Weather and SAD Related Mood Effects on the Financial Market (Supplementary Material)

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February 3, 2015

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Remark: This supplementary material has been composed for the editor and the referees of our paper "Weather and SAD Related Mood Effects on the Financial Market" to enable a deeper coverage of some details in which the referees showed particular interest. To distinguish cross-references in the *supplementary material* from those in the main text, *A-* will be put in front of the references that relate to the supplementary material.

A-1 Deseasonalization of the Weather Data

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

1. Question 1: If a seasonal component exists but the data is not deseasonalized, what is the impact on inference?
2. Question 2: If there is no seasonal component in the data but deseasonalization is applied, what is the impact on inference?

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

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

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

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

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

$$w_t = w_{1t} + w_{2t} = \sqrt{\omega}\tilde{w}_{1t} + \sqrt{1-\omega}\tilde{w}_{2t} \text{ where } \omega \in [0, 1] \ . \tag{A-1}$$

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

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

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

1. *Naive*: We do not believe in any cycle and assume that the data is *iid* (only stochastic weather component). Thus, we waive any deseasonalization: $\hat{w}_{2t}^{Naive} = w_t$. This would be the correct specification only for $\omega = 0$.

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

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

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

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

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

With $\hat{w}_{2t}^{Week}$ we can proceed in the same way: The naive setting is a nested model of the $Fourier$ as well as of the $Week$ methodology. Therefore we are able to use (A-2) also to test the null hypothesis of no season against the alternative of a seasonal component described by $Week$. This can be done by calculating SSR^{Week} and replacing in equation (A-2) $SSR^{Fourier,p}$ by SSR^{Week} and $SSR^{Fourier,q}$ by $SSR^{Fourier,0} = SSR^{Naive}$. The number of parameters p to derive SSR^{Week} is given by the number of weeks per year (i.e. 52).

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

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

(i) The approximation errors for $Week$ and $Fourier$ are small. For the simulated w_t described at the beginning of this section the Fourier deseasonalization technique with $p=1$ results in the lowest approximation error of the cyclical component for all ω. For $\omega = 0.1$ and 0.5 (low or medium seasonality) the Fourier setting with $p=6$ is better than the methodology $Week$, while with $\omega = 0.9$ (strong seasonality) $Week$ results in smaller errors than $Fourier$ with $p=6$. The observation that the Fourier model slightly dominates $Week$ is not a big surprise since in our simulations the data generating process includes a Fourier cycle (see step `S1`). With empirical weather data, the data generating process is unknown. However from the simulations we observe that $Week$ provides us with a reasonable tool to filter out seasonal components even if the true data generating process is different. (ii) The F-test described by (A-2) detects the correct Fourier model (true p) in more than 95% of the simulation runs. This test also works with $Week$ to differentiate between a model with and without cyclical component. Based on these observations we conclude that the $Week$ deseasonalization technique used in the Behavioral Finance literature provides us with a good fit to the data even if the true data generating process is based on a one year cosine-cycle (see step `S1`). In addition, testing for the presence of a seasonal component is feasible.

In the next step we want to find out whether (i) neglecting deseasonalization if a seasonal component exists or (ii) performing deseasonalization if no seasonal component exists has an impact on the estimation and inference of the weather parameters. In other words we want to check whether the above methodologies detect/reject weather effects if they are present/ are not present. We proceed as follows: The response variable y_t is generated by means of

$$y_t = \beta_0 + \beta_w w_{2t} + \beta_c c_t + \varepsilon_t \ , \ t = 1, \ldots, T. \tag{A-3}$$

$\varepsilon_t \sim \mathcal{N}(0, \sigma_R^2)$. $\sigma_R^2 = 0, 0.1, 0.5$ or 1 (0 is only applied with $\omega > 0$). $c_t \in \mathbb{R}$ is a further prediction variable, which we simulated from a standard normal distribution. w_{2t} is the deseasonalized component derived above. We set $\beta_w = 0$ (no impact of the non-cyclical component of the prediction variable w_t) or $\beta_w = 1$ (there is an impact of the non-cyclical component of the prediction variable).

Remark 1. The experiment in this appendix can be linked to our weather analysis as follows: y_t corresponds to the financial market variable (e.g. the S&P 500 return or the VIX), w_{2t} corresponds to the non-cyclical (deseasonalized) part of a weather variable and c_t stands for a control variable. Suppose that the financial variable y_t, the (non-deseasonalized) weather variable w_t and the control variable c_t can be observed. Then: (i) Suppose that the deseasonalized weather w_{2t} has an impact on the financial market variable (i.e. $\beta_w \neq 0$): We use w_t, apply the $Week$ deseasonalization technique and then the test described in (A-2). Based on this test we can decide to take either $\hat{w}_{2t} = w_t$ (if the test statistic in (A-2) favors no season) or $\hat{w}_{2t} = w_{2t}^{Week}$ (if the test statistic supports a seasonal component). In a next step, we estimate the regression parameters, where y_t is the response variable and the predictors are $\hat{w}_{2t}$ and c_t. Finally, we analyze if β_w is significantly different from zero. (ii) Suppose that there is no weather effect ($\beta_w = 0$): Proceed in the same way as in (i). Equally, we want to know if β_w is insignificant or not. That is, this simulation analysis should provide us with information if weather effects can be detected if present, or if weather effects are rejected if no weather effects are in the data.

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

1. $\beta_w = 1$, $\omega = 0$ or $\omega = 0.1$ (impact of the non-cyclical weather component exists, majority of the weather variable w_t is non-cyclical): The false null hypotheses $\beta_w = 0$ and $\beta_c = 0$ are rejected in almost all simulation runs.

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

3. $\beta_w = 1$, $\omega = 0.5$ (impact of the non-cyclical weather component exists, half of the weather variable w_t is cyclical): The results are similar to scenario 1.

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

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

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

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

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

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

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

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

However, in our simulation experiments we also investigated the effect of deseasonalization on the rejection rates for the intercept parameter β_0. For example in an asset pricing application, the intercept term could stand for Jensen's Alpha. In this case information on the intercept term is very important. Consider a multiple regression model with a true intercept parameter $\beta_0 = 0$. Suppose that there is no seasonal component in the weather variable w_t. We observe that without deseasonalization the rejection rates are close to the significance levels $\alpha_c = 0.01, 0.05$ and 0.1. However, when applying a deseasonalization routine, we observed strong oversizing (i.e. the rejection rates of t-test are too high). Thus, we find that deseasonalization in the absence of any seasonal component has an impact on the rejection rates for the intercept term β_0.

Altogether, we decided to deseasonalize weather variables only if the F-test rejects the null hypothesis that there is no seasonal component. This decision has been taken in order not to manipulate the data too much and to avoid the risk to get spurious results, to avoid the above effect on the intercept and as it would be counterintuitive to eliminate something (namely a seasonal component) from the data that is not included in the data. Concerning the deseasonalization method we stick to the method used in the Behavioral Finance literature.

As the temperature was the only weather variable that showed a season, we decided to deseasonalize only the temperature. We use the symbol $TEMP_{DS}$ for the deseasonalized temperature.

A-2 Descriptive Statistics

The goal of this section is to analyze whether concerns regarding multicollinearity of the regressors are appropriate. Therefore, the mutual correlations between the regressors are investigated. The paper contains in Table ?? descriptive statistics of and the mutual correlations between the different weather/SAD variables $\mathbf{w}_t$. In addition, this section presents descriptive statistics of the financial market variables, mutual correlations between the financial market variables and the respective correlation coefficients between weather and financial market variables.

TABLES A-1 and A-2 ABOUT HERE

As can be seen from the Tables ??, A-1 and A-2, the highest absolute value of a correlation coefficient is observed for the two bond indexes (0.95). Especially, all correlation coefficients between variables that occur in the same regression are in an acceptable range, namely between -0.25 and 0.85. Hence, we do not expect any problems arising from multicollinearity. In addition, we observe that R does not indicate any problems with the matrix inversion, when the parameters are estimated.

