daily temperature isn't really meaningful. Instead we run a regression using dummy variables that mirrors the temperature intervals used in the 5-bin test in the previous section; the 20% highest temperatures in the sample makes one interval, the 20-40% highest makes another, and so on.

The regression equation is as follows;

$$Return_{it} = \alpha + \delta_1 * up20 + \delta_2 * up20\_40 + \delta_3 * low20\_40 + \delta_4 * low20 + u \ ,$$

where the dependent variable return$_{it}$ is the return of an index *i* on day *t* and *up20,…, low20* are binary variables that equals 1 if the observed temperature falls within the relevant temperature interval, and 0 otherwise. The middle (40-60%) temperature interval works as the base group (k-1 intervals created to avoid dummy variable trap). Results are presented in table 4.

Table 4: Regression Analysis with Seasonality

$Return_{it} = \alpha + \delta_1 * up20 + \delta_2 * up20\_40 + \delta_3 * low20\_40 + \delta_4 * low20 + u$

	α		δ_1		δ_2	δ_3		δ_4		Adj. R^2
Market	0.0003289		-0.0005934		-0.0001536	0.0003415		-0.0001256		0.0000
	(0.0003567)		(0.0006409)		(0.0004904)	(0.0005401)		(0.0010316)		
	0.922		-0.926		-0.313	0.632		-0.122		
Clean Energy Abnormal	-0.0010743	***	0.0012440	**	0.0006913	0.0013506	***	0.0020703	**	0.0016
	(0.0003402)		(0.0006112)		(0.0004677)	(0.0005151)		(0.0009838)		
	-3.158		2.035		1.478	2.622		2.104		
Oil/Gas Abnormal	0.0001239		-0,0006542		-0,0001977	-0,0000094		0.0007509		0.0000
	(0.0002674)		(0.0004805)		(0.0003677)	(0.0004049)		(0.0007734)		
	0.463		-1.361		-0.538	-0.023		0.971		

Note:
1. The first row contains the parameter estimates, the second row contains the standard errors, while the third row shows the t-values.
2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.
3. All parameter estimates (and standard errors) are in decimal form. I.e., in order to obtain the percentage effect, the estimates must be multiplied by 100.
*4. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

The sign of the temperature coefficients across indices is generally consistent with bin test results, and show the exact same pattern in returns. This is to be expected as the regression analysis pretty much mirrors the 5-bin test. However, not only does it work to confirm the bin-test results, it also emphasizes the observed tendency in a different way. The regression output clearly shows that both warm and cold temperatures have a positive effect on clean energy returns, with the intercept and three out of four dummy variables being statistically significant. Alternatively you could say that, for the middle temperature range, the clean energy index has statistically significant negative abnormal returns. Whereas for the oil/gas index the effect of temperature on stock returns is generally monotonic and follows the same pattern as the market. The negative coefficient on *up20* and positive coefficient on *low20* suggests that oil/gas stocks react negatively to warm temperatures and positively to cold temperatures, relative to the market. With both t-stats being quite different from zero, the relationship seems relatively strong.

So far, we have established that clean energy stocks seemingly benefits from both high and low temperatures, relative to the market. A possible explanation could be that whenever temperatures are high or low, investors may get concerned about environmental issues, and as a consequence allocate more capital toward clean energy companies. The same relationship is not observed for the oil/gas index, which instead seems to react negatively to warm temperatures. Although the coefficient isn't quite significant, the observed relationship is also supported by bin test results.

Further on we are able to conclude that low temperatures are associated with greater returns, and this relationship is consistent across indices. This is interesting as it could indicate that investors' willingness to take on risk is generally higher when temperatures drop. Related to theory and previous research, the feeling of aggressiveness seem to be present in cold temperatures, while apathy seem to be the dominating factor when the weather gets warm.

Such a relationship would be indicative of a temperature anomaly in stock returns. However, as already mentioned, the observed overall negative correlation could also potentially be down to a seasonal effect on stock market returns.

We will continue our study by looking at whether or not the observed negative correlation in the market is impacted by a seasonal effect on stock returns, and further how temperature impacts clean energy returns when the data is stripped of seasonality. However, we first want to address the representativeness of New York as a predictor of temperature impacts on stock market returns.

