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The Influence of Temperature on Stock Market Returns in Mild Climates: A New Perspective on the Temperature Anomaly[1]

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Abstract

This paper studies the influence of temperature on stock returns in mild climates. Psychological studies have shown that the weather affects mood, leading to alterations in the behaviour and perception of investors. This paper examines European financial markets in mild climates for the existence of the temperature anomaly. In addition, I propose a new perspective on the influence of temperature on stock returns. This new approach uses the temperature changes in respect to the preceding day instead of absolute temperatures, taking the reference dependence of thermal perception and the absence of extreme temperatures into consideration. I apply both methods on four European financial stock indices using ordinary least squares regressions. The analysis reveals no inevitable prove that the temperature anomaly exists in financial markets with mild climates. However, I find a positive relationship between stock market returns and temperature changes in respect to the preceding day, analogous to the linkage between sunshine and stock market returns.

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[1] The views stated in this thesis are those of the author and not necessarily those of Erasmus School of Economics or Erasmus University Rotterdam.

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1. Introduction

Financial theories, such as the Efficient Market Hypothesis, traditionally assume that investors behave rational, and the market reflects all relevant available information (Fama, 1970). However, studies often find systematic patterns (*hereafter: anomalies*) that are inconsistent with these assumptions and cannot be elucidated by information or risk. These anomalies can be related with numerous factors. For example, various anomalies originate from calendar based patterns (Gultekin & Gultekin, 1983; Lakonishok & Smidt, 1988; Agrawal & Tandon, 1994; Hawawini & Keim, 1995)[1], while other anomalies are related to nature based patterns (Saunders, 1993; Kamstra, Kramer & Levi, 2000; Hirshleifer & Shumway, 2003; Kamstra, Kramer & Levi, 2003; Cao & Wei, 2005)[2].

It is improbable that the previous stated factors change the risks of or the available information about stocks. However, psychologists found that our mood influences our risk-aversion, cognitive abilities and information-processing, thus influencing our decisions and our perspective towards potential risks and new information (Johnson & Tversky, 1983; Schwarz & Clore, 1983; Schwartz, 1990; Pham, 1998; Romer, 2000; Loewenstein, Weber, Hsee & Welch, 2001; Bruyneel, de Witte, Franses & de Kimpe, 2009). Consequently, our actions diverge when our perspectives change, even though the potential risks and available information are unaltered. For instance, aggression is associated with more risk-taking behavior. A decline in risk-aversion increases the willingness to take risks, thus the willingness to take a gamble on a stock and pay a higher price (Loewenstein et al., 2001).

A mood alteration of an individual investor does not significantly shift the market price. However, there are factors that influence all investors. For instance, numerous psychology studies found that weather variables have a direct effect on mood and behavior (Schwartz & Clore, 1983; Howarth & Hoffman, 1984; Rind, 1996; Parsons, 2001; Pilcher, Nadler & Busch, 2002; Peng et al., 2016). As investors are all affected by the weather and the conjoint mood transfigurations, it is cogent that the market price reflects these patterns.

[1] Calendar based anomalies occur consistently at a certain period of time. Examples of calendar based anomalies are the January-effect (Gultekin & Gultekin, 1983), the turn-of-the-month effect (Agrawal & Tandon, 1994; Lakonishok & Smidt, 1988) and the Monday-effect (Hawawini & Keim, 1995).
[2] Nature based anomalies occur conjoint with nature related patterns.

There is a lot of literature on the relationship between weather variables and stock returns[3]. However, in the field there are two empirically leading studies. The first predominant study is from Hirshleifer & Shumway (2003) on the relationship between sunshine and stock returns. Hirshleifer & Shumway (2003) found a strong positive correlation between sunshine and stock returns. They hypothesized that being in a good mood, induced by sunlight, makes individuals react more optimistic to new information. This while being in a bad mood, caused by the lack of sunlight, makes individuals react more pessimistic and skeptical towards new information.

The second leading empirical study on the relationship between stock returns and weather variables is from Cao & Wei (2005). Cao & Wei (2005) examined the relationship between stock returns and temperature and found a strong negative correlation. They theorized that lower temperatures are linked to higher stock returns, while higher temperatures are linked to lower stock returns. Cao & Wei (2005) postulated that lower temperatures are related to aggression while higher temperatures are, in conjunction to aggression, also interrelated to apathy and hysteria. Hence, Cao & Wei (2005), associating aggression with risk-taking and apathy with risk-aversion, hypothesized that temperature induced mood alterations produced the negative correlation between temperature and stock returns.