Obs.	$\Delta r_{F_{2year},t}$	$SPRE.$	VIX_t	$\mathbb{I}_{Aaa,t}$	$\mathbb{I}_{Baa,t}$
Mean	0.0020	0.0368	18.6546	5.6086	6.5632
Median	0.0031	0.0697	16.0750	5.5200	6.4100
max	0.2616	5.7315	45.0800	6.6200	8.0500
min	-0.2603	-4.1536	10.2300	4.7600	5.6400
Sd	0.0581	1.0592	7.5963	0.4079	0.5454
Skewness	0.0987	0.3273	1.2878	0.4597	0.8550
Kurtosis	5.6932	6.3693	3.7090	2.4920	2.8880
Jarque-Bera test on Gaussian distribution					
Jarque-Bera	288.9522	456.0023	276.5468	42.3882	112.8063
p-values	<0.001	<0.001	<0.001	<0.001	<0.001
1^{st} to 5^{th} order ACF_j and p-values from Box-Ljung test					
ACF_1	0.0130	-0.0570	0.9670	0.9560	0.9550
p-value	0.6920	0.0830	<0.001	<0.001	<0.001
ACF_2	-0.0220	0.0380	0.9560	0.9470	0.9480
p-value	0.7370	0.1150	<0.001	<0.001	<0.001
ACF_3	-0.0440	-0.0370	0.9450	0.9360	0.9400
p-value	0.4750	0.1320	<0.001	<0.001	<0.001
ACF_4	0.0230	-0.0340	0.9400	0.9330	0.9400
p-value	0.5590	0.1520	<0.001	<0.001	<0.001
ACF_5	-0.0020	-0.0110	0.9330	0.9230	0.9340
p-value	0.7000	0.2340	<0.001	<0.001	<0.001
Correlation matrix with p-values					
$\Delta r_{F_{2year},t}$	1.0000				
p-value	–				
$SPRETURNS_t$	0.2006	1.0000			
p-value	<0.001	–			
VIX_t	-0.1063	-0.0870	1.0000		
p-value	0.0012	0.0082	–		
$\mathbb{I}_{Aaa,t}$	-0.0233	-0.0186	0.7508	1.0000	
p-value	0.4795	0.5728	<0.001	–	
$\mathbb{I}_{Baa,t}$	-0.0499	-0.0072	0.8506	0.9461	1.0000
p-value	0.1306	0.8267	<0.001	<0.001	–

TABLE A-1. Descriptive statistics and correlations for the financial market variables (first difference of the two-year risk free rate, $\Delta r_{F_{2year},t}$, S&P 500 returns, $SPRETURNS_t$, VIX_t volatility index, and the two corporate bond indexes $\mathbb{I}_{Aaa,t}$ and $\mathbb{I}_{Baa,t}$). Sd stands for the standard deviation. ACF_j stands for the autocorrelation coefficient of lag j. $SPRE.$ is an abbreviation of $SPRETURNS_t$.

	Correlation matrix with p-values							
	$CLO.$	$VIS.$	$PRE.$	$TEM.$	$HUM.$	$BAR.$	$WIN.$	SAD_t
$\Delta r_{F_{2year},t}$	0.061	0.003	-0.022	0.066	0.021	-0.026	-0.002	-0.007
p-value	0.066	0.934	0.510	0.047	0.525	0.429	0.958	0.842
$SPRETURNS_t$	0.057	0.019	0.028	0.015	0.019	-0.013	-0.002	0.005
p-value	0.088	0.565	0.391	0.642	0.560	0.693	0.943	0.888
VIX_t	-0.021	-0.014	-0.025	-0.176	0.067	0.078	-0.005	0.114
p-value	0.525	0.665	0.449	0.000	0.042	0.018	0.871	0.001
$\mathbb{I}_{Aaa,t}$	-0.029	-0.030	-0.033	-0.099	0.033	0.052	0.033	0.128
p-value	0.386	0.373	0.318	0.003	0.314	0.119	0.322	<0.001
$\mathbb{I}_{Baa,t}$	-0.032	-0.022	-0.023	-0.120	0.061	0.035	0.013	0.203
p-value	0.341	0.517	0.495	<0.001	0.064	0.280	0.699	<0.001

TABLE A-2. Descriptive statistics: Correlations between the different weather/SAD variables and the financial market variables. $CLO.$, $VIS.$, $PRE.$, $TEM.$, $HUM.$, $BAR.$, $WIN.$ are abbreviations for $CLOUDCOVER_t$, $VISIBILITY_t$, $PRECIPITATION_t$, $TEMP_{DS,t}$, $HUMIDITY_t$, $BAROPRESS_t$ and $WINDSPEED_t$.

A-3 Unit Root Tests

To specify the regression setting more closely, we had to find out for each of the variables described in Section **??** if it was stationary or not. While levels can be used for stationary data, for non-stationary variables first differences (denoted by Δ) are more appropriate (if necessary even higher order differences have to be used).[2]

Providing a brief summary, let us start with the *corporate bond spreads.* We observed that the Levin et al. (2002) panel unit root test did not reject the null hypothesis of a unit root, the other panel unit root tests implemented in EViews (Breitung (2000) test, assuming a common autoregressive coefficient, and Im et al. (2003) test, allowing for different autoregressive terms) however did. To get a clearer picture, we performed unit root tests on a single time series basis:

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

namely the Dickey/Fuller test, the Augmented Dickey/Fuller test and the Phillips/Perron test (for a description of these tests see, e.g., Hamilton (1994)). With all these tests the null hypothesis of a unit root was rejected, both with and without including a time trend. Based on these results we decide to treat the corporate bond spreads as stationary random variables and work with the spread levels.

Based on the unit root tests the *S&P 500 returns* can be considered as stationary. The same statement holds for the *individual stock returns* STR_{it}. For the *VIX* volatility index we observe p-values of 14.65% and 8.1% for the Augmented Dickey Fuller tests without and with a time trend, respectively. By this result we assume that VIX_t is stationary. We observed a similar behavior for the corporate bond indexes, where we also assume that $\mathbb{I}_{Aaa,t}$ and $\mathbb{I}_{Baa,t}$ are stationary.

Things are less clear with the *risk-free rates*, as due to their unit root or quasi unit root behavior they are difficult to investigate. According to economic intuition and also economic theory we expect stationary interest rates. However, with different tests we receive different answers to the question whether interest rates are stationary or not. Since the serial correlation of the interest time series is very high, unit root tests often do not reject the null hypothesis of a unit root. Although issues on power and size of these tests are still discussed in current econometrics literature (see, e.g., Vogelsang and Wagner, 2013), working with levels can result in spurious outcomes. Also, with close to unit root behavior the usual asymptotic theory usually works poorly (on close to unit root asymptotics see, e.g., Phillips et al., 2001). Based on this trade-off between economic intuition and the spurious results, we prefer to work with first differences in the regressions.

Since the *distance to default* are calculated based on non-stationary variables (e.g. risk-free rates, market capitalization) we applied first differences. In addition, we performed several unit root tests for the *debt to value ratio*. They reject the null hypothesis in most cases. Therefore we use levels for the debt to value ratio. As regards the *weather variables* we observe that for the deseasonalized temperature, barometric pressure, visibility, precipitation, wind speed, cloud cover and humidity the null hypothesis of a unit root has to be rejected. Thus, we work with levels.

A-4 Parameter Estimation and Inference

In the main text we consider the indirect effects specification (**??**):

$$
\begin{aligned}
y_{it} &= \begin{cases} \alpha_i + \boldsymbol{\mu}_t^\top \mathbf{b}_w + \mathbf{c}_{it}^\top \boldsymbol{\beta}_c + \varepsilon_{it} & \text{if } y_{it} \text{ is a forward-looking variable} \\ \alpha_i + (\boldsymbol{\mu}_t^\top, \boldsymbol{\mu}_{t-1}^\top)\mathbf{b}_w + \mathbf{c}_{it}^\top \boldsymbol{\beta}_c + \varepsilon_{it} & \text{if } y_{it} \text{ is an ex-post return} \end{cases} \\
\boldsymbol{\mu}_t &= \mathbf{A}_w \mathbf{w}_t + \boldsymbol{\eta}_t \ . \qquad \text{(A-4)}
\end{aligned}
$$

$\mathbf{b}_w$ is a k_μ dimensional vector of regression parameters for forward-looking variables. Alternatively, a $2k_\mu$ dimensional vector of regression parameters is used for the ex-post returns. $\mathbf{b}_w$ measures the impact of the mood on the financial market variable y_{it}. $\mathbf{A}_w$ is a $k_\mu \times k_w$ matrix describing the impact of the weather/SAD variables on the vector of the different mood variables. $\boldsymbol{\beta}_c$ is a vector of regression parameters measuring the impact of the control variables on the respective financial market variable. $\boldsymbol{\eta}_t$ is a stochastic vector of dimension k_μ. y_{it}, ε_{it} and α_i are scalars. The noise terms ε_{it} and $\boldsymbol{\eta}_t$ have an expectation of zero. In addition, ε_{it} and $\boldsymbol{\eta}_t$ are independent. This implies, $\mathbb{E}(\varepsilon_{it}\varepsilon_{js}) = 0$, $\mathbb{E}(\boldsymbol{\eta}_t\boldsymbol{\eta}_s^\top) = \mathbf{0}_{k_\mu \times k_\mu}$, for all $t \neq s$ or $i \neq j$, and $\mathbb{E}(\varepsilon_{it}\boldsymbol{\eta}_t^\top) = \mathbf{0}_{1\times k_\mu}$, for all i and $s, t \in \mathbb{Z}$.

From (**??**) the statistical model presented in equation (**??**) follows. This equation can be expressed in more compact terms by means of

$$
y_{it} = \alpha_i + \boldsymbol{\beta}^\top \mathbf{x}_{it} + u_{it} \ . \qquad \text{(A-5)}
$$

y_{it} is the scalar response random variable and $\mathbf{x}_{it}$ is a $k_{\boldsymbol{\beta}} \times 1$ vector of prediction random variables. N is the fixed cross-sectional dimension and T is the time series dimension. Let $\mathbf{y}_t := (y_{1t}, \ldots, y_{Nt})^\top$ of dimension $N \times 1$, $\mathbf{x}_t = (\mathbf{x}_{1t}, \ldots, \mathbf{x}_{Nt})^\top$ of dimension $N \times k_\beta$. $\mathbf{x}_{it} \in \mathbb{R}^{k_\beta}$ contains all the right-hand side variables such as the weather/SAD variables $\mathbf{w}_t$ and the other control variables $\mathbf{c}_{it}$. The $N \times N$ covariance matrix of the noise term $\mathbf{u}$ is $\mathbb{V}(\mathbf{u})$. The instruments are $\mathbf{z}_{it} \in \mathbb{R}^{\kappa_\beta}$, which are collected in $\mathbf{z}_t = (\mathbf{z}_{1t}, \ldots, \mathbf{z}_{Nt})^\top$ of dimension $N \times \kappa_\beta$.

