Does the sun shine really shine on the financial markets?*

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Abstract

After a series of papers has provided – partially ambiguous – results on the impact of weather variables on stock (index) returns, this article studies the impact of weather on a wide variety of financial market instruments, namely "risk-free" interest rates, the US corporate bond market, stock returns, stock index returns and the VIX volatility index. First, we construct a model that combines asset pricing and results from psychology to show how weather variables can affect asset prices in different market segments via mood. Second, in our empirical analysis we use several weather variables from the National Climatic Data Center (NCDC) and control variables motivated by economic theory. Applying various econometric techniques and using different market segments (motivated by differences in the risk level and institutional differences) allows to give a more detailed picture on the impact of weather on financial market prices. We demonstrate that on none of the market segments analyzed the weather has any significant impact.

Keywords: Mood Effects, Weather Effects, Behavioral Finance.

JEL: C51, G12, E43.

1 Introduction

There are different streams of literature analyzing the impact of mood (driven by external determinants) on financial market data. To be more precise, there are different branches of literature analyzing if asset prices are related to *seasonal affective disorder (SAD)* (see e.g. Kamstra et al. (2000), Kamstra et al. (2003), Garrett et al. (2005), Kamstra (2005), Kamstra et al. (2009)), sports events (see e.g. Ashton et al. (2003), Edmans et al. (2007)), the environmental pollution (see Lepori (2009)), the movie program (see Lepori (2010)) or the weather (see e.g. Saunders (1993) or Hirshleifer and Shumway (2003)). This paper focuses on the impact of weather on different financial market segments.

There is substantial empirical evidence that the weather affects people's moods (see e.g. Goldstein (1972), Persinger (1975), Cunningham (1979), Sanders and Brizzolara (1982), Kals (1982), Howarth and Hoffman (1984), Parrott and Sabini (1990) or Keller et al. (2005)). Mood, in turn, can have an impact on the individuals' accuracy and quality of decision-making (negative relation detected by Au et al. (2003)), optimism (positive relation, see e.g. Cunningham (1979), Howarth and Hoffman (1984), Arkes et al. (1988) or Wright and Bower (1992)), perception of risk (overconfidence) (Johnson and Tversky (1983), Arkes et al. (1988) or Au et al. (2003)) and risk aversion (Kliger and Levy (2003), Au et al. (2003)). Concerning the impact of mood on the risk aversion, according to the psychological literature there are two alternative and counteracting hypotheses: The *affect infusion model* (see e.g. Forgas and Bower (1987) or Forgas (1995)) postulates that an improvement in the mood reduces the risk aversion. By contrast, the mood maintenance hypothesis (see Isen and Patrick (1983) or Isen and Geva (1987)), often neglected in the Behavioral Finance literature, argues that an improvement in the mood increases the risk aversion (in order to maintain the positive mood). For evidence of the mood maintenance hypothesis in a Behavioral Finance context see e.g. Lepori (2010).

The impact of mood on decision-making may also depend on the situation. Forgas (1995) argued that higher complexity and uncertainty increases the impact of mood on decision-making. Similarly, Slovic et al. (2002) proposed that using affective impressions, rather than assessing probabilities, to make decisions is much easier in situations involving risk and uncertainty, especially when the decision is complex. Since financial decisions are very complex decisions, it is reasonable to conclude that mood plays a role in investment decision-making and, consequently, asset prices.

Even though the actual weather hardly affects (most) asset fundamentals, it may have an impact on financial assets' prices. A possible channel of this effect could be that weather changes mood which, due to the impact of mood on optimism, risk perception or risk aversion, changes the supply of and demand for assets in different risk classes. This functional chain will be studied in this article.

The relationship between weather and stock market returns has been the subject of empirical studies to a recently increasing extent. In this context, different papers show contradicting results: Saunders (1993) found that the returns on the NYSE were negatively related to cloud cover in New York City. The higher stock returns on sunny days were supposed to have resulted from the positive mood, induced by good weather, of floor traders and brokers. Other papers extended the literature by using additional weather variables: Krämer and Runde (1997) include cloud cover, humidity and barometric pressure. Keef and Roush (2002), Keef and Roush (2005) and Keef and Roush (2007) investigate the influence of wind, temperature, rain, humidity, sunshine and cloud cover on stock returns. Dowling and Lucey (2005) evaluate weather effects using cloud, rain, humidity and geomagnetic storms. Goetzmann and Zhu (2005) include cloud cover, rain and snow, and Theissen (2007) uses cloud cover, sunshine, rain and temperature.

However, the impact of the weather on stock returns is not undisputed. E.g. Trombley (1997) for the US stock market and Krämer and Runde (1997) for the German stock market found that the sunshine effect was less clear than claimed by Saunders. Similarly, Pardo and Valor (2003) for Spain, Levy and Galili (2008) for Israel and Jacobsen and Marquering (2008) for 48 countries reject the hypothesis of weather effects.

Summarizing the growing literature of weather effects on international stock markets, there is currently no general agreement in literature if there is an impact of weather on stock returns. However, the results from psychological literature and the findings on the stock market are significant enough to raise the question whether other market segments are influenced by the weather. Keef and Roush (2007) integrated fixed income securities into the analysis. They regressed returns from stock indexes, government bonds and bank bills in Australia on the weather (sunshine, wind) in Auckland and Wellington.

As the results of existing literature on weather effects on the stock market are ambiguous, we want to shed more light on this. We start our analysis establishing a theoretical model of the impact of mood on asset prices. This enables to see the impact of weather/mood on the stock market returns and volatility, which is required for our empirical analysis. Our model predicts that if the weather affects the mood and the affect infusion model holds, with better weather the prices of all risky assets increase, the ex-ante expected returns decrease and the volatility decreases. These effects are pronounced the more, the higher is the risk of the respective security.

Based on the theoretical model we examine the impact of weather on different financial sub-markets, namely risk-free interest rates, corporate bond yield spreads, stock returns, the S&P 500 returns and the VIX volatility index. By this, we investigate if there are weather effects on the aggregate market level (risk-free interest rates, S&P 500 returns and VIX) and on a more disaggregated firm-by-firm or bond-by-bond level (stock returns, corporate bond yield spreads).

The reasons why we look at a variety of market segments are easily described: First, psychological literature says that weather-induced changes in mood have an impact on risk aversion. As stated above, our model claims that the effect of weather on asset prices should be an increasing function of the asset's risk. E.g. the impact on stock returns should be more pronounced than that on corporate bond spreads due to the higher risk. To test this hypothesis, we have to study various market segments that differ in the risk level.

Second, the degree of rationality used in decision-making is decreasing with increasing complexity of the problem (see Conlisk (1996) or MacGregor et al. (2000)). Also, if mood affects the risk aversion via the affect infusion model or via the mood maintenance hypothesis depends (among others) on the complexity (see Forgas (1995)). Similarly, the impact of complexity in the valuation of a security on the significance of sentiment in the price formation has been described by Baker and Wurgler (2007). Therefore, as the different market segments analyzed in our study also vary in terms of valuation complexity, it makes sense to look at each of them.

Third, there are institutional differences between the different market segments. E.g. stock markets are said to be more dominated by retail investors whereas corporate bond markets are assumed to be populated more by institutional investors (an effect that is reinforced in our paper as we eliminated small trades from the corporate bond database). Much of the Behavioral Finance literature detects more irrationality with retail investors than with institutional investors as retail investors are more independent in their decisions, while institutional investors are more sophisticated in their decision structures and often trade via algorithmic trading (see e.g. Grinblatt and Keloharju (2001) or Shapira and Venezia (2001)). In line with this, Shu (2008) shows for the stock market that weather effects are more prevailing with individuals than with institutional investors.

Another institutional difference that provides an argument to investigate a variety of market segments is that on some of the segments (e.g. the corporate bond market) trading is done electronically while on other segments (e.g. the stock market analyzed by us) floor trading occurs. Often electronic trading is said to eliminate any mood effects. E.g. Lepori (2009) shows that mood changes have an impact on decisions of the trading floor community which vanishes once the trading floor is replaced by a computerized and decentralized trading system. Similarly, Shon and Zhou (2009) observe that NYSE stocks are influenced by the weather in N.Y. while this is not the case for NASDAQ stocks. They argue that this is due to the fact that NASDAQ is a decentralized trading platform.

Fourth, omitted variable problems might occur. To give an example: Imagine that the risk-free rates significantly influence the stock market, but we analyze the impact of the weather on the stock market without including the risk-free rates as a determinant (similar to some related literature in this field): If the weather is correlated with the risk-free rates (via mood and risk aversion), then some of the prediction variables are correlated with the regression residual. If this is the case the least squares estimate in the stock market regression is biased. By contrast, if the risk-free rates are independent of the weather, the least squares estimates are not biased (but still less efficient). A similar example would be the impact of the volatility index VIX on the corporate bond spreads.

Fifth, if some financial sub-market X is influenced by the weather and the prices on this sub-market X have an impact on another sub-market Y, then the overall weather effect on sub-market Y consists of the indirect weather effect (acting via sub-market X) and the direct weather effect (shown for the weather variables in the regression for sub-market Y). Thus, the findings found on sub-market Y have to be interpreted only as the additional effect.

Finally, an impact of the weather on a variety of asset prices and spreads would mean a higher correlation between different securities and thereby reduce the effects of diversification.

A few words on econometric models for studying weather effects on financial markets: Based on existing psychological literature and our asset pricing model there should be a functional chain from weather via mood to asset prices. The problem is that in the empirical data one does not observe the mood of each market participant. To cope with this problem we consider weather as a proxy of the unobserved mood. From an econometric point of view we are facing an "errors in variables" problem. To cope with this, instrumental variable estimation will provide us with consistent and unbiased parameter estimates.

Our major findings are summarized as follows: The regression setting has a strong impact regarding the question whether significant weather effects can be found. This involves the danger to identify weather effects that do not really exist. Using the appropriate regression technique (especially adjusting for heteroscedasticity and instrumental variable estimation), we cannot identify any weather effects on a five percent significance level. This finding is stable for the different sub-markets considered.

The paper is structured as follows: In Section 2 we develop an asset pricing model to derive predictions how a mood variable influences asset prices, returns and volatilities. In Section 3 we describe the data used in our study. Section 4 outlines the methodology and the results. Finally, Section 5 concludes.

2 Mood and Asset Prices

In this section we consider a general equilibrium setting without production, which will provide us with the *capital asset pricing* model (CAPM). We point out that the purpose of this section is not to reproduce the CAPM, but to get an understanding of the impact of some mood variable μ on asset prices, asset returns and asset volatilities. According to the psychological literature cited in Section 1, μ should be positively affected by improving weather conditions w.[1] In addition we consider a parameter ϱ_μ describing the degree of absolute risk aversion. Following psychological literature the impact of mood μ on risk aversion ϱ_μ is ambiguous. According to the *affect infusion* model ϱ_μ decreases when μ rises, while with the *mood maintenance* hypothesis the opposite is observed. In the neoclassical finance literature the effect of μ on ϱ_μ is (assumed to be) zero or at least not significant. According to Hirshleifer and Shumway (2003) and the literature cited there mood can also have an influence on the agents' perception of the payoff distribution, i.e. expected payoffs rise and their perceived variances decrease with improving mood. This argument can be easily integrated into our model, as well. Throughout this section we follow Werner and Ross (2000) and Blume (2011). Other ways to approach the CAPM and to implement it empirically are e.g. provided in Campbell

[1] In our theoretical model μ and w are treated as scalars to reduce the complexity. An extension to vector valued mood and weather variables is straightforward. Each component of this vector μ can then be influenced by some components of the vector of weather variables w. With such an extension the aggregate effect is obtained by adding up the corresponding partial derivatives.

et al. (1996) or Cochrane (2005).

Consider an economy with n risky assets paying $\Phi_1, \ldots, \Phi_n$ units in terms of the consumption good. Assets are traded at the beginning of the period, Φ_k is realized at the end of the period. In addition, we assume that there exists a risk-free asset paying Φ_0. The expected payoffs of the risky assets are $\phi = (\phi_1, \ldots, \phi_n)^\top$. The covariance matrix is denoted by v. The elements of v are v_{jk}, the diagonal elements are v_{kk}, $k, j = 1, \ldots, n$. For the risk-free asset $\phi_0 = \Phi_0$. By including the risk-free asset we get the expected payoff vector $\tilde{\phi} = (\phi_0, \phi_1, \ldots, \phi_n)^\top$.

The vector $\tilde{q} = (q_0, q_1, \ldots, q_n)^\top$ is the portfolio chosen by the consumer at the beginning of the period; $q_k \in \mathbb{R}$, $k = 0, 1, \ldots, n$; i.e. short selling is permitted. The quantities of the risky assets held are $q = (q_1, \ldots, q_n)^\top$. The expected payoff of the portfolio $\tilde{q}$ is $m = \tilde{q}^\top \tilde{\phi}$, the variance is given by $V = q^\top v q$. Given the portfolio $\tilde{q}$ the agents consume $\tilde{q}^\top (\phi_0, \Phi_1, \ldots, \Phi_n)^\top$ at the end of the period. The aggregate supply of the risky assets is fixed and given by the vector $a = (a_1, \ldots, a_n)^\top$. The supply of the risk-free asset is perfectly elastic. The prices for the risky assets are $p = (p_1, \ldots, p_n)^\top$, while when including the risk-free asset we get $\tilde{p} = (p_0, p_1, \ldots, p_n)^\top$. This results in the budget set $\{\tilde{q} \in \mathbb{R}^{n+1} | \tilde{q}^\top \tilde{p} \leq \omega\}$. Without loss of generality the initial wealth of the consumer is normalized to $\omega = 1$. With $q = a$ we get the expected payoff and the variance of the market portfolio, $m_M = a^\top \phi$ and $V_M = a^\top v a$, respectively.

The preferences of the representative agent are described by a *constant absolute risk aversion* (CARA) utility function (see e.g. Mas-Colell et al. (1995)[Chapter 6]).[2] The larger ϱ_μ the larger the risk aversion (see e.g. Mas-Colell et al. (1995)[Theorem 6.C.2]). Assuming that the random vector $\Phi = (\Phi_1, \ldots, \Phi_n)^\top$ is jointly normal with mean ϕ and covariance matrix v,

[2] Our model remains close to traditional asset pricing literature assuming that preferences can be described by means of a utility function. For von Neumann-Morgenstern expected utility functions resulting in a mean-variance representation of preferences the reader e.g. is referred to Werner and Ross (2000)[Chapter 19].

maximizing the expected utility is equivalent to maximizing

$$u_\mu(m,V) = m - \frac{\varrho_\mu}{2}V \ . \tag{1}$$

Given (1) we observe $\frac{\partial u_\mu}{\partial m} = 1 > 0$ and $\frac{\partial u_\mu}{\partial V} = -\varrho_\mu/2 < 0$, i.e. more expected payoff is appreciated, while the agent dislikes higher volatility. The mood μ affects the risk aversion ϱ_μ, where $\frac{\partial \varrho_\mu}{\partial \mu} > 0$ corresponds to the mood maintenance hypothesis while $\frac{\partial \varrho_\mu}{\partial \mu} < 0$ describes the affect infusion model. Given the above assumptions we consider the utility maximizing problem

$$\max_{\tilde{q}} u_\mu(m,V) \quad s.t. \ \tilde{q}^\top \tilde{p} \le \omega = 1 \ . \tag{2}$$

(2) yields the Lagrangian $L(\tilde{q},\zeta) = u_\mu(m,V) + \zeta(1-\tilde{q}^\top\tilde{p})$ and the first order conditions:

$$\begin{aligned}
\frac{\partial L(\tilde{q},\zeta)}{\partial q_0} &= \frac{\partial u_\mu(m,V)}{\partial m}\phi_0 - \zeta p_0 = 0 \ , \\
\frac{\partial L(\tilde{q},\zeta)}{\partial q_k} &= \frac{\partial u_\mu(m,V)}{\partial m}\phi_k + 2\frac{\partial u_\mu(m,V)}{\partial V}\sum_{j=1}^{n} v_{kj}q_j - \zeta p_k = 0 \ \ , \ k = 1,\dots,n \ , \\
\frac{\partial L(\tilde{q},\zeta)}{\partial \zeta} &= \tilde{q}^\top\tilde{p} - 1 = 0 \ .
\end{aligned} \tag{3}$$

Since the numeraire good can be freely chosen in a general equilibrium setup, we choose the normalization $p_0 = \phi_0$.[3] Thus, prices are expressed in terms of the risk-free asset. This results in

[3] Alternatively, we could choose the normalization $p_0 = \frac{\phi_0}{1+r_f}$, where r_f is motivated by time preferences. With this alternative normalization the expected return of the risk-free asset would be r_f, such that $\mathbb{E}(r_k) = r_f + \beta_k\left(\mathbb{E}(r_M) - r_f\right)$, i.e. we would get returns in Sharpe-Lintner form. To keep the formal analysis simple we continue with $p_0 = \phi_0$. The predictions of the model do not depend on the normalization chosen.

$$\zeta = \frac{\partial u_\mu(m,V)}{\partial m} = 1 \ , \quad -2\frac{\frac{\partial u_\mu(m,V)}{\partial V}}{\frac{\partial u_\mu(m,V)}{\partial m}} = \varrho_\mu \ ,$$

$$p_0 = \phi_0 = 1 \ , \quad p_k = \phi_k - \varrho_\mu \sum_{j=1}^{n} v_{kj} q_j \ , \ k = 1, \ldots, n \ . \tag{4}$$

From the above assumptions on the partial derivatives of the utility function $\lambda := -2\frac{\frac{\partial u_\mu(m,V)}{\partial V}}{\frac{\partial u_\mu(m,V)}{\partial m}} > 0$. λ is often called *market price of risk*, while $-\lambda$ is the *marginal rate of substitution* between the expected return and the variance.