Although the theorem of Cao & Wei (2005) is well-established, there are some controversies. First, as discussed by Jacobsen & Marquering (2008), the found correlation might only reflect the relationship between stock returns and seasonality[4]. Second, prior empirical evidence is inconsistent in results regarding financial markets with mild climates. And third, Cao & Wei (2005) predominately based their hypothesis on studies about the relationship between mood and extreme temperatures (Wyndham, 1969; Bell & Baron, 1976; Howarth & Hoffman, 1984; Pilcher, Nadler & Busch, 2002). In addition to the controversies, Cao & Wei (2005) and latter studies tested predominantly for a uniform relationship between temperature and stock returns, however, it is not unlikely that the relationship is climate dependent. This raises the question what the relationship is between temperature and stock

[3] Howarth & Hoffman (1984) found that temperature, sunshine and humidity were the weather variables with the strongest influence on mood. Consequently, most studies look at one of these variables.

[4] Although Jacobsen & Marquering (2008) make a point, one could argue that the influence of seasonality on stock returns is interrelated with weather variables as temperature.

market returns in countries with mild climates. Although several papers used mild climate countries to test for the existence of the temperature anomaly (Cao & Wei, 2005; Dowling & Lucey, 2008; Floros, 2008; Floros, 2011), there is a deficiency of studies scoping on the particular relationship between temperatures and stock returns in mild climates. This motivates my paper, which studies the relationship between temperature and stock market returns in four European countries with mild climates.

One of the perplexities of the temperature anomaly theorem is that extreme temperatures are scarce, especially in mild climates. This paper presents a new, yet simple, perception on the relationship between temperature and stock returns. I start with a model conformed to the model of Cao & Wei (2005), which studies the correlation between temperature and stock returns while controlling for well-known anomalies. Under these conditions it is possible to test for the presence of the temperature anomaly in the sense of Cao & Wei (2005). The traditional concept of the temperature anomaly assumes the frequent occurrence of extreme temperatures. I present a new approach to the relationship between temperature and stock returns for when extreme temperatures are scarce. This new method, inspired by the reference dependence principle of Kahneman & Tversky (1979)[5], uses temperature changes with respect to the preceding day instead of the absolute temperature, while also controlling for well-known anomalies. The new approach is based on the concept that thermal perception is reference dependent.

I applied both models on the indices of four financial market; the AEX index (Amsterdam, the Netherlands); the FTSE-100 index (London, United Kingdom); the ISEQ index (Dublin, Ireland); and the DAX index (Frankfurt, Germany). The financial markets are all located in developed European countries with a *Cfb* Köppen-Geiger climate classification (Peel, Finlayson & McMahon, 2007). I used developed European countries in the prospect that it would increase the consistency of the results.

The results reveal no inevitable prove on the existence of the traditional temperature anomaly in financial markets with mild climates. However, the results do present a significantly positive correlation between the day-to-day temperature differences and stock returns. The positive correlation is comparable to the linkage between sunshine and stock returns, which is assumed to be caused by good moods. The positive relation between day-

[5] The reference dependence principle states that people evaluate outcomes relative to the reference point (Kahneman & Tversky, 1979).

to-day temperature differences and stock market returns illuminates that stock market returns are affected by temperature in mild climates.

The rest of this paper are structured as follows, Section 2 covers the theoretical framework and hypotheses. Section 3 describes the data and methods. Section 4 displays the empirical results. Section 5 discusses the results and limitations. In addition, Section 5 gives possible explanations and suggestions for future studies. Section 6 concludes.

2. Literature review

2.1. Mood and decisions

Numerous psychological studies have assessed the relation of mood and the process of decision-making. For instance, moods impact how humans process new information (Isen, Shalker, Clark & Karp, 1978; Schwarz & Clore, 1983; Schwarz, 1990; Petty, Gleicher & Baker, 1991; Bless et al., 1996; Pham, 1998; Schwartz, 2002). Studies indicate that good moods are associating with less critical assessment when processing information, while bad moods make people more analytical and critical towards new information (Schwarz, 1990; Petty et al., 1991; Schwarz, 2002). In addition, people in a good mood tend to find positive information more available (Petty et al., 1991). People in good moods also depend more on pre-existing knowledge structures (Bless et al., 1996). In addition, Bless et al. (1996), found that good moods do not necessarily decrease the cognitive ability to assess information.

Other studies have examined the influence of moods on risk-taking behavior (Johnson & Tversky, 1983; Lerner & Keltner, 2001; Loewenstein, 2001; Yuen & Lee, 2003; Bruyneel et al., 2009). Yuen & Lee (2003) found that downbeat moods cause a lower willingness to take risks. In addition, people with good moods tend to overestimate the probability of positive outcomes and underestimate the probability of negative outcomes (Johnson & Tversky, 1983). Lerner & Keltner (2001), on the other hand, found that fearful people assess risks more pessimistic, while angry people make more optimistic risk evaluations. Prior studies looked at the impact of bad versus good moods, Lerner & Keltner (2001) however, provided evidence that the relationship with risk-assessments was mood-specific. They found that the optimistic risk assessments of angry people are comparable to the risk assessments of happy people.