$\kappa_\beta \geq k_\beta$ by the order condition. Assumption **??** already demanded the requirements for instrumental variable estimation to be fulfilled.

To estimate $\boldsymbol{\beta}$ in a panel model different methods are available. For least squares estimation of a fixed effects model, we use the within-transform (`plm`(., ., `model` = "`within`") in the `R` package). Applying the within-transform to y_{it}, $\mathbf{x}_{it}$, $\mathbf{z}_{it}$ and u_{it}, results in $\tilde{y}_{it} := y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\tilde{\mathbf{x}}_{it} := \mathbf{x}_{it} - \frac{1}{T}\sum_{t=1}^{T} \mathbf{x}_{it}$, $\tilde{\mathbf{z}}_{it} := \mathbf{z}_{it} - \frac{1}{T}\sum_{t=1}^{T} \mathbf{z}_{it}$, and $\tilde{u}_{it} := u_{it} - \frac{1}{T}\sum_{t=1}^{T} u_{it}$ (see, e.g., Baltagi, 2008, page 14). $\tilde{\mathbf{y}}_i := (\tilde{y}_{i1}, \ldots, \tilde{y}_{iT})^\top$, $\tilde{\mathbf{x}}_i := (\tilde{\mathbf{x}}_{i1}, \ldots, \tilde{\mathbf{x}}_{iT})^\top$, $\tilde{\mathbf{z}}_i := (\tilde{\mathbf{z}}_{i1}, \ldots, \tilde{\mathbf{z}}_{iT})^\top$ and $\tilde{\mathbf{u}}_i := (\tilde{u}_{i1}, \ldots, \tilde{u}_{iT})^\top$ are of dimension $T \times 1$, $T \times k_\beta$, $T \times \kappa_\beta$ and $T \times 1$. By collecting terms, i.e. $\mathbf{Y} := (\mathbf{y}_{11}, \ldots, \mathbf{y}_{NT})$, $\mathbf{X} := (\mathbf{x}_1^\top, \ldots, \mathbf{x}_T^\top)$, etc., we obtain the $NT \times 1$ matrix $\mathbf{Y}$, the $NT \times k_\beta$ matrix $\mathbf{X}$, the $NT \times \kappa_\beta$ matrix $\mathbf{Z}$, the the $NT \times 1$ matrix, $\mathbf{U}$, the $NT \times 1$ matrix $\tilde{\mathbf{Y}}$, the $NT \times k_\beta$ matrix $\tilde{\mathbf{X}}$, the $NT \times \kappa_\beta$ matrix $\tilde{\mathbf{Z}}$ and the $NT \times 1$ matrix, $\tilde{\mathbf{U}}$. (If $N = 1$ the within-transform is not applied and the intercept α is estimated directly.) The within-transformed panel regression model (A-5) can now be written in compact form by means of

$$\tilde{\mathbf{Y}} = \tilde{\mathbf{X}}\boldsymbol{\beta} + \tilde{\mathbf{U}} \ . \tag{A-6}$$

The least squares estimator (LS) based on the within-transform is given by

$$\begin{aligned}\hat{\boldsymbol{\beta}}_{LS} &= \left(\sum_{t=1}^{T}\sum_{i=1}^{N}\left(\tilde{\mathbf{x}}_{it}\tilde{\mathbf{x}}_{it}^{T}\right)\right)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N}\left(\tilde{\mathbf{x}}_{it}\tilde{y}_{it}\right) \\ &= (\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}^\top\tilde{\mathbf{Y}} = (\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}^\top(\tilde{\mathbf{X}}\boldsymbol{\beta} + \tilde{\mathbf{U}}) \\ &= \boldsymbol{\beta} + (\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}^\top\tilde{\mathbf{U}} \ . \end{aligned}\tag{A-7}$$

$\hat{\mathbf{U}}_{OLS}$ is the $NT \times 1$ matrix of OLS residuals, containing $\hat{\mathbf{u}}_{t,OLS}$ and $\hat{u}_{it,OLS} := \tilde{y}_{it} - \hat{\boldsymbol{\beta}}_{OLS}\tilde{x}_{it}$. A two-stage least squares estimator based on within-transformed data is obtained by means of

$$\begin{aligned}\hat{\boldsymbol{\beta}}_{W2SLS} &= \left(\sum_{t=1}^{T}\sum_{i=1}^{N}\left(\tilde{\mathbf{x}}_{it}\tilde{\mathbf{z}}_{it}^{T}\left(\sum_{t=1}^{T}\sum_{i=1}^{N}\tilde{\mathbf{z}}_{it}\tilde{\mathbf{z}}_{it}^{T}\right)^{-1}\tilde{\mathbf{z}}_{it}\tilde{\mathbf{x}}_{it}\right)\right)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N}\left(\tilde{\mathbf{x}}_{it}\tilde{\mathbf{z}}_{it}^{T}\left(\sum_{t=1}^{T}\sum_{i=1}^{N}\tilde{\mathbf{z}}_{it}\tilde{\mathbf{z}}_{it}^{T}\right)^{-1}\tilde{\mathbf{z}}_{it}\tilde{y}_{it}\right)\\ &= \left(\tilde{\mathbf{X}}^{\top}\mathbf{P}_{\tilde{Z}}\tilde{\mathbf{X}}\right)^{-1}\tilde{\mathbf{X}}^{\top}\mathbf{P}_{\tilde{Z}}\tilde{\mathbf{Y}} = \boldsymbol{\beta} + \left(\tilde{\mathbf{X}}^{\top}\mathbf{P}_{\tilde{Z}}\tilde{\mathbf{X}}\right)^{-1}\tilde{\mathbf{X}}^{\top}\mathbf{P}_{\tilde{Z}}\tilde{\mathbf{u}}\\ &\quad \text{where } \mathbf{P}_{\tilde{Z}} := \tilde{\mathbf{Z}}\left(\tilde{\mathbf{Z}}^{\top}\tilde{\mathbf{Z}}\right)^{-1}\tilde{\mathbf{Z}}^{\top}\,. \end{aligned} \tag{A-8}$$

The corresponding residuals are $\hat{u}_{it,W2SlS} := \tilde{y}_{it} - \hat{\boldsymbol{\beta}}_{W2SLS}\tilde{\mathbf{x}}_{it}$ contained in $\hat{\mathbf{U}}_{W2SLS}$ and $\hat{\mathbf{u}}_{t,W2SLS}$. If $N = 1$, where the within-transform is not applied and $\mathbf{X}$ and $\mathbf{Z}$ include a constant term, (A-8) yields $\hat{\boldsymbol{\beta}}_{2SLS} = \left(\mathbf{X}^{\top}\mathbf{P}_{Z}\mathbf{X}\right)^{-1}\mathbf{X}^{\top}\mathbf{P}_{Z}\mathbf{Y}$. This estimator is used with the `R` function `ivreg`(., .).

To obtain instrumental variables estimates of $\boldsymbol{\beta}$ for $N > 1$, `R` does not use (A-8) but offers the opportunities to apply the Balestra and Varadharajan-Krishnakumar (1987) estimator or the Baltagi (1981) estimator; for a brief overview and a discussion on these estimators see Baltagi (2008)[Chapter 7.1]. In the following we use the Balestra and Varadharajan-Krishnakumar (1987) estimator for instrumental variable estimation with panel data. To do this, let $\boldsymbol{\Omega}_{UU} := \mathbb{E}(\mathbf{U}\mathbf{U}^{\top})$ and transform the data as follows: $\mathbf{Y}^{*} := \boldsymbol{\Omega}_{UU}^{-1/2}\mathbf{Y}$, $\mathbf{X}^{*} := \boldsymbol{\Omega}_{UU}^{-1/2}\mathbf{X}$, $\mathbf{Z}^{*} := \boldsymbol{\Omega}_{UU}^{-1/2}\mathbf{Z}$ and $\mathbf{U}^{*} = \boldsymbol{\Omega}_{UU}^{-1/2}\mathbf{U}$. Suppose that $\boldsymbol{\Omega}_{UU}$ is known, the parameter $\boldsymbol{\beta}$ can be estimated by means of

$$\begin{aligned}\hat{\boldsymbol{\beta}}_{G2SLS} &= \left(\mathbf{X}^{*\top}\mathbf{P}_{Z^{*}}\mathbf{X}^{*}\right)^{-1}\mathbf{X}^{*\top}\mathbf{P}_{Z^{*}}\mathbf{Y}^{*}\\ &\quad \text{where } \mathbf{P}_{Z^{*}} := \mathbf{Z}^{*}\left(\mathbf{Z}^{*\top}\mathbf{Z}^{*}\right)^{-1}\mathbf{Z}^{*\top}\,. \end{aligned} \tag{A-9}$$

To obtain a feasible estimator, $\boldsymbol{\Omega}_{UU}$ has to be replaced by an estimate $\hat{\boldsymbol{\Omega}}_{UU}$, which is obtained in a stepwise procedure. The corresponding residuals are $\hat{u}_{it,G2SlS} := y_{it}^{*} - \hat{\boldsymbol{\beta}}_{G2SLS}\mathbf{x}_{it}^{*}$ contained in $\hat{\mathbf{U}}_{G2SLS}$ and $\hat{\mathbf{u}}_{t,G2SLS}$, respectively.

