Weather & SAD Related Mood Effects on the Financial Market*

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January 15, 2014

Abstract

We investigate the relationship between weather/seasonal affective disorder (SAD) and the financial market. We use a wide variety of financial market data, namely risk-free interest rates, US corporate bond indexes, the spreads of individual US corporate bonds, stock index returns, stock returns and the VIX volatility index, as well as several weather variables and a SAD proxy. We distinguish between a model with a direct effect of the weather and SAD on the financial market and one with an indirect effect via a latent variable mood. Whereas only the latter model is justified by psychological literature, often the former model is used as an approximation. One major innovation of this paper is a consistent econometric implementation of the indirect effect assumption. We show that this demands for an analysis of various financial sub-markets instead of focusing on single market segments. We demonstrate that the approximation by direct effects yields biased estimates. Our study supports weather-related, but no SAD related, mood effects on the financial market.

Keywords: Mood Effects, Weather Effects, Seasonal Affective Disorder.

JEL: C51, G12, E43.

*This paper was initiated while Manfred Frühwirth was visiting professor at the Weatherhead Center for International Affairs at Harvard University. The author appreciates the support, resources and opportunities provided by the Weatherhead Center during this time. The authors appreciate helpful comments from Mark Kamstra, Michael Kisser, Lisa Kramer, Elke Lerch, Pegaret Pichler, Oleg Shibanov, Christian Wagner, Arne Westerkamp and the participants of the WU Brown Bag seminar in Finance and the 15^{th} Conference of the Swiss Finance Association.

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1 Introduction

There are different streams of literature analyzing the impact of mood on the financial market. This includes different branches of literature analyzing if asset prices are related to *seasonal affective disorder* (SAD) (see e.g. Kamstra et al. (2003)), the daylight savings anomaly (see Kamstra et al. (2000)), results of sports events (see e.g. Ashton et al. (2003), Edmans et al. (2007)), the movie program (see Lepori (2010)) or the weather (see e.g. Saunders (1993) or Hirshleifer and Shumway (2003)). As primarily weather and SAD data are available on a daily basis and show sufficient variation, this paper focuses on weather and SAD related mood effects on different financial market segments.

The relation between the financial market and SAD has been analyzed by Kamstra et al. (2003), Garrett et al. (2005), Kamstra (2005) and Kamstra et al. (2009). The correlation between the weather and the financial market (e.g. stock market returns) has been the subject of recent empirical studies. 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) included cloud cover, humidity and barometric pressure. Keef and Roush (2002), Keef and Roush (2005) and Keef and Roush (2007) investigated the influence of wind, temperature, rain, humidity, sunshine and cloud cover. Dowling and Lucey (2005) evaluated weather effects using cloud cover, rain, humidity and geomagnetic storms. Goetzmann and Zhu (2005) included cloud cover, rain and snow, and Theissen (2007) used cloud cover, sunshine, rain and temperature. Other papers extended the analysis to market segments other than the stock market. E.g. Keef and Roush (2007) integrated fixed income securities into the analysis, also investigating government bonds and bank bills. Symeonidis et al. (2010) analyzed the correlation between weather variables, a SAD proxy and the stock market volatility. However, the impact of the weather on the financial market 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.

In this article, in contrast to existing literature we differentiate between a direct functional chain, where weather and SAD have a direct impact on financial market variables, and an indirect functional chain, where weather and SAD influence mood and mood in turn influences financial market variables. The psychological literature, presented and discussed in Section 2, supports the indirect functional chain. Depending on the assumption on the functional chain, different econometric approaches are appropriate: With the direct chain, when sticking to a linear relationship (and to the assumption that the noise term of the regression is also uncorrelated with the control variables used) least squares estimation can be performed. With the indirect chain, however, we have to handle the fact that the investors' mood(s) cannot be observed but mood is a latent variable. Section 4 analytically demonstrates that in this case the presence of weather and SAD related mood effects creates correlation between some regressors (other financial market variables) and the noise term (*regressor endogeneity*). Therefore, ordinary least squares (OLS) estimation results in inconsistent estimates. As an alternative, we suggest and use instrumental variable estimation. Existing Behavioral Finance literature, e.g. Saunders (1993) and Hirshleifer and Shumway (2003), motivates weather effects by an indirect mechanism but applies OLS in their empirical analysis. This approach can be interpreted as an approximation of the indirect chain by means of a direct chain.

Whereas many existing papers on weather/SAD effects focus on *one* financial market segment (e.g. stock index returns), this article investigates weather and SAD related mood effects on a variety of financial sub-markets, represented by risk-free interest rates, two US corporate bond indexes, yield spreads of individual US corporate bonds, the S&P 500 returns, individual stock returns and the VIX volatility index. The reason why we look at many financial market segments is described as follows: On the financial market all sub-markets are related to each other by supply and demand (e.g. changes in the risk attitudes of market participants result in supply and demand shifts between different market segments). Our analysis in Section 4 will demonstrate that with this interdependence of different sub-markets and the presence of weather/SAD effects a joint analysis combined with instrumental variable estimation yields consistent parameter estimates if one includes the other financial market variables as regressors in the weather/SAD regressions.[1]A careful interpretation of weather/SAD effects in one sub-market requires the knowledge of the impact of weather/SAD on all the regressors (i.e. also on the other financial sub-markets). Thus, it is not sufficient to analyze weather/SAD effects only for one market segment alone.

This paper shows that the finding of weather/SAD effects is strongly driven by the assumption about the chain of causality between weather/SAD and financial market variables. Assuming, as an *approximation* of the indirect effects model, a *direct* relationship between weather/SAD and financial market variables (and assuming that the noise term and the control variables are uncorrelated), the resulting least squares estimation (where weather and SAD variables are used as regressors) with least squares standard errors shows many significant weather and SAD effects. Adjusting these least squares estimates for heteroscedasticity in the noise reduces the number of significant weather and SAD variables. However, we still observe some weather and SAD effects. As mentioned above, according to psychological literature, it is more plausible to assume that weather and SAD do *not directly* influence asset prices, but weather and SAD influence the mood and this (latent) mood variable has an impact on asset prices. Explicitly modeling this indirect relationship and performing instrumental variable estimation, this estimation shows some weather (but no SAD) effects. Also, we find that

[1]E.g. we shall demonstrate that if the mood is driven by some weather/SAD variable and mood affects asset prices, then the financial market variables are correlated with this weather/SAD variable. We also show that this effect results in correlation between the regression residual and the financial market variables used as control variables. Section 4 moreover shows that omitting these financial market variables as control variables results in biased least squares estimates, since the regression residual is then correlated with the weather/SAD variables ("omitted variables problem"). Although in general any variable correlated with the explanatory variables but uncorrelated with the noise term can be used as an instrument our analysis shows that including financial market variables as controls and their lagged values as instruments is an appropriate way to cope with regressor endogeneity in our model.

different weather variables have a different effect on the various financial market segments. Moreover, our estimates support the claim that different market segments are related to each other. This interdependences implies that when analyzing weather/SAD effects one cannot focus on individual financial market segments (as often done in the Behavioral Finance literature) but one needs a comprehensive model including all market segments. Using such a comprehensive model is another major innovation of our paper.

The significant weather variables inferred by the approximation of the indirect effects via direct effects deviate from the weather variables resulting from the explicit indirect modeling. Thus, this paper shows that an approximation of the indirect link via mood by a direct effects model as often done implicitly in the Behavioral Finance literature, leads to an interpretation of inconsistent and biased parameter estimates.

Another innovation of this paper is that we show how to convert the regression parameters relating the significant weather variables to different financial market segments into parameters showing the link between the mood components and the financial market segments. We provide estimates how actual mood components affect the financial market.

The paper is structured as follows: Section 2 presents findings from psychological literature on the relationship between weather/SAD and mood as well as mood effects, e.g. on risk aversion. In Section 3 we describe the data used in our study. In Section 4 we discuss how mood influences asset prices, returns, yields and volatilities. Section 5 outlines the methodology and describes our results. Finally, Section 6 concludes.

2 Mood and Mood Effects

This section covers the multi-dimensionality of mood, the influence of weather on mood, the relationship between SAD and mood and the effects of mood. Many previous studies in the psychological literature used for mood a single one-dimensional scale. E.g. Keller et al. (2005) and Forgas et al. (2009) use a one-dimensional "mood valence" measure ("positive mood" subtracted by "negative mood") where the mood is the better the higher the "mood" score. This approach assumes that all positive moods or all negative moods are more or less equivalent. However, Raghunathan and Pham (1999), among others, show that this is not the case.

Other authors have used multi-dimensional mood measures: Griffitt (1970) used a multidimensional mood scale meaasured by a "Mood Adjective Check List" (including e.g. "elation", "surgency" and "social affection" as mood components). Sanders and Brizzolara (1982) used three mood variables, namely "vigour", "social affection" and "elation". Denissen et al. (2008) differentiated between "positive affect" (measured by the items "active", "alert", "attentive", "determined", "enthusiastic", "excited", "inspired", "interested", "proud", and "strong"), "negative affect" (measured by the items "afraid", "scared", "nervous", "jittery", "irritable", "hostile", "guilty", "ashamed", "upset" and "distressed") and "tiredness" (measured by "sleepy", "tired", "sluggish", "drowsy", "quiet" and "still"). Kööts et al. (2011) used the mood components "positive affect" (including the sub-components "happy" and "surprised"), "negative affect" (containing "anger", "contempt", "disappointed", "disgust", "fear", "irritated" and "sad") and "Fatigue" (including "tired" and "sleepy"). In an extensive study, Howarth and Hoffman (1984) used ten mood components, namely concentration, cooperation, anxiety, potency, aggression, depression, sleepiness, scepticism, control and optimism and checked the influence of eight weather variables on these mood components.

Many authors show that the different mood components have different determinants or identical determinants but different directions. E.g. Goldstein (1972) and Howarth and Hoffman (1984) show that their various mood components are influenced by the weather variables in different ways (concerning extent and direction). Arguments in favor of using multiple mood variables instead of a global mood measure are described e.g. in Howarth and Hoffman (1984) who write on page 22, "The use of a multiple mood instrument reveals specific mood and weather relationships that are obscured when global measures, such as positive and negative mood, are employed." and "for a comprehensive analysis of the relationship between weather, mood and behavior, a multidimensional approach should be adopted in future studies".

Besides weather, seasonal affective disorder (SAD) has been introduced into the Behavioral finance literature by Kamstra et al. (2003), Garrett et al. (2005), Kamstra (2005) and Kamstra et al. (2009). The existing literature uses several SAD proxies to investigate the impact of SAD on the financial market. The first type of SAD proxy is the respective number of hours of daylight (e.g. Kamstra et al. (2003)). More recent literature uses a variable representing the onset of and recovery from seasonal depression (see Kamstra et al. (2012)). While for the first type of proxy a causal impact between the length of the day and mood can be assumed, the second type can be rather interpreted as a proxy for mood. The econometric treatment of both cases is equivalent.