2.2. Temperature and mood

There is a vast expanse of literature on the effect of temperature on an individual’s mood (Wyndham, 1969; Bell & Baron, 1976; Schneider, Lesko & Garrett, 1980; Howarth & Hoffman, 1984; Pilcher et al., 2002; Keller et al., 2005; Levinson, 2012; Peng et al., 2016). Empirical evidence suggests that both high and low temperatures influence our moods. Several studies indicate that temperatures above 25.5 degrees induce hysteria and apathy (Wyndham, 1969; Pilcher et al., 2002). Hysteria causes a more pessimistic assessment of risks and apathy decreases the willingness to take risks (Lerner & Keltner, 2001; Yuen & Lee, 2003). These moods are therefore often associated with risk-aversion. Additional studies found that aggression is induced by both extremely high- and low temperatures (Bell & Baron, 1976; Schneider et al., 1980; Howarth & Hoffman, 1984). As aggression is linked with a more optimistic assessment of risks and an increased willingness to take risks, it is often associated with more risk-taking behavior. Hence, Cao & Wei (2005) drew the assumptions that higher temperatures increase hysteria and apathy, while aggression is induced by both high and low temperatures. This would indicate more risk-taking behavior at lower temperatures and the possibility of a heightened risk-averseness at higher temperatures.

2.3. Temperature and stock returns

Saunders was in 1993 the first to link stock return patterns to weather variables. Using data from New York he showed that lower cloud coverage is correlated to higher stock returns. Later, in 2002, Keef & Roush and Cao & Wei first reported on the relationship between temperature and stock returns. Both studies found a negative correlation between temperature and stock returns (Keef & Roush, 2002; Cao & Wei, 2002).

After looking at eight global financial markets, Cao & Wei (2005) hypothesize that the negative correlation was initiated by the formerly mentioned relationship between temperature, aggression, apathy and hysteria. Jacobs & Marquering (2008), however, argue that the correlations between weather variables and stock returns merely reflects the influence of seasonality. They debate that it is premature to contribute the found patterns on mood and behavioral changes (Jacobs & Marquering, 2008). Nonetheless it is largely recognized that correlations between weather variables and stock returns derive from behavioral- and mood changes.

While posterior studies indeed mostly found a negative correlation between temperature and stock returns, the results recurrently did not reach statistical significance for financial markets in mild climates (Cao & Wei, 2005; Dowling & Lucey, 2008; Floros, 2008; Floros, 2011). As behavioral and mood changes were largely observed at severe temperatures, the scarcity of extreme temperatures could explain the frequent statistical insignificance in mild climates. Hence, this raises the question whether the temperature anomaly, in the sense of Cao & Wei (2005), exists in mild climates. I hypothesize that in European mild climates daily stock returns are negatively correlated with daily temperatures. As psychological argument for the influence of temperature on stock returns should apply universally and global empirical evidence predominantly suggests a negative relationship between temperature and stock returns.

2.4. Temperature differences and stock returns

An individual's thermal sensitivity is dependent on personal characteristics and prior environmental experiences (Auliciems, 1981; Shooshtarian & Ridley, 2016; Lam, Loughnan & Tapper, 2018). Thus, for example, someone living in a tropical climate perceives temperature dissimilar from someone living in a mild climate. I try to limit these possible deviations by using international financial markets with similar climates, cultures, financial environment and social atmosphere. In addition, thermal perception is dependent on the reference-point. For instance, fifteen degrees feels colder in the summer and warmer in the winter. Hence, intuitional that day-to-day temperature differences also influence moods, consequently, daily stock returns.

To prove that the temperature anomaly was not caused by seasonality, Cao & Wei (2005), already tried to capture the effect of daily temperature shocks on stock returns. They used the difference between historic daily temperature and daily temperature as the temperature deviations. While this does adjust for seasonality and climatic differences, it should be kept in mind that this does not actually capture daily temperature shocks. Day-to-day temperature differences in respect to the preceding day, however, do capture daily temperature shocks. In addition, it captures the reference dependence of thermal perception. The reference dependence of thermal perception suggests that moods are influenced by day-to-day temperature differences. I therefore hypothesize that day-to-day temperature differences are correlated with stock returns. The literature on the impact of day-to-day temperature differences on moods is limited, however, I assume a similar relationship with stock returns between day-to-day temperature differences as with temperature.

3. Data and Methodology

3.1. Data

To examine the relationship between temperature and stock returns in mild climates both financial data (daily closing stock prices) and weather data (daily mean temperature) were used. The financial data were collected from four stock indices to cover four financial markets; the AEX index (Amsterdam, the Netherlands); the FTSE-100 index (London, United Kingdom); the ISEQ index (Dublin, Ireland); and the DAX index (Frankfurt, Germany). These indices were chosen because of the *Cfb* Köppen-Geiger climate classification (Peel et al., 2007), geographic location, maturity of the market, availability of weather data and prior coverage in existing literature. The financial data is retrieved from Datastream and the weather data is retrieved from the European Climate Assessment & Dataset (ECA&D). The sample period of the analysis is from December 2012 to November 2017. To avert biased results this study only contains financial data from full business days, thus excluding weekends, holidays and early market closures.