5.3 Computing temperature impacts across regions

For obvious reasons, trades of a particular stock need not always be executed on the floor of the exchange, neither in the city or country where the exchange is located. In fact, as technology has evolved over the years, the trading process has become more electronic, more accessible to a wider audience and easier to handle for the said audience. Movement in stock prices are due to both local investors and market participants located elsewhere. Price movements for stocks registered on NYSE, for instance, is driven by investors located in New York, other parts of the country, and around the world. Naturally, investors in other parts of the US may experience different weather conditions than people in New York. Thus our study so far is subject to investor concentration in the city where the stock exchange is located, in our case New York. This issue is facing all case studies attempting to find correlation between some weather variable and stock market returns. Luckily, unlike other weather variables, temperatures tend to be highly correlated across regions (Cao and Wei, 2004).

As a measure of dealing with temperature differences across regions and possible impacts on results, we identify and collect temperature data from nine major cities in the US (including New York), and conduct a bin test and regression analysis to compare with results above. The data is obtained from NCDC and covers the same period as the original sample. The cities are chosen based jointly on size, economic importance and climatic variety. In the end, we identified the following 9 cities: Atlanta, Boston, Chicago, Houston, Los Angeles, New York, Philadelphia, Phoenix, and Seattle.

The approach is the same as described in the above sections, where the average of daily maximum and minimum temperatures make up the “daily temperature”. An equal weighted average is then computed based on daily temperatures for all 9 cities. Both a 5-bin test and regression analysis is conducted in the same way as in section 5.2. However, the bins are constructed equal in size, as opposed to equal temperature intervals. The reason is a very limited amount of observations in the “cold” temperature bin with the original bin construction.

We run the regression:

$$Return_{it} = \alpha + \delta_1 * up20 + \delta_2 * up20\_40 + \delta_3 * low20\_40 + \delta_4 * low20 + u$$

Bin-test results are presented in table 5, while the regression output can be found in table 6.

Table 5: Relationship Between Temperature and Stock Returns – Impacts Across Regions

		# of bins = 5					
		Bin 1	Bin 2	Bin 3	Bin 4	Bin 5	Z-score(1,5)
# of Observations		774	774	774	774	775	
Temperature Interval (°C)		(29.41 , 24.25)	(24.25 , 19.11)	(19.11 , 13.28)	(13.28 , 8.01)	(8 , -3.13)	
Market	Return Mean	-0,0218 %	0,0175 %	0,0649 %	0,0497 %	0,0265 %	-0,8342
	Std. Dev. of Return	1,08 %	1,24 %	1,15 %	1,26 %	1,20 %	
Clean Energy Abnormal	Return Mean	0,0178 %	-0,0478 %	-0,1303 %	-0,0150 %	0,0203 %	-0,0460
	Std. Dev. of Return	1,04 %	1,12 %	1,16 %	1,23 %	1,11 %	
Oil/Gas Abnormal	Return Mean	-0,0361 %	-0,0032 %	0,0146 %	0,0046 %	0,0215 %	-1,2448
	Std. Dev. of Return	0,89 %	0,84 %	0,93 %	0,87 %	0,93 %	

Note:

1. $z - score_{1,k}^{mean} = \frac{r_1 - r_k}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_k^2}{n_k}}}$ *, where r_i and σ_i are the return mean and standard deviation for bin i, while n_i is the number of observations in bin i.*

2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.

*3. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 6: Regression Analysis with Seasonality – Impacts Across Regions

$$\textbf{Return}_{it} = \alpha + \delta_1 * up20 + \delta_2 * up20\_40 + \delta_3 * low20\_40 + \delta_4 * low20 + u$$

	α		δ_1		δ_2	δ_3		δ_4		Adj. R^2
Market	0.0006491		-0.0008669		-0.0004740	-0.0001518		-0.0003841		0.0000
	(0.0004275)		(0.0006046)		(0.0006046)	(0.0006044)		(0.0006046)		
	1.518		-1.434		-0.784	-0.251		-0.635		
Clean Energy Abnormal	-0.0013031	***	0.0014807	**	0.0008256	0.0011528	**	0.0015059	***	0.0014
	(0.0004078)		(0.0005767)		(0.0005767)	(0.0005765)		(0.0005767)		
	-3.196		2.568		1.432	2.000		2.611		
Oil/Gas Abnormal	0.0001464		-0.0005071		-0.0001782	-0.0001003		0.0000686		0.0000
	(0.0003206)		(0.0004534)		(0.0004534)	(0.0004532)		(0.0004534)		
	0.457		-1.118		-0.393	-0.221		0.151		

Note:

1. The first row contains the parameter estimates, the second row contains the standard errors, while the third row shows the t-values.