To close the model we have to apply the *equilibrium condition* that asset supply is equal to asset demand. Since asset supply is fixed this yields $(q_1, \ldots, q_n)^\top = (a_1, \ldots, a_n)^\top$ or $q = a$ in vector notation, such that

$$p_0 = \phi_0 \ , \quad p_k = \phi_k - \varrho_\mu \sum_{j=1}^{n} v_{kj} a_j \ , \ k = 1, \ldots, n \ , \text{ and}$$

$$q_0 = \frac{1}{\phi_0}\left(1 - \sum_{k=1}^{n} a_k p_k\right) = \frac{1}{\phi_0}\left(1 - a^\top p\right) \ . \tag{5}$$

From the budget constraint and (5) we get the amount of money invested in all risky assets in the economy, ω_a, and the amount invested in the risk-free asset, ω_{rf}:

$$\omega_a = a^\top p \text{ and } \omega_{rf} = 1 - a^\top p \ . \tag{6}$$

Based on the discussion at the beginning of this section ϱ_μ depends on the mood μ. By taking the derivative with respect to μ in (5), we obtain the impact of μ on the prices. The expected payoffs ϕ, the covariance matrix v, the asset supply a and V_M are constants.[4] Given

[4]Given our utility function, the effect of μ on λ can be obtained in a straightforward way, as the marginal rate of substitution is constant for all values $(m, V) \in \mathbb{R} \times \mathbb{R}_+$. With more general utility functions the effects of

the affect infusion model, where $\frac{\partial \varrho_\mu}{\partial \mu} < 0$, we obtain the following result: If $\sum_{j=1}^n v_{kj} a_j > 0$ then

$$\frac{\partial p_k}{\partial \mu} = -\frac{\partial \varrho_\mu}{\partial \mu} \sum_{j=1}^{n} v_{kj} a_j > 0 \ . \tag{7}$$

Thus, if the affect infusion model is true, then with improving mood prices of risky assets increase.[5] For the mood maintenance hypothesis this effect goes into the opposite direction.

Remark 2.1. *According to psychological literature mood could also affect the agents' optimism and risk assessment, thus the perception of the payoff distribution, such that the perceived expected payoff rises and the perceived variance decreases with improving mood, i.e.* $\frac{\partial \phi_k}{\partial \mu} > 0$ *and* $\frac{\partial}{\partial \mu} \sum_{j=1}^n v_{kj} a_j < 0$ *in formal terms. Augmenting (7) by these two terms shows that* $\frac{\partial p_k}{\partial \mu}$ *is amplified if the affect infusion model holds.*[6] *Based on this finding we restrict our analysis to an investigation of the effects arising from mood on risk aversion, keeping in mind that with the affect infusion model the results remain the same, if the mood also has an impact on the expected payoffs and the variance.*

Let us investigate the individual asset returns and the market return. Using the above results the expected return and the variance of asset k is given by

$$\mathbb{E}(r_k) = \frac{\phi_k - p_k}{p_k} = \frac{\varrho_\mu \sum_{j=1}^n v_{kj} a_j}{\phi_k - \varrho_\mu \sum_{j=1}^n v_{kj} a_j} \text{ and } \mathbb{V}(r_k) = \frac{v_{kk}}{p_k^2} \ . \tag{8}$$

μ on λ need not be that clear. Results with a representation of the preferences where $u(m, V)$ is not additively separable are available from the authors on request.

[5] Since $a^\top va > 0$ need not imply that $\sum_{j=1}^n v_{kj} a_j > 0$ for all k, not all the asset prices have to increase in general given the affect infusion model. However the aggregate effect $a^T \nabla_\mu p = -\frac{\partial \varrho_\mu}{\partial \mu} a^\top va$ has to be positive. $\nabla_\mu p$ stands for the gradient vector arising from $\frac{\partial p_k}{\partial \mu}$, $k = 1, \ldots, n$. In the following discussion we assume that $\sum_{j=1}^n v_{kj} a_j > 0$ for all k.

[6] The effect with the mood maintenance hypothesis would be counteracted and can also be overcompensated. Note, that most of the literature investigating the impact of weather (see e.g. Saunders (1993)) or seasonal affective disorder (see e.g. Kamstra et al. (2003)) on stock prices is based on the affect infusion model and not on the mood maintenance hypothesis.

For the risk-free asset we get $\mathbb{E}(r_0) = 0$ and $\mathbb{V}(r_0) = 0$. Suppose that $\sum_{j=1}^{n} v_{kj} a_j > 0$ and $\phi_k > 0$. Then if $\frac{\partial \varrho_\mu}{\partial \mu} < 0$, we observe that

$$\frac{\partial \mathbb{E}(r_k)}{\partial \mu} = \frac{1}{p_k^2} \cdot \left(-\frac{\partial p_k}{\partial \mu} p_k - (\phi_k - p_k) \frac{\partial p_k}{\partial \mu} \right) = -\frac{1}{p_k^2} \cdot \frac{\partial p_k}{\partial \mu} \phi_k < 0 \tag{9}$$

and

$$\frac{\partial \mathbb{V}(r_k)}{\partial \mu} = v_{kk} \frac{-2}{p_k^3} \cdot \frac{\partial p_k}{\partial \mu} < 0 \ . \tag{10}$$

Therefore the model predicts that with increasing mood (μ) the expected returns and the volatilities decrease for all risky assets. Following equations (7), (9) and (10), the higher the risk measured in terms of $\sum_{j=1}^{n} v_{kj} a_j$, the stronger the impact of μ via ϱ_μ on the expected returns and their variances. In the same way as for the individual security k, we can show that the expected market return and market variance are decreasing with μ, if the affect infusion model prevails. In addition, one can demonstrate that with the affect infusion model with improving mood the percentage of money invested in the market portfolio increases and the percentage invested in the risk-free security decreases ($\frac{\partial \omega_a}{\partial \mu} > 0$ and $\frac{\partial \omega_{rf}}{\partial \mu} < 0$ with $\frac{\partial \varrho_\mu}{\partial \mu} < 0$).

Summing up we showed that with CARA preferences the market price of risk λ is equal to the degree of risk aversion ϱ_μ. Suppose that the risk of a security $\sum_{j=1}^{n} v_{kj} a_j > 0$ ($\approx$ market portfolio weighted sum of the covariances of asset k with all assets j and k itself) and the affect infusion model is true (i.e. $\frac{\partial \varrho_\mu}{\partial \mu} < 0$), then the expected asset returns, the variance of the asset returns, the expected market return and the variance of the market return decrease when μ increases. This can be interpreted economically as follows: With improving mood the risk aversion decreases which results in higher current prices for all risky assets, which - all other things (especially the future price) equal - creates lower returns in the next period. For the mood maintenance model the opposite effect takes place.

In the next step let us connect the above results to our empirical data: In the empirical analysis we will study different asset returns, interest rates and bond spreads. Our model predicts that with the affect infusion model the market price of risk (being equal to the risk aversion coefficient, in our model ϱ_μ) is negatively related to the mood variable μ. Thus, for all the asset classes investigated (bonds, stocks, VIX), the better the mood the higher the price. As the "risk-free" interest rates[7] and the corporate bond spreads are defined in a forward looking way (as yields), the better the mood, the higher the prices, thus the smaller the risk-free rates and the corporate bond yields. As corporate bonds are more risky than "risk-free" bonds, the corporate bond spread declines with better mood. For the stock returns, the issue is more tricky. On the one hand our model takes place in a one period setting providing us with expected (ex-ante) returns. Let us assume that the model provides us with a simplified description of the observed capital market where the model is repeated (maybe with different fundamentals $\tilde{\phi}$ and v) for a sequence of periods $t = 1, \ldots, T$. The stock returns studied in the Behavioral Finance literature, however, are ex-post realized returns:

$$r_{kt} = \frac{p_{kt} - p_{k,t-1}}{p_{k,t-1}} \tag{11}$$

where $p_{k,t-1}$ is the past price realization, while the current price p_{kt} should be described by (5). From this definition we see that the ex-post return is driven by both the actual mood μ_t and the previous mood μ_{t-1}. Taking partial derivatives in equation (11) with respect to μ_t and μ_{t-1} shows that $\frac{\partial r_{kt}}{\partial \mu_t} > 0$ and $\frac{\partial r_{kt}}{\partial \mu_{t-1}} < 0$ when assuming that the affect infusion model is correct. Therefore, the actual and the lagged variables should be used in the empirical analysis.

The volatility index VIX is another forward looking variable arising from implied option volatilities (for a description see Section 3.3). From the model derived above the variance of the market returns decreases with improving mood, given the affect infusion model, such

[7] Concerning the risk nature of the "risk-free" rate observed the reader is referred to the discussion in Section 3.1.

that a negative correlation between the VIX and mood can be expected. With the mood maintenance hypothesis the opposite is true.

In the empirical analysis the investors' moods can hardly be observed. An empirical study on an individual level would require for each investor daily data including his transactions and his mood. This data is not available. On an aggregate level there would be the additional problem of aggregating individual moods. Thus, we shall consider weather as a proxy of mood. Since μ could be multivariate, as well, we assume that the unobservable vector of mood variables is approximated by our set of weather variables. For the securities considered, we assume that the fundamentals are not influenced by the weather variables.[8]

We shall also include control variables. With respect to this simple model we can assume that these control variables (can) influence the "fundamentals" $\tilde{\phi}$ and v in our model above. Including these effects is important to avoid spurious regression results. In the following the empirical analysis will test the null hypothesis of no weather effects against the alternative that the weather influences asset prices.

3 Data

This study investigates the period from July 1, 2002 to March 31, 2006. Note that on purpose we used only data before the financial crisis 2007/08 because it is very plausible that during/since this tremendous financial crisis fundamental and non-weather behavioral effects may have dominated any weather-induced mood effects. We use daily data from the US market. Excluding holidays and weekends the observation period includes $T = 952$ days with data. Appendix B will provide some unit root tests for the data presented in the following paragraphs.

[8]Since no agricultural firms or utilities are included in the data set, this assumption seems plausible. The assumption that the weather variables act as mood proxies provides a further argument to apply instrumental variable estimation in Section 4.2.

3.1 Spot Rates and the "Risk-Free" Term Structure

In this paper the risk-free term structure is used as a dependent variable, as a control variable and in order to derive the corporate bond spreads. With respect to the risk-free term structure data we use the USD LIBOR for maturities of 1, 3, 6, 9 and 12 months from Bloomberg as well as USD swap rates (middle rates) for maturities 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 15, 20, 25 and 30 years from Datastream. These swap rates use the 6-month USD LIBOR as floating leg. After interpolation to get a series of equidistant swap rates at intervals of 6 months, we bootstrapped this data to obtain continuously compounded spot rates. Based on a selection of this data (the interest rates for 1, 3 and 6 months as well as 1, 2, 5, 7, 10, 15, 20 and 30 years) we got the spot rate for any arbitrary maturity by fitting a Svensson (1994) polynomial to the risk-free term structure data. These spot rates were used when calculating the corporate bonds spreads (see later). The vector of spot rates for the maturities $\{1/12, 1/4, 1/2, 1, 2, 5, 7, 10, 15, 20, 30\}$ years, abbreviated by r_F, will be used as a dependent variable.

Moreover, we will use one of these rates as a control variable in all regressions where the dependent variable is not the risk-free term structure. This can be motivated e.g. by the results of Longstaff and Schwartz (1995), Duffee (1998), Collin-Dufresne et al. (2001), etc. showing that the level of the "risk-free" term structure is a major determinant of corporate bond spreads. Similarly, concerning stock returns, asset pricing models often include the risk-free rate as a determinant of asset returns. We also use the risk-free rate as a control variable in the VIX regressions, because the risk-free rate is a well-known determinant of option prices (see e.g. the Binomial model or the Black/Scholes model). To have a parsimonious model we use for the level of the risk-free term structure only the risk-free rate with a maturity of two years which will be symbolized by $r_{F,2}$. Based on the unit root tests in Appendix B we will use the first difference, symbolized by $\Delta r_{F,2} = r_{F,2,t} - r_{F,2,t-1}$.

Remark 3.1. *Note that a risk-free asset, as modeled in Section 2, only exists in theory, as such an asset is assumed to be risk-free in terms of the consumption good. This assumption* *excludes e.g. inflation risk (see also Cochrane (2005)[p. 111]). Apart from inflation risk, the spot rates derived here are not completely risk-free, since LIBOR and swap rates include small but non-zero default risk. Therefore, the spot rates described above are close but not equal to the risk-free asset considered in the model. Keeping this in mind, we follow existing literature and call the spot rates r_F, described above, the "risk-free" term structure.*

We include the risk-free rate in our regressions for the following reason: Within our model in Section 2, these spot rates still include some (small) risk and therefore both according to the affect infusion model and the mood maintenance hypothesis should be influenced by the weather (see equation (9)). E.g. if the affect infusion model holds, then by equation (6) the investors put less wealth into the risky (so-called "risk-free") asset if the mood deteriorates due to worse weather. If, by contrast, we suppose that the investors consider these (nearly risk-free) spot rates to be risk-free, the opposite is true: E.g. if the affect infusion hypothesis holds, then according to equation (6) the investors put more wealth into the "risk-free" asset if the mood deteriorates because of worse weather. Thus, in both cases the weather could have an impact on the demand for this "risk-free" asset, affecting the spot interest rates.

Moreover, as a result of the previous two paragraphs we should check for weather effects with these "risk-free" spot rates since these rates also drive the other assets' market prices, especially they are used to calculated the corporate bonds spreads.

3.2 Corporate Bond Spreads

To get an initial sample of corporate bonds we selected all bonds that were included in the NASD Bloomberg Active Investment Grade U.S. Corporate Bond Index as of July 19, 2006. This is a corporate bond index generated solely from the actual transaction prices of actively traded bonds. It reflects activity for the most frequently traded fixed-coupon investment-grade bonds. The index membership is comprised of TRACE-eligible fixed-coupon corporate bonds, excluding all zero coupon bonds, 144As, convertible bonds, and bonds set to mature before the last day of the month for which index re-balance occurs. All bonds must have traded on average at least 3 times per day, with at least one transaction on 80% of the 60 trading days prior to the re-balance calculation date, and have a total issued amount outstanding available publicly. Appendix A describes in more detail how the sample was further restricted and how the transaction prices of these bonds were obtained from the TRACE database. The bond data collection procedure resulted in $N = 179$ bonds issued by 23 firms, observed on $T = 952$ days. Due to missing values and the fact that not all bonds were traded on all days within the time span considered, the number of observations is smaller than $N \cdot T$, however more than 80,000 observations are used in our empirical analysis.

From the bond prices we derived for these corporate bonds the yield spreads. s_{it} represents the spread for bond i at time t, in basis points. Based on the current gross price and the cash flow structure we derived the yield to maturity of each bond on each day. Then, for a fictitious risk-free bond with precisely the same cash flows we calculate the price of this fictitious risk-free bond (using the risk-free discount rates described in Section 3.1) and, based on that, its yield to maturity. The corporate bond spread is the difference between the two yields. Using the fictitious risk-free bond with the same cash flow structure we we can eliminate coupon effects.

3.3 Stock Market Data

For the 23 firms representing the bond sample in Section 3.2 we collected the corresponding daily stock prices and calculated the daily ex-post stock returns STR (measured in percentage terms).[9] To compare our results to previous studies and to check if weather effects are present on an aggregated vs. disaggregated level we included the S&P 500 index and computed the S&P 500 returns (measured in percentage terms), $SPRETURNS$. In addition, motivated by the results of Collin-Dufresne et al. (2001) and Pan and Singleton (2008) we control for the stock market volatility measured by the VIX index. VIX is a volatility index of the Chicago

[9] If for a firm no stock was traded but there was a close link to a related listed company (especially when a financing subsidiary or another privately held subsidiary issued the bonds), we used the stock returns of the related company as a proxy for the returns of the firm analyzed.

Board Options Exchange that measures the implied volatility of at-the-money put and call options on the S&P 500. It is also interpreted as "investor fear gauge" (measuring the fear of a future increase in stock market volatility; see Whaley (2000)).