3.2. Data transformation

I had to make a few data transformations to be able to use the data for this research. First, the daily stock returns were generated from the daily closing stock prices. This was imperative because stock prices tend to grow over time. Consequently, causing the stock prices to suffer from unit root, as the augmented Dickey-Fuller tests in *Appendix A* display, ensuing in spurious results. Thus, daily stock returns were used instead of stock prices. The stock returns were computed by taking the logarithmic difference of the stock prices with the following formula,

$$returns_t = \log\left(\frac{price_t}{price_{t-1}}\right) \tag{1}$$

Where Returns_t are the daily stock returns at time t for a given index, and Price_t is the closing stock price at time t for a given index.

Second, the day-to-day temperature differences were generated to be able to investigate the second hypothesis. The mean temperature of the preceding day was subtracted from the daily mean temperature to get the day-to-day temperature difference[6]. This was implemented through the following formula,

$$\Delta Temp_t = Temp_t - Temp_{t-1} \qquad (2)$$

Where $\Delta \mathrm{Temp}_t$ is the day-to-day temperature difference at time t, Temp is the daily mean temperature, and Temp_{t-1} is the daily mean temperature of the preceding day.

3.2.1. Anomalies and dummy variables

Like Kamstra et al. (2003) and Cao & Wei (2005) dummy variables were used to control for two well-known anomalies, the Monday effect and tax-loss effect[7]. The Monday dummy variable equals 1 when the day is a Monday and 0 on every other day. The dummy variable controlling for the tax-loss effect equals 1 on the first 10 days of the tax year and 0 on every other day. The tax year starts in the United Kingdom on the 6th of April and on the first of January in the other countries. The additional descriptive statistics can be found in Appendix A.

3.3. Methodology

I used ordinary least squares (*hereafter: OLS*) time series regressions to analyze the relationship between temperature and stock returns. This linear least squares method is an easy technique to test for correlation between two variables. OLS regressions have therefore frequently been used to examine the interrelation between weather variables and stock returns (Saunders, 1993; Cao & Wei, 2002; Cao & Wei, 2005; Keef & Roush, 2005; Dowling & Lucey, 2005; Novy-Marx, 2014).

3.3.1. Gauss-Markov theorem

Pursuant to the Gauss-Markov theorem several assumptions need to be met for an OLS regression to be the best linear unbiased estimator (*hereafter: BLUE*). These assumptions were tested prior to the final modelling to ensure that the regressions are BLUE. First, the

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[6] Take in mind that the preceding days were conformed to the Gregorian calendar and includes non-full business days.

[7] Both Kamstra et al. (2003) and Cao & Wei (2005) also used lagged stock returns to control for autocorrelation. However, the usage of Newey-West standard errors already controls for autocorrelation making it counterproductive to include an additional variable controlling for autocorrelation.

pivotal variables were tested on the normality of residuals. To assess the distribution Jarque-Bera tests were used (Jarque & Bera, 1987)[8]. The tests display that none of the variables are normally distributed and the normality assumption is violated. However, this does not lead to extensive complications because of the large sample size.

Second, the regressions were tested to see if the homoscedasticity- and independence assumptions hold. The homoscedasticity assumption states that the variance of the residuals must be identical for all predictor variables. The independence assumption assumes that there is no serial correlation in the residuals. Breusch-Pagan tests and Breusch-Godfrey tests were used to test for homoscedasticity and serial correlation respectively (Breusch, 1978; Godfrey, 1978). Newey-West standard errors correct for both heteroscedasticity and serial correlation (Newey & West, 1987). Hence, like Keef & Roush (2005), the OLS regressions ran with Newey-West standard errors if either the homoscedasticity- or independence assumption did not hold.

3.3.2. The models

This research comprises two models applied to four financial markets. The first OLS model was used to examine the correlation between stock returns and temperature. This model uses returns as the dependent variable and temperature as the independent variable. Like Kamstra et al. (2003) and Cao & Wei (2005) this model controls for both the Monday- and tax-loss effect. More specific, the model takes the following form,

$$returns_t = \alpha + \beta_1 Temp_t + \beta_2 monday_t + \beta_3 tax_t + \varepsilon_t \qquad (3)$$

Where $Returns_t$ are the daily stock returns at time t for a given index, α is the constant, Temp is the daily average temperature, $monday_t$ is the dummy variable controlling for the Monday effect which equals 1 on Mondays and 0 on every other day, tax_t is the dummy variable controlling for the tax-loss effect equaling 1 on the first 10 days of the tax year and 0 on every other day, β_1, β_2 and β_3 are the coefficients for the daily temperature, monday-effect and tax-loss effect respectively, and ε is the error term.

The second model was used to study the correlation between stock returns and day-to-day temperature differences. This model is somewhat analogous to the first model.

[8] The results of the Jarque-Bera tests can be found in in Appendix A.