If a dynamic panel model is considered, estimators based on the within-transform are not consistent in general. Estimators designed for dynamic panels such as the Arellano/Bond or the Blundell/Bond estimator did not work given the size of our data set. However, for the data investigated in this article the time series dimension T will be (much) 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 $T \to \infty$. In this case the estimator $\hat{\boldsymbol{\beta}}_{G2SLS}$ is still consistent (see Baltagi, 2008, Chapter 8).

When dealing with the indirect effects model we have to comment on regressor endogeneity. Irrespective of our analysis in Section **??**, 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 **??** that with the indirect effects model weather and SAD effects create additional regressor endogeneity. This also implies that some of the control variables have to be instrumented. For instance, 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 (see Table A-1) 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 $\Delta r_{F_{2year}}$ where the serial correlation is low. Here, we used the DAX and the NIKKEI indexes as instruments, because first stage regressions show that these variables are correlated with the S&P 500 and surprisingly also with $\Delta r_{F_{2year}}$. 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.

With instrumental variables, N fixed and heteroskedastic data, we obtain a heteroskedasticity and autocorrelation consistent (HAC) estimator of the asymptotic variance of $\sqrt{T}\left(\hat{\boldsymbol{\beta}}_{W2SLS} - \boldsymbol{\beta}\right)$ by means of (see, e.g., White, 2001, Davidson and MacKinnon, 1993, Vogelsang, 2012)

$$\hat{V}_{HAC}\left(\sqrt{T}\,(\boldsymbol{\beta}-\boldsymbol{\beta})\right) = \left(\frac{1}{T}\tilde{\mathbf{X}}^\top\mathbf{P}_Z\tilde{\mathbf{X}}\right)^{-1}\tilde{\mathbf{X}}^\top\tilde{\mathbf{Z}}\left(\tilde{\mathbf{Z}}^\top\tilde{\mathbf{Z}}\right)^{-1}\left((T)^{-1}\tilde{\mathbf{Z}}^\top\hat{\mathbf{u}}\hat{\mathbf{u}}^T\tilde{\mathbf{Z}}\right)\left(\tilde{\mathbf{Z}}^\top\tilde{\mathbf{Z}}\right)^{-1}\tilde{\mathbf{Z}}^\top\tilde{\mathbf{X}}\left(\frac{1}{T}\tilde{\mathbf{X}}^\top\mathbf{P}_Z\tilde{\mathbf{X}}\right)^{-1}$$
$$= \left(\tilde{\mathbf{X}}^\top\mathbf{P}_Z\tilde{\mathbf{X}}\right)^{-1}\tilde{\mathbf{X}}^\top\tilde{\mathbf{Z}}\left(\tilde{\mathbf{Z}}^\top\tilde{\mathbf{Z}}\right)^{-1}\hat{\boldsymbol{\Omega}}\left(\tilde{\mathbf{Z}}^\top\tilde{\mathbf{Z}}\right)^{-1}\tilde{\mathbf{Z}}^\top\tilde{\mathbf{X}}\left(\tilde{\mathbf{X}}^\top\mathbf{P}_Z\tilde{\mathbf{X}}\right)^{-1} . \quad \text{(A-10)}$$

For the estimator (A-9), $\tilde{\mathbf{X}}$ and $\tilde{\mathbf{Z}}$ have to be replaced by $\mathbf{X}^*$ and $\mathbf{Z}^*$.

To implement (A-10) an estimate of the covariance matrix has to be obtained. Let us start with $N = 1$, $\mathbf{u}_{it} = u_t$ is iid and $\tilde{\mathbf{x}}_t$ is uncorrelated with u_t. In this case we are allowed to use ordinary least squares, where $\mathbf{Z} = \mathbf{X}$. Since $N = 1$ the within-transform is not applied and a constant term is included in $\mathbf{X}$. Then $\hat{\boldsymbol{\beta}}_{2SLS} = \hat{\boldsymbol{\beta}}_{OLS} = \left(\mathbf{X}^\top\mathbf{X}\right)^{-1}\mathbf{X}^\top\mathbf{Y}$. For the lest squares estimator $\hat{V}_{OLS}(\sqrt{T}(\hat{\boldsymbol{\beta}}-\boldsymbol{\beta})) = \mathbb{V}(u_t)\mathbb{E}\left(\mathbf{X}^\top\mathbf{X}\right)^{-1}$, such that an estimator of the asymptotic covariance of the estimator $\hat{\boldsymbol{\beta}}$ is $\hat{\mathbb{V}}_{OLS}(\hat{\boldsymbol{\beta}}) = \frac{1}{T}\cdot\hat{\mathbb{V}}(u_t)\left(\frac{1}{T}\cdot\mathbf{X}^\top\mathbf{X}\right)^{-1} = \hat{\mathbb{V}}(u_t)\left(\mathbf{X}^\top\mathbf{X}\right)^{-1}$. With $N = 1$ and $\mathbf{Z} = \mathbf{X}$ but heteroskedasticity in the noise term u_t, White (1980) obtained the estimator $\hat{V}_{White}(\sqrt{T}(\hat{\boldsymbol{\beta}}-\boldsymbol{\beta}))= T\cdot\left(\frac{1}{T}\sum_{t=1}^{T}\mathbf{x}_t\mathbf{x}_t^\top\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T}\mathbf{x}_t\hat{u}_t\hat{u}_t\mathbf{x}_t^\top\right)\left(\frac{1}{T}\sum_{t=1}^{T}\mathbf{x}_t\mathbf{x}_t^\top\right)^{-1}$. In addition, robust inference can also account for possible serial correlation of the noise terms (i.e. the correlation of $\mathbf{x}_t u_t$ with $\mathbf{x}_s u_s$, where $t, s \in \mathbb{Z}$ and $t \neq s$). Regarding this issue, Newey and West (1987) used a nonparametric kernel estimate of the so called long-run covariance matrix to obtain the asymptotic variance of the parameter $\boldsymbol{\beta}$. In more detail, abbreviate the terms $\mathbf{x}_t\hat{u}_{t,2SLS}$ by $\hat{\mathbf{v}}_t$ (of dimension $\kappa_\beta \times 1$) and let

$$\hat{\boldsymbol{\Gamma}}_{vv,j} := \frac{1}{T}\sum_{t=j+1}^{T}\hat{\mathbf{v}}_t\hat{\mathbf{v}}_{t-j}^\top .$$

The nonparametric kernel HAC estimator of the $\kappa_\beta \times \kappa_\beta$ long-run covariance is given by

$$\hat{\boldsymbol{\Omega}}_{vv} = \hat{\boldsymbol{\Gamma}}_{vv,0} + \sum_{j=1}^{T-1}\mathtt{k}\left(\frac{j}{M}\right)\left(\hat{\boldsymbol{\Gamma}}_{vv,j} + \hat{\boldsymbol{\Gamma}}_{vv,j}^\top\right) . \quad \text{(A-11)}$$

$\mathtt{k}\left(\frac{j}{M}\right)$ is the kernel function with bandwidth M (see, e.g., Brockwell and Davis, 2006, p. 359). Amongst a lot of other HAC estimators provided in the `R` package for $N = 1$, we obtained the Newey and West (1987) standard errors by means of $\texttt{vcov.nw} <- \texttt{kernHAC}(., \texttt{bw} = \texttt{bwNeweyWest}); \ \texttt{coeftest}(., \texttt{vcov.nw})$.

Remark 2. Under standard asymptotic theory the impact of the kernel and the bandwidth chosen by the econometrician becomes zero if $T \to \infty$ (or $T, N \to \infty$). Recent literature also investigated the finite sample impact of the kernel and bandwidth chosen to perform inference. Regarding this issue we refer the reader to fixed-b inference investigated in Kiefer and Vogelsang (2005) and Vogelsang (2012).

In our paper we follow the standard asymptotic approach. For White (1980) standard errors $\hat{\mathbf{\Omega}}_{vv} = \hat{\mathbf{\Gamma}}_{vv,0}$, such that no kernel function has to be specified. Newey and West (1987) used a Bartlett kernel where $\texttt{k} = 1 - \frac{j}{1+M}$. For the choice of the bandwidth M the rule $M = T^{1/3} \cdot$ "number of parameters" was provided in Newey and West (1987). Alternatively, Newey and West (1994) proposed $M = \hat{\gamma} T^{1/3}$, where the derivation of $\hat{\gamma}$ is described in Newey and West (1994)[Equation (2.2)]. In our analysis we applied the default values used by R.