Mood, in turn, can have an impact on the individuals' accuracy and quality of decision-making (see Au et al. (2003)), optimism (see e.g. Cunningham (1979), Howarth and Hoffman (1984), Arkes et al. (1988) or Wright and Bower (1992)), perception of risk as well as overconfidence (Johnson and Tversky (1983), Arkes et al. (1988) or Au et al. (2003)) and risk aversion. Concerning the impact of mood on risk aversion, there are two alternative hypotheses in the psychological literature: The *affect infusion model* (see e.g. Forgas and Bower (1987) or Forgas (1995)) postulates that an improvement in mood reduces the risk aversion. 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 mood increases the risk aversion (in order to maintain the positive mood).

The impact of mood on decision-making may also depend on the situation. Forgas (1995) argued that higher complexity and uncertainty strengthens 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.

Summing up, even though the weather and seasonal affective disorder hardly affect (most) asset fundamentals, they may have an impact on asset prices via mood. Mood should be considered as a multivariate variable. Psychological literature supports the claim that on the one hand the vector of mood components is related to the weather and SAD and on the other hand mood has an impact on the financial market. Thus, for later purposes we keep in mind that for both the weather and the SAD proxy (weather/SAD in the following) there is an indirect relationship between weather/SAD and the financial market via mood. When testing the impact of the weather and SAD on asset prices via mood, the fact that mood can hardly be observed also creates an econometric problem. This problem will be discussed in Section 4 after describing our data.

3 Data

This study investigates the period from July 1, 2002 to March 31, 2006.[2] We use daily data from the US market. Excluding holidays and weekends the observation period includes $T = 952$ days with data.

In addition to aggregated data often used in literature (e.g. stock indexes), we also use data from individual stocks and bonds. This is for the following reasons: First, by including this data it might be possible to detect (additional) weather and SAD effects on a more disaggregated level. The second argument deals with the efficiency of the estimates: Working with panel data, as done in our regressions on a disaggregated level, is often motivated by an increase in the efficiency of the estimates. Increasing the volume of data in the time series dimension requires the assumption of stationary data, which with financial data is often a strong assumption. As an alternative, by using panel data we increase the volume of data in the cross-sectional dimension. Moreover, for the individual stocks and bonds additional control variables can be applied, which should have a further positive impact on the efficiency

[2]Note that on purpose we used only data before the financial crisis 2007/08 because it is very plausible that during this tremendous financial crisis fundamental and non-weather/SAD related behavioral effects may have dominated any weather/SAD-related mood effects. In addition, the assumption of stationary time series is a problem when data before and within the financial crisis are considered.

of our estimates. Appendix A provides a detailed description of the data. The most important aspects will be described below:

Risk-Free Term Structure: In this paper we use the risk-free term structure as a dependent variable when analyzing the risk-free market segment, as a control variable when analyzing the other market segments and as a component when deriving the corporate bond spreads. Based on data for a selected set of equidistant risk-free rates we fitted the Svensson (1994) polynomial. This enabled us to obtain the risk-free spot rate for any arbitrary maturity. These spot rates were used when calculating the corporate bonds spreads. For more details on this step we refer the reader to Appendix A.1.

In the regressions for the risk-free market segment we use as dependent variable a vector that includes a selection of spot rates for the maturities $\{1/12, 1/4, 1/2, 1, 2, 5, 7, 10, 15, 20, 30\}$ years. This vector will be abbreviated by r_F.

In the regression models for the other market segments we use the level of the risk-free term structure as control variable. We include as control variable not the whole vector of the risk-free spot rates, r_F, but only the rate with a maturity of two years, in order to have parsimonious models. This rate will be symbolized by $r_{F2,t}$. Based on the unit root tests[3] we will use the first difference, symbolized by $\Delta r_{F2} = r_{F2,t} - r_{F2,t-1}$.

Corporate Bond Spreads: 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. After excluding bonds with low liquidity we ended up with $N = 179$ bonds issued by 23 firms. Due to missing values (e.g. not all bonds were traded on all days within the time span considered) the number of observations is smaller than the number of bonds times the number of days, however more than 80,000 observations entered into our empirical analysis.

For each of these corporate bonds and for each day we obtained the prices from the TRACE database. Use of the TRACE database involves the benefit that all prices in our study are

[3]These tests are available from the authors on request.

based on real transactions. So we did not have to use a matrix algorithm (see Sarig and Warga (1989)) or prices computed in any way by database providers. From the bond prices we derived the yield spreads as follows: 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 corporate 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 above) and, based on that, its yield to maturity. The corporate bond spread is the difference between the two yields. By using the fictitious risk-free bond with the same cash flow structure we can eliminate coupon effects. For more details we refer the reader to Appendix A.2

Corporate Bond Indexes: We use the "'MOODY'S YIELD ON SEASONED CORPORATE BONDS - ALL INDUSTRIES Aaa" index and the "MOODY'S YIELD ON SEASONED CORPORATE BONDS - ALL INDUSTRIES Baa" index. These indexes show the (unweighted) average of yields of industrial bonds, with remaining maturities as close as possible to 30 years and current outstandings over \$ 100 million, that obtained the respective rating from Moody's. Bonds are eliminated from these indexes if the remaining life falls below 20 years, if the bond is susceptible to redemption or if the rating changes. Both indexes are denominated in "percent per year". The data is obtained from the FED H 15 webpage. These indexes will be abbreviated by $\mathbb{I}_{Aaa,t}$ and $\mathbb{I}_{Baa,t}$, respectively.

Stock market and option market data: For the 23 firms representing the issuers in the bond sample (see Appendix A.2) we collected the corresponding daily stock prices and calculated the daily ex-post stock returns STR (measured in percentage terms). 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), $SPRETURNS$. Furthermore, as will be described later we use the daily returns of the DAX and the NIKKEI indexes (as instruments). In addition, we consider the VIX volatility index, which measures the implied volatility of at-the-money put and call options on the S&P 500. This index is also interpreted as "investor fear gauge" (measuring the fear of a future increase in stock market volatility; see Whaley (2000)).

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, many 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 that stocks are primarily traded 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).

Therefore, we restrict our analysis to the weather in New York.[4] More precisely, we select

[4]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 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.

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 e.g. Saunders (1993), Krämer and Runde (1997), Hirshleifer and Shumway (2003) and Cao and Wei (2005).

The weather data consists of the variables $CLOUDCOVER$, $VISIBILITY$, $TEMP_{DS}$ (deseasonalized temperature), $PRECIPITATION$, $BAROPRESS$ (barometric pressure), $HUMIDITY$ and $WINDSPEED$. For more details (including a motivation of each weather variable, precise definitions and a discussion of deseasonalization issues) see Appendix A.3. In addition to these weather variables we define $TEMPDY_t = TEMP_{DS,t} \times \mathbf{1}_{\{Temp_t \geq median(Temp)\}}$; where $\mathbf{1}_{\{Temp_t \geq median(Temp)\}}$ is equal to one if the temperature on day t is equal to or above the median temperature for our observation period. 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 when the temperature is low compared to periods when the temperature is high (e.g. "a positive $TEMP_{DS}$ in the winter improves the mood since it is not so cold" while "a positive $TEMP_{DS}$ in the summer deteriorates the mood since it is even hotter").

SAD: As already mentioned in Section 2, some literature (e.g. Kamstra et al. (2003)) uses the number of hours of daylight as a proxy for the SAD variable. Instead, Kamstra et al. (2012) suggest using for SAD studies a variable representing the onset of and recovery from seasonal depression. We follow this suggestion and include the *Onset and Recovery* data available from the webpage of Mark Kamstra (*http://markkamstra.com/data.html*) as the SAD variable.

Additional Control Variables: In our corporate bond spread panel regression 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). Based on the unit root tests we will use the first difference, symbolized by $\Delta DD_t = DD_t - DD_{t-1}$. In addition, 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 use liquidity proxies as potential determinants. We use the time to maturity of the respective bond on the specific day, denoted as TM, following Amihud and Mendelson (1991), and the daily trading $VOLUME$ (as a proxy, since in the TRACE data base volumes beyond 5,000,000 are just listed as ">5,000,000").

In the regressions for the individual stocks we include the 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 (see $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french$).

Moreover, in all regressions we use a Monday dummy ($MONDAY$) that has the value 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. 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 quite common 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)).

4 Mood and Financial Market Variables

Asset pricing models including mood effects are provided by Shu (2010) and Frühwirth and Sögner (2013). Shu (2010) provides comparative statics for some parameters, which are considered to change with mood in a Lucas type model. Frühwirth and Sögner (2013) establish sufficient conditions for a positive/negative impact of mood on asset prices in a general equilibrium model. By contrast, this article provides an empirical analysis of weather and SAD related mood effects. As already mentioned, we shall study different financial market variables. Imagine that current mood has an impact on current asset prices: As the risk-free interest rates, the corporate bond yields/spreads and the corporate bond indexes are defined in a forward looking way, the current mood has an impact on the current risk-free rates and corporate bond yields (indexes). For the stock returns and the stock index returns, the issue is more tricky, since stock returns are ex-post returns

$$r_{it} = \frac{p_{it} - p_{i,t-1}}{p_{i,t-1}} \ , \tag{1}$$

where t is the time index and p_{it} and $p_{i,t-1}$ are the current and the most recent stock price realization. From equation (1) we see that the ex-post return r_{it} is driven by both the actual mood and the previous day's mood. Therefore, the actual and the lagged weather/SAD should be used in the empirical analysis. The volatility index VIX is another forward looking variable, i.e. here it is sufficient to work with the current weather/SAD variables.

According to the psychological literature described in Section 2, weather and SAD have an indirect influence on the financial market via mood. For an empirical study that wants to test any weather/SAD effects on the financial market, this means that actually one should consistently model an indirect impact. This way could be considered as cumbersome. Alternatively, one could take recourse to a simplification, as often used in the Behavioral Finance literature, namely to econometrically ignore the indirectness and instead *assume* a direct effect of weather/SAD on the financial market. Many existing weather/SAD papers base their econometrics on this simplification. Later in this section we will analyze if this approximation of a world with indirect effects by a model with direct effects creates a problem (i.e. economic/econometric inconsistencies). To do this, we first present, for didactical reasons, the direct effects model, where weather/SAD have a direct impact on the financial market variables and the econometric estimation is performed in line with this assumption. Second, we describe a model with indirect effects of weather/SAD on the financial market via a latent variable mood, with the econometric estimation being performed in line with this assumption. Finally, we investigate for a world with indirect effects of weather/SAD on the financial market the impact of the approximation of indirect effects by direct effects (i.e. the simplification mentioned above).