3.4 Weather Data

Following much of the Behavioral Finance literature (e.g. Saunders (1993), Trombley (1997), Hirshleifer and Shumway (2003), Goetzmann and Zhu (2005), Cao and Wei (2005)) we obtain the weather data for our observation period from the National Climatic Data Center (NCDC, data available at *http://www.ncdc.noaa.gov/oa/ncdc.html*). This database includes hourly measurements of weather variables of 221 stations throughout the U.S.

As regards the place of measurement of weather, we have to specify the psychological story behind more closely. Most papers dealing with weather effects on the stock markets (e.g. Saunders (1993) and Hirshleifer and Shumway (2003)) assume that the weather effects come from the impact of the weather on the mood of investors. This would require weather data at the place(s) where the investors are located. In this line Loughran and Schultz (2004), after observing trading of stocks primarily by shareholders located close to the company's headquarters, analyze the impact of the local weather, to which shareholders of a stock are exposed, on the returns of this stock. However, they find only little evidence for the impact of local weather on the stock returns. Similarly, Goetzmann and Zhu (2005) investigate the relationship between sunshine in five major U.S. cities with large population and the trading activities of people in these cities and find hardly any impact of local weather except for N.Y. They hypothesize that the reason for this is that the weather effect does not come from the trading patterns of individual investors but from the attitudes of market makers, news providers or other agents physically located in the city hosting the exchange. An impact of the weather via the market makers was also detected by Shon and Zhou (2009).[10]

[10]Note that, in contrast to the stock market (New York Stock Exchange), the corporate bond market is an OTC market where market-making is done by dealers. Schultz (1998) describes the structure of this market and finds that more than 70% of the trades involve the top 12 dealers (see Table 2 in that paper showing that

Therefore, we restrict our analysis to the weather in New York. More precisely, we select the weather station at La Guardia Field airport. Selection of the airport weather in the city where the stock exchange is located is also consistent with Saunders (1993), Krämer and Runde (1997), Hirshleifer and Shumway (2003) and Cao and Wei (2005).

We use the following weather variables (all of them collected from the NCDC "hourly data" database): Persinger (1975), Cunningham (1979) and Howarth and Hoffman (1984) show, that sunshine is one of the most important meteorological determinants of mood and Goldstein (1972) proposes that low cloud cover is linked to positive mood. As a result, cloud cover is the weather variable most frequently investigated in the Behavioral Finance literature. Much of the literature (e.g. Saunders (1993), Hirshleifer and Shumway (2003), Chang et al. (2006) and Yoon and Kang (2009)) shows a negative relation between cloud cover and stock returns. In line with this our first weather variable is cloud cover, denoted as $CLOUDCOVER$. Strong cloud cover will deteriorate the mood and thus according to the affect infusion model or the mood maintenance hypothesis will change the risk aversion of the market participants. This could result in a change in the demand for asset classes of different risk thereby changing the risk-free rates, the corporate bond spreads, stock prices, stock market indexes and volatility indexes.

The NCDC Global Integrated Surface Hourly database contains hourly readings of the Total Sky Cover that is measured by a code that maps the fraction in tenth of the total celestial dome covered by clouds or other obscuring phenomena to a scale between 0 and 8. The value of the variable CLOUDCOVER therefore ranges from 0 (none of the sky is covered by clouds) to 8 (all of the sky is covered by clouds). We proceeded as follows: First, we eliminated all data where the NCDC quality check code indicated "suspect" or "erroneous". Then, we computed for each day the daily cloud cover by taking the average of the remaining data. In analogy to Hirshleifer and Shumway (2003) and Goetzmann and Zhu (2005) we

e.g. Merrill Lynch Capital Markets accounts for about 10% and Morgan Stanley and Co. for close to 7% of the trades). These dealers are strongly represented in New York. In addition we know from Table 4 in Schultz (1998) that many important investors on the corporate bond market are also located in New York.

aggregate only the data measured between 7 a.m. and 5 p.m. This time frame is justified by the trading hours.[11] Use of weather before the beginning of the trading hours assumes an impact of weather on the mood even before the trading activity (e.g. on the way from home to business). This methodology is in line with Hirshleifer and Shumway (2003), Loughran and Schultz (2004) and Cao and Wei (2005).

In addition to cloud cover (and in line with Zadorozhna (2009) and Lu (2009)), we used the hourly visibility, defined as the horizontal distance at which an object can be seen and identified, denominated in meters and denoted as $VISIBILITY$. We used the same procedure as described for cloud cover to get a daily value: We eliminated all data where the NCDC quality check code indicated "suspect" or "erroneous" and computed the daily value by averaging the data between 7 a.m. and 5 p.m.

Motivated by Keef and Roush (2002), Hirshleifer and Shumway (2003), Dowling and Lucey (2005), Chang et al. (2006), Gerlach (2007) and Chang et al. (2008) we also used hourly precipitation volume data from 7.00 a.m. to 5.00 p.m. and (after considering the NCDC quality check) aggregated this data to a daily precipitation in milliliters. We denote this variable as $PRECIPITATION$.

Moreover, we used temperature as a weather variable: Cunningham (1979) and Howarth and Hoffman (1984) showed that temperature is positively related to mood. By contrast, Griffitt and Veitch (1971) and Goldstein (1972) proposed that low temperature is linked to positive mood. Moreover, psychological literature (e.g. Baron and Bell (1976) or Baron and Ransberger (1978), Howarth and Hoffman (1984)) shows an impact of temperature on the aggressiveness. Consistent with this, plenty of recent Behavioral Finance literature (e.g. Cao and Wei (2005), Chang et al. (2006), Keef and Roush (2007), Dowling and Lucey (2008), Shu (2008), Chang et al. (2008), Shu and Hung (2009) and Yoon and Kang (2009)) found that stock returns were related to the temperature. Many findings imply that low temper-

[11] An analysis of the transactions in our corporate bond database shows that also on the corporate bond OTC market most of the trades took place between 9.30 a.m. and 5 p.m.

ature goes hand in hand with lower risk aversion and high temperature leads to higher risk aversion. Cao and Wei (2005) however raised an alternative interpretation, namely that very low temperature could imply aggressive behavior (increasing the risk-taking propensity) and very high temperatures could cause apathic behavior (reducing the risk-taking propensity). We used hourly air temperature data in degrees Celsius (after the NCDC quality check) and aggregated them to daily data. For each day we computed the daily average temperature from 7.00 a.m. to 5.00 p.m. This variable will be denoted as $TEMP$ (or $TEMP_{DS}$ for the deseasonalized version, see below).

Our next weather variable is the percentage relative humidity (denoted as $HUMIDITY$). Goldstein (1972), Persinger (1975), Sanders and Brizzolara (1982) and Howarth and Hoffman (1984) showed that humidity is an important meteorological determinant of mood. Consequently, Keef and Roush (2002), Keef and Roush (2005), Dowling and Lucey (2005), Shu (2008) and Yoon and Kang (2009) use humidity as a determinant of security prices. As with the other weather variables, we used hourly data and (after considering the NCDC quality code) for each day calculated the mean over the times from 7 a.m. and 5 p.m.

Psychological studies (e.g. Goldstein (1972), Keller et al. (2005)) found that high barometric pressure was linked to positive mood. Moreover, Shu (2008) showed, that high barometric pressure is associated with high stock returns. Therefore, we also included barometric pressure into our analysis. We used the station pressure in Hectopascals from the NCDC hourly database and (after the NCDC quality check) for each day used the mean of the measurements between 7.00 a.m. and 5.00 p.m. We denoted this variable as $BAROPRESS$.

Troros et al. (2005) and Denissen et al. (2008) found that wind deteriorates the mood. In line with this, Keef and Roush (2005) and Shu and Hung (2009) found an impact of wind on security prices. Thus, we also integrated the windspeed as a weather variable. We used the hourly measurements of the windspeed in meters per second from the NCDC hourly database and (after the NCDC quality check) for each day calculated the mean of the measurements between 7.00 a.m. and 5.00 p.m. We denoted this variable as $WINDSPEED$.

After we had procured the weather data, we had to deal with deseasonalization of the weather time series, as frequently done in the Behavioral Finance literature to capture the "unexpected" component of that day's weather. In this context, we investigated if at all and which variables should be deseasonalized and how desaisonalization should be performed. A detailed analysis can be found in Appendix C. The most important results can be summarized as follows:

First, we compare the methodology usually used in the Behavioral Finance literature to trigonometric polynomials, often applied in Econometrics to filter out the cyclical components of a time series. Regarding the fit we observe only minor differences between the two methodologies. Second, we test econometrically which weather variables should be deseasonalized. By means of the residuals arising with non-deseasonalized and deseasonalized weather data, we are able to run an F-test to check whether deseasonalization is required at all for the time series considered (see equation (17) in Appendix C). By this, we find out that only for the temperature variable deseasonalization is necessary. Third, we also investigate the impact on inference of deseasonalization if no seasonal component exists as well as the impact on inference of a lack of deseasonalization if a seasonal component exists in the data. We observe that if the data are not deseasonalized but the seasonal component is sufficiently strong, we get a substantial bias. If data without any seasonal component are deseasonalized, no problems with respect to inference are observed. By this, we justify ex-post the technique, used in a lot of Behavioral Finance papers, to deseasonalize each weather variable. Also, our results show that it is very unlikely that in existing studies that showed an impact of weather on stock markets it was deseasonalization that has produced spurious weather effects.

Thus, for the rest of the paper only the temperature will be used in its deseasonalized form. Concerning the deseasonalization method we stick to the method used in the Behavioral Finance literature (Hirshleifer and Shumway (2003), Loughran and Schultz (2004) or Goetzmann and Zhu (2005)): First, we computed the average temperature of each calender week as the average of the temperatures of all days during this calender week. We then compute the "usual" temperature for each calender week of the year (week 1, week 2,..., week 52) as average of the four/five observations for that particular week of the year during our 4 2/3 year sample. Finally, we compute the daily seasonally-adjusted temperature value as the excess temperature of a particular day over the usual average temperature of the calender week to which it belongs.

Some descriptive statistics on the weather data are provided in Table 1. The null of Gaussian data is rejected for all weather time series when using the Jarque-Bera test. When looking at the autocorrelations we observe that for most weather variables the autocorrelation decays strongly such that the correlation of the current weather with the weather lagged by 2-5 five days is not very strong.[12] Additionally, Table 1 presents the cross-correlation coefficients of the weather variables used with the corresponding p-values. Based on this table, multicollinearity in the regressions yet to come, due to correlation in the weather variables, does not seem to be a problem.

TABLE 1 ABOUT HERE

3.5 Control Variables

This subsection includes several control variables taken from literature:

Credit risk: It goes without saying that e.g. the corporate bond spreads must depend on the credit risk of the bond. We use one very popular measure of credit risk, namely the rating. In our corporate bond spread regressions we use a credit risk proxy commonly applied in the fixed income literature and in industry (see Collin-Dufresne et al. (2001) or Berndt et al. (2008)), namely the distance to default, DD. We implemented the distance to default following the iterative procedure outlined by Crosbie and Bohn (2003). As this procedure requires

[12] When looking at the p-values arising from the Box-Ljung test the null of no serial correlation is rejected. Using the Barlett bounds (given by $\frac{1}{\sqrt{T}}$) to check whether the individual autocorrelation coefficient is still significant, we observe that for some whether variables $|ACF_j|$ becomes close to $\frac{1}{\sqrt{T}} = 0.0324$ for $j > 1$; (for more details see Brockwell and Davis (2006)). As observed later in Section 4.2, this decay in the serial correlation makes it difficult to instrument actual weather variables by means of higher order lagged weather variables.

	$CLOUD$ $COVER$	$VISI$ $BILITY$	$PRECI$ $PITATION$	$TEMP_{DS}$	$HUMI$ $DITY$	$BARO$ $PRESS$	$WIND$ $SPEED$
Obs.	950	952	952	952	952	942	952
Mean	5.1258	14453.9300	1.7824	0.0460	67.5060	1015.9560	4.6490
Median	5.6923	16008.4500	0.0000	-0.0108	66.2967	1016.4720	4.2458
max	8.0000	16076.0900	124.0000	15.4803	100.0000	1040.7230	14.2667
min	0.0000	960.0000	0.0000	-11.8265	24.2727	984.1174	0.8308
sd	2.5159	3043.2840	8.0319	3.9002	15.7699	7.7593	2.1325
Skewness	-0.4528	-2.1647	8.5324	0.1809	0.0908	-0.4538	0.8838
Kurtosis	1.8727	7.0443	98.5574	3.7225	2.1496	3.8935	3.7221
	Jarque-Bera test on Gaussian distribution						
JB-stat.	82.7664	1392.3170	3.73e5	25.9001	29.9954	63.6676	144.6213
p-values	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
	First to fifth order autocorrelation coefficients ACF_j						
ACF_1	0.1970	0.1090	0.0740	0.4700	0.3550	0.4310	0.2500
ACF_2	0.0580	-0.0140	0.0940	0.2100	0.1560	0.1140	0.0850
ACF_3	0.0300	-0.0020	-0.0080	0.1590	0.1470	0.0450	0.1300
ACF_4	0.0510	-0.0120	-0.0270	0.1900	0.1370	0.0850	0.1600
ACF_5	-0.0310	-0.0010	-0.0120	0.1220	0.1160	0.0560	0.1310
	Correlation matrix with p-values						
$CLOUD.$	1.0000						
	–						
$VISIB.$	-0.2364	1.0000					
p-values	< 0.001	–					
$PRECI.$	0.2402	-0.1271	1.0000				
p-values	< 0.001	0.0001	–				
$TEMP_{DS}$	0.1529	-0.0926	0.0603	1.0000			
p-values	< 0.001	0.0045	0.0646	–			
$HUMID.$	0.5811	-0.3899	0.3184	0.1678	1.0000		
p-values	< 0.001	< 0.001	< 0.001	< 0.001	–		
$BAROP.$	-0.2204	0.2345	-0.1072	-0.2662	-0.2053	1.0000	
p-values	< 0.001	< 0.001	0.0010	< 0.001	< 0.001	–	
$WINDS.$	0.0492	-0.0894	0.1930	-0.1969	-0.1106	-0.2502	1.0000
p-values	0.1314	0.0061	< 0.001	< 0.001	0.0007	< 0.001	–

TABLE 1. Descriptive Statistics and Correlations for the weather data. Obs. stands for number of observations, JB-stat. for Jarque-Bera statistic. sd stands for the standard deviation.

accounting data (volume of short-term debt and volume of long-term debt), we extracted for each issuer quarterly financial statements from the COMPUSTAT database. In addition, the stock prices described in Section 3.3 are required. If for a bond issuer no financial statements data were available but there was a close link to a related listed company, we used the financial statements data of the related company as a proxy for the company investigated. Thus, in these cases we extracted both the stock price and the financial statements for the related company. Based on the market capitalization and the book value of debt we also derive the debt to value ratio DVR (see e.g. Ericsson et al. (2009)).

Liquidity: Longstaff et al. (2005) show that the non-default component in corporate bond spreads is strongly related to liquidity. Therefore, in our corporate bond spread regressions we used a proxy for liquidity as a potential determinant. Following Amihud and Mendelson (1991) we use the time to maturity of the respective bond on the specific day, denoted as TM. Moreover, as a robustness check we also used daily trading volume, $VOLUME$, and the difference between the highest and the smallest price traded on that day, $RANGE$.

Weekday Seasonalities: We also used a Monday dummy ($MONDAY$) that has the value of 1 on Mondays and 0 else. We include weekday seasonalities for two reasons: First, there is literature showing weekday seasonalities in several financial market segments: E.g. e.g. French (1980) and Keim and Stambaugh (1984) detect weekday effects in the stock markets. Other articles (e.g. Flannery and Protopapadakis (1988), Johnston et al. (1991)) find, that weekday effects also occur in the fixed income/corporate bond segment. Second, including weekday effects is usual in the literature that investigates if the weather has an impact on stock returns (e.g. Saunders (1993), Trombley (1997), Goetzmann and Zhu (2005), Chang et al. (2008)).

Fama-French Factors: Since empirical asset pricing literature favors multi-factor models, we downloaded data for the small-minus-big market capitalization factor, SMB, and the high-minus-low book-to-market ratio factor, HML, from Kenneth French's web page (*http://mba.tuck.dartmouth.edu/pages/faculty/ken.french*). These two variables will be used as factors when analyzing the individual stock returns.

Autoregressive Term: We also include the lagged value of the respective financial market variable. This is in line with Saunders (1993) who did this for stock index returns. Also, it is consistent with bond pricing literature (e.g. Duffee (1998), Duffie et al. (2003), etc.) showing a strong persistence of corporate bond spreads or their components. Moreover, we shall observe that regression residuals are serially correlated if an autoregressive term is not included. If this is the case the variance covariance matrix of the regressors is not consistently estimated which implies that the inference about the parameters becomes incorrect. In order to get rid of this problem, we estimate a dynamic regression model with a lagged dependent variable (see e.g. Davidson and MacKinnon (1993)[Chapters 10 and 19.4]).