Equation (A-10) provides us with a heteroskedasticity and autocorrelation consistent estimate (HAC) of the asymptotic covariance of $\boldsymbol{\beta}$ for panel data and instrumental variables. (A-10) follows from the covariance of the $2SLS$ estimator and the fact that $\boldsymbol{\beta}$ is $\sqrt{T}$ consistent given our assumptions on the econometric model. With $\tilde{\mathbf{X}} = \tilde{\mathbf{Z}}$ and homoskedastic and independent noise terms we obtain $\hat{\mathbb{V}}_{LS}(\sqrt{T}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta})) = \left(\frac{1}{T}\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1}\left(\frac{1}{T}\sum_{i=1}^N \hat{\mathbb{V}}(u_{it})\sum_{t=1}^T \tilde{\mathbf{x}}_{it}\tilde{\mathbf{x}}_{it}^\top\right)\left(\frac{1}{T}\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1} = T \cdot \left(\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1}\left(\sum_{i=1}^N \hat{\mathbb{V}}(u_{it})\sum_{t=1}^T \tilde{\mathbf{x}}_{it}\tilde{\mathbf{x}}_{it}^\top\right)\left(\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1}$. Standard errors based on $\hat{\mathbb{V}}_{LS}(\hat{\boldsymbol{\beta}}) = \left(\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1}\left(\sum_{i=1}^N \hat{\mathbb{V}}(u_{it})\sum_{t=1}^T \tilde{\mathbf{x}}_{it}\tilde{\mathbf{x}}_{it}^\top\right)\left(\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1}$ are provided by the R package. In our tables these standard errors are abbreviated by SE. By accounting for heteroskedasticity we get the White (1980) covariance matrix $\hat{V}_{White}(\hat{\boldsymbol{\beta}}) = \left(\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1}\left(\sum_{i=1}^N \tilde{\mathbf{x}}_i\hat{\mathbf{u}}_i\hat{\mathbf{u}}_i^\top\tilde{\mathbf{x}}_i^\top\right)\left(\tilde{\mathbf{X}}^\top\tilde{\mathbf{X}}\right)^{-1}$. The R command $\texttt{vcovHC}(..., \texttt{type} = \texttt{"HC0"})$) provides us with White (1980) standard errors, $HC1$ to $HC4$ are modifications described in Croissant and Millo (2008) and the citations given in their article. To account for possible serial correlation and heteroskedasticity in panel data we apply a robust estimator developed in Driscoll and Kraay (1998). Driscoll and Kraay

(1998) standard errors, when using the option $type = "HC3"$, are abbreviated by SE_{DK}. A nonparameteric kernel estimator, like the Newey and West (1987) estimator, is currently not available in `R` for panel estimation.

R commands used in the estimation		library
`lm`	estimates linear regression model, $N = 1$	
`coeftest`(.,.)	obtains t-tests on individual parameters	`lmtest`
`vcovHC`(.,.)	obtains robust standard errors	`sandwich`
`vcovHAC`(.,.)	obtains Croissant and Millo (2008) robust standard errors, $N = 1$	`sandwich`
`vcovSCC`(.,.)	obtains Driscoll and Kraay (1998) robust standard errors	`sandwich`
`kernHAC`(.,.)	obtains robust covariance matrix of $\boldsymbol{\beta}$, $N = 1$	`sandwich`
`ivreg`(.,.)	obtains instrumental variable estimates for $N = 1$	`AER`
`plm`(.,.)	estimates panel model	`plm`

TABLE A-3. `R` *functions used in the estimation.*

Table A-3 provides the main functions used to estimate the parameters and their covariance matrix. For all models we estimated least squares standard errors (SE) and robust standard errors $SE_{HC.}$ by using the `vcovHC`(.,.) function with the options $HC0$ to $HC4$. With our data the differences in the p-values with different $HC.$ versions are minor. For all regressions with $N = 1$ we obtained additionally the standard errors based on `vcovHAC`(.,.) and Newey and West (1987). For the latter we used the abbreviation SE_{NW}. The differences in the p-values obtained with the default `vcovHAC`(.,.) variant and the Newey and West (1987) standard errors were modest. For the panel of interest rates and the panel of corporate bonds we derived standard errors based on `vcovSCC`(.,.) (abbreviation $SE_{SCCHC0}, \ldots, SE_{SCCHC3}, SE_{SCCHC4}$). For the individual stock returns `vcovSCC`(.,.) worked for the instrumental variable estimation, while with least squares the error message "Error in crossprod(Xt, ut) : non-conformable arguments") shows up (according to some web-pages this is a bug with `R`). Here we only used the function `vcovSCC`(.,.).

To test for regressor endogeneity a Hausman test can be constructed (see, e.g., Wooldridge, 2001, Chapters 6 and 10 and the references provided there). We assume that the econometric models investigated in our paper satisfy the conditions to apply this test. Based on this a t-test version of the Hausman test can be obtained as follows: Calculate the test-statistic

$$H_i = \frac{\hat{\beta}_{IV,i} - \hat{\beta}_{LS,i}}{\left(\hat{SE}\left(\beta_{IV,i}\right)^2 - \hat{SE}\left(\beta_{LS,i}\right)^2\right)^{0.5}} \ ,$$

where $\hat{\beta}_{IV,i} = \left[\hat{\boldsymbol{\beta}}_{IV}\right]_{(i)}$ is the i^{th} component of the instrumental variable estimate $\hat{\boldsymbol{\beta}}_{IV}$ and $\hat{\beta}_{LS,i} = \left[\hat{\boldsymbol{\beta}}_{LS}\right]_{(i)}$ is the i^{th} component of the ordinary least squares estimate $\hat{\boldsymbol{\beta}}_{LS}$. $\hat{SE}\left(\hat{\beta}_{.,i}\right)$ stands for an estimate of the standard error of $\hat{\beta}_{.,i}$, where robust estimates are used. The asymptotic distribution of the test statistic H_i is a standard normal distribution. By applying this test to our regression results we observe that for the risk-free term structure the null hypothesis $\beta_{IV,i} = \beta_{LS,i}$ has not been rejected for the weather and SAD variables (at a 10% significance level or lower). For the S&P returns the null hypothesis $\beta_{IV,i} = \beta_{LS,i}$ has been rejected for the variable $CLOUDCOVER$ (which is the only significant weather variable in this regression), while for the other weather and SAD variables the null hypothesis was not rejected. For the VIX, the corporate bond indexes, the panel of corporate bond spreads and the panel of individual stock returns the null hypothesis has been rejected at a 1% significance level for almost all weather and SAD variables. In these regressions the difference between the parameters is large compared to the estimate of the standard error. Based on these tests, we conclude that (except for the risk-free term structure) endogeneity cannot be neglected. Since the first stage regressions do not indicate problems with weak instruments, the instrumental variable estimates (e.g. the estimates for the indirect specification) should be used from an econometric point of view. Hence, these tests provide empirical evidence of endogeneity, which was already theoretically motivated by the psychological and economic models in Section **??**.

Regarding the disaggregated analysis performed in Section **??**, Tables A-18 and A-19 present an instrumental variable panel regression of model (**??**), where the sample of stocks is split up into stocks, where $\hat{\beta}_{Mi} = \left[\hat{\boldsymbol{\beta}}_{FFi}\right]_{(1)} \leq 1$ and a subsample where $\hat{\beta}_{Mi} = \left[\hat{\boldsymbol{\beta}}_{FFi}\right]_{(1)} > 1$ ($\hat{\beta}_{Mi}$ is the first component of the three dimensional vector of the Fama-French factor loading $\hat{\boldsymbol{\beta}}_{FFi}$. An estimate $\hat{\beta}_{Mi} = \left[\hat{\boldsymbol{\beta}}_{FFi}\right]_{(1)}$ is obtained from estimating (**??**) with all $N = 23$ stocks).

The motivation behind is that firms with higher (systematic) risk could be influenced by weather and SAD effects to a stronger extent. This split-up into subsamples is used instead of working with dummy variables to reduce the number of parameters to be estimated. With a similar goal we proceed with the corporate bond spreads in Table A-20, differentiating between bonds with a AAA rating, hence $\mathbf{1}_{AAA_{it}} = 1$, and bonds with the worst rating in our data set, which is a BBB rating, where $\mathbf{1}_{BBB_{it}} = 1$.

Remark 3. In addition to these robust standard errors used in our article, the literature provides a lot of further alternatives to obtain robust standard errors, such as bootstrapping methods (see, e.g., Cameron and Trivedi, 2005, and a long list of references provided there). A further alternative to the methods used in our article are clustered standard errors (see, e.g., Cameron et al., 2011). Such error specifications are reasonable in case of group fixed effects. Petersen (2009) assumes within group correlation and no correlation between different groups (see Petersen, 2009, Equations (4-6)). These statistical assumptions hardly fit our data, since the weather data is the same for all firms (e.g. we have perfect correlation instead of zero correlation between the different groups) and variables like the distance to default are correlated via the correlation of the asset prices. A model with perfectly correlated variables and within-group varying variables has been investigated in Donald and Lang (2007). In their propositions the authors showed under which conditions the t-statistics follow student-t distributions. Additionally, Donald and Lang (2007) show that standard asymptotics fail if the number of groups is small. Based on our observation that the method to obtain standard errors has an important impact on the significance levels of the weather variables, these further alternatives might result in further non-unique answers regarding the presence of weather and SAD effects.