2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.

3. All parameter estimates (and standard errors) are in decimal form. I.e., in order to obtain the percentage effect, the estimates must be multiplied by 100.

*4. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

As seen in both table 5 and 6, results are very similar to the comparable observations in table 3 and 4 above. The relationship between temperature and abnormal clean energy returns are very much the same, with a positive reaction to both warm and cold temperatures. The statistical significance is still present, and equally strong. For the oil/gas index, the relationship is also preserved, with each coefficient having the same sign as in the comparable results above. The results for the market index are a little different, but the overall negative correlation is still intact. The small differences could for example be down to the bin construction.

Based on the above observations, it would seem as though New York is generally quite representative of the investor population. Thus results obtained in this study should not be particularly biased by the sample data. This is consistent with results from a previous study by Cao & Wei (2004). They also looked at temperature impacts across regions as part of their study, although for an earlier time period. They argued that temperatures tend to correlate across regions, thus exposing investors to much of the same variations in daily temperatures.

5.4 Computing "deseasonalized" temperature impacts

So far, we have observed tendencies of a general negative correlation between temperature and stock returns. However, this relationship could mainly be impacted by seasonal variations in returns. For instance, "Sell in May and go away" has become a popular phrase in financial markets due to a repeated seasonal pattern. By removing the level effect, any impact from temperature on stock returns should, in theory, be purely down to the day-to-day variations in temperature, as opposed to any seasonal trends. Another interesting factor is whether abnormal temperatures affect clean energy returns differently. For example, one can imagine that 30°C in the summer might have a greater impact than 10°C in the winter, even though the latter deviates further from the mean. Thus, it might be reasonable to assume that temperature could have less of an impact when the level effect is removed.

"Deseasonalized", or abnormal temperatures are computed as described in section 4. Bin tests are conducted in the same way as in section 5.1, with the number of bins set at two, three, four, and five[11]. As the number of bins increases, the observations within each bin decreases, particularly in the extreme temperate intervals. One effect of this could be that the extreme bins are affected quite extensively by large abnormal returns. As a preventive measure, the sample data is winsorized at the top and bottom 1% of returns[12].

Further on we construct an alternative 3-bin test based on the standard deviation of abnormal temperatures. We define all observations within one standard deviation as "normal" temperatures. Observations exceeding one standard deviation are labeled as either abnormally warm or abnormally cold, depending on the direction. Intuitively, this seems like a good way of measuring impacts of temperature related returns, and should hopefully help uncover a potential relationship between temperature and stock market returns, as well as capturing any differences between indices.

Bin test results are presented in table 7 and 8:

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[11] For brevity, we only present the results of the 3 and 5 bin cases.

[12] That is, we remove the 1% highest and lowest return data , which leaves us with 3748 matching observations for the "deseasonalized" sample.

Table 7: Relationship Between Temperature and Stock Returns - ”Deseasonalized” Bin Tests