4 Methodology and Results

We investigate the effect of the weather on financial market variables performing the following panel regression analysis:

$$y_{it} = \alpha_i + \beta_w w_t + \beta_c c_{it} + \varepsilon_{it} \ . \tag{12}$$

Equation (12) models the variable y_{it} as a linear function of the weather variables w_t and the control variables c_{it}. y_{it} stands for one of the dependent variables studied (r_F, corporate bond spreads, S&P 500 returns, individual stock returns, VIX). We observe $i = 1, \ldots, N$ cross sections, while in the time-series dimension we observe $t = 1, \ldots, T$ periods. w_t represents a vector containing the weather variables (to be more precise: cloud cover, visibility, deseasonalised temperature, precipitation amount, humidity, wind speed and barometric pressure at time t *and* the lagged weather variables for the regressions of ex-post returns) and c_{it} represents a vector containing the control variables on day t (e.g. the first differences of the level of the risk-free term structure, S&P 500 returns, ..., the lagged y_{it}). ε_{it} is the error term. From equation (12) it is clear that we assume a linear impact of the control and the weather variables on y_{it}. In addition, we implicitly assume that the explanatory variable affects all y_{it} in the same linear way.

α_i can be treated as a deterministic parameter (*fixed effects model*), a random variable (*random effects model*) or equal for all assets i (*pooled model*). For more precise definitions and model assumptions we refer the reader to related literature, such as Ruud (2000), Wooldridge (2001), Hsiao (2003) and Baltagi (2008). While for the pooled or the random effects model parameters for variables constant over t can be estimated, with the fixed effects specification these impacts are included in the parameters α_i. Note that the pooled setting puts a lot of structure on the intercept that may not be justified by the data. E.g. with corporate bonds the literature (e.g. Collin-Dufresne et al. (2001) or Driessen (2005)) suggests that bond-specific effects are included in the spreads. Such bond-specific effects may be caused e.g. by the term structure of credit risk. This would be an argument against pooled least squares estimation and in favor of fixed or random effects.

We tested these different specifications against each other. First, we tested a pooled model against the alternative of a fixed effects model. We did this by testing the joint null hypothesis that all coefficients of these regressors α_i are zero (pooled model) versus the alternative that at least one of them is non-zero (fixed effects model) by means of a standard likelihood ratio test (see e.g. Bickel and Doksum (2001), Wooldridge (2001)). For our data, the p-value is very close to zero, such that the null hypothesis of a pooled model has to be rejected. The fixed effects model dominates the pooled model for all panel settings considered in this article.

In a second step to decide between the random effects and the fixed effects model, we perform a Hausman test (see the textbooks cited above). Although the Hausman test assumes homogeneity in the residuals, a p-value for the Hausman test statistic very close to zero is a convincing argument, that a fixed effects model should be preferred over a random effects model. With all panels analyzed (i.e. risk-free term structure, corporate bond spreads and firm-by-firm stock returns) these tests favor the fixed effects model.

The results of these tests remain the same for the specifications estimated in Section 4.1 and

Section 4.2, respectively. Based on these tests we work with a fixed effects model. Therefore, only the results for the fixed effects regressions will be presented in the following.

Remark 4.1. *Variables which remain constant in the time series dimension cannot be used in a standard fixed effects setting. In our data set the rating dummies exhibit very little variation over time. This implies that rating dummies cannot be used in our fixed effects regression – there is an insufficient degree of time series variation with this explanatory variable. Possible effects arising from the rating are included in the intercept terms* α_i.

4.1 Baseline Fixed Effects Regressions

To check for weather effects we proceed in the following way:

1. First we check whether there are weather effects in the market variables such as the risk-free interest rate, the S&P 500 index and the VIX volatility index.

2. Since these market variables are used as regressors on the disaggregated level (corporate bond spreads and individual stock returns), the results or the interpretation of the results on the disaggregated level depend on the results for the market variables. If there are any weather effects on the market variables, any weather effects with the (firm-by-firm and bond-by-bond) disaggregated analysis have to be interpreted as *additional* weather effects. If no weather effects can be detected on the aggregate level, the regressions on the disaggregate level test for the existence of weather effects on the disaggregated level.

This dependence in the interpretation is one of the reasons why we study the impact of weather on a multitude of financial sub-markets.

In a first step we estimate the fixed effects models by means of least squares. Columns two to four of Tables 2 - 6 present the results. The estimates of α_i and the fixed effects are not reported in these tables. The aggregated financial market data is investigated in Tables 2 - 4, then Tables 5 and 6 present the results on the disaggregated level.

Equation (12) is used to find the determinants of the risk-free rates, the corporate bond spreads, the S&P returns and the VIX. For the individual stock returns the regression coefficient for the S&P 500 returns is estimated on a firm-by-firm basis to include the fact that different firms bear different systematic risk. Therefore, the model

$$STR_{it} = \alpha_i + \beta_w w_t + \beta_c c_{it} + \beta_{ci}(SPRETURNS_t, SMB_t, HML_t) + \varepsilon_{it} \ , \tag{13}$$

is estimated. The first element of β_{ci} corresponds to the estimate of the beta factor in a Black-style implementation of the CAPM (that assumes that no risk-free interest rate is available; for more details see Campbell et al. (1996)[Chapter 6]). The second and the third are the factor loadings for the Fama-French factors. Thus, equation (13) is a standard econometric implementation of an asset pricing model with weather variables included. The fixed effects α_i and the component-specific effects β_{ci} are not reported in Table 6. Although not reported, these β_{ci} are highly significant for the S&P 500 returns as can be expected by prior applications of the CAPM. For the Fama-French factors significant parameters have been observed for most firms. The increase in the coefficient of determination R^2 when switching from a model with the S&P 500 returns to a model with these returns and the two remaining Fama-French factors is relatively low (approximately one percentage point). In addition to the market factors we check for a dependence on the interest rate $r_{F,2}$ and on the market volatility represented by the VIX index.

By applying the "default" significance level of 5%, the p-values in the fourth column suggest the following: (i) For the risk-free term structure precipitation, temperature, wind-speed and the barometric pressure have a significant impact on the changes in the risk-free interest rates r_F. Visibility would by significant, as well, when applying a 10% significance level. (ii) For the S&P 500 returns no significant weather effects are observed. (iii) The weather variables show no significant impact on the VIX index. (iv) The deseasonalized temperature affects the corporate bond spreads, precipitation is close to the 10% border. (v) The individual stock returns are influenced by the barometric pressure and lagged visibility. For the lagged cloud cover we observe a p-value of 8%. We get close to 10% significance with the lagged cloud cover and the lagged precipitation amount. Without having a closer look on the residuals or without being concerned whether the least squares assumptions are fulfilled one might conclude that some weather variables significantly influence asset prices. Further investigations will take more care on these issues.

In a next step we analyze the residuals from these regressions: First of all, even by a visual inspection we observe a high degree of heterogeneity within the residuals (heterogeneity over time - which is plausible given the extensive literature on GARCH effects and stochastic volatility) as well as between the residuals of different assets. E.g. we observe that for most rates/spreads/returns the mean squared residuals differ by at least one standard deviation from the mean squared residual of the whole sample of all the rates/spreads/returns considered. To get a clearer picture, we estimated a fixed effects model, where the squared residuals are used as response variable, while only the α_i parameters are used as predictors. By checking whether in such a model a fixed effects specification is preferred to a pooled specification, we test for heteroscedasticity.[13] The null hypothesis of this test implies that the squared residuals are the same across all the rates/spreads/returns considered. The p-value of this test, is very close to zero. Therefore, we conclude that substantial heteroscedasticity exists in the residuals for all the data considered above. Inference based on ordinary least squares standard errors is problematic. Robust standard errors should be used instead.

Thus, we present the White (1980) standard errors and the corresponding p-values in the last two columns of Tables 2-6. Also Loughran and Schultz (2004) and Dowling and Lucey (2005) applied this method in their analysis of the impact of the weather on stock returns. Note that, by this approach, the regression parameters remain the same, but the covariance matrix of the parameters is calculated in a different way. For the rest of the paper we stick to White

[13]Note, that this regression is a test on heterogeneity in the residuals (heteroscedasticity) and should not be confused with the models estimated in the above tables.

(1980) standard errors and use the p-values based on these standard errors. Looking at the last column we immediately observe that no weather variable has a significant impact on the risk-free interest rates and the VIX index. For the S&P 500 returns the lagged barometric pressure is significant, the actual barometric pressure is significant at an 8% level. Also, for the bond spreads we cannot detect any weather effects. For the individual stock returns no weather variables show up with a p-value smaller than 5%, but the lagged visibility has a p-values smaller than 10%. Therefore, we conclude that when sticking to the least squares estimates but adjusting for heterogeneity in the residuals almost all weather effects which have been "detected" with least squares estimates and least squares standard errors are swept away. Although the next section will argue that the least squares estimators may cause problems, we see that even with least squares almost all weather effects disappear when taking care of the heterogeneity in the residuals.

TABLES 2-6 ABOUT HERE

Variable	β_i	$SE(\beta_i)$	p-value	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	9.9E-7	2.6E-6	0.7000	6.6E-6	0.8805
$VISIBILITY$	3.3E-9	1.9E-9	0.0822	5.2E-9	0.5276
$PRECIPITATION$	5.3E-6	1.5E-6	0.0003	3.5E-6	0.1348
$TEMP_{DS}$	-1.6E-6	7.3E-7	0.0286	1.5E-6	0.2838
$HUMIDITY$	-4.0E-7	7.6E-7	0.5958	2.0E-6	0.8387
$BAROPRESS$	1.4E-6	4.6E-7	0.0017	1.2E-6	0.2237
$WINDSPEED$	6.1E-6	2.8E-6	0.0270	7.5E-6	0.4181
$MONDAY$	2.4E-5	1.4E-5	0.0792	3.2E-5	0.4507
VIX	-4.5E-6	7.0E-7	< 0.001	1.9E-6	0.0190
$SPRETURNS$	7.2E-5	4.9E-6	< 0.001	1.7E-5	< 0.001
$\Delta r_{F,t-1}$	7.4E-3	9.9E-3	0.4592	0.0323	0.8196
			R^2=0.0325		

TABLE 2. "risk-free" interest rates Δr_F as decimal, Least Squares Estimates, fixed effects model ($N = 11$ maturities, $T = 952$; 9,625 observations, intercept and fixed effects not reported), SE is the standard error based on least squares. The fourth column presents the p-values obtained from the estimate of β_i and its corresponding standard errors. SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

Variable	β_i	$SE(\beta_i)$	p-value	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0057	0.0111	0.6092	0.0101	0.5739
$VISIBILITY$	5.9E-6	8.2E-6	0.4708	8.4E-6	0.4829
$PRECIPITATION$	0.0055	0.0037	0.1379	0.0042	0.1921
$TEMP_{DS}$	0.0042	0.0078	0.5940	0.0086	0.6283
$HUMIDITY$	0.0016	0.0021	0.4411	0.0021	0.4396
$BAROPRESS$	-0.0013	0.0040	0.7449	0.0039	0.7442
$WINDSPEED$	-0.0075	0.0124	0.5449	0.0123	0.5417
$CLOUDCOVER_{t-1}$	0.0081	0.0112	0.4733	0.0124	0.5171
$VISIBILITY_{t-1}$	-4.1E-6	8.0E-6	0.6096	8.1E-6	0.6142
$PRECIPITATION_{t-1}$	0.0003	0.0031	0.9202	0.0024	0.8961
$TEMP_{DS,t-1}$	-0.0038	0.0076	0.6136	0.0081	0.6362
$HUMIDITY_{t-1}$	-0.0014	0.0021	0.4936	0.0023	0.5429
$BAROPRESS_{t-1}$	-0.0023	0.0042	0.5783	0.0040	0.5658
$WINDSPEED_{t-1}$	0.0004	0.0123	0.9750	0.0130	0.9763
$MONDAY$	0.4081	0.0585	< 0.001	0.0623	< 0.001
VIX	-0.7957	0.0211	< 0.001	0.0289	< 0.001
$\Delta r_{F,2}$	-0.7706	0.9570	0.4209	0.9170	0.4009
VIX_{t-1}	0.7900	0.0211	< 0.001	0.0297	< 0.001
$\Delta r_{F,2,t-1}$	-0.0871	0.9883	0.9298	0.7415	0.9066
$SPRETURNS_{t-1}$	-0.0124	0.0210	0.5544	0.0279	0.6566
		R^2=0.6341			

TABLE 3. S&P 500, Least Squares Estimates (T = 952 observations, intercept not reported), SE is the standard error based on least squares. The fourth column presents the p-values obtained from the estimate of β_i and its corresponding standard errors. SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

Variable	β_i	$SE(\beta_i)$	p-value	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0174	0.0106	0.1004	0.0108	0.1095
$VISIBILITY$	1.9E-7	7.8E-6	0.9810	7.4E-6	0.9801
$PRECIPITATION$	0.0009	0.0060	0.8820	0.0060	0.8828
$TEMP_{DS}$	0.0018	0.0030	0.5468	0.0024	0.4579
$HUMIDITY$	-0.0017	0.0031	0.5799	0.0028	0.5445
$BAROPRESS$	0.0021	0.0019	0.2721	0.0018	0.2522
$WINDSPEED$	-0.0012	0.0113	0.9161	0.0109	0.9134
$MONDAY$	0.4888	0.0556	< 0.001	0.0575	< 0.001
VIX_{t-1}	0.9906	0.0029	< 0.001	0.0041	< 0.001
$SPRETURNS$	-0.2388	0.3691	0.5177	0.4215	0.5712
$\Delta r_{F,2}$	-0.7870	0.0207	< 0.001	0.0342	< 0.001
			R^2=0.9930		

TABLE 4. VIX, Least Squares Estimates ($T = 952$ observations, intercept not reported), SE is the standard error based on least squares. The fourth column presents the p-values obtained from the estimate of β_i and its corresponding standard errors. SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

4.2 Instrumental Variable Estimation

An issue that has already been raised in Section 1 and at the end of Section 2, is the functional chain argument that weather affects asset prices via mood. That is to say, weather does not directly cause changes in the asset prices but it influences the mood which affect the asset price. In terms of econometrics such a problem can be investigated in several ways. Here we follow the idea that the weather variables are a *proxy* for the unobserved mood variables. In terms of econometrics this results in an *errors in variables problem.* Consider the mood μ_t, and assume that

$$y_{it} = \alpha_i + \beta_\mu \mu_t + \beta_c c_{it} + \varepsilon_{it} \quad \text{and} \quad w_t = \mu_t + u_t \tag{14}$$

where ε_{it} and u_t are independent. In this case the least squares estimates in Section 4.1 are biased and inconsistent.[14] In addition to the basic instrumental variable assumptions we

[14] For more details on errors in variables see Appendix D. In addition, it is well known that with missing variables the least squares estimator becomes inconsistent, as well. We tried to avoid this problem by including

Variable	β_i	$SE(\beta_i)$	p-value	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	0.0025	0.0154	0.8685	0.0462	0.9561
$VISIBILITY$	9.9E-6	1.1E-5	0.3732	3.2E-5	0.7588
$PRECIPITATION$	0.0132	0.0085	0.1191	0.0235	0.5741
$TEMP_{DS}$	-0.0099	0.0041	0.0165	0.0146	0.4974
$HUMIDITY$	-0.0058	0.0044	0.1904	0.0128	0.6513
$BAROPRESS$	0.0013	0.0028	0.6433	0.0089	0.8844
$WINDSPEED$	0.0161	0.0161	0.3170	0.0509	0.7525
$MONDAY$	0.7423	0.0813	< 0.001	0.2436	0.0023
DVR	0.2451	0.0130	< 0.001	0.0380	< 0.001
ΔDD	-0.7902	0.7121	0.2671	1.2412	0.5244
VIX	2.9310	0.2833	< 0.001	0.4237	< 0.001
TM	2.3496	0.1577	< 0.001	0.4574	< 0.001
$\Delta r_{F,2}$	1.1820	0.0993	< 0.001	0.2917	< 0.001
$SPRETURNS$	0.4073	0.0434	< 0.001	0.1215	< 0.001
$s_{i,t-1}$	0.8017	0.0021	< 0.001	0.0071	< 0.001
			R^2=0.9058		

TABLE 5. Corporate bond yield spreads s_{it} in basis points, Least Squares Estimates, fixed effects model ($N =$ 179 bonds, $T = 952$; 80,801 observations, intercept and fixed effects not reported), SE is the standard error based on least squares. The fourth column presents the p-values obtained from the estimate of β_i and its corresponding standard errors. SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