4.1 The Direct Effects Model

We start with the econometric model that assumes a direct impact of the weather and SAD variables on the financial market variables. In the following, T is the time series dimension and N is the cross-sectional dimension, i.e. $t = 1, \ldots, T$ and $i = 1, \ldots, N$. y_{it} stands for one of the dependent financial market variables studied. w_t represents a k_w dimensional vector containing weather/SAD variables. Throughout the analysis we consider w_t as a strictly exogenous variable (for a definition see e.g. Davidson and MacKinnon (1993)). For all forward looking variables (interest rates, corporate bond spreads, corporate bond index, VIX) the current w_t is included, while for all ex-post returns (S&P and individual stock returns), where both w_t and w_{t-1} could affect the returns via p_t and p_{t-1}, the current and the lagged w_t have to be used. c_{it} represents a vector containing the control variables. Based on these considerations we obtain:

Assumption 1 (Direct Effects Model)**.** *The financial market variables y_{it}, the control variables c_{it} and the weather/SAD variables w_t are related in the following way:*

$$y_{it} = \begin{cases} \alpha_i + w_t^\top \beta_w + c_{it}^\top \beta_c + \varepsilon_{it} & \textit{if } y_{it} \textit{ is a forward looking variable} \\ \alpha_i + (w_t^\top, w_{t-1}^\top)\beta_w + c_{it}^\top \beta_c + \varepsilon_{it} & \textit{if } y_{it} \textit{ is an ex-post return} \end{cases} . \qquad (2)$$

β_w is a k_w dimensional vector of regression parameters with the model for the forward looking variables (alternatively a $2k_w$ dimensional vector of regression parameters with the models for ex-post returns) measuring the impact of weather/SAD on the financial market variable y_{it}. β_c is a vector of regression parameters measuring the impact of the control variables on the financial market variables, with dimension equal to the number of controls, k_c, for this

financial market variable. y_{it}*,* ε_{it} *and* α_i *are scalars.* ε_{it} *is iid and has an expectation of zero.*

The parameters α_i can be treated as *fixed effects*, as a random variable (*random effects model*) or equal for all assets i (*pooled model*). For 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. We stress that the pooled setting puts a lot of structure on the intercept that may not be justified by the data.

If *all* conditions of Assumption 1 are satisfied, consistent estimates of β_c and β_w can be obtained by means of ordinary least squares estimation.[5] If the noise term ε_{it} is not homoscedastic but still uncorrelated with the regressors c_{it}, w_t and w_{t-1}, then β_c and β_w can still be estimated by ordinary least squares, but some robust standard errors should be used to account for the heteroscedastic innovations. In the following we shall use White (1980) standard errors.

4.2 The Indirect Effects Model

In contrast to Assumption 1, the psychological literature presented in Section 2 supports the claim that weather and SAD have an impact on different mood components. In the following, for ease of wording, "mood" stands for the vector of mood components μ_t. The dimension of μ_t is k_μ. According to the psychological literature (see Section 2), mood in turn could affect the agents' risk aversion as well as their optimism and risk assessment, i.e. the perceived expected payoff could rise and the perceived variance could decreases with improving mood. Hence, a mood effect on financial market variables can be expected. In the empirical analysis the investors' moods can hardly be observed. An empirical study on an individual level would

[5] In the data set investigated in this article, when panel data are considered the time series dimension T will be larger than the cross-sectional dimension N. Based on this, when the asymptotic properties of the estimators are considered we assume that N is fixed and $T \to \infty$; for more technical details we refer the reader to e.g. Ruud (2000), Wooldridge (2001), Hsiao (2003) and Baltagi (2008).

require for each investor daily data including his transactions and his mood (e.g. captured by mood diaries as often used in psychological literature, see e.g. Denissen et al. (2008)). This data is not available. Moreover, self-reported mood can be biased (for this argument see Denissen et al. (2008), p. 667). Therefore, we consider mood as a latent variable.

In this paper we restrict our analysis to an investigation of *weather and SAD related* mood effects.[6] For the financial market variables considered, we assume that the fundamentals are not influenced by the weather and SAD variables.[7] Based on this discussion we can expect a relationship as presented in Figure 1.

$$\begin{aligned} y_{it} = g(&\text{Mood Variables, Control Variables}) + \text{Noise } \varepsilon_{it} \\ &\Uparrow \\ &\text{Mood Variables} = f(\text{Weather / SAD Variables}) + \text{Noise } \eta_t \end{aligned}$$

FIGURE 1. Assumed relationship between mood (μ_t), weather / SAD (w_t), control variables c_{it} and the financial market variable y_{it}. $g(.)$ and $f(.)$ symbolize functions.

It is important to note that y_{it} is influenced by the current mood μ_t for all forward looking financial market variables, while for the ex-post stock and stock index returns y_{it} is influenced by the current mood μ_t and the lagged mood μ_{t-1}. Based on these psychological arguments we get:

Assumption 2 (Indirect Effects Model)**.** *The relationships in Figure 1 are described by the*

[6] Of course, *other* mood effects like the impact of sports events and the movie program may still arise. Note that for the econometric analysis carried out in Section 5 it is sufficient for the other mood determinants to be uncorrelated with the variables weather, SAD and the other control variables. In terms of Assumption 2 these other mood determinants will be part of the noise term η_t in equation (3), where η_t and w_t as well as η_t and ε_{it} are uncorrelated. For the results of sports events and the movie program this seems to be a plausible assumption.

[7] Since no agricultural firms or utilities are included in the data set, this assumption seems plausible.

linear system

$$\begin{aligned} y_{it} &= \begin{cases} \alpha_i + \mu_t^\top B_w + c_{it}^\top \beta_c + \varepsilon_{it} & \textit{if } y_{it} \textit{ is a forward looking variable} \\ \alpha_i + (\mu_t^\top, \mu_{t-1}^\top) B_w + c_{it}^\top \beta_c + \varepsilon_{it} & \textit{if } y_{it} \textit{ is an ex-post return} \end{cases} \\ \mu_t &= A_w w_t + \eta_t \ . \end{aligned} \tag{3}$$

B_w is a k_μ dimensional vector of regression parameters with the model for the forward looking variables (alternatively a $2k_\mu$ dimensional vector of regression parameters for the ex-post returns) measuring the impact of mood on the financial market variable y_{it}. A_w is a $k_\mu \times k_w$ matrix describing the impact of the weather/SAD variables on the vector of the different mood variables. β_c is a vector of regression parameters measuring the impact of the control variables on the respective financial market variable, with dimension equal to the number of controls k_c. η_t is a stochastic vector of dimension k_μ. y_{it}, ε_{it} and α_i are scalars. Since mood is only measurable on an ordinal scale (an example of mood measurements is e.g. provided in Howarth and Hoffman (1984)), we did not include any intercept when modeling mood.

The noise terms ε_{it} and η_t have an expectation of zero. In addition, ε_{it} and η_t are independent, i.e. $\mathbb{E}(\varepsilon_{it}\varepsilon_{js}) = 0$ and $\mathbb{E}(\eta_t\eta_s) = 0$ for all $t \neq s$ or $i \neq j$.

Assumption 2 implies that both the relationship between the weather/SAD variables and mood and the relationships between mood and the financial market variables are linear. The reader should note that by the strict exogeneity of w_t, the variable w_t is uncorrelated with all η_s and ε_{is}, $s \in \mathbb{Z}$. To increase the flexibility, Assumption 2 allows correlation between ε_{it} and some components of c_{it} (i.e. regressor endogeneity). This includes e.g. correlations between the noise and some controls due to the interdependence of the financial sub-markets. In addition, we implicitly assume that each explanatory variable affects the whole cross section y_{it}, $i = 1, \ldots, N$, in the same linear way. With Assumption 2 we get[8]

[8]With the individual stock returns Fama-French factors will be added (see equation (9)).

$$y_{it} = \begin{cases} \alpha_i + w_t^\top A_w^\top B_w + c_{it}^\top \beta_c + \eta_t^\top B_w + \varepsilon_{it} & \text{if forward looking} \\ \alpha_i + (w_t^\top, w_{t-1}^\top)\left(\mathbf{I}_2 \otimes A_w^\top\right) B_w + c_{it}^\top \beta_c + (\eta_t^\top, \eta_{t-1}^\top) B_w + \varepsilon_{it} & \text{if ex-post return} \end{cases}$$

$$= \begin{cases} \alpha_i + w_t^\top \beta_w + c_{it}^\top \beta_c + v_{it} & \text{if } y_{it} \text{ is a forward looking variable} \\ \alpha_i + (w_t^\top, w_{t-1}^\top)\beta_w + c_{it}^\top \beta_c + v_{it} & \text{if } y_{it} \text{ is an ex-post return} \end{cases} . \tag{4}$$

The vector β_w measures the indirect impact of weather/SAD on the financial market variable. In more detail: For the forward looking variables, $\beta_w = A_w^\top B_w$ is a k_w dimensional vector. In the case of ex-post returns $\beta_w = \left(\mathbf{I}_2 \otimes A_w^\top\right) B_w$ is a $2k_w$ dimensional vector. $\mathbf{I}_2$ stands for the two dimensional identity matrix and $\otimes$ stands for the Kronecker product. Note that $\left(\mathbf{I}_2 \otimes A_w^\top\right)$ simply transforms the $k_w \times k_\mu$ matrix $A_w^\top$ to a $2k_w \times 2k_\mu$ blocked matrix, where the blocks in the north-west and in the south-east are $A_w^\top$ and the other elements are zero. Moreover, $v_{it} = \eta_t^\top B_w + \varepsilon_{it}$ for forward looking variables, while $v_{it} = (\eta_t^\top, \eta_{t-1}^\top) B_w + \varepsilon_{it}$ for ex-post returns. When the parameters are estimated by least squares, v_{it} and the regressors w_t and c_{it} have to be uncorrelated to obtain consistent estimates. As already discussed before, it is plausible to assume that v_{it} and w_t are uncorrelated since the weather/SAD is exogenous. By contrast for the controls c_{it} and v_{it} this is more difficult to justify. The following example motivates why this orthogonality assumption is hard to justify, especially if the weather/SAD has an indirect effect on y_{it} and shows that an *approximation of indirect effects by direct effects* results in inconsistent estimates:

Example 1 (Indirect Effects and Regressor Endogeneity)**.** *We consider an economy with two sub-markets, where the financial market variable y_{1t} in sub-market 1 affects y_{2t} on the financial sub-market 2 and vice versa. In addition, we assume that both assets are influenced by mood. For simplicity the intercepts α_i are zero, $k_\mu = k_w = 1$ and $N = 1$; both variables y_{1t} and y_{2t} are forward looking. To keep it simple, the only control variable in the y_{1t} equation is $c_{1t} = y_{2t}$, and in the y_{2t} equation the only control variable is $c_{2t} = y_{1t}$. The term $A_w = 1$. Given these* *assumptions we obtain $B_{w1} = \beta_{w1}$ and $B_{w2} = \beta_{w2}$. Then based on equation (3) we obtain*

$$\begin{aligned} y_{1t} &= \beta_{w1}\mu_t + \beta_{cy1}y_{2t} + \varepsilon_{1t} \ , \\ y_{2t} &= \beta_{w2}\mu_t + \beta_{cy2}y_{1t} + \varepsilon_{2t} \ , \\ \mu_t &= w_t + \eta_t \ . \end{aligned} \tag{5}$$