		# of bins = 3				# of bins = 5					
		Bin 1	Bin 2	Bin 3	Z-score (1,3)	Bin 1	Bin 2	Bin 3	Bin 4	Bin 5	Z-score(1,5)
# of Observations		321	2952	475		58	624	2064	922	80	
Temperature Interval (°C)		(16.4 , 6.1)	(6.0 , -4.3)	(-4.2 , -14.7)		(16.4 , 10.2)	(10.1 , 4.0)	(3.9 , -2.2)	(-2.3 , -8.5)	(-8.6 , -14.7)	
Market	Return Mean	0,0347 %	0,0245 %	0,0983 %	-1,0402	0,0331 %	0,0106 %	0,0288 %	0,0607 %	0,0781 %	-0,3595
	Std. Dev. of Return	0,87 %	0,91 %	0,81 %		0,73 %	0,90 %	0,90 %	0,90 %	0,73 %	
	% of Positive Returns	55,45 %	53,18 %	56,63 %	-0,3290	53,45 %	53,85 %	53,34 %	54,45 %	58,75 %	-0,6195
Clean Energy Abnormal	Return Mean	-0,0447 %	-0,0449 %	0,0313 %	-0,9683	0,0226 %	0,0003 %	-0,0646 %	-0,0025 %	0,0279 %	-0,0251
	Std. Dev. of Return	1,11 %	1,06 %	1,04 %		1,28 %	1,04 %	1,06 %	1,07 %	1,14 %	
	% of Positive Abn Returns	48,29 %	47,59 %	52,21 %	-1,0859	48,28 %	50,16 %	46,85 %	49,57 %	53,75 %	-0,6353
Oil/Gas Abnormal	Return Mean	-0,0141 %	-0,0093 %	0,0582 %	-1,2773	-0,1726 %	-0,0116 %	-0,0179 %	0,0470 %	0,0829 %	-1,9384 *
	Std. Dev. of Return	0,80 %	0,86 %	0,76 %		0,79 %	0,84 %	0,87 %	0,80 %	0,73 %	
	% of Positive Abn Returns	49,53 %	48,64 %	54,53 %	-1,3864	36,21 %	48,88 %	48,74 %	51,84 %	55,00 %	-2,2337 **

Note:

1. $z-score_{1,k}^{mean} = \frac{r_1 - r_k}{\sqrt{\frac{\sigma_1^2}{n_1}+\frac{\sigma_k^2}{n_k}}}$, and $z-score_{1,k}^{frequency} = \frac{\boldsymbol{p_1 - p_k}}{\sqrt{\frac{\boldsymbol{p_1(1-p_1)}}{\boldsymbol{n_1}}+\frac{\boldsymbol{p_k(1-p_k)}}{\boldsymbol{n_k}}}}$ *, where r_i and σ_i are the return mean and standard deviation for bin i, while n_i is the number of observations in bin i. p_i is the percentage of positive returns in bin i.*

2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.

*3. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 8**:** Relationship Between Temperature and Stock Returns - Alternative ”Standard deviation Test”

		# of bins = 3			
		Bin 1	Bin 2	Bin 3	Z-score (1,3)
# of Observations		622	2638	488	
Temperature Interval (°C)		(16.40 , 4.26)	(4.25 , -4.25)	(-4.26 , -14.66)	
Market	Return Mean	0,0176 %	0,0267 %	0,1000 %	-1,6053
	Std. Dev. of Return	0,89 %	0,91 %	0,82 %	
	% of Positive Returns	54,18 %	53,22 %	56,56 %	-0,7913
Clean Energy Abnormal	Return Mean	0,0009 %	-0,0556 %	0,0292 %	-0,4381
	Std. Dev. of Return	1,08 %	1,06 %	1,05 %	
	% of Positive Abn Returns	49,68 %	47,19 %	52,05 %	-0,7844
Oil/Gas Abnormal	Return Mean	-0,0346 %	-0,0042 %	0,0581 %	-1,9504 *
	Std. Dev. of Return	0,82 %	0,86 %	0,76 %	
	% of Positive Abn Returns	47,75 %	48,90 %	54,71 %	-2,3100 **

Note:

1. $z - score^{mean}_{1,k} = \frac{r_1 - r_k}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_k^2}{n_k}}}$, and $z - score^{frequency}_{1,k} = \frac{p_1 - p_k}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_k(1-p_k)}{n_k}}}$ *, where r_i and σ_i are the return mean and standard deviation for bin i, while n_i is the number of observations in bin i. p_i is the percentage of positive returns in bin i.*

2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.