Variable	β_i	$SE(\beta_i)$	p-value	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0015	0.0051	0.7683	0.0064	0.8138
$VISIBILITY$	-1.8E-7	3.8E-6	0.9613	5.3E-6	0.9722
$PRECIPITATION$	0.0015	0.0017	0.3729	0.0017	0.3865
$TEMP_{DS}$	0.0032	0.0036	0.3769	0.0044	0.4733
$HUMIDITY$	-0.0004	0.0010	0.6901	0.0014	0.7734
$BAROPRESS$	0.0034	0.0018	0.0591	0.0023	0.1398
$WINDSPEED$	-0.0010	0.0057	0.8560	0.0081	0.8979
$CLOUDCOVER_{t-1}$	0.0083	0.0052	0.1092	0.0070	0.2398
$VISIBILITY_{t-1}$	7.9E-6	3.7E-6	0.0333	4.5E-6	0.0837
$PRECIPITATION_{t-1}$	0.0022	0.0014	0.1283	0.0019	0.2452
$TEMP_{DS,t-1}$	-0.0025	0.0035	0.4784	0.0044	0.5687
$HUMIDITY_{t-1}$	-0.0013	0.0009	0.1771	0.0013	0.3264
$BAROPRESS_{t-1}$	-0.0017	0.0019	0.3855	0.0025	0.5003
$WINDSPEED_{t-1}$	0.0055	0.0057	0.3303	0.0069	0.4270
$MONDAY$	0.0115	0.0277	0.6771	0.0353	0.7440
VIX	0.0098	0.0159	0.5366	0.0256	0.7018
$\Delta r_{F,2}$	-0.6513	0.1755	0.0002	0.2846	0.0221
VIX_{t-1}	-0.0071	0.0158	0.6538	0.0251	0.7777
$\Delta r_{F,2,t-1}$	-0.3551	0.1735	0.0407	0.2415	0.1416
STR_{t-1}	0.0060	0.0056	0.2841	0.0112	0.5909
			R^2=0.4105		

TABLE 6. Stock returns STR, Least Squares Estimates, fixed effects model ($N = 23$ stocks, $T = 952$; 19,928 observations; intercept, fixed effects and component-specific effects (β_{ci}) of $SPRETURNS$ not reported), SE is the standard error based on least squares. The fourth column presents the p-values obtained from the estimate of β_i and its corresponding standard errors. SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

assume that $\mathbb{E}(\mu_t) = 0$ and $\mathbb{E}(\mu_t^3) \neq 0$. While the second assumption is purely technical, the first assumption simply normalizes the mood variable to a certain level such that the impact $\beta_\mu \mu_t$ is zero in the mean. For more details we refer the reader to Econometrics textbooks, such as Davidson and MacKinnon (1993), Ruud (2000), Wooldridge (2001) or Baltagi (2008). For a discussion and examples in Finance literature we refer the reader to Roberts and Whited (2011). Therefore, we proceed with an instrumental variable estimation. The instruments will be abbreviated by z_t.[15]

Unfortunately instrumental variable estimation is not as easy as applying least squares since "good instruments" are necessary. The drawback with instrumental variable estimation is associated with *weak instruments* resulting in large standard errors. This becomes a problem when performing inference (see e.g. the above textbooks and the discussion in Angrist and Pischke (2009)[Chapter 4]). We use lagged weather variables as instruments. Since the naive forecast "the weather today is the weather tomorrow" does not perform so bad (see the first order serial correlations in Table 1), the lagged weather variables provide us with good instruments. According to the lag structure we apply *Hansen's J-test* (see textbooks cited above) to check if weather variables of lag j are still valid instruments. Here we find out that the just identified model should be used according to this test. That is to say, for the ex-ante variables where only the actual weather has to be instrumented, only the lag one weather variables should be used. For the models where the current and the lagged weather have to be instrumented (S&P 500 and STR), the two and three day lagged weather variables did not provide us with good instruments. We also observed that two lags for the weather are not sufficiently informative; that is to say w_{t-3} is not a good instrument (this is in line

the control variables. Instrumental variable estimation performed in this section is an additional tool to solve the omitted variables problem.

[15] Another possible problem may come from the fact that prices on different financial sub-markets, such as risk-free bonds, stocks and corporate bonds, need not be independent of each other. Given the general equilibrium setting of Section 2 all asset prices are determined jointly. However, the CAPM allows us to express this joint dependence by means of one market factor. Deviations of the returns from the market return should be idiosyncratic if this model is correct. The weather variables are exogenous. Based on the assumption that the CAPM holds, we can still assume that ε_{it} in (12) is orthogonal to the regressors. When working with a multi-factor empirical asset pricing model the same arguments still hold.

with our observations in Table 1 where a sharp decay of the serial correlation of most weather variables is observed; an standard test on significance are the Barlett bounds already discussed in footnote 12). By the assumption that the mood is normalized to zero we can show that u_t is orthogonal to $\tilde{w}_t^2$, where $\tilde{w}_t = w_t - (\frac{1}{T}\sum_{t=1}^{T} w_t)$ and $\tilde{w}_t^2 = \left(\tilde{w}_{1t}^2, \ldots, \tilde{w}_{kt}^2\right)^\top$ when k weather variables are used. This provides us with further instruments.

We estimate equation (12) for the risk-free term structure, the VIX index and the corporate bond spreads by means of Two-Stage Least Squares (*2SLS*). The instruments z_t used are all lagged weather variables and the controls from Section 4.1. The results are presented in Tables 7, 9 and 10. All p-values are based on White (1980) standard errors. Once again, the fixed effects setting dominates the random effects as well as the pooled model, and no weather effects can be detected.

The S&P 500 and the individual stock returns are ex-post returns, such that also the lagged explanatory variables have to be used as predictors. As already stated in the above paragraphs it was more difficult to find good instruments for these two regressions. For the S&P 500 the squared demeaned weather variables (actual and lag one) $\tilde{w}_t^2$ and $\tilde{w}_{t-1}^2$ have been used as instruments; here we observed smaller standard errors compared to a model with instruments w_{t-2} and w_{t-3}. For the individual stock returns, STR, where model (13) is estimated, the most efficient estimates have been obtained with the instruments w_{t-2} and $\tilde{w}_{t-1}^2$. The results are presented in Tables 8 and 11. For neither the S&P 500 nor the individual stock returns any weather effects can be detected. Although not presented in the table, for the individual stock returns especially the S&P 500 market factor was significant.

TABLES 7-11 ABOUT HERE

4.3 Robustness Checks

In this section we want to add a few robustness checks. We start with some robustness checks for the corporate bond regressions. First, we want to differentiate between the data according to credit risk with the hypothesis in mind that a split of the sample could show that there

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-2.7E-5	4.5E-5	0.5579
$VISIBILITY$	-9.1E-9	3.4E-8	0.7917
$PRECIPITATION$	9.1E-6	6.8E-6	0.1839
$TEMP_{DS}$	-8.6E-6	2.1E-5	0.6797
$HUMIDITY$	-7.7E-7	4.8E-6	0.8724
$BAROPRESS$	5.7E-6	6.5E-6	0.3781
$WINDSPEED$	1.3E-5	4.0E-5	0.7379
$MONDAY$	2.7E-5	3.7E-5	0.4638
VIX	-5.1E-6	2.4E-6	0.0335
$SPRETURNS$	0.0001	1.9E-5	< 0.001
$\Delta r_{F,t-1}$	0.0077	0.0340	0.8200

TABLE 7. "risk-free" interest rates Δr_F as a decimal, 2SLS Estimates, fixed effects model ($N = 11$ maturities, $T = 952$; 9,625 observations, intercept and fixed effects not reported). SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

are weather effects of different significance for bonds with different credit risk. If there is an impact of the bond's credit risk on the strength of the weather effects, it may be the aggregation of the sample that could have generated the non-existence of weather effects in our study. The hypothesis could be that AAA bonds are less risky than bonds with an inferior rating. From the model presented in Section 2 we know that mood and weather should have a smaller impact with less risky assets. The opposite is true for bonds with higher credit risk (e.g. BBB bonds). An analysis like this is also consistent with Baker and Wurgler (2006) showing that investors' sentiment has a stronger impact on the pricing of stocks that exhibit higher risk. The hypothesis is also in line with Forgas (1995), Conlisk (1996) and Slovic et al. (2000) showing that the impact of irrationality is increasing with the complexity of the decision-making situation. Hence we constructed the regressors "weather variable$\times\mathbf{1}_{AAA}$" and "weather variable$\times\mathbf{1}_{BBB}$" (i.e. we included fourteen additional prediction variables; these variables can be considered as exogenous). $\mathbf{1}_{AAA}$ ($\mathbf{1}_{BBB}$) is an indicator variable which for time t and bond i has a value of one if the bond i has the rating AAA (BBB) on day t, otherwise the value is zero. Estimating the model by two stage least squares again shows no

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0064	0.0202	0.7498
$VISIBILITY$	1.9E-5	1.7E-5	0.2609
$PRECIPITATION$	0.0081	0.0061	0.1864
$TEMP_{DS}$	-0.1027	0.0760	0.1769
$HUMIDITY$	-0.0007	0.0041	0.8651
$BAROPRESS$	-0.0162	0.0162	0.3182
$WINDSPEED$	-0.0496	0.0447	0.2676
$CLOUDCOVER_{t-1}$	-0.0163	0.0271	0.5477
$VISIBILITY_{t-1}$	-7.5E-6	1.8E-5	0.6756
$PRECIPITATION_{t-1}$	0.0039	0.0036	0.2821
$TEMP_{DS,t-1}$	0.0333	0.0372	0.3707
$HUMIDITY_{t-1}$	0.0018	0.0040	0.6518
$BAROPRESS_{t-1}$	0.0101	0.0144	0.4847
$WINDSPEED_{t-1}$	-0.0120	0.0270	0.6553
$MONDAY$	0.3298	0.1108	0.0030
VIX	-0.8186	0.0526	< 0.001
$\Delta r_{F,2}$	31.3140	21.7488	0.1503
VIX_{t-1}	0.8085	0.0507	< 0.001
$\Delta r_{F,2,t-1}$	-25.6663	22.4776	0.2538
$SPRETURNS_{t-1}$	-0.0265	0.0536	0.6205

TABLE 8. S&P 500, 2SLS Estimates (T = 952 observations, intercept not reported). SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	0.1220	0.1612	0.4493
$VISIBILITY$	-0.0001	0.0002	0.3994
$PRECIPITATION$	-0.0145	0.0121	0.2303
$TEMP_{DS}$	-0.0294	0.0303	0.3322
$HUMIDITY$	-0.0040	0.0162	0.8041
$BAROPRESS$	-0.0274	0.0524	0.6012
$WINDSPEED$	-0.1369	0.1579	0.3860
$MONDAY$	0.4375	0.0930	< 0.001
VIX_{t-1}	0.9941	0.0065	< 0.001
$SPRETURNS$	-0.7828	0.0431	< 0.001
$\Delta r_{F,2}$	-0.4345	0.6368	0.4952

TABLE 9. VIX, 2SLS Estimates (T=952 observations, intercept not reported). SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	1.7283	3.5928	0.6305
$VISIBILITY$	-0.0026	0.0051	0.6136
$PRECIPITATION$	-0.0400	0.2075	0.8472
$TEMP_{DS}$	-0.4366	0.9708	0.6529
$HUMIDITY$	-0.0742	0.1990	0.7094
$BAROPRESS$	-0.4907	0.9311	0.5982
$WINDSPEED$	-2.7227	5.2179	0.6018
$MONDAY$	-0.6985	2.9237	0.8112
DVR	0.5747	0.7003	0.4119
ΔDD	-1.1077	3.0248	0.7142
VIX	2.7818	1.2142	0.0220
TM	-1.9718	9.0161	0.8269
$\Delta r_{F,2}$	-1.9968	6.4767	0.7579
$SPRETURNS$	0.6308	0.6169	0.3065
$s_{i,t-1}$	0.7907	0.0226	< 0.001

TABLE 10. Corporate bond yield spreads s_{it} in basis points, 2SLS Estimates, fixed effects model (N = 179 bonds, T = 952, 80,801 observations, intercept and fixed effects not reported). SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	0.3759	1.3462	0.7801
$VISIBILITY$	0.0002	0.0007	0.8184
$PRECIPITATION$	0.0041	0.7007	0.9953
$TEMP_{DS}$	0.0536	0.2971	0.8569
$HUMIDITY$	-0.0166	0.1816	0.9272
$BAROPRESS$	-0.1347	0.3179	0.6718
$WINDSPEED$	0.0661	0.7483	0.9296
$CLOUDCOVER_{t-1}$	-0.0735	0.3376	0.8277
$VISIBILITY_{t-1}$	0.0001	0.0002	0.6147
$PRECIPITATION_{t-1}$	-0.0099	0.0319	0.7557
$TEMP_{DS,t-1}$	-0.0292	0.1122	0.7948
$HUMIDITY_{t-1}$	0.0298	0.0909	0.7427
$BAROPRESS_{t-1}$	0.0506	0.1485	0.7334
$WINDSPEED_{t-1}$	0.1453	0.3169	0.6465
$MONDAY$	-0.0333	0.6168	0.9570
VIX	0.1554	0.5079	0.7597
$\Delta r_{F,2}$	0.6588	4.8118	0.8911
VIX_{t-1}	-0.1484	0.5232	0.7768
$\Delta r_{F,2,t-1}$	1.6744	5.6698	0.7678
STR_{t-1}	-0.9940	2.1977	0.6511

TABLE 11. Stock returns STR, 2SLS Estimates, fixed effects model ($N = 23$ stocks, $T = 952$; 19,928 observations; intercept, fixed effects and component-specific parameters for $SPRETURNS$ not reported). SE_W is the White (1980) adjusted standard error with the corresponding p-value in the last column.

significant weather effects. Based on this analysis we conclude even when splitting up the weather effects for different classes of credit risk, no weather effects can be detected.

For the corporate bond spreads we also used other liquidity proxies, namely a proxy of the daily trading $VOLUME$ (proxy, since in the TRACE data base volumes beyond 5,000,000 are just listed as ">5,000,000") and a variable $RANGE$ representing the difference between the highest and the smallest price on that day. Adding these two variables to the regressors used in Tables 5 and 10 does not show any weather effects.

Also, with the corporate bond spreads regression we replaced the S&P 500 returns by the stock returns of that particular issuer. Also, here we do not observe any weather effects. R^2 does not improve with the individual stock returns.

Working with levels of the bond spreads and the VIX index and with the first differences of the risk-free rate (r_F) was based on unit root tests presented in Appendix B. In contrast to this approach we also run the regressions of Sections 4.1 and 4.2 for r_F in levels and for the VIX volatility index and the bond spreads in first differences. Here we did not observe any weather effects, either.

Proceeding with the stock market regressions, as, in contrast to the other regressions, here the dependent variable is an ex-post return, we used both the actual and the lagged weather variables. Alternatively and for comparison, we run these regressions with only the actual weather variables using the lagged weather variables as instruments. Although this neglects the possible impact of yesterday's weather on today's stock returns, we simply check if the weather shows any effects in this setting. For both the two stage least squares estimates and the instrumental variable estimates, we did not observe any weather effects at a 5% significance level. Two lags for the weather are not sufficiently informative.

Moreover, the instruments $\tilde{w}_t^2$ and $\tilde{w}_{t-1}^2$ have been used in Table 8, while $\tilde{w}_{t-1}^2$ and w_{t-2} have been used for the stock returns in Table 11. For completeness, we also check whether different combinations from the set $\{\tilde{w}_t^2, \tilde{w}_{t-1}^2, w_{t-2}, w_{t-3}\}$ provide us with more efficient results or results where some weather variables are significant. With these specifications we can observe neither any improvements regarding the standard errors nor significant weather effects.

Another robustness check involves the lagged weather: Persinger (1975) detects an impact of the weather two days ago on the current mood. Therefore, we also regressed the financial market variables on the two and three days lagged weather using least squares. However, we did not find any significant impact.

At the beginning of Section 4.2 we already mentioned that an endogeneity problem might arise due to the interdependence of different financial sub-markets. To cope with possible endogeneity we performed additional instrumental variable estimation for the aggregated data, which are the risk-free interest rate, the S&P 500 index and the VIX index. Similar to the robustness checks in Jacobsen and Marquering (2008), the variables $\Delta r_{F,2}$, S&P 500 returns and VIX were instrumentalized by their lags. Since in the regressions with the response variables S&P 500 return and the panel of the risk-free rates the first order autocorrelation is low, it was hard to find good instruments. With this specification we do not observe any weather effects either. Additionally, two stage least squares estimates on a disaggregated level, where $\Delta r_{F,2}$, SPR and VIX are instrumentalized by their lags, do not show any weather effects. Another way to cope with possibly endogenous control variables is to perform instrumental variable estimation with the weather variables only. With this analysis we cannot detect any weather effects, either. The smallest p-value for the weather variables was 8% (temperature) for r_F, 8% (cloud cover) for the S&P 500, 16% (barometric pressure) for the VIX, 16% (temperature) for the bond spreads and 8% (cloud cover) for the individual stock returns.