Plugging in $\mu_t = w_t + \eta_t$ in the y_{1t} and y_{2t} equations yields

$$\begin{aligned} y_{1t} &= \beta_{w1}(w_t + \eta_t) + \beta_{cy1}y_{2t} + \varepsilon_{1t} = \beta_{w1}w_t + \beta_{cy1}y_{2t} + [\beta_{w1}\eta_t + \varepsilon_{1t}] \qquad (6) \\ &= \beta_{w1}w_t + \beta_{cy1}y_{2t} + v_{1t} \ , \\ y_{2t} &= \beta_{w2}w_t + \beta_{cy2}y_{1t} + [\beta_{w2}\eta_t + \varepsilon_{2t}] = \beta_{w2}w_t + \beta_{cy2}y_{1t} + v_{2t}. \qquad (7) \end{aligned}$$

Based on equation (6) we observe that even if y_{2t} and ε_{1t} are uncorrelated ($\mathbb{E}(\varepsilon_{1t}y_{2t}) = 0$), the term $v_{1t} = \beta_{w1}\eta_t + \varepsilon_{1t}$ is correlated with the regressor y_{2t} since both v_{1t} (see equation (5)) and y_{2t} (if $\beta_{w2} \neq 0$, see equation (7)) depend on η_t via μ_t. Therefore, in the indirect effects model a correlation exists between the regression residual v_{1t} and the regressor y_{2t}. The same is true for the correlation between the regression residual v_{2t} and the regressor y_{1t}. Thus, estimating the equations (6) and (7) by ordinary least squares yields biased and inconsistent estimates. It is important to note that simply omitting the other financial market variable (e.g. omitting y_{2t} from the vector of control variables in equation (6)) does not solve this problem. To see this, consider the model

$$y_{1t} = \beta_{w1}w_t + \tilde{v}_{1t} \ , \ \text{where } \tilde{v}_{1t} = \beta_{cy1}y_{2t} + v_{1t} = \beta_{cy1}y_{2t} + \beta_{w1}\eta_t + \varepsilon_{1t} \ . \tag{8}$$

Since y_{2t} depends on w_t via μ_t (if $\beta_{w2} \neq 0$, see equation (7)), the regressor w_t and the noise term $\tilde{v}_{1t}$ are still correlated in this case (see equation (8)). Therefore, we are facing an omitted variable problem in equation (8). Moreover, to perform instrumental variable estimation we need instruments correlated with w_t but uncorrelated with $\tilde{v}_{1t} = \beta_{cy1}y_{2t} + \beta_{w1}\eta_t +$

ε_{1t}. *Imagine, there is an instrument correlated with* w_t*. Since* y_{2t} *is correlated with* w_t *as well, (see equation (6)), we observe that this (potential) instrument correlated with* w_t *is automatically correlated with* y_{2t}*. However, since* y_{2t} *is a component of* $\tilde{v}_{1t}$*, the noise term* $\tilde{v}_{1t}$ *is correlated with* w_t *and is therefore correlated with this potential instrument. Therefore, we cannot find any instrument for equation (8). Alternatively, by including* y_{2t} *as a regressor, instrumental variable estimation becomes feasible by using e.g.* $y_{2,t-1}$ *as an instrument.*

From this example we conclude that, if *indirect* weather/SAD effects exist with the financial market variables we obtain a further source of endogeneity. Therefore, with Assumption 2 an estimation technique taking into account endogeneity has to be used. In the following we will apply instrumental variable estimation, in particular two-stage least squares estimation.[9] As ordinary least squares does not care for endogeneity, OLS results in inconsistent estimates. Thus, the above-mentioned approximation of indirect effects by direct effects gives inconsistent estimates and should not be performed. In our empirical analysis in Section 5 we shall observe that this econometric issue significantly distorts the parameter estimates of the weather/SAD variables.

In addition, from the last paragraph of the example we conclude that a model of the form $y_{it} = w_t^\top \beta_w + \tilde{v}_{it}$, where the other financial market variables are ignored (instead of included as control variables), cannot be estimated consistently since the noise term $\tilde{v}_{it} = c_{it}^\top \beta_c + v_{it}$ is correlated with w_t (e.g. y_{2t} is an element of c_{1t}). Finding instruments correlated with w_t and uncorrelated with $\tilde{v}_{it} = c_{it}^\top \beta_c + v_{it}$ is impossible. By contrast, including the financial market variables as control variables, as done in equation (4), enables us to obtain consistent estimates of β_w by means of instrumental variable estimation.

[9] 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 the Finance literature we refer the reader to Roberts and Whited (2011). Higher order moment conditions on the noise terms and further regularity conditions e.g. such as the rank for the regressors, the rank condition for the instruments etc. are assumed to be satisfied when parameter estimation and inference are performed. Regarding these regularity conditions the reader is referred to the above textbooks.

5 Methodology and Results

5.1 Methodology

In the following, we investigate weather and SAD related mood effects on financial market variables by estimating (panel) regression models. We do this for the *indirect effects model*, described by Assumption 2, and to empirically see the difference between the correct econometric technique and the approximation of indirect effects by direct effects, for a *direct effects model* based on Assumption 1.

For the S&P returns, the corporate bond indexes and the VIX the cross-sectional dimension $N = 1$, while for the individual corporate bonds ($N = 179$), the individual stock returns ($N = 23$) and the risk-free rates ($N = 11$) we consider panel data. In each regression we use as control variables the (other) aggregate financial market variables (e.g. S&P 500 returns and VIX for the regression explaining the risk-free rates), the Monday dummy and the lagged dependent variable to account for possible serial correlation in the residual. In addition, for the individual corporate bond spreads we use the distance to default, the time to maturity and the trading volume as credit risk and liquidity proxies. For the risk-free rates, the individual corporate bond yield spreads, the corporate bond indexes, the S&P 500 returns and the VIX we use equations (2) and (4), in the direct and the indirect effects model respectively. By contrast, for the individual stock returns the regression coefficients for the S&P 500 returns are estimated on a firm-by-firm basis to include the fact that different firms bear different systematic risk. To be more precise, when assuming indirect effects the model

$$STR_{it} = \alpha_i + (w_t^\top, w_{t-1}^\top)\beta_w + c_{it}^\top \beta_c + (SPRETURNS_t, SMB_t, HML_t)\beta_{ci} + v_{it} \ , \qquad (9)$$

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. (1997)[Chapter 6]). The second and the third are the factor loadings for the Fama-French factors. Thus, equation (9) is a standard econometric implementation of an asset pricing model with additional weather/SAD variables included. For the direct effects model v_{it} is replaced by an ε_{it} which is assumed to be independent of the controls such that ordinary least squares can be applied. With the indirect effects model v_{it} and c_{it} are allowed to be correlated, which demands for instrumental variable estimation.

In a next step we check which specification for α_i in (2), (4) and (9) should be used when panel data is considered. We tested the 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 e.g. Ruud (2000)). 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, individual corporate bond spreads and individual stock returns) these tests favor the fixed effects model.[10] Therefore, only the results for the fixed effects regressions will be presented in the following.

Given the specifications above, we check for weather and SAD related mood effects in the following way:

1. First, we test whether there are effects in the aggregate market variables such as the risk-free interest rates, the corporate bond indexes, the S&P 500 index and the VIX

[10] Variables that remain constant or exhibit only little variation in the time series dimension cannot be used as regressors in a standard fixed effects setting. E.g. rating dummies exhibit very little variation over time. This implies that rating dummies cannot be used in our fixed effects regression as explanatory variable. Thus, possible effects arising from the rating are mostly included in the fixed effects α_i.

volatility index.

2. Afterwards we investigate the disaggregated level (individual corporate bond spreads and individual stock returns). Since the aggregate market variables are used as regressors on the disaggregated level, the interpretation of the results on the disaggregated level depends on the results for the aggregated market variables. If step 1 shows any effects on the market variables, any effects with the (firm-by-firm or bond-by-bond) disaggregated analysis have to be interpreted as *additional* effects. If no effects can be detected on the aggregate level, the regressions on the disaggregate level test for the existence of firm-specific/bond-specific effects on the disaggregated level. This ambiguous interpretation is one of the reasons why we study the impact of weather and SAD related mood on a multitude of financial sub-markets.

When dealing with the indirect effects model we have to comment on regressor endogeneity. Irrespective of our analysis in Section 4, regressor endogeneity arises from the fact that prices on different financial sub-markets, such as risk-free bonds, stocks, corporate bonds and options (VIX) need not be independent of each other. Moreover, we showed in Section 4 that with the indirect effects model weather and SAD effects create further regressor endogeneity. This also implies that some of the control variables have to be instrumented. E.g. if the VIX index is considered to be an endogenous regressor, we need an instrument for the VIX. Unfortunately, instrumental variable estimation is not as easy as ordinary least squares estimation since it requires "good instruments". With instrumental variable estimation, *weak instruments* result in large standard errors, which creates a problem when performing inference (see e.g. the discussions in Angrist and Pischke (2009)[Chapter 4] and Roberts and Whited (2011)). Due to its high serial correlation the lagged VIX provides us with a good instrument. Finding an instrument is more difficult with the S&P 500 returns and the first differences in the interest rate Δr_{F2} where the serial correlation is low. Here, we used the DAX and the NIKKEI index as instruments, because first stage regressions show that these variables are correlated with the S&P 500 and surprisingly also with Δr_{F2}. We apply *Hansen's J-test* (see Davidson and

MacKinnon (1993) and Ruud (2000)) to test whether $c_{i,t-1}, \ldots, c_{i,t-j}$ is still a valid instrument. According to this test we find out that a low number of instruments should be used. The instruments in the respective regressions will be provided in the captions of the corresponding tables.

5.2 Results

5.2.1 Approximation via Direct Effects

First, as much of the literature in Behavioral Finance implicitly uses the approximation of the indirect effects by a direct effects model, we present the results for this approximation. By using ordinary least squares estimates, ordinary least squares standard errors and significance levels of 5% or 10%, we observe:[11] (i) For the risk-free term structure precipitation, temperature, wind-speed and humidity have a significant impact (5% level) on the first differences in the risk-free interest rates r_F. Visibility is significant, as well, when applying a 10% significance level. (ii) For the S&P 500 returns the lagged barometric pressure is significant (5% level) and the current barometric pressure is significant at the 10% level. (iii) Concerning the VIX index the cloud cover shows a significant impact at the 10% level. (iv) Concerning the corporate bond indexes, for the Aaa bond index humidity is close to a 10% significance level and for the Baa index the p-value of humidity is 6.4%. (v) The individual corporate bond spreads are influenced by the barometric pressure and the SAD variable on a 5% level. (vi) The individual stock returns are influenced by the barometric pressure, the lagged visibility, SAD and the lagged SAD variable on a 5% level. For the lagged precipitation we observe a p-value of 6%.

Without having a closer look on the residuals or without being concerned whether the ordinary least squares assumptions are fulfilled, one might conclude that several weather variables significantly influence asset prices. Further investigations will take more care on these issues.

[11] The results in this subsection are available from the authors on request.