A-5 Parameter Estimates with Different Types of Standard Errors

In this section we present the results from different regressions. For each market segment, we estimated both the direct and the indirect effects specification. As already mentioned in Section ??, for $N = 1$, with the direct effects specification we used OLS estimation and with the indirect effects specification we used two stage least squares. With $N > 1$ we used for the direct effects specification the within-transform (see, e.g., Baltagi, 2008, Chapter 1) and for the indirect effects specification the Balestra and Varadharajan-Krishnakumar (1987) estimator. This section provides tables with the results of these different estimations. In addition, different standard errors as described in Section A-4 are reported in these tables. Finally, we present the tables for the regressions that investigate any bond/stock specific effects, as described in Section ??.

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{DK}	p-value
$CLOUDCOVER_t$	-2.14E-4	2.73E-4	0.4315	1.69E-4	0.2041	1.69E-4	0.2052	7.20E-4	0.7658
$VISIBILITY_t$	2.13E-7	1.99E-7	0.2863	1.37E-7	0.1194	1.37E-7	0.1193	5.62E-7	0.7049
$TEMP_{DS,t}$	3.30E-4	1.92E-4	0.0855	7.40E-5	8.31E-6	7.40E-5	8.21E-6	4.65E-4	0.4773
$PRECIPITATION_t$	-1.99E-4	7.63E-5	0.0093	4.37E-5	5.43E-6	4.43E-5	7.26E-6	1.83E-4	0.2781
$BAROPRESS_t$	9.53E-6	5.68E-6	0.0934	3.82E-6	0.0127	3.87E-6	0.0138	1.69E-5	0.5733
$HUMIDITY_t$	1.85E-4	4.96E-5	0.0002	4.82E-5	0.0001	4.83E-5	0.0001	1.35E-4	0.1708
$WINDSPEED_t$	8.19E-4	2.75E-4	0.0029	1.88E-4	1.37E-5	1.89E-4	1.46E-5	8.33E-4	0.3252
$TEMPDY_t$	4.01E-4	2.98E-4	0.1778	1.32E-4	0.0023	1.32E-4	0.0023	7.59E-4	0.5973
SAD_t	-2.93E-3	2.54E-3	0.2496	1.28E-3	0.0227	1.28E-3	0.0228	6.04E-3	0.6282
$MONDAY_t$	2.50E-3	1.41E-3	0.0757	1.01E-3	0.0132	1.01E-3	0.0133	3.28E-3	0.4462
VIX_t	-4.66E-4	7.39E-5	3.10E-10	5.50E-5	<2.2E-16	5.51E-5	<2.2E-16	1.85E-4	0.0119
$\Delta r_{Fi,t-1}$	4.91E-3	0.0103	0.6347	7.93E-3	0.5360	7.95E-3	0.5373	0.0307	0.8730
$SPRETURNS_t$	0.0188	8.07E-4	<2.2E-16	3.87E-3	1.21E-6	3.88E-3	1.28E-6	2.46E-3	2.04E-14

TABLE A-4. Dependent variable: First differences in risk-free interest rates Δr_{Fit} in percentage terms, fixed effects model, panel estimation method based on the Balestra and Varadharajan-Krishnakumar (1987) transformation ($N = 11$ maturities, $T = 952$ days; fixed effects not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are the White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007). Instruments: VIX_{t-1}, $SPRETURNS_{t-1}$, DAX_t, $NIKKEI_t$. The exogenous/predetermined variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t, $\Delta r_{F,t-1}$ and $MONDAY_t$.

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{DK}	p-value
$CLOUDCOVER_t$	9.04E-5	2.60E-4	0.7282	1.49E-4	0.5443	1.49E-4	0.5450	6.65E-4	0.8919
$VISIBILITY_t$	3.28E-7	1.90E-7	0.0848	1.22E-7	0.0073	1.22E-7	0.0073	5.17E-7	0.5256
$TEMP_{DS,t}$	4.62E-4	1.83E-4	0.0117	5.95E-5	9.06E-15	5.97E-5	1.09E-14	4.34E-4	0.2872
$PRECIPITATION_t$	-1.55E-4	7.35E-5	0.0350	4.10E-5	1.59E-4	4.15E-5	1.91E-4	1.64E-4	0.3458
$BAROPRESS_t$	1.48E-5	5.15E-6	0.0040	3.14E-6	2.35E-6	3.18E-6	3.13E-6	1.38E-5	0.2824
$HUMIDITY_t$	1.52E-4	4.72E-5	0.0013	4.53E-5	7.96E-4	4.53E-5	8.08E-4	1.27E-4	0.2321
$WINDSPEED_t$	7.59E-4	2.63E-4	0.0039	1.86E-4	4.35E-5	1.86E-4	4.61E-5	7.84E-4	0.3327
$TEMPDY_t$	1.84E-4	2.85E-4	0.5187	1.14E-4	0.1083	1.15E-4	0.1089	7.15E-4	0.7972
SAD_t	-2.73E-3	2.44E-3	0.2645	1.27E-3	0.0324	1.28E-3	0.0326	6.44E-3	0.6721
$MONDAY_t$	2.69E-3	1.35E-3	0.0459	1.00E-3	0.0073	1.00E-3	0.0073	3.09E-3	0.3841
VIX_t	-4.17E-4	7.01E-5	2.78E-9	4.57E-5	<2.2E-16	4.58E-5	<2.2E-16	1.80E-4	0.0205
$\Delta r_{Fi,t-1}$	6.86E-3	9.91E-3	0.4890	8.39E-3	0.4134	8.41E-3	0.4146	0.0296	0.8166
$SPRETURNS_t$	7.17E-3	4.87E-4	<2.2E-16	1.57E-3	5.10E-6	1.58E-3	5.33E-6	1.67E-3	1.73E-5

TABLE A-5. Dependent variable: First differences in risk-free interest rates Δr_{Fit} in percentage terms, LS Estimates, fixed effects model, panel estimation method based on taking the within-transform ($N = 11$ maturities, $T = 952$ days; fixed effects not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are the White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007).

Variable	β	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	-0.0241	0.0135	0.0731	0.0132	0.0671	0.0136	0.0769	0.0135	0.0732
$VISIBILITY_t$	1.80E-6	1.01E-5	0.8590	9.57E-6	0.8508	1.02E-5	0.8595	8.74E-6	0.8367
$TEMP_{DS,t}$	5.00E-3	0.0110	0.6485	0.0127	0.6941	0.0133	0.7083	0.0125	0.6901
$PRECIPITATION_t$	5.21E-3	5.27E-3	0.3233	5.09E-3	0.3060	5.70E-3	0.3608	5.22E-3	0.3187
$BAROPRESS_t$	-6.48E-5	2.77E-4	0.8150	2.65E-4	0.8072	2.87E-4	0.8212	2.76E-4	0.8149
$HUMIDITY_t$	3.84E-3	2.55E-3	0.1321	2.62E-3	0.1433	2.73E-3	0.1608	2.57E-3	0.1361
$WINDSPEED_t$	-5.74E-3	0.0152	0.7052	0.0146	0.6950	0.0152	0.7062	0.0195	0.7683
$TEMPDY_t$	-0.01050	0.01988	0.5974	0.01893	0.5791	0.01989	0.5975	0.01818	0.5636
SAD_t	-1.09700	3.25200	0.7361	2.97730	0.7127	3.11170	0.7246	2.80060	0.6955
$CLOUDCOVER_{t-1}$	8.25E-3	0.0183	0.6513	0.0181	0.6492	0.0192	0.6682	0.0167	0.6219
$VISIBILITY_{t-1}$	-1.01E-5	9.54E-6	0.2895	9.03E-6	0.2631	9.43E-6	0.2838	8.40E-6	0.2288
$TEMP_{DS,t-1}$	-9.32E-3	0.0116	0.4232	0.0116	0.4230	0.0121	0.4415	0.0120	0.4364
$PRECIPITATION_{t-1}$	1.02E-3	3.90E-3	0.7940	3.50E-3	0.7714	3.96E-3	0.7975	3.74E-3	0.7856
$BAROPRESS_{t-1}$	-4.22E-4	4.08E-4	0.3012	3.71E-4	0.2549	4.15E-4	0.3096	3.30E-4	0.2011
$HUMIDITY_{t-1}$	-2.55E-3	4.73E-3	0.5905	4.89E-3	0.6023	5.23E-3	0.6261	4.62E-3	0.5810
$WINDSPEED_{t-1}$	3.98E-3	0.0154	0.7958	0.0156	0.7983	0.0163	0.8074	0.0128	0.7552
$TEMPDY_{t-1}$	0.02452	0.01536	0.1107	0.01538	0.1113	0.01612	0.1285	0.01599	0.1256
SAD_{t-1}	1.10500	3.22200	0.7317	2.97010	0.7099	3.10330	0.7218	2.77950	0.6910
$MONDAY_t$	0.5570	0.5870	0.3426	0.6960	0.4236	0.7612	0.4646	0.7479	0.4566
VIX_t	-1.1160	0.3590	0.0019	0.3790	0.0033	0.4096	0.0066	0.3678	0.0025
VIX_{t-1}	1.1080	0.3500	0.0016	0.3706	0.0029	0.4012	0.0059	0.3601	0.0022
$\Delta r_{F_{2year},t}$	3.6930	10.4000	0.7225	10.8020	0.7325	11.6070	0.7504	10.1690	0.7166
$\Delta r_{F_{2year},t-1}$	-0.5349	0.8390	0.5241	0.9455	0.5717	1.0398	0.6071	0.8711	0.5393
$SPRETURNS_{t-1}$	-0.0258	0.1130	0.8197	0.1220	0.8329	0.1298	0.8424	0.1160	0.8239

TABLE A-6. Dependent variable: S&P 500 returns in percentage terms, multiple linear regression model, 2SLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987). Instruments: VIX_{t-1}, VIX_{t-2}, DAX_t, $NIKKEI_t$, $\Delta r_{F_{2year},t-1}$, $\Delta r_{F_{2year},t-2}$. The exogenous/predetermined 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 $j = 0, 1$, $SPRETURNS_{t-1}$ and $MONDAY_t$.