However, it uses the day-to-day temperature differences instead of the temperature as the independent variable, while still controlling for the Monday- and tax-loss effect. The model is defined as,

$$returns_t = \alpha + \beta_1 \Delta Temp_t + \beta_2 monday_t + \beta_3 tax_t + \varepsilon_t \qquad (4)$$

Where $Returns_t$ are the daily stock returns at time t for a given index, α is the constant, Temp is the daily average temperature, $\Delta Temp_t$ is the temperature difference at time t, $monday_t$ is the dummy variable controlling for the Monday effect which equals 1 on Mondays and 0 on every other day, tax_t is the dummy variable controlling for the tax-loss effect equaling 1 on the first 10 days of the tax year and 0 on every other day, $\beta_{1,}$ β_2 and β_3 are the coefficients for the day-to-day temperature differences, Monday-effect and tax-loss effect respectively, and ε is the error term.

4. Results

4.1. Testing the OLS assumptions

As previously noted, a few assumptions needed to be examined before running the actual regressions. In section 3.2.1. it was already established that the pivotal variables are not normally distributed. However, this does not result into major problems because of the large sample size. In addition, it had to be established whether the OLS regressions suffer from heteroscedasticity or serial correlation. The Breusch-Pagan tests show that, using a 5% significance level, all regressions deal with heteroscedasticity. Furthermore, the Breusch-Godfrey tests show that, using a 5% significance level, only the regressions on the Irish financial market experience serial correlation. Thus, Newey-West standard errors were used in the actual regressions to correct for the spoken heteroscedasticity and serial correlation. The results of the Breusch-Pagan- and Breusch-Godfrey tests can be found in Appendix B.

4.2. Regression analysis: temperature and stock returns

The first model was implemented on the four financial markets independently to test if daily temperature and stock returns are negatively correlated in mild climates. The results, displayed in table 3, shows that the regressions uniformly have a negative coefficient for temperature. This is conform to the first hypothesis which hypothesize that daily temperature and stock returns are negatively correlated.

Table 1: Regressions on the relationship between temperature and stock returns

	The Netherlands	Ireland	United Kingdom	Germany
Temperature	- 0.00008*	- 0.00010	- 0.00005	- 0.00010**
	(0.00005)	(0.00007)	(0.00004)	(0.00004)
Monday	- 0.00064	- 0.00123	- 0.00112	- 0.00025
	(0.00071)	(0.00089)	(0.00077)	(0.00083)
Tax year	- 0.00275	0.00035	0.00279*	- 0.00409*
	(0.00209)	(0.00177)	(0.00152)	(0.00206)
Constant	0.00140**	0.00181**	0.00088	0.00174***
	(0.00060)	(0.00076)	(0.00058)	(0.00060)
N	1,277	1,258	1,260	1,263
F test (P > F)	0.1948	0.3051	0.0592	0.0727

Note: *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

However, the temperature coefficient does not reach statistical significance in most of the regressions (Students t-test, except Germany all $\rho > 0.05$). Only the German financial market has a statistically significant temperature coefficient (Student t-test, $\rho < 0.05$). Thus, for the regressions of the Netherlands, Ireland and the United Kingdom, I cannot reject the statistical hypothesis that temperature and stock returns are not correlated. Even though, it should be kept in mind that all regressions have homogenously negative temperature coefficients which suggests that temperature and stock returns are negatively correlated. However, for the financial markets of the Netherland, Ireland and the United Kingdom, this simply has not been proven by the statistics.

4.3. Regression analysis: temperature differences and stock returns

The second model was applied on the four financial markets to investigate if day-to-day temperature differences and stock returns are correlated. The results in table 4, show that day-to-day temperature differences and stock returns are statistical significantly correlated for the Netherlands, United Kingdom and Germany (Students t-test, $\rho < 0.01$). Only the *ΔTemp* coefficient of Ireland is not statistically significant (Student t-test, $\rho > 0.05$). Thus, for the financial markets of the Netherlands, United Kingdom and Germany, we can reject the hypothesis that day-to-day temperature differences and stock returns are not correlated.

Table 2: Regressions on the relationship between day-to-day temperature and stock returns

	The Netherlands	Ireland	United Kingdom	Germany
ΔTemp	0.00039***	0.00013	0.00049***	0.00049***
	(0.00011)	(0.00015)	(0.00015)	(0.00012)
Monday	- 0.00065	- 0.00123	- 0.00119	- 0.00014
	(0.00069)	(0.00088)	(0.00076)	(0.00082)
Tax year	- 0.00243	0.00074	0.00286*	- 0.00346
	(0.00207)	(0.00175)	(0.00156)	(0.00243)
constant	0.00056*	0.00080**	0.00024	0.00056
	(0.00031)	(0.00033)	(0.00034)	(0.00035)
N	1,277	1,258	1,260	1,263
F test (P > F)	0.0044	0.3916	0.0009	0.0002

Note: *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

The predominant statistically significant *ΔTemp* coefficients seem to confirm that day-to-day temperature changes influence stock returns. However, it should be noted that the

ΔTemp coefficients are homogenously positive. Thus, while the proven correlation is in alignment with the hypothesis, the sign is antithetical with the expected. The positive *ΔTemp* coefficients indicate that an increase in temperature with respect to the preceding day is linked with an increase in stock returns, whilst an inverse relationship between the two variables was assumed.