Heteroscedasticity and Robust Inference: 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 over the cross-section). To get a clearer picture, we estimated a fixed effects model, where the squared residuals were used as response variables, while only the α_i parameters were used as predictors. By checking whether in such a model a fixed effects specification is preferred over a pooled specification, we tested for heteroscedasticity.[12] The null hypothesis of this test implies that the squared residuals are the same across all the rates/spreads/returns/values 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. Therefore, inference based on ordinary least squares standard errors is distorted. Robust standard errors should be used instead.

With White (1980) standard errors we observe: (i) No significant effects of weather and SAD on the risk-free rates, (ii) p-values around 6% for the current and the lagged barometric pressure for the S&P 500, (iii) a p-value of 10.8% for the cloud cover with the VIX. (iv) For the corporate bond indexes, humidity is close to a 10% significance level with the Aaa bond index, and with the Baa index its p-value is 7%. (v) For the individual corporate bond spreads SAD is significant with a p-value of 9.5%. (vi) Regarding the individual stock returns the current barometric pressure is significant at a 9% level, while for the lagged precipitation we observed a p-value of 10.4%. Both the current and the lagged SAD variable have p-values around 1.5%. All the other p-values of the weather/SAD variables in these regressions are significantly larger than 10%. Altogether, there seem to be some weather/SAD effects.

[12] 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 paragraphs to find out if a fixed effects model, a random effects model or a pooled regression model is to be preferred for the risk-free rates, individual corporate bond spreads and the individual stock returns.

5.2.2 Indirect Effects Model

As already outlined in Section 4, if asset prices are influenced by a non-observable set of mood components that in turn are influenced by weather/SAD, instrumental variable estimation is to be preferred over OLS. The results of this estimation are presented in Tables 1 to 6. All p-values are based on White (1980) standard errors. By applying the "default" significance levels of 5% or 10%, the p-values in the fourth column suggest the following: (i) For the risk-free term structure the parameter for the deseasonalized temperature is significantly different from zero on a 10% significance level and humidity is significant on a 5% significance level. (ii) For the S&P 500 and the VIX the precipitation is significant at a 10% significance level. (iii) For the corporate bond indices the parameters β_w are neither significant on a 5% nor on a 10% level. Here the smallest p-value among the variables in w_t is about 11.4%. (iv) On the disaggregated level, i.e. for the corporate bond spreads and the stock returns the parameters are insignificant. Thus, there are no *additional* effects. The fixed effects α_i and the component-specific parameters 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 from prior applications of the CAPM. For the Fama-French factors we can observe significant parameters for most firms. Summing up, the econometric analysis based on Assumption 2 gives some empirical evidence for weather related mood effects but no significant SAD related mood effects. The absence of a SAD effect is in line with e.g. Kelly and Meschke (2010).

TABLES 1-6 ABOUT HERE

Comparing the results in Tables 1-6 to those in Section 5.2.1, we observe that with the indirect effects model other elements of the weather and SAD variables w_t are significant compared to the approximation by the direct model. As motivated in Section 2, psychological literature supports the indirect effects approach. Therefore, we consider the results obtained in this subsection as the more reliable ones. Therefore, the econometric problems raised in Section 4 turn into substantial differences regarding the parameter estimates and their significance.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0011	0.0013	0.4276
$VISIBILITY$	1.9E-7	8.4E-7	0.8218
$TEMP_{DS}$	-0.0025	0.0014	0.0798
$PRECIPITATION$	-0.0003	0.0003	0.3081
$BAROPRESS$	0.0004	0.0004	0.3543
$HUMIDITY$	0.0006	0.0003	0.0401
$WINDSPEED$	0.0009	0.0013	0.5103
$TEMPDY$	0.0017	0.0014	0.2234
SAD	0.0155	0.0151	0.3034
$MONDAY$	0.0008	0.0060	0.8883
VIX	-0.0077	0.0033	0.0184
$\Delta r_{F,t-1}$	-0.0730	0.0612	0.2330
$SPRETURNS$	0.0116	0.0069	0.0925

TABLE 1. Dependent variable: First differences in risk-free interest rates Δr_F in percentage terms, 2SLS Estimates, fixed effects model ($N = 11$ maturities, $T = 952$ days; 9,625 observations, intercept and fixed effects not reported). SE_W is the White (1980) adjusted standard error. Instruments: VIX_{t-1}, DAX_{t-1}, $NIKKEI_{t-1}$. The exogenous variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t and $MONDAY$.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	0.0766	0.0820	0.3504
$VISIBILITY$	4.9E-5	5.0E-5	0.3255
$TEMP_{DS}$	-0.4838	0.3384	0.1533
$PRECIPITATION$	0.0495	0.0276	0.0732
$BAROPRESS$	0.0013	0.0194	0.9485
$HUMIDITY$	0.0130	0.0145	0.3713
$WINDSPEED$	-0.1458	0.0995	0.1435
$TEMPDY$	1.0630	0.7446	0.1538
$CLOUDCOVER_{t-1}$	0.0607	0.0527	0.2499
$VISIBILITY_{t-1}$	2.4E-6	3.6E-5	0.9484
$TEMP_{DS,t-1}$	0.1829	0.1567	0.2435
$PRECIPITATION_{t-1}$	0.0047	0.0139	0.7371
$BAROPRESS_{t-1}$	-0.0096	0.0229	0.6743
$HUMIDITY_{t-1}$	-0.0142	0.0099	0.1508
$WINDSPEED_{t-1}$	0.0066	0.0558	0.9052
$TEMPDY_{t-1}$	-0.3361	0.2634	0.2024
SAD	6.0724	11.8101	0.6073
SAD_{t-1}	-6.1082	11.7697	0.6039
$MONDAY$	-0.0056	0.2921	0.9847
VIX	0.0113	0.0143	0.4291
Δr_{F2}	30.6583	5.1268	< 0.001
$SPRETURNS_{t-1}$	-0.1222	0.1561	0.4339

TABLE 2. Dependent variable: S&P 500 returns in percentage terms, 2SLS Estimates ($T = 952$ observations, intercept not reported). SE_W is the White (1980) adjusted standard error. Instruments: VIX_{t-2}, DAX_{t-1}, $NIKKEI_{t-1}$, $SPRETURNS_{t-2}$, $\Delta r_{F2,t-2}$. The exogenous variables are $CLOUDCOVER_{t-j}$, $VISIBILITY_{t-j}$, $TEMP_{DS,t-j}$, $PRECIPITATION_{t-j}$, $BAROPRESS_{t-j}$, $HUMIDITY_{t-j}$, $WINDSPEED_{t-j}$, $TEMPDY_{t-j}$, SAD_{t-j} where $j = 0, 1$ and $MONDAY$.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0074	0.0143	0.6059
$VISIBILITY$	8.6E-6	1.2E-5	0.4851
$TEMP_{DS}$	-0.0011	0.0194	0.9566
$PRECIPITATION$	0.0123	0.0070	0.0778
$BAROPRESS$	-0.0022	0.0040	0.5758
$HUMIDITY$	0.0007	0.0030	0.8102
$WINDSPEED$	-0.0107	0.0156	0.4929
$TEMPDY$	-0.0871	0.1552	0.5749
SAD	0.0158	0.0431	0.7137
$MONDAY$	0.5323	0.0819	< 0.001
VIX_{t-1}	0.9924	0.0057	< 0.001
Δr_{F2}	-0.7529	2.8954	0.7949
$SPRETURNS$	-1.2338	0.2420	< 0.001

TABLE 3. Dependent variable: VIX, 2SLS Estimates (T=952 observations, intercept not reported). SE_W is the White (1980) adjusted standard error. Instruments: VIX_{t-1}, DAX_{t-1}, $NIKKEI_{t-1}$, $\Delta r_{F2,t-1}$. The exogenous variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t and $MONDAY$.

In the next step we come to the interpretation of our two-stage least squares estimates in Tables 1-6. First, we can observe that there are neither weather nor SAD effects for corporate bond indexes or individual corporate bond spreads. Moreover, we observe that for different financial market segments different components of w_t have a significant impact. For example, the first differences of the risk-free rates, Δr_F, are significantly driven by the humidity (on a 5% level) and the (deseasonalized) temperature (on a 10% level, see Table 1). By contrast, the S&P 500 returns and the VIX do not significantly depend on humidity or deseasonalized temperature but on precipitation (on a 10% level, see Tables 2 and 3). Another source of complexity, making the results hard to interpret, is the fact that the financial market variables are permitted to depend on each other. Continuing the above example, the S&P 500 returns do not depend on humidity or deseasonalized temperature, however (among other variables) on the risk-free rate (which in turn depends on humidity and deseasonalized temperature). Thus, there is a second order effect of humidity and deseasonalized temperature on the S&P

	Bondindex Aaa			Bondindex Baa		
Variable	β_i	$SE_W(\beta_i)$	p-value	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-4.5E-5	0.0009	0.9584	-0.0006	0.0009	0.5139
$VISIBILITY$	4.9E-7	6.6E-7	0.4609	4.7E-7	6.7E-7	0.4814
$TEMP_{DS}$	-1.5E-5	0.0007	0.9831	-0.0001	0.0006	0.8816
$PRECIPITATION$	4.8E-5	0.0004	0.8968	0.0003	0.0004	0.4653
$BAROPRESS$	-0.0003	0.0002	0.2168	-0.0004	0.0002	0.1135
$HUMIDITY$	0.0002	0.0002	0.2708	0.0002	0.0002	0.1851
$WINDSPEED$	-1.2E-5	0.0009	0.9890	-0.0005	0.0008	0.5106
$TEMPDY$	0.0007	0.0009	0.4688	0.0008	0.0009	0.3874
SAD	-0.0012	0.0074	0.8657	-0.0001	0.0072	0.9932
$MONDAY$	0.0087	0.0040	0.0284	0.0080	0.0037	0.0336
VIX	0.0006	0.0005	0.1739	0.0009	0.0006	0.1356
Δr_{F2}	0.1919	0.0808	0.0178	0.1783	0.0872	0.0411
$SPRETURNS$	-0.0039	0.0151	0.7963	0.0050	0.0159	0.7529
$\mathbb{I}_{.,t-1}$	0.9832	0.0083	< 0.001	0.9828	0.0089	< 0.001

TABLE 4. Dependent variable: Corporate Bond Indexes $\mathbb{I}_{Aaa}$, $\mathbb{I}_{Baa}$, 2SLS Estimates ($T = 952$; intercept not reported). SE_W is the White (1980) adjusted standard error. Instruments: VIX_{t-1}, DAX_{t-1}, $NIKKEI_{t-1}$. The exogenous variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t and $MONDAY$.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0577	0.0773	0.4552
$VISIBILITY$	-2.2E-5	0.0001	0.6612
$TEMP_{DS}$	0.2633	0.3168	0.4059
$PRECIPITATION$	-0.0175	0.0185	0.3438
$BAROPRESS$	-0.0237	0.0169	0.1602
$HUMIDITY$	-0.0112	0.0181	0.5378
$WINDSPEED$	0.0651	0.1024	0.5252
$TEMPDY$	-0.5847	0.7791	0.4530
SAD	-0.3694	0.6407	0.5642
$MONDAY$	0.7112	0.3898	0.0681
VIX	0.2824	0.0448	< 0.001
ΔDD	-46.4337	44.0082	0.2914
TM	0.6069	0.2751	0.0274
Δr_{F2}	-10.3463	18.7710	0.5815
$SPRETURNS$	-0.5675	1.7898	0.7512
$s_{i,t-1}$	0.8049	0.0085	< 0.001
$VOLUME$	7.63E-8	3.55E-8	0.0315

TABLE 5. Dependent variable: 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. Instruments: VIX_{t-1}, DAX_{t-1}, $NIKKEI_{t-1}$, $SPRETURNS_{t-1}$, $\Delta r_{F2,t-1}$, $VOLUME_{t-1}$. The exogenous variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t and $MONDAY$.