Variable	β	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	-6.96E-3	0.0109	0.5222	9.92E-3	0.4831	0.0102	0.4964	9.47E-3	0.4628
$VISIBILITY_t$	5.75E-6	8.04E-6	0.4752	8.42E-6	0.4951	8.76E-6	0.5121	8.34E-6	0.4908
$TEMP_{DS,t}$	7.93E-3	8.86E-3	0.3709	0.0103	0.4428	0.0108	0.4611	0.0113	0.4811
$PRECIPITATION_t$	2.68E-3	3.03E-3	0.3756	3.31E-3	0.4175	4.02E-3	0.5043	3.37E-3	0.4260
$BAROPRESS_t$	1.51E-4	2.24E-4	0.4993	1.51E-4	0.3182	1.75E-4	0.3872	1.54E-4	0.3252
$HUMIDITY_t$	1.77E-3	2.05E-3	0.3899	2.13E-3	0.4078	2.22E-3	0.4258	2.20E-3	0.4213
$WINDSPEED_t$	-4.61E-3	0.0114	0.6868	0.0107	0.6678	0.0112	0.6809	0.0118	0.6950
$TEMPDY_t$	-9.36E-3	0.0125	0.4558	0.0127	0.4606	0.0132	0.4788	0.0138	0.4973
SAD_t	-1.4860	2.4490	0.5440	2.4231	0.5398	2.5018	0.5526	2.4854	0.5500
$CLOUDCOVER_{t-1}$	0.0109	0.0110	0.3227	0.0119	0.3579	0.0123	0.3755	0.0126	0.3878
$VISIBILITY_{t-1}$	-4.25E-6	7.84E-6	0.5883	7.43E-6	0.5678	7.75E-6	0.5838	7.11E-6	0.5502
$TEMP_{DS,t-1}$	-6.63E-3	8.85E-3	0.4543	9.66E-3	0.4928	0.0100	0.5094	0.0107	0.5367
$PRECIPITATION_{t-1}$	6.51E-4	3.07E-3	0.8322	2.49E-3	0.7936	2.76E-3	0.8138	2.44E-3	0.7895
$BAROPRESS_{t-1}$	-2.82E-4	2.25E-4	0.2106	1.89E-4	0.1378	2.17E-4	0.1957	1.91E-4	0.1405
$HUMIDITY_{t-1}$	-1.04E-3	2.04E-3	0.6088	2.19E-3	0.6347	2.28E-3	0.6480	2.06E-3	0.6121
$WINDSPEED_{t-1}$	1.57E-3	0.0116	0.8925	0.0113	0.8895	0.0116	0.8930	0.0113	0.8901
$TEMPDY_{t-1}$	0.0105	0.0127	0.4105	0.0136	0.4419	0.0142	0.4606	0.0143	0.4651
SAD_{t-1}	1.4930	2.4390	0.5405	2.4307	0.5391	2.5095	0.5519	2.5045	0.5511
$MONDAY_t$	0.3852	0.0568	2.10E-11	0.0603	2.78E-10	0.0626	1.12E-9	0.0637	2.12E-9
VIX_t	-0.7852	0.0208	<2E-16	0.0284	<2.2E-16	0.0298	<2.2E-16	0.0296	<2.2E-16
VIX_{t-1}	0.7798	0.0207	<2E-16	0.0292	<2.2E-16	0.0306	<2.2E-16	0.0297	<2.2E-16
$\Delta r_{F_{2year},t}$	1.2010	0.3720	0.0013	0.4568	0.0087	0.4747	0.0116	0.4939	0.0152
$\Delta r_{F_{2year},t-1}$	-0.4616	0.3750	0.2184	0.3642	0.2053	0.3791	0.2237	0.3621	0.2027
$SPRETURNS_{t-1}$	-0.0243	0.0208	0.2422	0.0266	0.3615	0.0279	0.3837	0.0276	0.3799

TABLE A-7. Dependent variable: S&P 500 returns in percentage terms, multiple linear regression model, OLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987).

Variable	β	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	0.0102	0.0181	0.5721	0.0184	0.5784	0.0189	0.5892	0.0212	0.6298
$VISIBILITY_t$	1.84E-5	1.31E-5	0.1593	1.23E-5	0.1358	1.27E-5	0.1481	1.30E-5	0.1558
$TEMP_{DS,t}$	-3.26E-3	0.0129	0.8013	0.0110	0.7674	0.0113	0.7725	9.62E-3	0.7352
$PRECIPITATION_t$	-2.20E-3	5.38E-3	0.6823	4.26E-3	0.6051	4.49E-3	0.6241	3.66E-3	0.5478
$BAROPRESS_t$	-1.42E-4	3.74E-4	0.7049	2.30E-4	0.5383	2.61E-4	0.5875	2.28E-4	0.5344
$HUMIDITY_t$	2.50E-3	3.26E-3	0.4437	3.22E-3	0.4378	3.29E-3	0.4479	3.45E-3	0.4689
$WINDSPEED_t$	-3.98E-3	0.0185	0.8296	0.0175	0.8203	0.0179	0.8241	0.0180	0.8250
$TEMPDY_t$	-0.0302	0.0204	0.1391	0.0193	0.1183	0.0198	0.1273	0.0212	0.1553
SAD_t	0.0175	0.1670	0.9166	0.1690	0.9172	0.1720	0.9190	0.1650	0.9153
$MONDAY_t$	0.1676	0.0954	0.0793	0.0941	0.0754	0.0967	0.0836	0.1010	0.0967
VIX_{t-1}	0.9887	5.26E-3	$<$2E-16	8.60E-3	$<$2E-16	8.86E-3	$<$2E-16	7.52E-3	$<$2E-16
$\Delta r_{F_{2year},t}$	-0.9348	4.1300	0.821	5.0600	0.8535	5.2500	0.8587	4.4600	0.8342
$SPRETURNS_t$	-10.4700	11.9000	0.3798	0.1660	0.5272	0.1720	0.5438	0.1310	0.4227

TABLE A-8. Dependent variable: VIX_t, multiple linear regression model, 2SLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987). Instruments: $SPRETURNS_{t-1}$, $\Delta r_{F_{2year},t-1}$, DAX_t, $NIKKEI_t$. The exogenous/predetermined variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t, VIX_{t-1} and $MONDAY_t$.

Variable	β	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	7.60E-3	0.0177	0.6681	0.0183	0.6776	0.0186	0.6837	0.0207	0.7134
$VISIBILITY_t$	1.57E-5	1.30E-5	0.2301	1.21E-5	0.1949	1.24E-5	0.2074	1.25E-5	0.2115
$TEMP_{DS,t}$	-3.98E-4	0.0129	0.9755	0.0106	0.9701	0.0108	0.9707	9.38E-3	0.9662
$PRECIPITATION_t$	-1.31E-3	5.05E-3	0.7961	3.55E-3	0.7135	3.76E-3	0.7285	3.29E-3	0.6921
$BAROPRESS_t$	-1.14E-4	3.71E-4	0.7587	2.39E-4	0.6337	2.75E-4	0.6779	2.29E-4	0.6187
$HUMIDITY_t$	1.30E-3	3.30E-3	0.6931	3.16E-3	0.6798	3.23E-3	0.6860	3.35E-3	0.6969
$WINDSPEED_t$	-3.37E-3	0.0181	0.8525	0.0173	0.8456	0.0177	0.8487	0.0184	0.8547
$TEMPDY_t$	-0.0298	0.0198	0.1326	0.0189	0.1162	0.0193	0.1243	0.0201	0.1396
SAD_t	0.0389	0.1670	0.8158	0.1640	0.8131	0.1680	0.8166	0.1560	0.8032
$MONDAY_t$	0.1595	0.0915	0.0817	0.0861	0.0642	0.0879	0.0698	0.0900	0.0766
VIX_{t-1}	0.9840	5.81E-3	<2E-16	0.0101	<2E-16	0.0104	<2E-16	8.12E-3	<2E-16
$\Delta r_{F_{2year},t}$	-0.0759	0.0422	0.0724	0.0404	0.0608	0.0413	0.0664	0.0330	0.0215
$SPRETURNS_t$	-6.8810	3.3300	0.03902	5.2300	0.1883	5.3600	0.1999	4.6200	0.1366

TABLE A-9. Dependent variable: VIX_t, multiple linear regression model, OLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987).