5. Discussion

This paper has investigated the relationship between temperature and daily stock returns in countries with mild climates. My study examines the relationship between stock returns and temperature from two perspectives; the absolute temperature and temperature changes in respect to the preceding day. I found little evidence on the existence of the traditional temperature anomaly in mild climate countries. Although, like previous studies, the results uniformly display a negative coefficient for temperature, it seldom reached statistical significance. I did find a significant positive correlation between day-to-day temperature differences and stock returns. Stock returns appeared to increase when the temperature is higher in respect to the preceding day.

Finding little evidence on the existence of the traditional temperature anomaly is unsurprising. Extreme temperatures, which the temperature anomaly theorem depends on, are scarce in *Cfb* climates. As psychological studies mostly found changes in aggression and apathy at extreme temperatures (Wyndham, 1969; Bell & Baron, 1976; Howarth & Hoffman, 1984; Pilcher et al., 2002), this would explain the statistical insignificance of the variable in this study. It should be kept in mind that, although statistically insignificant, the regressions do uniformly display a negative coefficient for temperature. This is consistent with the temperature anomaly in the sense of Cao & Wei (2005) and suggests that their findings were not just the effect of spurious results.

Finding a strong positive correlation between day-to-day temperature differences and stock returns is unexpected, considering that a negative relationship was anticipated and most empirical studies found negative coefficients for temperature (Keef & Roush, 2002; Cao & Wei, 2005; Floros, 2008). This suggests that day-to-day temperature differences do not stimulate the same moods that absolute temperature stimulates. Though it does not seem like day-to-day temperature differences affect stock returns through aggression, apathy and hysteria, it still is plausible that the correlation has mood- and behavioral foundations.

Empirical evidence suggests a positive relationship between sunshine and stock returns (Hirschleifer & Shumway, 2003; Chang, Nieh, Yang & Yang, 2006)[9], not much dissimilar from the relationship between day-to-day temperature differences and stock returns. The

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[9] Hirshleifer & Shumway (2003) suggest that being in a good mood makes you respond more favorable on news events, while being in a bad mood causes a more skeptical and pessimistic interpretation of news events. Chang et al. (2006) suggest that people are more likely to believe the stock prices to fall when lacking sunlight.

literature agrees that the positive relationship between sunshine and stock returns is caused by good moods, such as happiness and optimism. This may also explain the positive correlation with day-to-day temperature differences, as several psychological and environmental studies provide evidence on a positive relationship between rising temperatures and stock returns (Howarth & Hoffman, 1984; Keller et al., 2005; Levinson, 2012; Peng et al., 2016)

Keller et al. (2005), for instance, found that rising temperatures during the spring relate to better moods when time is spent outdoors. While Levinson (2012) reports a significant effect of temperature on life satisfaction. Howarth & Hoffman (1984) found that rising temperatures lead to less skepticism, and Peng et al. (2016) found a positive relationship between happiness and rising temperatures in mild and cold climates. On the whole, it appears that in mild climates, like sunshine, an increase in temperature with respect to the preceding day leads to a more upbeat mood. While a decrease in temperature with respect to the preceding day leads to a more pessimistic and skeptical mood. Thus, I propose the following explanation for the found positive correlation between day-to-day temperature differences and stock returns.

An increase in temperature with respect to the preceding day leads to a more upbeat mood. An upbeat mood causes investors to be more optimistic towards stocks and new information (Isen et al., 1978; Alarcon, Bowling & Khazon, 2013). Consequently, investors are more confident in the future prospects of a stock (Johnson & Tversky, 1983), this results in more buying behavior and less selling behavior. Additionally, upbeat investors tend to process new information less critically (Schwarz, 1990). This contributes to higher stock returns on days where the temperature has increased in respect to the preceding day.

A decrease in the day-to-day temperature, on the other hand, causes investors to be more skeptical and pessimistic towards stocks and new information (Howarth & Hoffman, 1984). Subsequently, investors have less confidence in the future prospects of a stock and tend to more selling behavior. Pessimistic and skeptical investors tend to overreact to bad news and underreact to good news. Hence a decrease in the temperature in respect to the preceding day contributes to lower stock returns. The counterbalance between upbeat and downbeat moods could explain the found positive correlation.

This study does not provide any evidence on the existence of the traditional temperature anomaly in mild climates. This deviates from previous findings that temperature and stock returns are negatively correlated (Keef & Roush, 2002; Cao & Wei, 2005; Floros, 2008). It should be kept in mind, though, that this study only used financial markets with mild climates. On the other hand, the results do indicate that day-to-day temperature fluctuations are positively correlated with stock returns. Hence I hypothesize that, although the relationship between absolute temperature and stock returns is not of statistical significance, in mild climates temperatures influence stock returns.