*3. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

Based on results above, the negative correlation between temperature and stock returns seem to be present also after removing seasonality from the data. Very similarly to the earlier tests, results indicate a positive effect from both abnormally warm and cold temperatures for the clean energy index. This is very evident in the 5-bin test as well as the "standard deviation" test, but not so much in the 3-bin test. Perhaps indicating that the effect of temperature on clean energy returns is a little weaker when the level effect is gone. For the oil/gas index the negative correlation remains very monotonic, with a statistically significant z-score for both abnormal returns and frequency of positive abnormal returns, in both the 5-bin test and "standard deviation" test. Generally, the frequency of positive returns aligns well with the observed pattern in results, for all indices. Both the clean energy and oil/gas indices have the highest (lowest) frequency in the best (worst) performing interval. All indices have the highest frequency when temperatures are cold. Even though cold temperatures still yields greater overall returns, a noticeable difference in the "deseasonalized" sample is a seemingly less monotonic relationship for the market index. In both the 3 –and 5-bin cases, returns are higher in the warmest temperature intervals than in the more normal intervals, and average returns are positive in the warm bin for all tests, except the 4-bin case.

The alternative 3-bin test ("standard deviation shock" test) showcases much of the same tendencies seen in the previous tests, but with a seemingly stronger and more profound overall result. All z-scores are negative and generally very different from zero, with significant scores for the oil/gas index. Results show that returns are higher when temperatures are abnormally cold, and this follows for all indices. The clean energy index has the highest returns of the three indices in the high bin (abnormally warm temperatures) and the lowest returns in the "normal temperature" bin. Returns increases as temperature decreases for both the market, and oil/gas indices. The oil/gas index has negative returns for abnormally warm temperatures. The most even distribution is seen for the market, being the only index with positive returns in each bin.

Based on the tests conducted so far, it seems like there is indeed a negative relationship between temperature and stock market returns, even after controlling for seasonality. With data stripped of any seasonal effects, it's difficult to assign these observations to anything else but the daily impacts of temperature shocks. The results indicate that the strength of the negative correlation differs between indices. Interestingly, the clean energy index yields greater overall returns than both the market, and in particular the oil and gas index, for warm temperatures. However, as the bin tests show, this relationship isn't strictly monotonic, but rather shifting throughout different "warm" intervals. For the temperature range we define as "normal", the clean energy index performs far worse than the comparing indices, which is very consistent with results in section 5.1 and 5.2. Further on, the index seemingly performs better in both absolute and relative terms when temperatures are abnormal, which is a very interesting observation. Keeping in mind that the overall performance of the index is worse than the comparable indices over the sample period, contributes positively to the reliability of the results.

We continue with regression analysis to see whether further testing gives any substance to the observations above.
Several different regressions are estimated, with the general form of;

$$\text{Return}_{it} = \alpha + \beta * \text{temperature} + \varepsilon\ (u)\ ,$$

where dependent variable, Return_{it} is the estimated (abnormal) return for index *i* on day *t*. The temperature variable can take four different forms; *temp_abn* is the difference between the daily temperature and the moving average, i.e., the abnormal temperature for the day. The second temperature measure consists of binary variables, where *std_up* (*std*_down) takes a value of 1 when temperatures are abnormally warm (cold), and zero otherwise. The third temperature variable, *abn_warm* (*abn_cold*) equals *temp_abn* for abnormally warm (cold) temperatures and zero otherwise. Lastly, *abn_warm^2* (*abn_cold*^ 2) measures the quadratic effect of abnormal temperatures.

Once again, we can tell from the bin tests that returns on clean energy stocks do not exhibit a monotonic pattern. Thus, as in section 5.2, running a simple linear regression on *temp_abn* isn't really meaningful. With the range of abnormal temperatures being narrower than that of average temperatures, regression analysis based on the 5-bin case above isn't as viable as in the initial tests. Due to the limited number of observations in the outlying temperature intervals, getting significant results would be an issue. The bin test that intuitively and seemingly captures the overall relationship in the best way is the "standard deviation" 3-bin test. We begin by running the following regression:

$$\text{Return}_{it} = \alpha + \delta_1 * std\_up + \delta_2 * std\_down + u \ ,$$

where the dummy *std_up* equals 1 for abnormally warm temperatures (<1 std.) and zero otherwise, while *std_down* takes the value 1 for abnormally cold temperatures (< -1 std.) and zero otherwise. The intercept (α) covers the "normal temperatures" (up to 1 std. in either direction). Results are presented in table 9.