Variable	β_i	$SE_W(\beta_i)$	p-value
$CLOUDCOVER$	-0.0287	0.0241	0.2345
$VISIBILITY$	-1.3E-5	1.4E-5	0.3342
$TEMP_{DS}$	0.1169	0.1161	0.3140
$PRECIPITATION$	-0.0040	0.0091	0.6589
$BAROPRESS$	0.0005	0.0046	0.9201
$HUMIDITY$	-0.0034	0.0039	0.3800
$WINDSPEED$	0.0243	0.0302	0.4224
$TEMPDY$	-0.2526	0.2447	0.3021
$CLOUDCOVER_{t-1}$	0.0098	0.0149	0.5122
$VISIBILITY_{t-1}$	4.6E-6	1.1E-5	0.6624
$TEMP_{DS,t-1}$	-0.0364	0.0954	0.7025
$PRECIPITATION_{t-1}$	0.0026	0.0025	0.3062
$BAROPRESS_{t-1}$	0.0023	0.0059	0.6968
$HUMIDITY_{t-1}$	-0.0028	0.0050	0.5670
$WINDSPEED_{t-1}$	0.0091	0.0183	0.6180
$TEMPDY_{t-1}$	0.0442	0.1982	0.8235
SAD	-3.4502	2.5603	0.1778
SAD_{t-1}	3.5166	2.5475	0.1675
$MONDAY$	-0.0410	0.0666	0.5378
VIX	0.0068	0.0044	0.1190
Δr_{F2}	1.1861	4.9571	0.8109
$STR_{i,t-1}$	-0.0134	0.0444	0.7633

TABLE 6. Dependent variable: Stock returns STR in percentage terms, 2SLS Estimates, fixed effects model (N = 23 stocks, T = 952; 19,928 observations; intercept, fixed effects and component-specific parameters (e.g. Fama-French factors) not reported). SE_W is the White (1980) adjusted standard error. Instruments: DAX_{t-1}, $NIKKEI_{t-1}$, VIX_{t-2}, $\Delta r_{F2,t-2}$. The exogenous variables are $CLOUDCOVER_{t-j}$, $VISIBILITY_{t-j}$, $TEMP_{DS,t-j}$, $PRECIPITATION_{t-j}$, $BAROPRESS_{t-j}$, $HUMIDITY_{t-j}$, $WINDSPEED_{t-j}$, $TEMPDY_{t-j}$, SAD_{t-j} where $j = 0, 1$ and $MONDAY$.

500 index via the risk-free rate. Similarly, as the risk-free rates depend on the S&P 500 returns (on a 10% level) as well as the VIX (on a 5% level) and these financial market segments in turn depend on precipitation, we have a second order effect of precipitation on the risk-free rates via the S&P 500 returns and the VIX. For the other financial market variables one can detect similar chains of arguments. This provides an argument against analyzing the impact of weather/SAD only for one market segment, e.g. the stock market index, without taking care of the interaction between different sub-markets.

Of course, technically, this complex interpretation could have been "streamlined" by reducing the number of weather/SAD variables in the regressions or by the unrealistic assumption that the different financial sub-markets are independent. Concerning the latter assumption, neither economic theory nor our regression results support this independence assumption. Concerning a possible ex-ante selection of weather and SAD variables (e.g. using only $CLOUDCOVER$, the most frequently used weather variable, and SAD), we must say that all the weather/SAD variables in our regressions have been used and shown to be significant in existing Behavioral Finance papers (see the introduction and Appendix A.3). Moreover, using various weather variables is also supported by the psychological literature. E.g. as described in Section 2, different weather variables can have different impacts on the components of mood (see e.g. Howarth and Hoffman (1984)). In addition, the significance of various weather variables in our regressions shows that it is not possible to ex-ante cut down the number of weather/SAD variables to just $CLOUDCOVER$ and SAD. As a further robustness check we also estimated the above models with two-stage least squares with w_t consisting only of $CLOUDCOVER$ and SAD. With this procedure we do not get any significant results. The fact that also the ordinary least squares estimation yielded different significant components of w_t for different financial market variables (see Section 5.2.1), is evidence against a potential claim of a spurious outcome caused by the econometric method used in this subsection. Summing up, these arguments support to work with a broad set of weather variables as done in our study, even though the results are more difficult to interpret.

One big advantage of the indirect modeling approach is that it enables to investigate the impact of the mood components on the various financial market variables. With the estimates for the indirect effects model, we obtained estimates of β_w, linking weather/SAD to the financial market. Complementing this by an analysis in the sake of Kööts et al. (2011), who estimated regressions of different mood components on various weather variables, one can construct the matrix A_w that measures the translation between the weather variables and the mood components. Given estimates of β_w and the matrix A_w, one can identify the matrix B_w, that shows how the significant mood components (elements of μ_t) affect the respective financial market variables. To the best of our knowledge this is the first paper that covers the quantification of the link between the mood components and the financial markets.[13]

To add some empirical evidence, Kööts et al. (2011) used the mood components "Positive Affect" (PA), "Negative Affect" (NA) and "Fatigue" and the weather variables temperature, humidity, barometric pressure and luminance. PA includes the sub-components "happy" and "surprised", NA contains "anger", "contempt", "disappointed", "disgust", "fear", "irritated" and "sad", and Fatigue includes "tired" and "sleepy". For the respective definitions and measurement scale of each component see Kööts et al. (2011). In a multivariate regression they showed that temperature affects all three mood components, humidity affects NA and PA, the barometric pressure is insignificant and luminance affects NA and Fatigue (with a 5% significance level). We use their estimates (on a 5% significance level) to construct parts of our matrix A_w (only parts of the matrix since some of our weather variables were not included in Kööts et al. (2011)). Consistent with this 5% significance level, we use our estimates of β_w on a 5% level which reduces the significant weather/SAD effects to the impact of the temperature on the risk-free rate. Based on β_w and the matrix A_w, we can identify B_w. This yields $B_w = (-1.25, -0.42, 0.21)^\top$ which can be interpreted as follows: An increase of PA in the

[13] In more formal terms, as can be seen from equation (4): If y_{it} is a forward looking variable, we obtain the k_μ dimensional vector B_w by means of $B_w = \left(A_w^\top\right)^+ \beta_w$ where $\left(A_w^\top\right)^+$ is the pseudo-inverse matrix. For the ex-post returns the $2k_\mu$ dimensional vector B_w is derived by means of $B_w = \left[\mathbf{I}_2 \otimes \left(A_w^\top\right)^+\right] \beta_w$ where $\mathbf{I}_2$ stands for the two dimensional identity matrix and $\otimes$ stands for the Kronecker product.

measurement unit of Kööts et al. (2011) decreases the risk-free rate by 1.25 percentage points, a rise in NA by 1 causes the risk-free rate to fall by 0.42 percentage points. An augmentation in Fatigue by one unit raises the risk-free rate by 0.21 percentage points. The magnitude of the mood effects is quite large. This goes back to the measurement of mood in Kööts et al. (2011) (see the descriptive statistics in their Table 2). An increase of one unit in PA, NA or Fatigue is a very large effect. The limitations of these results are as follows: We used in our regressions the deseasonalized temperature whereas Kööts et al. (2011) used the (non-deseasonalized) temperature. In addition, the methodology applied here implicitly assumes that the Kööts et al. (2011) results, that are based on a wide range of people, are representative of the respective asset market traders. Therefore these results should be interpreted as a first approximation.

5.3 Robustness Checks

In this section we want to add a few robustness checks. We start with some robustness check for the corporate bond spreads. First, we want to discriminate between bonds of different credit risk with the hypothesis in mind that a split of the sample could show that there are effects of different significance for bonds with different credit risk. The hypothesis could be that AAA bonds are less risky than bonds with an inferior rating (e.g. BBB bonds) and therefore are less exposed to mood effects. An analysis like this resembles Baker and Wurgler (2006) who show that investors' sentiment has a stronger impact on the pricing of stocks that exhibit higher risk. Note that such an effect should already show up with the bond indexes already discussed in Section 5.2. When considering Table 4 this presumed effect is hardly supported by the bond index data. Since more data points are available and additional control variables can be used with the individual bonds, this robustness check serves as an additional investigation of the claim that bonds with a better rating are less exposed to mood effects.

Hence, we constructed the regressors "weather/SAD variable$\times\mathbf{1}_{AAA}$" and "weather/SAD variable$\times\mathbf{1}_{BBB}$" (i.e. we included eighteen additional predictor variables; these variables can be considered as exogenous). $\mathbf{1}_{AAA_{it}}$ ($\mathbf{1}_{BBB_{it}}$) is an indicator variable which for time t and bond i has a value of one if bond i has the rating AAA (BBB) on day t, otherwise the value is zero. Estimating the model by two-stage least squares shows no additional significant mood effects.

Another robustness check involves lagged weather/SAD variables: Persinger (1975) detects an impact of the weather two days ago on the current mood. Consequently, we checked whether the lagged variables w_{t-2} and w_{t-3} also have an impact. However, with these specifications we can neither observe any improvements regarding the standard errors nor further significant weather/SAD effects.

6 Conclusions

In this study we investigated the possible impact of weather and SAD on the financial market. Corresponding to the psychological literature and the Behavioral Finance literature there is an *indirect* link between weather/SAD and the financial market caused by mood.

We show that, when analyzing the effect of weather/SAD on the financial market, the interdependence of different market segments and this indirect link create regressor endogeneity. We also suggest how to implement this indirect link econometrically in a consistent way using instrumental variable estimation. By consistently estimating such an indirect effects model, we observe no SAD related mood effects but some weather related mood effects on the financial market. Also, we find that different weather variables have a different effect on the various financial market segments. Moreover, we observe that neither the individual corporate bond spreads nor the corporate bond indexes are influenced by weather or SAD first order effects.

Moreover, our estimates show that the different market segments are related to each other. This creates second order weather/SAD effects. These second order effects on the one hand make the interpretation of the results more complex. On the other hand they show that when analyzing weather/SAD effects one should not focus on individual financial market segments but one needs a comprehensive model including all market segments. Using such a comprehensive model is another major innovation of our paper.

We also convert the regression parameters relating the significant weather variables to different financial market segments into a link between the mood components and these financial market segments.