My analysis has several limitations. The sample period was from December 2012 to November 2017, covering only five years. The short sample period may cause the results to suffer from small sample bias (Nelson & Kim, 1993). However, on the other hand, the European financial markets suffered a recession, caused by the subprime mortgage crisis, prior to December 2012. Thus, it was chosen to keep the sample period restricted, as the impact of the small sample bias was expected to be limited.

Although the sample period has been restricted to limit the interference of a recession it should be kept in mind that it still covers a timeframe with a significant magnitude of investors uncertainty. During the latter part of the sample period, 2015-2017, an abnormal degree of event uncertainty was present on the stock market because of macro-political events (Cox & Graffith, 2018). The possible departure of the United Kingdom from the European Union caused European investors to be ambiguous about future excess- and prospects of stocks. In addition, the threat of a trade war between the United States of America and Europe heightened the investors' uncertainty. Because of the distinctiveness of the test period, future studies may use multiple time periods to look whether the found results are time consistent and have future implications.

I used only developed European financial markets in Cfb climates. It is undetermined whether day-to-day temperature differences will still be positively correlated with stock returns when using undeveloped countries or different geographical environments. Empirical evidence suggests that the sign of the linkage between good moods and day-to-day temperature differences is reliant on the climate (Rehdanz & Maddinson, 2005; Peng et al., 2016). Another interesting topic for future research is whether the sign is indeed climatically dependent, and if stock returns and day-to-day temperature differences are still correlated in different climate.

My results on day-to-day temperature differences are comparable with the empirical evidence on the relationship between sunshine and stock returns. It is debatable whether the found correlation is not a reflection of the relationship between sunshine and stock returns, as environmental evidence suggests a close interrelation between sunshine duration and rising temperatures (Matuszko & Weglarczyk, 2015) However, the significance of the results does not indicate that day-to-day temperature differences only reflect sunshine. Nonetheless, further research is required to test whether the positive correlation with day-to-day temperature differences is not a reflection of the relationship between sunshine and stock returns.

6. Conclusion

The temperature anomaly theorem suggests that temperatures induce certain moods, consequently affecting stock returns. This study examined the relationship between temperature and stock returns in financial markets with mild climates. I tested for the presence of the traditional temperature anomaly, in the sense of Cao & Wei (2005), while controlling for known anomalies. In addition, I have presented a new perception on the influence of temperature on stock returns. This new approach examines the relationship between stock returns and temperature changes in respect to the preceding day, taking the reference dependence of thermal perception and absence of extreme temperatures into consideration. I applied both ordinary least squares models on the indices of four European financial markets located in mild climates.

The results provided no inevitable prove that absolute temperatures are negatively correlated with stock returns in mild climates. The results do show a negative correlation between temperature and stock returns, however, it seldom reached statistical significance. This study shows a statistical significant positive correlation between day-to-day temperature differences and stock returns. It provides evidence that in mild climates day-to-day temperature fluctuation have an influence on daily stock returns.

The effect of day-to-day temperature differences on stock returns on one hand, and the lack of evidence on the traditional temperature anomaly theorem on the other hand, illuminates that temperatures affect financial markets and stock returns, even in mild climates. I postulate that the absence of the traditional temperature anomaly derives from the absence of extreme temperatures. In addition, I conjecture that the positive relationship between stock returns and day-to-day temperature differences originates from mood alterations. The, by day-to-day temperature fluctuations induced, mood alterations make investors perceive risks and process information different, consequently impacting stock returns.

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Appendix A: Descriptive statistics

Appendix A contains the descriptive statistics of stock returns, temperature and day-to-day temperature differences. In addition, Appendix A contains the Jaque-Bera tests and augmented Dickey-Fuller tests to examine the distribution of the residuals and stationarity, respectively.

Table 3: Descriptive statistics of stock returns

	AEX	ISEQ	FTSE-100	DAX
Mean	0.00037	0.00059	0.00011	0.00044
Median	0.00061	0.00052	0.00050	0.00091
Maximum	0.03971	0.04447	0.05308	0.04852
Minimum	- 0.05873	- 0.10415	- 0.09211	- 0.07067
SD	0.00995	0.01078	0.01074	0.01124
Skewness	- 0.33105	- 1.20206	- 0.61590	- 0.38003
Kurtosis	6.11582	13.46217	10.82151	5.49458
Jarque-Bera test χ^2 ($P > \chi^2$)	539.890 (0,000)	6040.298 (0,000)	3291.401 (0,000)	357.887 (0,000)
ADF (Level)	- 1.335	- 1.777	- 2.911	- 1.344
ADF (1st diff.)	- 33.990	- 32.438	- 33.798	- 35.485
ADF test critical value at 5%	- 2.860	- 2.860	- 2.860	- 2.860
N	1,277	1,258	1,260	1,263

Note, ADF is an abbreviation for the augmented Dickey-Fuller test. The ADF (Level) is the augmented Dickey Fuller test on stock prices, and ADF (1st diff.) is the augmented Dickey-Fuller test on stock returns.