Table 9: Regression Analysis - Winsorized and "Deseasonalized" Sample

	$\text{Return}_{it} = \alpha + \delta_1 * std\_up + \delta_2 * std\_down + u$			
	α	δ_1	δ_2	Adj. R^2
Market	0.0002667	-0,0000912	0.0007335 *	0.0003
	(0.0001738)	(0.0003979)	(0.0004398)	
	1.535	-0.229	1.668	
Clean Energy Abnormal	-0.0005563 ***	0.0005658	0.0008485	0.0004
	(0.0002073)	(0.0004746)	(0.0005247)	
	-2.683	1.192	1,617	
Oil/Gas Abnormal	-0,0000422	-0,0003041	0.0006229	0.0004
	(0.0001639)	(0.0003752)	(0.0004148)	
	-0.257	-0.810	1.502	

Note:

1. The first row contains the parameter estimates, the second row contains the standard errors, while the third row shows the t-values.

2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.

3. All parameter estimates (and standard errors) are in decimal form. I.e., in order to obtain the percentage effect, the estimates must be multiplied by 100.
*4. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

The signs of the coefficients are as expected, given the observed pattern of results from the "standard deviation 3-bin test". For the market index, the positive value on *std_down* is significant at the 10% level, meaning that there is a statistically significant positive impact of cold temperatures on stock returns is statistically significant. Abnormal returns on the clean energy index have a positive value for both the abnormally warm and cold temperatures, with a t-value above 1 for both coefficients. The coefficient on the intercept is negative and highly significant at the 1% level, confirming that the index clearly underperforms under "normal" temperatures. For the oil/gas index, the coefficient on warm temperatures is negative, while the coefficient on cold temperatures has a positive value, with both t-stats being very different from zero. Under a one-sided test, the coefficient on cold temperatures would have been significant at 10% for all indices.

Further on, we construct a similar model to the "standard deviation test" above:

$$\text{Return}_{it} = \alpha + \beta_1 * abn\_warm + \beta_2 * abn\_cold + u \ ,$$

where *abn_warm* (*abn_cold*) equals *temp_abn* for temperatures above (below) zero, and zero otherwise. Results can be found in table 10 below.

Table 10: Regression Analysis - Winsorized and "Deseasonalized" Sample

$$\textbf{Return}_{it} = \alpha + \beta_1 * \textbf{\textit{abn\_warm}} + \beta_2 * \textbf{\textit{abn\_cold}} + \textbf{\textit{u}}$$

	α		β₁	β₂		Adj. R^2
Market	0.0002356		0.0000010	-0,0000814		0.0000
	(0.0002335)		(0.0000642)	(0.0000687)		
	1.009		0.016	-1.185		
Clean Energy Abnormal	-0.0007497	***	0.0001144	-0.0001417	*	0.0004
	(0.0002785)		(0.0000766)	(0.0000819)		
	-2.692		1.493	-1.730		
Oil/Gas Abnormal	-0,0001589		0.0000059	-0,0001013		0.0003
	(0.0002202)		(0.0000606)	(0.0000648)		
	-0.722		0,098	-1.565		

Note:

1. The first row contains the parameter estimates, the second row contains the standard errors, while the third row shows the t-values.

2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.

3. All parameter estimates (and standard errors) are in decimal form. I.e., in order to obtain the percentage effect, the estimates must be multiplied by 100.

*4. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

These results differ slightly from the ones above, in that they give a precise estimate of the temperature effect. From the previous regression (5.2) we couldn't measure the precise effect of a specific temperature, but rather how different ranges of temperature impacts stock returns. Just like we have observed throughout, the clean energy index seems to benefit from any abnormal temperature, either positive or negative. The intercept is negative and statistically significant at 1%. The coefficients on "warm" and "cold" temperatures are positive and negative, respectively, with the latter being significant at 10%. The "warm" temperature coefficient would also have been significant with a one-sided test. Further establishing the seemingly negative correlation for the market in general, both the benchmark and oil/gas indices have negative coefficients for *abn_cold,* with t-values very different from zero.

To get a better understanding of the economic significance of the temperature effect, we look at how a standard deviation shock in temperature affects the abnormal returns of the clean energy index. As previously mentioned, the standard deviation of abnormal temperature in New York City is 4.25 °C. The impact of a positive and negative standard deviation shock in temperature would be about 0.049%, and 0.060%, respectively. However, for the index to have expected positive abnormal returns, the positive temperature shock would have to be above 6.55 °C, while the negative shock would have to exceed 5.29 °C.