Concerning aggregated market data vs. disaggregated bond-by-bond or stock-by-stock data, we show that an analysis of aggregated market data is sufficient and does not have to be complemented by an analysis of disaggregated data. The disaggregated analysis does not show any additional effects. This is an important finding justifying to some extent existing and future literature that neglects disaggregated data.

Approximating the indirect effects via direct effects (i.e. assuming a direct linear link between weather/SAD and financial market data), makes one use ordinary least squares estimation. With this approximation, however, variables other than with the consistent estimation technique turn out to be significant. Thus, the assumed interdependence structure between weather/SAD, mood and the financial market variables has an important impact on the question whether one finds weather/SAD effects on the financial market or not. According to the psychological literature the relationship between weather/SAD and the financial market is indirect via the mood. As this paper shows, an approximation of the indirect link via mood by a direct effects model, i.e. ignoring the latent variable between weather/SAD and the financial market as often done implicitly in the Behavioral Finance literature, leads to an analysis based on inconsistent and biased parameter estimates. E.g. the approximation shows effects of weather and SAD on the corporate bond market that cannot be confirmed by a consistent parameter estimation assuming an indirect link. Therefore, one should not perform the approximation but an approach like the one developed in this paper.

A Detailed Description of Data

A.1 Risk-Free Term Structure

With respect to the risk-free term structure data we used 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. All these swap rates are based on 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 obtained 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 yield spreads.

A.2 Corporate Bond Yield 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.

We 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. We further restricted the sample by eliminating bonds with embedded options (callable and puttable 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. 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), Bessembinder and Maxwell (2008), Bessembinder et al. (2009) or Bao et al. (2011). 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 we eliminated all transactions within the last year of the bond's life. This is in analogy to Elton et al. (2001), Eom et al. (2004) and Driessen (2005). As the intra-day 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 used 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 intra-firm comparisons of 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. Tables 7-10 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 7-10 ABOUT HERE

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. As already stated in the main text, 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 Appendix A.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 eliminates any coupon effects.

A.3 Weather Data

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. Cloud cover is also the weather variable most frequently investigated in the Behavioral Finance literature. In line with this, our first weather variable is cloud cover, denoted as $CLOUDCOVER$. Strong cloud cover is supposed to deteriorate the mood. 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

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 7

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 8

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 9

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 10

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 aggregate only the data measured between 7 a.m. and 5 p.m. This time frame is justified by the trading hours.[14] 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 a.m. to 5 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 was positively related to mood. By contrast, Griffitt and Veitch (1971) and Goldstein (1972) proposed that low temperature was linked to positive mood. Moreover, psychological literature (e.g. Baron and Bell (1976) or Baron and

[14] 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.

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. 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 a.m. to 5 p.m. This variable has been denoted as $TEMP$ (or $TEMP_{DS}$ for the deseasonalized version, see Section 3). As already mentioned in Section 3, we moreover define $TEMPDY_t = TEMP_{DS,t} \times \mathbf{1}_{\{Temp_t \geq median(Temp)\}}$; where $\mathbf{1}_{\{Temp_t \geq median(Temp)\}}$ is equal to one if the temperature on day t is equal to or above the median temperature for the total observation period.

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 was 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 a.m. and 5 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 asset 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 a.m. and 5 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 (see e.g. Hirshleifer and Shumway (2003), Loughran and Schultz (2004) or Goetzmann and Zhu (2005)) to capture the "unexpected" component of that day's weather. This works as follows, described at the example of the temperature variable: First, one computes the average temperature of each calender week as the average of the temperatures of all days during this calender week. Then one computes the "usual" temperature for each calender week of the year (week 1, week 2, . . . , week 52) as average of the observations for that particular week of the year during the sample. Finally, one computes 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.

In our study, we investigated if at all and which variables should be deseasonalized and how desaisonalization should be performed.[15] 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 and Natural Sciences 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. 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

[15] A detailed analysis is available on request.

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. Given the results of our deseasonalization investigation, in our study only the temperature was used in its deseasonalized form. Concerning the deseasonalization method we sticked to the method used in the Behavioral Finance literature.

Some descriptive statistics on the weather data are provided in Table 11. 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.[16] Additionally, Table 11 presents the cross-correlation coefficients of the weather variables used (with the corresponding p-values). Based on this table, multi-collinearity in our regressions, due to correlation in the weather variables, does not seem to be a problem.

TABLE 11 ABOUT HERE

[16]When looking at the p-values arising from the Box-Ljung test the null of no serial correlation is rejected. Using the Bartlett bounds (given by $\frac{1.96}{\sqrt{T}} \approx 0.0636$) the serial correlations $|ACF_j|$ become insignificant for $j > 1$ for some of the weather variables considered; (for more details see Brockwell and Davis (2006), p. 223).

	$CLO.$	$VIS.$	$PRE.$	$TEM.$	$HUM.$	$BAR.$	$WIN.$	SAD
Obs.	950.000	952.000	952.000	952.000	952.000	942.000	952.000	952.000
Mean	5.126	14453.930	1.782	0.046	67.506	1015.956	4.649	0.007
Med.	5.692	16008.450	0.000	-0.011	66.297	1016.472	4.246	0.011
max	8.000	16076.090	124.000	15.480	100.000	1040.723	14.267	0.433
min	0.000	960.000	0.000	-11.827	24.273	984.117	0.831	-0.433
sd	2.516	3043.284	8.032	3.900	15.770	7.759	2.133	0.220
Skew.	-0.453	-2.165	8.532	0.181	0.091	-0.454	0.884	-0.073
Kurt.	1.873	7.044	98.557	3.722	2.150	3.894	3.722	2.680
			Jarque-Bera test on Gaussian distribution					
JB	82.766	1392.317	3.7E5	25.900	29.995	63.668	144.621	4.915
p-val.	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.086
			First to fifth order autocorrelation coefficients ACF_j					
ACF_1	0.197	0.109	0.074	0.470	0.355	0.431	0.250	0.998
ACF_2	0.058	-0.014	0.094	0.210	0.156	0.114	0.085	0.994
ACF_3	0.030	-0.002	-0.008	0.159	0.147	0.045	0.130	0.989
ACF_4	0.051	-0.012	-0.027	0.190	0.137	0.085	0.160	0.982
ACF_5	-0.031	-0.001	-0.012	0.122	0.116	0.056	0.131	0.974
			Correlation matrix with p-values					
$CLO.$	1.000							
	–							
$VIS.$	-0.236	1.000						
p-val.	< 0.01	–						
$PRE.$	0.240	-0.127	1.000					
p-val.	< 0.01	< 0.01	–					
$TEM.$	0.153	-0.093	0.060	1.000				
p-val.	< 0.01	< 0.01	0.065	–				
$HUM.$	0.581	-0.390	0.318	0.168	1.000			
p-val.	< 0.01	< 0.01	< 0.01	< 0.01	–			
$BAR.$	-0.220	0.235	-0.107	-0.266	-0.205	1.000		
p-val.	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	–		
$WIN.$	0.049	-0.089	0.193	-0.197	-0.111	-0.250	1.000	
p-val.	0.131	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	–	
SAD	-0.030	0.046	-0.005	0.098	0.064	0.205	-0.092	1.000
p-val.	0.351	0.156	0.884	< 0.01	0.050	< 0.01	< 0.01	–

TABLE 11. Descriptive Statistics and Correlations for the weather and SAD data. Obs. stands for number of observations, JB stands for Jarque-Bera statistic. sd stands for the standard deviation. $CLO.$, $VIS.$, $PRE.$, $TEM.$, $HUM.$, $BAR.$, $WIN.$ are abbreviations for $CLOUDCOVER$, $VISIBILITY$, $PRECIPITATION$, $TEMP_{DS}$, $HUMIDITY$, $BAROPRESS$ and $WINDSPEED$.

References

Amihud, Y. and Mendelson, H. (1991). Liquidity, maturity, and the yield on U.S. treasury securities. *The Journal of Finance*, 46(4):1411–1425.

Angrist, J. and Pischke, J. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Arkes, H., Herren, L., and Isen, A. (1988). The role of potential loss in the influence of affect on risk-taking behavior. *Organizational Behavior and Human Decision Processes*, 42(2):181–193.

Ashton, J., Gerrard, B., and Hudson, R. (2003). Economic impact of national sporting success: Evidence from the London stock exchange. *Applied Economics Letters*, 10(12):783–785.

Au, K., Chan, F., Wang, D., and Vertinsky, I. (2003). Mood in foreign exchange trading: Cognitive processes and performance. *Organizational Behavior and Human Decision Processes*, 91(2):322–338.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4):1645–1680.

Baltagi, B. H. (2008). *Econometric Analysis of Panel Data*. Whiley, Chichester, UK, 4th edition.

Bao, J., Pan, J., and Wang, J. (2011). The illiquidity of corporate bonds. *The Journal of Finance*, 66(3):911–946.

Baron, R. and Bell, P. (1976). Aggression and heat: The influence of ambient temperature, negative affect and a cooling dring on physical aggression. *Journal of Personality and Social Psychology*, 33(3):245–255.

Baron, R. and Ransberger, V. (1978). Ambient temperature and the occurrence of collective violence: The "long, hot summer" revisited. *Journal of Personality and Social Psychology*, 36(4):351–360.

Berndt, A., Douglas, R., Duffie, J. D., Ferguson, M., and Schranz, D. (2008). Measuring Default Risk Premia from Default Swap Rates and EDFs. Working Paper, Stanford University.

Bessembinder, H. and Maxwell, W. (2008). Markets: Transparency and the corporate bond market. *Journal of Economic Perspectives*, 22(2):217–234.

Bessembinder, H., Maxwell, W., Kahle, K., and Xu, D. (2009). Measuring abnormal bond performance. *The Review of Financial Studies*, 22(10):4219–4258.

Bickel, P. and Doksum, K. (2001). *Mathematical Statistics*. Prentice Hall, New Jersey, 2nd edition.

Brockwell, P. J. and Davis, R. A. (2006). *Time Series: Theory and Methods*. Springer Series and Statistics. Springer, New York, 2nd edition.

Campbell, J. Y., Lo, A. W., and MacKinlay, A. C. (1997). *The Econometrics of Financial Markets*. Princeton University Press, Princeton.

Cao, M. and Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance*, 29(6):1559–1573.

Chang, T., Chen, C., Chou, R., and Lin, Y. (2008). Weather and intraday patterns in stock returns and trading activity. *Journal of Banking and Finance*, 32(9):1754–1766.

Chang, T., Nieh, C., Yang, M., and Yang, T. (2006). Are stock market returns related to the weather effects? Empirical evidence from Taiwan. *Physica A*, 364:343–354.

Collin-Dufresne, P., Goldstein, R. S., and Martin, J. S. (2001). The determinants of credit spread changes. *Journal of Finance*, 56(6):2177–2207.

Crosbie, P. and Bohn, J. (2003). Modeling default risk - Modeling methodology. *KMV corporation.*

Cunningham, M. (1979). Weather, mood and helping behavior: Quasi-experiments with the sunshine samaritan. *Journal of Personality and Social Psychology*, 37(11):1947–1956.