Based on the discussion of the latent mood variable and the weather in Section 2, as an alternative to instrumental variable estimation we tried to estimate linear state space models (for the dependent variables considered) of the form

$$\begin{aligned} y_{it} &= \alpha_i + \beta_\mu \mu_t + \beta_c c_{it} + \varepsilon_{it} \\ \mu_t &= \gamma_0 + \gamma_\mu \mu_{t-1} + \gamma_w w_t + u_t \ . \end{aligned} \qquad (15)$$

Unfortunately this estimation was not feasible. The variance of the noise term u_t was estimated to be very close to zero, such that the software package was not able to calculate standard errors of the parameters. Therefore, we cannot obtain any reliable results by using (15). This is also consistent with our regression results showing that the weather does not have any impact on security prices: If in equation (15) the weather has no significant influence on the latent μ_t (and no further first order autoregressive latent process with variance larger zero exists), then μ_t would follow a deterministic trend. In this case (15) is not identified.

One could argue that we could have an omitted variable problem in the regressions so far, because the mood could be additionally driven by seasonal affective disorder (see e.g. Kamstra et al. (2000) and the literature already cited in Section 1). If SAD has an impact on mood and mood influences the prices on the financial market and if the SAD variable and some weather variables are correlated, the least squares estimator is biased in the regression considered above (*omitted variable problem*). To cope with this issue, we downloaded SAD proxy (SAS Onset and Recovery) data from the web-page of Mark Kamstra (*http* : *//markkamstra.com/data.html*) and included this variable in all our regression settings (least squares and instrumental variable estimation). Neither the SAD proxy nor the weather variables turned out to have a significant impact.

Finally, we added the weather variable $TEMP_{DS} \times \mathbf{1}_{\{Temp \geq median(Temp)\}}$; where $\mathbf{1}_{\{Temp \geq median(Temp)\}}$ is equal to one if the temperature on day t is equal to or above the median temperature for the time span considered. This variable can be motivated by the claim, in line with Keller et al. (2005), that deviations from the weekly mean, measured by $TEMP_{DS}$, are different in periods where the temperature is low compared to periods where the temperature is high (e.g. "a positive $TEMP_{DS}$ in the winter improves mood since it is not so cold" while "a positive $TEMP_{DS}$ in the summer deteriorates mood since it is even hotter"). This variable has been added to all the models estimated in Section 4. Also, this weather variable turned out to be insignificant.

4.4 Discussion of the Results

Our results of no significant impact of the weather variables are consistent e.g. with Trombley (1997), Krämer and Runde (1997), Pardo and Valor (2003), Levy and Galili (2008) or Jacobsen and Marquering (2008), however conflict with some other literature that shows a significant impact of weather on stock returns (e.g. Saunders (1993), Hirshleifer and Shumway (2003), Cao and Wei (2005) or Goetzmann and Zhu (2005)). There are several potential reasons why in our study weather effects often detected on the stock market do not show up:

(i) Psychological arguments and changes in the environment: One potential explanation of the fact that we do not find any weather effects on these financial sub-markets is that there is no or only a small impact of weather on the mood. This potential interpretation would be consistent with the findings of Clark and Watson (1988) or Watson (2000) who detect only a small impact of weather on mood. A related argument comes from Keller et al. (2005) finding that the impact of weather on mood is driven by two moderator variables, namely the season and the time spent outside. As people in industrialized countries spend a large percentage of their time inside (e.g. in trading rooms without windows) and thus are largely disconnected from the weather outside (see Woodcock and Custovic (1998)), the people's mood may be less driven by the weather. Moreover there are also other mood determinants, that we did not control for, e.g. natural disasters or personal life events. In this context we also refer the reader to the streams of literature analyzing the impact of cinema program (Lepori (2010)) or sport results (Ashton et al. (2003), Edmans et al. (2007)) (via mood) on asset prices.

Moreover, as a result of the first papers in this field the market participants could have become more rational and learned to filter out the impact of weather-induced mood on their investment decisions (successful "'debiasing"'). However, two arguments speak against this interpretation: Neglecting the impact of weather-induced mood on risk-taking behavior seems to oppose plenty of literature in the field of psychology as cited in the introduction. Also, this would contradict Hirshleifer (2001) and Menkhoff and Nikiforow (2009) who argue that "behavioral finance patterns are so deeply rooted in human behavior that they are difficult to overcome by learning".

Alternatively, firms (asset management companies, brokers, ...) may have reacted to the findings on the impact of weather on mood and indirectly on the quality of decision-making and in order to prevent irrational decisions have shielded their employees from weather conditions (e.g. by installing air condition ...); see Cao and Wei (2005)[p. 1562] for a related argument. This explanation would be consistent with a trend in the results of the studies that investigate weather effects on the stock market. Even though Yoon and Kang (2009) report that after the 1997 financial crisis the presence of a weather effect disappeared and that the weather effect was weakened over time, maybe as the result of heightened market efficiency, and Saunders (1993) shows a similar vanishing of the weather effect in the last years of his observation period, overall, it is not the case that old studies show an impact whereas new studies do not show an impact of weather on stock returns.

(ii) Aggregation: Another problem may occur from the aggregation of mood effects of all market participants. The same changes in weather variables may affect the mood of people in very different ways (see Denissen et al. (2008), or Keller et al. (2005) showing differences in the direction of the effect of weather on mood depending on the time spent outside) which would blur the link between weather and aggregated mood. Apart from this the link between mood and risk aversion is ambiguous. Some investors could react according to the affect infusion model (positive mood implies a decrease in risk aversion) whereas other investors could be subject to the mood maintenance hypothesis (positive mood implies an increase in risk aversion). Similarly, as we show in Remark 2.1, if people follow the mood maintenance hypothesis (good mood increases the risk aversion) and nice weather increases the people's optimism, it may be that weather has an impact on mood, but the effects work against each other and may cancel out each other. So, measured over all market participants the different effects of weather via mood on the risk-taking behavior could cancel out each other resulting in insignificant results.

(iii) Econometrics & Data: Consistent with the findings of Trombley (1997), Krämer and

Runde (1997) and Jacobsen and Marquering (2008), our study shows a strong impact of the statistical method used (see Tables 2 to 11). In addition, most studies use different data sets to test for weather effects. Since different samples from the *full population* can produce different results, there is still the opportunity of the type one and the type two error, i.e. weather effects are inferred although they are not present and vice versa.

5 Conclusions

This article investigates the possible impact of the weather on financial market data. The main finding of this paper is that weather variables do not have an effect on the risk-free interest rates, corporate bond spreads, the S&P 500 index, the individual stock returns and the VIX volatility index.

In more detail, first we show that of all the weather variables used, the temperature is the only variable that needs to be deseasonalized. So, the standard technology used in the Behavioral Finance literature, namely to deseasonalize all weather variables is not necessary, however it does not cause wrong inference. Second, using least squares estimates for a fixed effects model, not accounting for heteroscedasticity, would suggest that financial data are significantly influenced by the weather. Accounting for the existing heteroscedasticity present in the residuals, almost all weather effects vanish. So, the weather effects that would be "detected" by means of least squares standard errors vanish as soon as robust standard errors are used. Thus, misspecification of the model may give erroneously the illusion of weather effects on the financial markets.

Third, we also investigated the claim that weather affects mood, while mood influences asset prices via risk aversion and perceptions of the risk and expected return. An asset pricing model is constructed to describe this mechanism. E.g. based on the affect infusion model, where positive mood reduces the risk aversion, the model predicts that with improving weather the ex-ante expected asset returns and the asset volatilities decrease. Given our data we use the weather data as a proxy for mood and perform an instrumental variable estimation. In this analysis no significant weather effects can be observed, either.

A Bond Sample

This appendix gives a more detailed survey of the bonds used and how the bond spreads were calculated. At the end we present tables with the bonds used in the empirical analysis. For the initial sample of bonds (bonds included in the NASD Bloomberg Active Investment Grade U.S. Corporate Bond Index as of July 19, 2006; see Section 3.2), we obtained the bond characteristics and essential issuer characteristics from Bloomberg. Afterwards, we further restricted our bond sample according to the following guidelines: We excluded all bonds from issuers outside the USA and bonds denominated in currencies other than USD. By eliminating bonds with embedded options (callable and putable bonds) and sinking fund provisions, floating rate notes, bonds with a time-dependent coupon (step up bonds), bonds where the coupon was rating-sensitive, subordinated bonds and secured bonds we further restricted the sample. Concerning the allocation of bonds to issuers, we considered bonds issued by a (financing) subsidiary and guaranteed by its parent as issued by the parent.

For these bonds, we obtained transaction by transaction bond prices from the TRACE system. TRACE (”Transaction Reporting and Compliance Engine”) is an over-the-counter (OTC) corporate bond market real-time price dissemination service, that has been created by the NASD (National Association of Security Dealers), which meanwhile merged into the Financial Industry Regulatory Authority (FINRA). The purpose of this service was to increase the price transparency in the secondary corporate bond market. As of July 1, 2002, NASD required that transaction information be disseminated for investment grade securities with an initial issue size of $1 billion or greater. Meanwhile it provides information on almost 100 percent of OTC secondary market activity representing over 99 percent of total U.S. corporate bond market activity in over 30,000 securities. All brokers/dealers who were NASD member firms were obliged to report transactions in corporate bonds to TRACE under an SEC approved set of rules. Each record indicates the bond identifier, the transaction date and time, the clean price and the volume of the transaction (par value traded, truncated at

$1 million for speculative grade bonds and at $5 million for investment grade bonds). For further information on TRACE see Goldstein et al. (2007), Bao et al. (2008), Bessembinder and Maxwell (2008) or Bessembinder et al. (2009). Use of TRACE data involves the benefit that all prices in our study are based on real transactions. So we do not have to make use of a matrix algorithm (see Sarig and Warga (1989)) or use prices computed by database providers in any way. Also, the use of transaction prices instead of prices merely provided by an exchange is strongly favored in literature (see e.g. Sarig and Warga (1989) and Warga (1991)).

Due to low liquidity and in analogy to Elton et al. (2001), Eom et al. (2004) and Driessen (2005), we eliminated all transactions within the last year of the bonds life. As the intraday volatility of bond prices in the TRACE system is enormous (see Goldstein et al. (2007)) we converted transaction prices into daily prices using the following algorithm: First, we eliminated small trades (volume less than 50,000 USD). From the remaining transactions, we computed for each day the mean of the individual transactions' prices and excluded all transactions on day t where the price deviated by more than 5% (in either direction) from the previous day's price or the mean of that day. In the sequel, we use as daily price the median of the prices of the remaining transactions. It goes without saying that we obtained the gross price (dirty price) by adding accrued interest. Also, we paid attention to any short/long first or short/long last coupons.

We excluded all bonds where (after the algorithm described above) more than 20% of the days between July 1, 2002 (or the later issue of the bond) and March 31, 2006 (or the earlier date that represents one year prior to maturity of the bond) were days without a (remaining) transaction.

We added one more restriction: For each issuer we required that on each day between July 1st, 2002, (or the later date described before) and March 31^{st}, 2006, (or the earlier date described above) at least two bonds fulfilling the criteria above exist (not necessarily traded on that particular day), because pairwise comparisons of intra-firm spreads enable us to additionally check the quality of the data. If this was not the case but could be achieved by restricting to a shorter issuer-specific observation period (e.g. two bonds existed only from a date after July 1st, 2002, or only up to a date before March 31^{st}, 2006), we did this. I. e. for each issuer we computed the first and the last date where at least two bonds were traded. We discarded all issuers, where after the steps described so far this time period was less than two years. After all these steps, 179 bonds, issued by 23 issuers, remained. This resulted in a total of more than 80,000 bond observations.

Tables 12-15 show the bonds used in the empirical analysis. The characteristics presented in these tables are:

No.	...	Number of the bond in our study.
Bond ID	...	Trace code of the bond.
Issued	...	Issue date of the bond (MM/DD/YYYY).
Maturity	...	Maturity of the bond (MM/DD/YYYY).
Amount	...	Amount issued of the bond (in USD).
Coupon	...	Coupon rate of the bond (% of face value).
Miss	...	Percentage of missing values (between issue date and maturity), as a decimal.

TABLES 12-15 ABOUT HERE

No.	Bond ID	Issued	Maturity	Amount	Coupon	Miss
1	AXP.GD	9/12/2001	9/12/2006	1,000,000,000	5.5	0.15
2	AXP.IE	11/20/2002	11/20/2007	750,000,000	3.75	0.14
3	AXP.IN	7/24/2003	7/15/2013	1,000,000,000	4.875	0.12
4	AXP.JQ	6/17/2004	6/17/2009	500,000,000	4.75	0.14
5	AXP.IL	5/16/2003	5/16/2008	1,000,000,000	3	0.09
6	AXP.KH	12/2/2005	12/2/2010	600,000,000	5	0.02
7	AIG.QR	9/30/2002	10/1/2012	1,000,000,000	5.375	0.06
8	BAC.GF	10/9/2001	10/15/2006	1,000,000,000	4.75	0.07
9	BAC.GG	1/31/2002	2/1/2007	1,500,000,000	5.25	0.06
10	BAC.XQ	9/25/2002	9/15/2012	1,000,000,000	4.875	0.07
11	BAC.XV	11/7/2002	11/15/2014	1,000,000,000	5.125	0.16
12	BAC.YK	11/26/2002	1/15/2008	1,000,000,000	3.875	0.06
13	BAC.ZB	1/23/2003	1/15/2013	1,000,000,000	4.875	0.13
14	BAC.GBX	7/22/2003	8/15/2008	1,000,000,000	3.25	0.09
15	BAC.GDF	11/18/2003	12/1/2010	1,000,000,000	4.375	0.08
16	BAC.GEE	1/29/2004	2/17/2009	1,000,000,000	3.375	0.18
17	BAC.GHT	8/26/2004	10/1/2010	750,000,000	4.25	0.13
18	BAC.GMI	7/26/2005	8/1/2015	1,250,000,000	4.75	0.18
19	BAC.GMK	7/26/2005	8/1/2010	1,250,000,000	4.5	0.08
20	ONE.IF	8/8/2001	8/1/2008	1,250,000,000	6	0.10
21	ONE.QC	6/18/2003	6/30/2008	1,000,000,000	2.625	0.19
22	BAC.PK	2/8/1999	2/15/2009	1,500,000,000	5.875	0.11
23	BSC.QL	11/6/2002	11/15/2014	1,700,000,000	5.7	0.18
24	BSC.HI	1/15/2002	1/15/2007	1,000,000,000	5.7	0.10
25	BSC.QT	12/26/2002	1/31/2008	1,000,000,000	4	0.11
26	BSC.SC	6/25/2003	7/2/2008	1,000,000,000	2.875	0.16
27	BSC.UK	10/28/2003	10/28/2010	1,100,000,000	4.5	0.09
28	BSC.GDA	6/23/2005	6/23/2010	1,000,000,000	4.55	0.17
29	BSC.GDJ	10/31/2005	10/30/2015	1,000,000,000	5.3	0.13
30	CIT.GX	11/3/2003	11/3/2008	500,000,000	3.875	0.17
31	CIT.SJ	11/3/2005	11/3/2010	500,000,000	5.2	0.09
32	CIT.PK	4/1/2002	4/2/2007	1,250,000,000	7.375	0.17
33	CIT.PM	9/25/2002	9/25/2007	850,000,000	5.75	0.20
34	CIT.GB	12/2/2002	11/30/2007	800,000,000	5.5	0.18
35	CIT.PO	5/8/2003	5/8/2008	500,000,000	4	0.13
36	CIT.HU	2/13/2004	2/13/2014	750,000,000	5	0.18
37	CIT.JW	11/3/2004	11/3/2009	500,000,000	4.125	0.20
38	CIT.QH	2/1/2005	2/1/2010	750,000,000	4.25	0.17
39	CIT.QI	2/1/2005	2/1/2015	750,000,000	5	0.17
40	CIT.SO	11/23/2005	11/24/2008	500,000,000	5	0.05
41	CIT.SZ	1/30/2006	1/30/2016	750,000,000	5.4	0.08
42	CIT.HI	12/9/2003	12/15/2010	750,000,000	4.75	0.06
43	C.OA	1/16/2001	1/18/2011	2,500,000,000	6.5	0.07
44	C.OF	8/9/2001	8/9/2006	1,500,000,000	5.5	0.10
45	C.OG	2/21/2002	2/21/2012	1,500,000,000	6	0.14