Finally, we want to see whether temperature has an increasing or decreasing effect on returns Based on intuition, and theory on perceived climate change, we would expect to see a increased effect of temperature on returns. Bin tests also indicate this might be the case. We run the following regression:

$$\text{Return}_{it} = \alpha + \beta_1 * abn\_warm\hat{\ }2 + \beta_2 * abn\_cold\hat{\ }2 + u \ ,$$

where the independent variables are quadratic terms. Results are presented in table 11.

Table 11: Regression Analysis with Quadratics - Winsorized and "Deseasonalized" Sample

	$\mathbf{Return_{it}} = \alpha + \beta_1 * abn\_warm\text{^}2 + \beta_2 * abn\_cold\text{^}2 + u$			
	α	β1	β2	Adj. R^2
Market	0,0002791	-6.938e-07	9.391e-06	0.0000
	(0.0001740)	(6.146e-06)	(7.593e-06)	
	1.604	-0.113	1.237	
Clean Energy Abnormal	-0,0005543 **	6.937e-06	0.0000163 *	0.0005
	(0.0002075)	(7.330e-06)	(9.056e-06)	
	-2.672	0.946	1.801	
Oil/Gas Abnormal	0,0000403	-5.048e-06	0.0000101	0.0003
	(0.0001640)	(5.795e-06)	(7.160e-06)	
	-0.245	-0.871	1.411	

Note:
1. The first row contains the parameter estimates, the second row contains the standard errors, while the third row shows the t-values.
2. The clean energy and oil/gas estimates are for abnormal returns, relative to the market index. See section 4.1.
3. All parameter estimates (and standard errors) are in decimal form. I.e., in order to obtain the percentage effect, the estimates must be multiplied by 100.
*4. The asterisks *, **, and ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

As seen in table 11, all three indices seem to have an increasing effect from abnormally cold temperatures. Indicating that the colder the temperature, the greater the effect on positive returns. The relationship is significant at the 10% level for clean energy stocks. It is seen that the coefficient on warm temperatures is positive for the clean energy index, and negative for the other two indices. Both sector indices have t-stats quite different from zero, suggesting that warm temperatures have an increasing effect on clean energy returns, and a decreasing effect for oil/gas stocks. However, this effect is clearly stronger for cold temperatures.

By now, we have seemingly uncovered a temperature anomaly in clean energy stocks, where returns are positively influenced by both warm and cold weather. Further to this, we have found evidence to support the existence of an overall negative correlation across the market. The negative correlation is particularly strong for the oil/gas index. Overall, apathy and aggressiveness seem to dominate for warm and cold temperatures, respectively. However, high temperatures seem to affect the way in which investors perceive the threat of climate change, resulting in a positive impact on clean energy returns, and possibly a added negative effect on oil/gas stocks. This effect might not be as strong for colder temperatures, given the positive impact on oil/gas companies. Thus the positive impact on clean energy returns for cold temperatures is probably mostly down to investors increased appetite for risk.

Although the statistical significance isn't necessarily present for all indices in each of the tests, the general pattern is quite strong and consistent throughout. Suggesting that there is certainly some truth to the observations. The results also seem robust to several types of tests and two different measures of temperature, which should further enhance credibility of the results.

6. Discussion

Today, stocks are primarily purchased electronically, which makes it easier for consumers all around the world to buy stocks listed on NYSE. The fact that people purchasing stocks is located in different parts of the world, raises one issue for this research paper. When we are looking at the effect temperature has on stocks in three different indices, it is reasonable to think that the purchasers are influenced by different climate conditions. So, if temperature is a deciding factor, one consumer may be under the weather conditions, which tells him to enter a more passive state, while another individual wants to take risk. Also, individuals living in usually cold environment might respond differently to an unusual warm day, then consumers who are used to a hot climate. In this paper, we have gathered weather data from New York, which will assess purchasers from New York and locations with the same weather conditions in a good way. We also measured weather data from nine different cities in America, and the results were similar. But it could be a good idea to test for other indices listed in stock markets outside America, to see if temperature has a similar impact in different markets.