Table 4: Descriptive statistics of temperature

	The Netherlands	Ireland	United Kingdom	Germany
Mean	11.02	9.94	11.40	11.48
Median	11.20	9.90	11.50	11.60
Maximum	26.10	22.00	29.40	29.40
Minimum	- 5.30	- 2.00	- 6.70	- 6.70
SD	6.00814	4.49364	7.25448	7.27833
Skewness	- 0.13357	- 0.02425	0.03397	0.02414
Kurtosis	2.38184	2.11966	2.20810	2.20055
Jarque-Bera test χ^2 ($P > \chi^2$)	24.129 (0.000)	40.746 (0.000)	33.165 (0.000)	33.756 (0.000)
ADF (Level)	- 6.723	- 8.782	- 6.341	- 6.378
ADF test critical value at 5%	- 2.860	- 2.860	- 2.860	- 2.860
N	1,277	1,258	1,260	1,263

Note, ADF is an abbreviation for the augmented Dickey-Fuller test.

Table 5: descriptive statistics of day-to-day temperature differences

	The Netherlands	Ireland	United Kingdom	Germany
Mean	- 0.00031	0.02297	- 0.01802	0.00024
Median	0.00	0.10	0.10	0.10
Maximum	9.50	6.50	10.10	10.10
Minimum	- 9.80	- 8.30	- 12.20	- 12.20
SD	2.23194	2.02814	2.50000	2.57164
Skewness	0.08358	- 0.20881	- 0.20688	- 0.18539
Kurtosis	4.46715	3.24128	4.55010	2.57164
Jarque-Bera test χ^2 ($P > \chi^2$)	116,019 (0.000)	12,193 (0.000)	135.135 (0.000)	16.877 (0.000)
ADF (Level)	- 37.058	- 39.507	- 35.756	- 36.660
ADF test critical value at 5%	- 2.860	- 2.860	- 2.860	- 2.860
N	1,277	1,258	1,260	1,263

Note, ADF is an abbreviation for the augmented Dickey-Fuller test.

Appendix B: Additional regression analyses

Appendix B contains the regression analyses without Newey-West standard errors. In addition, Appendix B contains the Breusch-Godfrey tests and Breusch-Pagan tests to assess for serial correlation and homoscedasticity, respectively.

Table 6: Regressions without Newey-West standard errors- and additional tests on the relationship between temperature and stock returns.

	The Netherlands	Ireland	United Kingdom	Germany
Temperature	- 0.00008	- 0.00010	- 0.00005	- 0.00010**
	(0.00005)	(0.00007)	(0.00004)	(0.00004)
Monday	- 0.00064	- 0.00123	- 0.00124	- 0.00025
	(0.00070)	(0.00077)	(0.00776)	(0.00080)
Tax year	- 0.00275	0,00035	0.00296	- 0.00409**
	(0.00180)	(0.00198)	(0.00186)	(0.00204)
Constant	0.00140**	0.00181**	0.00088	0.00174***
	(0.00061)	(0.00076)	(0.00059)	(0.00063)
N	1,277	1,258	1,260	1,263
R^2	0.0041	0.0038	0.0053	0.0063
Breusch-Godfrey	2.719	9.100	2.420	0.061
test χ^2 $(P > \chi^2)$	(0.099)	(0.003)	(0.120)	(0.805)
Breusch-Pagan	4.570	28.650	5.500	8.610
test χ^2 $(P > \chi^2)$	(0.033)	(0.000)	(0.019)	(0.003)

Note: *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7: Regressions without Newey-West standard errors- and additional tests onthe relationship between temperature and stock returns

	The Netherlands	Ireland	United Kingdom	Germany
ΔTemp	0.00039***	0.00013	0.00049***	0.00049***
	(0.00012)	(0.00015)	(0.00015)	(0.00012)
Monday	- 0.00065	- 0.00123	- 0.00119	- 0.00014
	(0.00070)	(0.00077)	(0.00077)	(0.00079)
Tax year	- 0.00243	0.00074	0.00286	- 0.00346*
	(0.00178)	(0.00196)	(0.00186)	(0.00200)
Constant	0.00056*	0.00800**	0.00024*	0.00056
	(0.00031)	(0.00078)	(0.00034)	(0.00035)
N	1,277	1,258	1,260	1,263
R^2	0.0098	0.0027	0.0128	0.0148
Breusch-Godfrey	2.613	8.743	2.387	0.9279
test χ^2 $(P > \chi^2)$	(0.106)	(0.003)	(0.122)	(0.008)
Breusch-Pagan	6.430	18.110	5.050	4.970
test χ^2 $(P > \chi^2)$	(0.011)	(0.000)	(0.025)	(0.026)

Note: *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.