TABLE 12

No.	Bond ID	Issued	Maturity	Amount	Coupon	Miss
46	C.OH	3/6/2002	3/6/2007	1,500,000,000	5	0.07
47	C.GMV	1/31/2003	2/1/2008	3,000,000,000	3.5	0.03
48	C.HDA	2/9/2004	2/9/2009	1,500,000,000	3.625	0.14
49	C.HDI	5/5/2004	5/5/2014	1,750,000,000	5.125	0.13
50	C.HDO	7/29/2004	7/29/2009	1,000,000,000	4.25	0.06
51	C.HEK	8/3/2005	8/3/2010	1,250,000,000	4.625	0.16
52	C.HEM	12/8/2005	1/7/2016	1,000,000,000	5.3	0.07
53	C.HEQ	2/14/2006	2/14/2011	2,000,000,000	5.125	0.03
54	CCR.KN	8/8/2001	8/1/2006	1,625,000,000	5.5	0.05
55	CCR.LA	1/29/2002	2/1/2007	1,000,000,000	5.5	0.13
56	CCR.LG	5/17/2002	5/15/2007	1,000,000,000	5.625	0.14
57	CCR.LS	12/17/2002	12/19/2007	750,000,000	4.25	0.16
58	CCR.LY	5/21/2003	5/21/2008	1,000,000,000	3.25	0.10
59	CCR.MB	3/22/2004	3/22/2011	1,350,000,000	4	0.11
60	CCR.MN	9/16/2004	9/15/2009	1,250,000,000	4.125	0.07
61	DCX.GY	8/24/1999	9/1/2009	2,000,000,000	7.2	0.08
62	DCX.HN	1/16/2002	1/15/2012	1,500,000,000	7.3	0.16
63	DCX.SD	1/16/2003	1/15/2008	2,000,000,000	4.75	0.09
64	DCX.VC	6/10/2003	6/4/2008	2,500,000,000	4.05	0.05
65	DCX.XO	11/6/2003	11/15/2013	2,000,000,000	6.5	0.07
66	DCX.GDY	6/9/2005	6/15/2010	1,000,000,000	4.875	0.13
67	DE.IP	3/22/2002	3/15/2012	1,500,000,000	7	0.20
68	DE.IW	1/10/2003	1/15/2008	850,000,000	3.9	0.18
69	GE.AGS	5/2/2003	5/1/2008	2,000,000,000	3.5	0.03
70	GE.AIF	6/5/2003	6/15/2009	500,000,000	3.25	0.17
71	GE.GAV	8/19/2003	8/15/2007	800,000,000	3.5	0.07
72	GE.GBT	9/17/2003	9/25/2006	750,000,000	2.75	0.07
73	GE.GDN	12/1/2003	12/1/2010	1,000,000,000	4.25	0.04
74	GE.GDS	12/5/2003	12/5/2007	400,000,000	3.5	0.15
75	GE.GEK	1/13/2004	1/15/2007	1,000,000,000	2.8	0.10
76	GE.GGW	3/29/2004	4/1/2009	1,000,000,000	3.125	0.07
77	GE.GLD	9/17/2004	9/15/2014	1,250,000,000	4.75	0.18
78	GE.GMJ	10/29/2004	12/15/2009	1,000,000,000	3.75	0.09
79	GE.GMY	11/19/2004	11/21/2011	750,000,000	4.375	0.05
80	GE.GPM	3/4/2005	3/4/2008	1,600,000,000	4.125	0.04
81	GE.GPN	3/4/2005	3/4/2015	1,000,000,000	4.875	0.08
82	GE.GUW	10/21/2005	10/21/2010	1,250,000,000	4.875	0.06
83	GE.GWN	1/9/2006	1/8/2016	1,250,000,000	5	0.05
84	GE.TK	1/19/2000	1/19/2010	1,500,000,000	7.375	0.17
85	GE.UQ	2/21/2001	2/22/2011	1,825,000,000	6.125	0.10
86	GE.WA	2/15/2002	2/15/2007	1,250,000,000	5	0.07
87	GE.WB	2/15/2002	2/15/2012	2,650,000,000	5.875	0.04
88	GE.ZE	3/20/2002	3/15/2007	2,275,000,000	5.375	0.06
89	GE.AAD	6/7/2002	6/15/2012	4,150,000,000	6	0.04
90	GE.AAA	6/7/2002	6/15/2007	2,250,000,000	5	0.04

TABLE 13

No.	Bond ID	Issued	Maturity	Amount	Coupon	Miss
91	GE.ZY	9/24/2002	9/15/2009	1,350,000,000	4.625	0.03
92	GE.ACE	12/6/2002	1/15/2013	3,000,000,000	5.45	0.05
93	GE.ACF	12/6/2002	1/15/2008	2,000,000,000	4.25	0.03
94	GS.JO	5/19/1999	5/15/2009	1,800,000,000	6.65	0.05
95	GS.JR	9/29/1999	10/1/2009	1,000,000,000	7.35	0.13
96	GS.KJ	1/16/2001	1/15/2011	2,850,000,000	6.875	0.06
97	GS.OU	8/27/2002	9/1/2012	1,500,000,000	5.7	0.08
98	GS.PB	11/15/2002	11/15/2014	1,300,000,000	5.5	0.16
99	GS.PX	1/13/2003	1/15/2008	2,000,000,000	4.125	0.03
100	GS.QK	3/31/2003	4/1/2013	1,200,000,000	5.25	0.15
101	GS.RC	7/15/2003	7/15/2013	2,000,000,000	4.75	0.04
102	GS.RO	10/14/2003	10/15/2013	1,750,000,000	5.25	0.07
103	GS.UG	1/12/2005	1/15/2015	2,250,000,000	5.125	0.03
104	GS.VN	1/17/2006	1/15/2016	2,500,000,000	5.35	0.03
105	GS.VO	1/17/2006	1/15/2011	750,000,000	5	0.03
106	GS.RX	1/13/2004	1/15/2009	1,500,000,000	3.875	0.07
107	GS.RW	1/13/2004	1/15/2014	1,500,000,000	5.15	0.06
108	HI.KJ	6/17/1998	6/17/2008	1,750,000,000	6.4	0.08
109	HI.KP	2/5/1999	2/1/2009	1,300,000,000	5.875	0.06
110	HI.KT	3/1/2000	3/1/2007	1,500,000,000	7.875	0.13
111	HI.KZ	10/23/2001	10/15/2011	2,000,000,000	6.375	0.08
112	HI.LA	1/30/2002	1/30/2007	2,500,000,000	5.75	0.04
113	HI.AAB	5/22/2002	5/15/2012	1,750,000,000	7	0.16
114	HI.HEL	7/21/2003	7/15/2013	1,250,000,000	4.75	0.08
115	HI.HJF	12/10/2003	12/15/2008	1,500,000,000	4.125	0.03
116	HI.HLX	5/26/2004	5/15/2009	1,250,000,000	4.75	0.08
117	HI.HPN	11/23/2004	11/16/2009	1,750,000,000	4.125	0.05
118	AIG.LY	10/17/2001	10/15/2006	700,000,000	5.75	0.14
119	AIG.QJ	5/29/2002	6/1/2007	900,000,000	5.625	0.11
120	AIG.SA	4/29/2003	5/1/2013	600,000,000	5.875	0.19
121	AIG.GHW	4/11/2005	4/15/2010	800,000,000	5	0.10
122	AIG.GJT	8/23/2005	9/1/2010	600,000,000	4.875	0.06
123	JPM.MA	8/14/2001	8/15/2006	2,000,000,000	5.625	0.10
124	JPM.MB	3/6/2002	3/1/2007	1,500,000,000	5.35	0.13
125	JPM.QF	5/30/2002	5/30/2007	2,000,000,000	5.25	0.06
126	JPM.QY	1/30/2003	2/1/2008	1,000,000,000	4	0.12
127	JPM.RL	4/24/2003	5/1/2008	800,000,000	3.625	0.13
128	JPM.TH	11/7/2003	11/15/2010	750,000,000	4.5	0.08
129	JPM.TZ	12/11/2003	12/11/2006	500,000,000	3.125	0.13
130	JPM.VI	3/9/2004	3/15/2009	1,000,000,000	3.5	0.17
131	JPM.ZZ	12/14/2004	1/15/2012	850,000,000	4.5	0.11
132	KFT.GC	11/2/2001	11/1/2006	1,250,000,000	4.625	0.07
133	KFT.GD	11/2/2001	11/1/2011	2,000,000,000	5.625	0.07
134	KFT.GH	5/20/2002	6/1/2007	1,000,000,000	5.25	0.11
135	KFT.GG	5/20/2002	6/1/2012	1,500,000,000	6.25	0.17

TABLE 14

No.	Bond ID	Issued	Maturity	Amount	Coupon	Miss
136	KFT.GL	11/12/2004	11/12/2009	750,000,000	4.125	0.16
137	LEH.OQ	1/21/2003	1/22/2008	1,500,000,000	4	0.04
138	LEH.RV	7/28/2003	8/7/2008	1,000,000,000	3.5	0.09
139	LEH.ZZ	7/13/2005	7/26/2010	1,000,000,000	4.5	0.10
140	LEH.GBX	12/21/2005	1/14/2011	750,000,000	5	0.05
141	LEH.MW	1/10/2002	1/18/2012	1,500,000,000	6.625	0.18
142	LEH.TX	2/25/2004	3/13/2014	1,150,000,000	4.8	0.16
143	LEH.XS	1/11/2005	1/27/2010	1,100,000,000	4.25	0.17
144	MER.HE	2/17/1999	2/17/2009	2,000,000,000	6	0.06
145	MER.VF	11/15/2002	11/15/2007	1,000,000,000	4	0.05
146	MER.GBI	4/21/2003	4/21/2008	950,000,000	3.7	0.15
147	MER.GDA	9/15/2003	9/14/2007	500,000,000	3.375	0.14
148	MER.GDN	11/4/2003	11/4/2010	700,000,000	4.5	0.14
149	MER.GDW	12/4/2003	1/15/2009	1,075,000,000	4.125	0.09
150	MER.GGW	9/10/2004	9/10/2009	1,000,000,000	4.125	0.08
151	MER.GHM	11/22/2004	1/15/2015	1,850,000,000	5	0.06
152	MER.GIC	2/7/2005	2/8/2010	1,500,000,000	4.25	0.08
153	MER.GKF	8/4/2005	8/4/2010	1,300,000,000	4.79	0.05
154	PFE.GH	2/3/2004	3/15/2007	700,000,000	2.5	0.20
155	PFE.GI	2/3/2004	2/15/2014	750,000,000	4.5	0.20
156	PG.GI	9/16/1999	9/15/2009	1,000,000,000	6.875	0.10
157	PG.GR	6/11/2002	6/15/2007	1,000,000,000	4.75	0.08
158	PG.GS	8/7/2002	8/15/2008	500,000,000	4.3	0.14
159	WB.MV	11/2/2001	11/1/2006	1,750,000,000	4.95	0.05
160	WB.NO	7/25/2003	8/15/2008	750,000,000	3.5	0.13
161	WB.NR	2/6/2004	2/17/2009	1,250,000,000	3.625	0.15
162	WMT.GO	8/10/1999	8/10/2009	3,500,000,000	6.875	0.04
163	WMT.GT	7/31/2001	8/1/2006	1,500,000,000	5.45	0.05
164	WMT.HE	7/12/2002	7/12/2007	1,500,000,000	4.375	0.04
165	WMT.HN	4/29/2003	5/1/2013	1,500,000,000	4.55	0.04
166	WMT.HO	10/2/2003	10/1/2008	1,000,000,000	3.375	0.05
167	WMT.HP	2/18/2004	2/15/2011	2,000,000,000	4.125	0.03
168	WMT.HR	1/20/2005	1/15/2010	1,000,000,000	4	0.10
169	WMT.HT	6/9/2005	7/1/2010	1,250,000,000	4.125	0.11
170	WMT.HU	8/15/2005	8/15/2010	800,000,000	4.75	0.05
171	WM.HF	1/11/2002	1/15/2007	1,000,000,000	5.625	0.19
172	WM.IE	11/3/2003	1/15/2009	1,000,000,000	4	0.10
173	WFC.IF	2/5/2002	2/15/2007	1,500,000,000	5.125	0.06
174	WFC.KD	3/25/2003	4/4/2008	1,100,000,000	3.5	0.05
175	WFC.KK	3/24/2004	4/1/2009	1,500,000,000	3.125	0.18
176	WFC.GBX	12/6/2004	1/15/2010	2,500,000,000	4.2	0.06
177	WFC.GCJ	3/9/2005	3/10/2008	1,100,000,000	4.125	0.11
178	WFC.GCS	8/8/2005	8/9/2010	1,000,000,000	4.625	0.09
179	WFC.GCV	1/12/2006	1/12/2011	1,500,000,000	4.875	0.10

TABLE 15

B Unit Root Tests

To specify the regression setting more closely, we have to find out for each of the variables described in Section 3 if it is stationary or not. While levels can be used for stationary data, for non-stationary variables first differences (denoted by Δ) are more appropriate (if necessary higher order differences have to be used).[16] Providing a brief summary, let us start with the corporate bond spreads. With the panel unit root tests we observe that the Levin et al. (2002) test does not reject the null hypothesis of a unit root, the other panel unit root tests implemented in EViews (Breitung (2000) test, assuming a common autoregressive coefficient, and Im et al. (2003) test, allowing for different autoregressive terms) however do. To get a clearer picture, we performed unit root tests on a single time series basis: namely the Dickey/Fuller test, the Augmented Dickey/Fuller test and the Phillips/Perron test (for a description of these tests see e.g. Hamilton (1994)). With all these three tests the null hypothesis of a unit root was rejected, both with and without including a time trend. Based on these results we decide to treat the spreads as stationary random variables and work with the spread levels. Similarly, for the variables $VOLUME$ and $RANGE$ all unit root tests reject the null of a unit root.

Based on the unit root tests the S&P 500 returns can be considered to be stationary. The same statement holds for the individual stock returns STR. A further critical candidate is the VIX volatility index. We observe p-values of 14.65 and 8.1 percent for the Augmented Dickey Fuller tests without and with a time trend, respectively. By this result we assume that the VIX is stationary. Things are less clear with the risk-free rates. With different tests we receive different answers to the question whether interest rates are stationary or not. Thus, in

[16] Detailed results of these tests for all variables can be obtained from the authors on request. Throughout this paper the EViews package was used. In all these tests the null hypothesis of a unit root process is tested against the alternative of no unit root. In the simplest setting, under the null the process follows $x_t = x_{t-1} + u_t$, where $u_t \in \mathbb{R}$ is iid with finite second moment, which implies that the support of x_t is the real axis. Although for a lot of the random variables considered here the range is only a proper subset of the real axis, we follow applied econometrics and quantitative finance literature and still use the unit root tests to check for possible non-stationarity.

the regressions we work with first differences. Since the distance to default is calculated based on non-stationary variables we applied first differences. As regards the weather variables we observe that for the deseasonalized temperature, barometric pressure, visibility, precipitation, wind speed, cloud cover and humidity the null hypothesis of a unit root has to be rejected. Thus, we work with levels.

C Deseasonalization of the Weather Data

The goal of this appendix is to compare different deseasonalization techniques, to check the necessity of deseasonalization and to investigate the impact of (lacking) deseasonalization on parameter estimation and inference. The questions investigated in the latter part are:

1. Question 1: If a seasonal component exists but the data are not deseasonalized, what is the impact on inference?

2. Question 2: If there is no seasonal component in the data but deseasonalization is applied, what is the impact on inference?

To find answers to these questions we generate a (weather) variable, x_t, with a cyclical and a stochastic component, that may have an impact on a simulated (financial market) variable y_t. Based on these simulated time series we perform standard t tests for the regression parameters that should provide us with answers to the questions raised.

We generate simulated data by means of the steps `S1` to `S4` as follows:

`S1` The cyclical deterministic component $\tilde{x}_1$ is modeled by means of $\tilde{x}_1(\tau) = 1/\sqrt{\pi}\cos(2\pi\tau)$. Note that $\tilde{x}_1(\tau)$ corresponds to a *Fourier polynomial* of order $p = 1$ (see e.g. Harrison and West (1997)[Chapter 8]). To derive discrete data at period t, $t = 1, \ldots, T$, we calculate $\tilde{x}_1(t\Delta)$; $\Delta = 1/252$ is the step-width. $\tau = 1$ should correspond to one year. This results in the values $\tilde{x}_{1t}$ for the cyclical component at period t.

`S2` The non-cyclical, stochastic component $\tilde{x}_{2t} \sim \mathcal{N}(0, \sigma^2)$, where we use $\sigma^2 = 1$.

`S3` The simulated prediction variable observed, x_t, is the sum of the scaled cyclical component (x_{1t}) and the scaled non-cyclical component (x_{2t}):

$$x_t = x_{1t} + x_{2t} = \sqrt{\omega}\tilde{x}_{1t} + \sqrt{1-\omega}\tilde{x}_{2t} \text{ where } \omega \in [0, 1] . \tag{16}$$

This random variable x_t has an expected value of zero and a variance of one. ω represents the impact of the cyclical part, $\tilde{x}_{1t}$, on the variance of x_t. $\omega \cdot 100$ measures this impact in percentage terms. The higher ω the stronger the impact of the cyclical part. In our further analysis $\omega = \{0, 0.1, 0.5, 0.9\}$ will be used.

S4 Suppose that neither x_{1t} nor x_{2t} but only the sum x_t is observed. We want to estimate the scaled cyclical component x_{1t} from observations of x_t. $\hat{x}_{1t}$ is an estimate of the cyclical part $x_{1t} = \sqrt{\omega}\tilde{x}_{1t}$. An estimate of the non-cyclical term, x_{2t}, is derived by $\hat{x}_{2t} = x_t - \hat{x}_{1t}$.

Based on this simulated data we want to compare the following three deseasonalization approaches:

1. $Naive$: We do not believe in any cycle and assume that the data are *iid*. Thus, we waive any deseasonalization: $\hat{x}_{2t}^{Naive} = x_t$. For $\omega = 0$ this would be the correct specification.