Our study suggests the impact of temperature on clean energy returns is pretty consistent, independent of what measure of temperature is used. However the effect is seemingly strongest when the level effect is present. A possible explanation was mentioned briefly in section 5, but for clarity reasons we want to elaborate on this. The effect of very warm or cold temperatures may be greater than that of abnormally warm or cold temperatures. In other words, the level effect may be stronger than the relative temperature effect. For instance, 30 °C in a summer month may have greater effect on clean energy stock returns than 10 °C in a winter month, even though the deviation from the mean may be the same. In the same way, -10 °C in a winter month may have greater impact than 15 °C in a summer month, even though the temperatures may deviate from the mean by the same amount. The above example shows a quite plausible scenario of a twofold impact by season and temperature on clean energy returns that is not fully reflected when temperatures are “deseasonalized”. The thought is that a possible increase in perceived climate change, and a general heightened consciousness related to global warming is stronger when temperatures are unpleasantly warm or cold, than when they are simply abnormal. Thus taking away the seasonality from the observations might not be the most efficient way of measuring the impact of temperature related returns for the specific case of clean energy stocks.

Even though the bin tests and regression analysis seem to uncover a very interesting effect of temperature on stock returns, the observed values for R-squared are very low. This is to be expected, and just highlights the fact that temperature is, at best, one of many explanatory variables on stock returns. Thus it come as no surprise, that although significant, the economic impact of the temperature anomaly isn't great. Trying to exploit the temperature effect through trading strategies would probably be difficult, and positive returns would more often than not, vanish with trading fees and other transaction costs.

Further research might analyze the effect of longer periods of abnormal temperatures on stock market returns, or perhaps the effect on the day(s) after unusually warm or cold weather. The effect of increased climate change belief (or thoughts associated with climate change) would probably be even stronger after longer periods of abnormal temperatures. In theory, the day following an abnormally warm or cold day could also be affected. Perhaps even more so than the actual day of the observation? On the day, investors could be influenced by the temperature on the way to work, during lunch, conversing with colleagues, weather forecasts, news etc. However, the possibility of properly experiencing the temperature impact should be quite limited, since during the opening hours of the stock exchange most investors would be working indoors in air-conditioned environments. Thus, first-hand experience of the daily temperature would primarily be collected after working hours. Possibly leading to an effect on the following day(s).

7. Summary and Conclusion

With average temperatures continuously rising, climate change is becoming a growing reason for concern for more and more people. A key factor in dealing with climate change is to reduce greenhouse gas emissions. Thus, managing the impacts of climate change can be done through greater investment in clean energy resources and a reduction in the use of fossil fuels.

In this study we attempt to identify the relationship between temperature and stock market returns. We specifically look at how temperature affects returns for the clean energy sector, relative to the market and an oil/gas index. Psychological research suggests that abnormally high and low temperatures have an effect on people's perception of climate change. We are interested in whether this has an impact on investors' decision-making, possibly resulting in a positive impact on clean energy returns. In other words, we study whether clean energy companies are affected differently by temperature than the general market.

After examining and comparing three different US stock indices, we find evidence to support the presence of a temperature anomaly in the US stock market. Our analysis reveals an overall negative correlation between temperature and returns, with returns generally decreasing in temperature. We find that this relationship is far from monotonic for clean energy stocks, which instead reacts positively to both warm and cold temperatures, confirming our initial hypotheses. Furthermore, we are able to confirm our prediction of clean energy stocks outperforming the oil/gas index when temperatures rise. The observed anomalies in temperature related returns seem to be present both before and after controlling for seasonal effects.

The observation of a negative correlation in temperature related returns is in accordance with the majority of existing literature in general, as well as Cao and Wei (2004) who study New York in particular. However, we have also expanded on previous studies by having a primary focus on the clean energy sector. Although generally correlating with the market, we have uncovered that both high and low temperatures have a positive impact on clean energy returns, and results are consistent for both sets of temperature measures. These observations have, to the best of our knowledge, not been documented in previous literature.

As a new and rapidly growing sector, the potential for further research on clean energy stocks is considerable. Closely related to this paper, it would be interesting to study whether yesterday's temperature has an effect on tomorrow's stock returns. Another interesting possibility would be to study a different market with other climatic conditions, to see whether climate is a deciding factor for the temperature effect.

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