Davidson, R. and MacKinnon, J. G. (1993). *Estimation and Inference in Econometrics.* Oxford University Press, New York.

Denissen, J. J., Butalid, L., Penke, L., and van Aken, M. A. (2008). The effects of weather on daily mood: A multilevel approach. *Emotion*, 8(5):662–667.

Dowling, M. and Lucey, B. (2005). Weather, biorhythms, beliefs and stock returns - some preliminary Irish evidence. *International Review of Financial Analysis*, 14(3):337–355.

Dowling, M. and Lucey, Brian, M. (2008). Robust global mood influences in equity pricing. *Journal of Multinational Financial Management*, 18(2):145–164.

Driessen, J. (2005). Is default event risk priced in corporate bonds? *The Review of Financial Studies*, 18(1):165–195.

Edmans, A., Garcia, D., and Norli, O. (2007). Sports sentiment and stock returns. *The Journal of Finance*, 62(4):1967–1998.

Elton, E. J., Gruber, M. J., Agrawal, D., and Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance*, 56(1):247–278.

Eom, Y. H., Helwege, J., and Huang, J.-Z. (2004). Structural models of corporate bond pricing: An empirical analysis. *The Review of Financial Studies*, 17(2):499–544.

Flannery, M. J. and Protopapadakis, A. A. (1988). From T-bills to common stocks: Investigating the generality of intra-week return seasonality. *Journal of Finance*, 43(2):431–450.

Forgas, J. (1995). Mood and judgment: The affect infusion model (AIM). *Psychological Bulletin*, 117(1):39–66.

Forgas, J. and Bower, G. (1987). Mood effects on person-perception judgments. *Journal of personality and social psychology*, 53(1):53–60.

Forgas, J., Goldenberg, L., and Unkelbach, C. (2009). Can bad weather improve your memory? An unobtrusive field study of natural mood effects on real-life memory. *Journal of Experimental Social Psychology*, 54:254–257.

French, K. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, 8(1):55–69.

Frühwirth, M. and Sögner, L. (2013). Mood and asset prices in a general equilibrium framework. Working paper, IHS Vienna and WU Vienna.

Garrett, I., Kamstra, M., and Kramer, L. (2005). Winter blues and time variation in the price of risk. *Journal of Empirical Finance*, 12(2):291–316.

Gerlach, J. (2007). Macroeconomic news and stock market calendar and weather anomalies. *Journal of Financial Research*, 30(2):283–300.

Goetzmann, W. N. and Zhu, N. (2005). Rain or shine: Where is the weather effect? *European Financial Management*, 11(5):559–578.

Goldstein, K. (1972). Weather, mood, and internal-external control. *Perceptual Motor Skills*, 35(3):786.

Goldstein, K., Hotchkiss, E., and Sirri, E. (2007). Transparency and liquidity: A controlled experiment on corporate bonds. *The Review of Financial Studies*, 20(2):235–273.

Griffitt, W. (1970). Environmental effects on interpersonal affective behavior: Ambient effective temperature and attraction. *Journal of Personality and Social Psychology*, 15:240–244.

Griffitt, W. and Veitch, R. (1971). Hot and crowded: Influences of population density and temperature on interpersonal affective behavior. *Journal of Personality and Social Psychology*, 17(1):92–98.

Hirshleifer, D. A. and Shumway, T. (2003). Good Day Sunshine: Stock Returns and the Weather. *The Journal of Finance*, 58(3):1009–1032.

Howarth, E. and Hoffman, M. (1984). A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology*, 75:15–23.

Hsiao, C. (2003). *Analysis of Panel Data*. Cambridge University Press, Econometric Society Monographs No. 34, Cambridge.

Isen, A. and Geva, N. (1987). The influence of positive affect on acceptable level of risk: The person with a large canoe has a large worry. *Organization Behavior and Human Decision Processes*, 39:145–154.

Isen, A. and Patrick, R. (1983). The effect of positive feelings on risk taking: When the chips are down. *Organizational Behavior and Human Decision Processes*, 31:194–202.

Jacobsen, B. and Marquering, W. A. (2008). Is it the Weather? A comment on studies linking weather and stock market behaviour. *Journal of Banking and Finance*, 32(4):526–540.

Johnson, E. and Tversky, A. (1983). Affect, generalization and the perception of risk. *Journal of Personality and Social Psychology*, 45(1):20–31.

Johnston, E., Kracaw, W., and McConnell, J. (1991). Day-of-the-week effects in financial futures: An analysis of GNMA, T-bond, T-note, and T-bill contracts. *Journal of Financial and Quantitative Analysis*, 26(1):23–44.

Kamstra, Mark, J., Kramer, L. A., and Levi, M. D. (2009). Is it the weather? Comment. *Journal of Banking & Finance*, 33(3):578–582.

Kamstra, M. (2005). Reduced daylight and investors. *Canadian Investment Review*, 18(4):R15–R15.

Kamstra, M., Kramer, L., and Levi, M. (2012). Seasonal variation in treasury returns. Working Paper, York University.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2000). Losing sleep at the market: The daylight saving anomaly. *American Economic Review*, 90(4):1005–1011.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2003). Winter Blues: A SAD Stock Market Cycle. *American Economic Review*, 93(1):324–343.

Keef, S. and Roush, M. (2002). The weather and stock returns in New Zealand. *Quarterly Journal of Business & Economics*, 41(1, 2):61–79.

Keef, S. and Roush, M. (2005). Influence of weather on New Zealand financial securities. *Accounting & Finance*, 45(3):415–437.

Keef, S. and Roush, M. (2007). Daily weather effects on the returns of Australian stock indices. *Applied Financial Economics*, 17(3):173–184.

Keim, D. B. and Stambaugh, R. F. (1984). A further investigation of the weekend effects in stock returns. *Journal of Finance*, 39(3):819–835.

Keller, M., Fredrickson, B., Ybarra, O., Cote, S., Johnson, K., Mikels, J., Conway, A., and Wager, T. (2005). A warm heart and a clear head. *Psychological Science*, 15(9):724–731.

Kelly, P. J. and Meschke, F. (2010). Sentiment and stock returns: The SAD anomaly revisited. *Journal of Banking & Finance*, 34(6):1308 – 1326.

Kööts, L., Realo, A., and Allik, J. (2011). The influence of the weather on affective experience: An experience sampling study. *Journal of Individual Differences*, 32(2):74–84.

Krämer, W. and Runde, R. (1997). Stocks and the weather: An exercise in data mining or yet another capital market anomaly? *Empirical Economics*, 22(4):637–641.

Lepori, G. M. (2010). Positive mood, risk attitudes, and investment decisions: Field evidence from comedy movie attendance in the U.S. Working Paper, Copenhagen Business School, Department of Finance.

Levy, O. and Galili, I. (2008). Stock purchase and the weather: Individual differences. *Journal of Economic Behavior and Organization*, 67(3, 4):755–767.

Longstaff, F. A., Mithal, S., and Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance*, 60(5):2213–2253.

Loughran, T. and Schultz, P. (2004). Weather, stock returns, and the impact of localized trading behavior. *Journal of Financial and Quantitative Analysis*, 39(2):343–364.

Lu, J. (2009). Does weather have impact on returns and trading activities in order driven stock market: Some evidences from Chinese stock market. Working Paper, Chongqing University, China.

Pardo, A. and Valor, E. (2003). Spanish stock returns: Where is the weather effect? *European Financial Management*, 9(1):117–126.

Persinger, M. (1975). Lag response in mood reports to changes in the weather matrix. *International Journal of Biometeorology*, 19(2):108–114.

Raghunathan, R. and Pham, M. T. (1999). All negative moods are not equal: Motivational influences of anxiety and sadness on decision making. *Organizational Behavior and Human Decision Processes*, 79(1):56–77.

Roberts, M. R. and Whited, T. M. (2011). Endogeneity in empirical corporate finance. forthcoming in: George Constantinides, Milton Harris, and Rene Stulz, eds. Handbook of the Economics of Finance, Volume 2, Elsevier.

Ruud, P. A. (2000). *An Introduction to Classical Econometric Theory.* Oxford University Press, New York.

Sanders, J. and Brizzolara, M. (1982). Relationship between mood and weather. *Journal of General Psychology*, 107(1):157–158.

Sarig, O. and Warga, A. (1989). Bond price data and bond market liquidity. *Journal of Financial and Quantitative Analysis*, 24(3):367–378.

Saunders, J. (1993). Stock prices and the Wall Street weather. *American Economic Review*, 83(5):1337–1345.

Schultz, P. (1998). Corporate bond trading costs and practices: A peek behind the curtain. Working Paper, University of Notre Dame.

Shon, J. and Zhou, P. (2009). Are earnings surprises interpreted more optimistically on very sunny days? Behavioral bias in interpreting accounting information. *Journal of Accounting, Auditing & Finance*, 24(2):211–232.

Shu, H. (2008). Weather, investor sentiment and stock market returns: Evidence from Taiwan. *Journal of American Academy of Business*, 14(1):96–102.

Shu, H. and Hung, M. (2009). Effect of wind on stock market returns: Evidence from European markets. *Applied Financial Economics*, 19(11):893–904.

Shu, H.-C. (2010). Investor mood and financial markets. *Journal of Economic Behavior & Organization*, 76(2):267 – 282.

Slovic, P., Finucane, M., Peters, E., and MacGregor, D. (2002). Rational actors or rational fools: Implications of the affect heuristic for behavioral economics. *Journal of Socio-Economics*, 31(4):329–342.

Svensson, L. (1994). Estimating and interpreting forward interest rates: Sweden 1992-1994. IMF Working papers 94/114, International Monetary Fund.

Symeonidis, L., Daskalakis, G., and Markellos, R. N. (2010). Does the weather affect stock market volatility? *Finance Research Letters*, 7(4):213–223.

Theissen, E. (2007). An analysis of private investors' stock market return forecast. *Applied Financial Economics*, 17(1):35–43.

Trombley, M. (1997). Stock prices and Wall Street weather: Additional evidence. *Quarterly Journal of Business & Economics*, 36(3):11–21.

Troros, H., Deniz, A., Saylan, L., Sen, O., and Baloglu, M. (2005). Spatial variability of chilling temperature in Turkey and its effect on human comfort. *Meteorology and Atmospheric Physics*, 88(1-2):107–118.

Warga, A. (1991). Corporate bond price discrepancies in the dealer and exchange markets. *Journal of Fixed Income*, 1(3):7–16.

Whaley, R. E. (2000). The investor fear gauge - Explication of the CBOE VIX. *Journal of Portfolio Management*, 26(3):12–17.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4):817–838.

Wooldridge, J. (2001). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge.

Wright, W. and Bower, G. (1992). Mood effects on subjective probability assessment. *Organizational Behavior and Human Decision Processes*, 52(2):276–291.

Yoon, S. and Kang, S. (2009). Weather effects on returns: Evidence from the Korean stock market. *Physica A*, 388(5):682–690.

Zadorozhna, O. (2009). Does weather affect stock returns across emerging markets? PhD-Thesis, Kyiv School of Economics.