2. $Week$: We create buckets of weekly data and calculate weekly means. This results in $\hat{x}_{1t}^{Week}$. This technique is e.g. presented in Harrison and West (1997)[Chapter 8.2] and has developed as the standard in the Behavioral Finance literature (see e.g. Hirshleifer and Shumway (2003), Loughran and Schultz (2004), Goetzmann and Zhu (2005), Keef and Roush (2005) or Chang et al. (2008)).

3. $Fourier$: We approximate x_t by a Fourier polynomial (*trigonometric polynomial*) of order p. This is a standard way to filter out cyclical components in many disciplines (see e.g. Harrison and West (1997)[Chapter 8]). The polynomial has $1 + 2p$ parameters. This results in $\hat{x}_{1t}^{Fourier,p}$.

   To compare the models we use the following F-test: For each $p = 1, 2, \ldots,$ the residuals $\hat{x}_{2t}^{Fourier,p} = x_t - \hat{x}_{1t}^{Fourier,p}$ result in the sums of squared residuals $SSR^{Fourier,p}$. Comparing a Fourier approximation of degree p to an approximation of degree q, $q < p$, the statistic

$$\frac{(SSR^{Fourier,q} - SSR^{Fourier,p})/(2(p-q))}{SSR^{Fourier,p}/(T-2p)} \tag{17}$$

is F distributed with $2(p-q)$ degrees of freedom in the numerator and $T-2p$ degrees of freedom in the denominator. T is the number of observations. Since a constant can be considered as polynomial of degree zero, $q=0$ corresponds to $Naive$.

With $\hat{x}_{2t}^{Week}$ we can proceed in the same way: The naive setting is a nested model of the $Fourier$ as well as of the $Week$ methodology. Therefore we are allowed to use (17) also to test the null hypothesis of no season against the alternative of a seasonal component described by $Week$. This can be done by calculating SSR^{Week} and replacing in equation (17) $SSR^{Fourier,p}$ by SSR^{Week} and $SSR^{Fourier,q}$ by $SSR^{Fourier,0} = SSR^{Naive}$. The number of parameters p to derive SSR^{Week} is given by the number of weeks per year.

We used this methodology to check for each weather variable if there is a need for deseasonalization when using $Week$. The results of this investigation have been reported in Section 3.

Equipped with these tools, for the data simulated by means of steps `S1-S4`, we observe the following results:

(i) The approximation errors for $Week$ and $Fourier$ are small. For the simulated x_t described at the beginning of this section the Fourier deseasonalization technique with $p=1$ results in the lowest approximation error of the cyclical component for all ω. For $\omega=0.1$ and 0.5 (low or medium seasonality) the Fourier setting with $p=6$ is better than the methodology $Week$, while with $\omega=0.9$ (strong seasonality) $Week$ results in smaller errors than $Fourier$ with $p=6$. The observation that the Fourier model slightly dominates $Week$ is not a big surprise since in our simulations the data generating process includes a Fourier cycle (see step `S1`). With empirical weather data the data generating process is unknown. However from the simulations we observe that $Week$ provides us with a reasonable tool to filter out seasonal components even if the true data generating process is different. (ii) The F-test described by (17) detects the correct Fourier model (true p) in more than 95% of the simulation runs. This test also works with $Week$ to differentiate between a model with and without cyclical component. Based on these observations we conclude that the $Week$ deseasonalization technique used in the Behavioral Finance literature provides us with a good fit to the data even if the true data generating process is based on a one year cosine-cycle (see step `S1`). In addition testing for the presence of a seasonal component is feasible.

In the next step we want to find out whether (i) neglecting deseasonalization if a seasonal component exists or (ii) performing deseasonalization if no seasonal component exists has an impact on parameter estimation and inference. In other words we want to check whether the above methodologies detect weather effects if they are present, and vice versa. We proceed as follows: The response variable y_t is generated by means of

$$y_t = \beta_0 + \beta_2 x_{2t} + \beta_3 x_{3t} + \varepsilon_t \ , \ t = 1, \ldots, T. \tag{18}$$

$\varepsilon_t \sim \mathcal{N}(0, \sigma_R^2)$. $\sigma_R^2 = 0, 0.1, 0.5$ or 1 (0 is only applied with $\omega > 0$). x_{3t} is a further predictor variable which we simulated by means of a standard normally distributed variable. x_{2t} is the deseasonalized component derived above. We set $\beta_2 = 0$ (no impact of the non-cyclical component of the predictor variable x_t) or $\beta_2 = 1$ (there is an impact of the non-cyclical component of the predictor variable).

Remark C.1. *The experiment in this appendix can be linked to our weather analysis as follows: y_t corresponds to the financial market return, risk-free rate, yield spread or VIX level, x_{2t} corresponds to the non-cyclical (deseasonalized) part of a weather variable and x_{3t} stands for a control variable. Suppose that the financial variable y_t, the (non-deseasonalized) weather variable x_t and the control variable x_{3t} can be observed. Then: (i) Suppose that the deseasonalized weather x_{2t} has an impact on the financial market variable (i.e. $\beta_2 \neq 0$): We use x_t, apply the $Week$ deseasonalization technique and then the test described in (17). Based on this test we can decide to take either $\hat{x}_{2t} = x_t$ (if the test statistic in (17) favors no season)* *or $\hat{x}_{2t} = x_{2t}^{Week}$ (if the test statistic supports a seasonal component). In a next step, we run the regression where y_t is the response variable and the predictors are $\hat{x}_{2t}$ and x_{3t}. Finally, we analyze if β_2 is significantly different from zero. (ii) Suppose that there is no weather effect ($\beta_2 = 0$): Proceed in the same way as in (i). Equally, we want to know if β_2 is insignificant or not. I.e. this simulation analysis should provide us with information if weather effects can be detected if present, or if weather effects are rejected if no weather effects are in the data.*

As stated above, y_t, x_t and x_{3t} can be observed. Then the deseasonalized components $\hat{x}_{2t}^{(.)}$ will be estimated by means of the $Fourier$ setting with $p = 1$, $Week$ and $Naive$.[17] α will represent the usual significance levels 0.01, 0.05 and 0.1, respectively. Each simulation experiment is replicated 1000 times. Here we observe the following:

1. $\beta_2 = 1$, $\omega = 0$ or $\omega = 0.1$ (impact of the non-cyclical weather component exists, majority of the weather variable x_t is non-cyclical): All approaches ($Naive$, $Week$ and $Fourier$) reject the null hypothesis that $\beta_0 = 0$ in approximately $1 - \alpha\%$ of the simulation runs. This is in line with the desired results. The false null hypotheses $\beta_2 = 0$ and $\beta_3 = 0$ are rejected in almost all simulation runs.

2. $\beta_2 = 0$, $\omega = 0$ or $\omega = 0.1$ (no impact of the non-cyclical weather component, majority of the weather variable x_t is non-cyclical): We observe for $\beta_0 = 0$ and $\beta_3 = 0$ the same results as in scenario 1 (i.e. the "$\beta_2 = 1$, $\omega = 0$ or 0.1" scenario). The true null hypothesis that $\beta_2 = 0$ is not rejected in slightly more than $1 - \alpha\%$ of the simulation runs. This is true for all deseasonalization approaches analyzed.

3. $\beta_2 = 1$, $\omega = 0.5$ (impact of the non-cyclical weather component exists, half of the weather variable x_t is cyclical): The results are similar to scenario 1. The only (small) difference to scenario 1 is that the $Naive$ approach does not reject the true null hypothesis for β_0 with a probability slightly smaller than α.

[17] According to step `S1` the Fourier model with $p = 1$ is the true model.

4. $\beta_2 = 0$, $\omega = 0.5$ (no impact of the non-cyclical weather component, half of the weather variable x_t is cyclical): This scenario gives results very close to scenario 2 (where $\beta_2 = 0$, $\omega = 0$ or 0.1).

5. $\beta_2 = 1$, $\omega = 0.9$ (impact of the non-cyclical weather component exists, majority of the weather variable x_t is cyclical): With all three deseasonalization approaches the true null hypothesis that $\beta_0 = 0$ is rejected in α + 2-3% more of the simulation runs. The false null of $\beta_2 = 0$ is still rejected for almost all runs with $Week$ and $Fourier$. Depending on the α used (1%, 5% or 10%), this false null is not rejected in 6-20% of the simulation runs with the $Naive$ approach. Thus, with this setting the $Naive$ approach does not work well anymore. This is plausible as the majority of x_t is cyclical in this setting.

6. $\beta_2 = 0$, $\omega = 0.9$ (no impact of the non-cyclical component, majority of the weather variable x_t is cyclical): For all approaches the true null that $\beta_2 = 0$ is not rejected in approximately $1-\alpha$% of the simulation runs. This is clear, as the non-cyclical component of the predictor variable has no impact on the response variable.

According to the questions raised at the beginning of this section we observe that:

1. ad Question 1: Suppose that a seasonal component exists in x_t (i.e. $\omega > 0$) and the data are not deseasonalized (with the "Naive" approach): If the response variable is influenced by the non-cyclical part of x_t ($\beta_2 \neq 0$), we observe from items 1, 3 and 5 that with a rising seasonal component (ω increasing), we obtain a substantial bias. If, however, the response variable is not influenced by the non-cyclical part of x_t ($\beta_2 = 0$), inference is not badly influenced (see items 2, 4 and 6).

2. ad Question 2: Suppose that there is no seasonal component in x_t (i.e. $\omega = 0$) but the deseasonalization technique $Week$ is applied: If the response variable is influenced by the non-cyclical part of x_t ($\beta_2 \neq 0$) as in item 1, we observe no problem if $Week$ is applied. If there is no impact of the weather (i.e. $\beta_2 = 0$) item 2 also shows that using the deseasonalization approach $Week$ does not result in problems.

Summing up, we observe only minor differences between the *Week* deseasonalization approach used in the Behavioral Finance literature and the smooth *Fourier* methodology used in many other fields, not only in terms of the approximation quality (as already observed in the above comparison) but also in terms of power and size of the parameter tests. If some response variable is a linear function of the non-cyclical component and only the response variable and a predictor including some seasonal effects are observed, the approach used in the Behavioral Finance literature performs well to detect a linear dependence of the response variable on the non-cyclical component of a predictor variable observed. The question whether the data should be deseasonalized can be investigated by means of a test. Neglecting a seasonal component has a negative impact on inference, while applying deseasonalization in the absence of a seasonal component does not significantly deteriorate the performance of the significance tests for the individual regression parameters.

D A Note on Errors in Variables

The goal of this appendix is first to show that the least squares estimates become biased if the error term and some predictor variable are correlated and second to describe a generalized version of our setting in Section 4.2 with weather and mood in a multivariate context (i.e. several weather variables, several mood dimensions). First, suppose that the weather influences a latent variable called mood and the mood affects the response variable y_t. In the following formal steps we shall observe that the prediction variable may be correlated with the error term, such that least squares estimates are biased. Consider the linear model:

$$y_t = x_t^\top \beta + \varepsilon_t \ , \tag{19}$$

where $y_t \in \mathbb{R}$, $x_t \in \mathbb{R}^k$ (k is the number of prediction variables) and ε_t is *iid* with an expectation of 0 and variance σ^2. β and σ^2 are the true parameters. We observe y_t and x_t from $t = 1, \ldots, T$. By stacking y_t, ε_t and x_t we get the $T \times 1$ matrix Y, the $T \times 1$ matrix e, and the $T \times k$ matrix X respectively.

The following steps are mainly based on Ruud (2000)[Chapter 19], assuming that the rank condition is met. Therefore, if X has rank k and conditional on X the variance of Y is $\sigma^2 I_T$, then the Gauss-Markov theorem holds: $\hat{\beta}_{OLS} = (X^\top X)^{-1} X^\top Y$ is unbiased and efficient (see Ruud (2000)[page 187]). Let us consider the OLS estimator

$$\begin{aligned} \hat{\beta}_{OLS} &= (X^\top X)^{-1} X^\top Y = (X^\top X)^{-1} X^\top (X\beta + e) \\ &= \beta + (X^\top X)^{-1} X^\top e = \beta + \mathbb{E}_T(x_t^\top x_t)^{-1} \mathbb{E}_T(x_t \varepsilon_t) \ . \end{aligned} \tag{20}$$

$\hat{\beta}_{OLS}$ is consistent if $\mathbb{E}_T(x_t\varepsilon_t) = \frac{1}{T}\sum_t x_t \varepsilon_t$ converges to zero in probability ($\mathbb{E}_T(.)$ stands for the conditional expectation $\mathbb{E}(.|\mathcal{F}_T)$ with $\mathcal{F}_T = \sigma(x_1, \ldots, x_T)$). Moreover, the estimator $\hat{\beta}_{OLS}$ is unbiased (i.e. $\mathbb{E}(\hat{\beta}_{OLS} - \beta) = 0$) if the last summation term in equation (20) has an expectation of zero, which requires that $\mathbb{E}(x_t \varepsilon_t) = 0$. This condition is fulfilled if $\mathbb{E}(\varepsilon_t | x_t) = 0$.

However, if ε_t and x_t are correlated this requirement is not fulfilled and the OLS estimator results in biased and inconsistent estimates.

Second, let us consider the following *errors in variables* problem:[18] In Section 4.2, μ_t stands for the mood and w_t for the weather variables driving the mood μ_t. For simplicity, both μ_t and w_t are of dimension k_w. Assume that $\mathbb{E}(y_t|\mu_t) = \mu_t^\top \beta_w$ but only a noisy linear transformation of the mood vector μ_t is observed. We assume that this noisy linear transformation is represented by the weather variables. Therefore, suppose that $\mu_t = Aw_t - u_t$. A is a $k_w \times k_w$ matrix of full rank, u_t is *iid* with an expectation of zero and a finite second moment. The matrix A in this appendix measures the impact of the various weather variables on the different mood variables. A is unknown, only positive or negative signs can be deduced from psychological literature.[19] In our quantitative analysis we cannot observe μ_t but only $w_t = A^{-1}(\mu_t + u_t)$. Then

$$\begin{aligned} y_t &= \mu_t^\top \beta_w + c_t^\top \beta_c + \varepsilon_t = (w_t^\top A^\top - u_t^\top)\beta_w + c_t^\top \beta_c + \varepsilon_t \\ &= w_t^\top \tilde{\beta}_w - u_t^\top \beta_w + c_t^\top \beta_c + \varepsilon_t = w_t^\top \tilde{\beta}_w + c_t^\top \beta_c + \eta_t \end{aligned} \tag{21}$$

where $\eta_t = -u_t^\top \beta_w + \varepsilon_t$ and $\tilde{\beta}_w = A^\top \beta_w$. c_t is a vector of exogenous control variables. Direct calculations show that $\mathbb{E}(\eta_t w_t) = -\mathbb{E}(u_t u_t^\top)\beta_w$ which is in general not equal to zero. Note that due to the term $(X^\top X)^{-1}$ in equation (20), $\mathbb{E}(\eta_t w_t) \neq 0$ also results in biased estimates of β_c. Suppose that we are interested in the estimates of $\tilde{\beta}_w = A^\top \beta_w$. Then by equation (20) and the fact that $\mathbb{E}(\eta_t w_t) \neq 0$, the OLS estimator provides us with inconsistent and biased estimates. However, by means of instrumental variable estimation consistent and unbiased

[18] To keep the presentation simple we consider a standard regression setting. A fixed effects model can be estimated by applying the *within transform* to the data (see e.g. Baltagi (2008)). After this transform has to been implemented we end up with model (21) where y_t and x_t are the data transformed. After the parameters β_w and β_c are estimated, the fixed effects α_i follow from these estimates and the original data.

[19] This analysis can be extended to a structure where there are different dimensions of mood and weather. Suppose that $\mu_t = Bw_t - \tilde{u}_t$, where $\mu_t \in \mathbb{R}^{k_\mu}$, $w_t \in \mathbb{R}^{k_w}$ and B is a $k_\mu \times k_w$ matrix. Then $\tilde{\beta}_w = B^\top \beta_w$. w_t follows from $\mu_t = Bw_t - \tilde{u}_t$ as long as a $k_w \times k_\mu$ pseudo-inverse matrix of B exists.

estimates can be derived.

Let us connect these results to Section 4.2: Equation (14) is a special case of this generalized setting, where we set A equal to the $k_w \times k_w$ identity matrix and $\tilde{\beta}_w = \beta_w$. This special case has been selected to improve the readability of Section 4.2. Therefore the model $y_t = w_t^\top \tilde{\beta}_w + c_t^\top \beta_c + \eta_t$ (structurally identical to the model in Section 4.2) is a reduced form representation of the larger model described in this appendix. Instrumental variable estimates provide us with consistent and unbiased estimates of $\tilde{\beta}_w = A^\top \beta_w$. If element j of $\tilde{\beta}_w$ is significant, then there is an impact of the weather variable j on the vector of mood variables μ_t and μ_t then has an impact on the (financial market/response) variable y_t.

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