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	-6.40E-4	1.42E-3	0.6532	1.33E-3	0.6301	1.36E-3	0.6369	1.39E-3	0.6455
$VISIBILITY_t$	5.61E-8	1.03E-6	0.9565	1.02E-6	0.9562	1.05E-6	0.9573	1.04E-6	0.9570
$TEMP_{DS,t}$	-3.83E-4	1.01E-3	0.7053	8.43E-4	0.6498	8.63E-4	0.6575	9.27E-4	0.6795
$PRECIPITATION_t$	1.13E-4	4.20E-4	0.7881	3.87E-4	0.7705	4.30E-4	0.7931	4.14E-4	0.7849
$BAROPRESS_t$	3.16E-5	2.91E-5	0.2785	1.60E-5	0.0481	1.81E-5	0.0821	1.62E-5	0.0511
$HUMIDITY_t$	-2.36E-4	2.56E-4	0.3568	2.52E-4	0.3480	2.57E-4	0.3587	2.65E-4	0.3734
$WINDSPEED_t$	1.96E-4	1.45E-3	0.8927	1.53E-3	0.8985	1.59E-3	0.9019	1.68E-3	0.9073
$TEMPDY_t$	-1.25E-3	1.59E-3	0.4351	1.63E-3	0.4451	1.66E-3	0.4533	1.70E-3	0.4641
SAD_t	4.90E-3	0.0133	0.7117	0.0132	0.7110	0.0134	0.7153	0.0155	0.7518
$MONDAY_t$	-3.34E-3	7.52E-3	0.6569	6.53E-3	0.6092	6.67E-3	0.6166	6.72E-3	0.6190
VIX_t	0.0018	6.56E-4	0.0076	6.82E-4	0.0103	6.96E-4	0.0119	7.90E-4	0.0267
$\Delta r_{F_{2year},t}$	1.1400	0.3100	0.0003	0.3560	0.0014	0.3720	0.0022	0.4380	0.0094
$SPRETURNS_t$	-3.3790	0.8970	0.0002	1.0900	0.0020	1.1600	0.0036	1.3700	0.0135
$\mathbb{I}_{Aaa,t-1}$	0.9734	0.0112	<2E-16	0.0118	<2.2E-16	0.0120	<2.2E-16	0.0148	<2.2E-16

TABLE A-10. Dependent variable: Corporate Bond Index $\mathbb{I}_{Aaa,t}$, multiple linear regression model, 2SLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987). Instruments: VIX_{t-1}, DAX_t, $NIKKEI_t$, $SPRETURNS_{t-1}$, $\Delta r_{F_{2year},t-1}$. The exogenous/predetermined variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t, $\mathbb{I}_{Aaa,t-1}$ and $MONDAY_t$.

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	-6.61E-4	1.46E-3	0.6518	1.37E-3	0.6307	1.40E-3	0.6376	1.44E-3	0.6476
$VISIBILITY_t$	-8.17E-8	1.06E-6	0.9383	1.04E-6	0.9376	1.07E-6	0.9391	1.11E-6	0.9411
$TEMP_{DS,t}$	-4.79E-4	1.04E-3	0.6452	8.55E-4	0.5751	8.77E-4	0.5850	9.60E-4	0.6177
$PRECIPITATION_t$	1.94E-4	4.33E-4	0.6542	4.11E-4	0.6371	4.64E-4	0.6762	4.47E-4	0.6648
$BAROPRESS_t$	2.84E-5	2.99E-5	0.3436	1.33E-5	0.0338	1.51E-5	0.0606	1.34E-5	0.0353
$HUMIDITY_t$	-2.69E-4	2.63E-4	0.3064	2.58E-4	0.2969	2.64E-4	0.3080	2.73E-4	0.3241
$WINDSPEED_t$	1.03E-4	1.49E-3	0.9448	1.59E-3	0.9481	1.65E-3	0.9501	1.74E-3	0.9528
$TEMPDY_t$	-1.02E-3	1.64E-3	0.5329	1.65E-3	0.5346	1.68E-3	0.5415	1.72E-3	0.5508
SAD_t	6.38E-3	0.0139	0.6463	0.0136	0.6400	0.0139	0.6455	0.0164	0.6971
$MONDAY_t$	-3.81E-3	7.73E-3	0.6226	6.68E-3	0.5694	6.83E-3	0.5775	6.81E-3	0.5767
VIX_t	1.49E-3	8.14E-4	0.0672	8.30E-4	0.0726	8.51E-4	0.0801	9.21E-4	0.1056
$\Delta r_{F_{2year},t}$	1.1870	0.3230	0.0002	0.3730	0.0015	0.3910	0.0025	0.4630	0.0105
$SPRETURNS_t$	-3.2430	0.9350	0.0005	1.1631	0.0054	1.2421	0.0092	1.4770	0.0284
$\mathbb{I}_{Baa,t-1}$	0.9875	0.0108	<2E-16	0.0109	<2.2E-16	0.0110	<2.2E-16	0.0126	<2E-16

TABLE A-11. Dependent variable: Corporate Bond Index $\mathbb{I}_{Baa,t}$, multiple linear regression model, 2SLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987). Instruments: VIX_{t-1}, DAX_t, $NIKKEI_t$, $SPRETURNS_{t-1}$, $\Delta r_{F_{2year},t-1}$. The exogenous/predetermined variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t, $\mathbb{I}_{Baa,t-1}$ and $MONDAY_t$.

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	1.86E-4	8.13E-4	0.8189	7.51E-4	0.8044	7.64E-4	0.8076	8.05E-4	0.8172
$VISIBILITY_t$	1.12E-7	5.95E-7	0.8509	5.42E-7	0.8366	5.55E-7	0.8402	5.42E-7	0.8366
$TEMP_{DS,t}$	-1.90E-5	5.84E-4	0.9741	5.15E-4	0.9707	5.24E-4	0.9712	5.49E-4	0.9725
$PRECIPITATION_t$	-3.56E-4	2.32E-4	0.1247	1.72E-4	0.0382	1.83E-4	0.0518	1.74E-4	0.0405
$BAROPRESS_t$	2.31E-5	1.68E-5	0.1710	1.28E-5	0.0721	1.47E-5	0.1174	1.29E-5	0.0743
$HUMIDITY_t$	-1.55E-4	1.48E-4	0.2954	1.42E-4	0.2742	1.44E-4	0.2824	1.44E-4	0.2807
$WINDSPEED_t$	9.92E-4	8.32E-4	0.2337	7.70E-4	0.1979	7.85E-4	0.2066	7.45E-4	0.1837
$TEMPDY_t$	-8.03E-5	9.06E-4	0.9294	8.78E-4	0.9271	8.96E-4	0.9286	9.35E-4	0.9316
SAD_t	5.76E-3	7.69E-3	0.4539	7.44E-3	0.4389	7.57E-3	0.4465	8.13E-3	0.4787
$MONDAY_t$	3.19E-3	4.23E-3	0.4504	4.15E-3	0.4417	4.23E-3	0.4503	4.21E-3	0.4488
VIX_t	7.56E-4	3.31E-4	0.0225	3.23E-4	0.0196	3.29E-4	0.0220	3.43E-4	0.0277
$\Delta r_{F_{2year},t}$	0.0218	0.0284	0.4426	0.0266	0.4117	0.0272	0.4218	0.0260	0.4005
$SPRETURNS_t$	-0.0024	1.56E-3	0.1249	1.47E-3	0.1031	1.50E-3	0.1105	1.43E-3	0.0944
$\mathbb{I}_{Aaa,t-1}$	0.9852	6.08E-3	<2E-16	6.33E-3	<2E-16	6.44E-3	<2E-16	6.57E-3	<2E-16

TABLE A-12. Dependent variable: Corporate Bond Index $\mathbb{I}_{Aaa,t}$, multiple linear regression model, OLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987).

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{NW}	p-value
$CLOUDCOVER_t$	2.30E-4	8.14E-4	0.7780	7.49E-4	0.7592	7.63E-4	0.7633	7.63E-4	0.7633
$VISIBILITY_t$	-3.87E-8	5.96E-7	0.9480	5.60E-7	0.9449	5.73E-7	0.9462	5.39E-7	0.9428
$TEMP_{DS,t}$	-8.02E-5	5.85E-4	0.8910	5.11E-4	0.8753	5.20E-4	0.8776	5.15E-4	0.8764
$PRECIPITATION_t$	-3.04E-4	2.32E-4	0.1910	1.69E-4	0.0729	1.83E-4	0.0982	1.80E-4	0.0920
$BAROPRESS_t$	1.96E-5	1.69E-5	0.2440	1.30E-5	0.1314	1.50E-5	0.1898	1.29E-5	0.1281
$HUMIDITY_t$	-1.91E-4	1.48E-4	0.1990	1.43E-4	0.1811	1.45E-4	0.1891	1.41E-4	0.1762
$WINDSPEED_t$	1.00E-3	8.33E-4	0.2290	7.69E-4	0.1928	7.84E-4	0.2017	7.27E-4	0.1685
$TEMPDY_t$	2.41E-4	9.08E-4	0.7910	8.65E-4	0.7808	8.83E-4	0.7852	9.35E-4	0.7968
SAD_t	7.26E-3	7.85E-3	0.3560	7.50E-3	0.3335	7.64E-3	0.3421	8.25E-3	0.3789
$MONDAY_t$	3.06E-3	4.24E-3	0.4710	4.11E-3	0.4567	4.19E-3	0.4655	4.18E-3	0.4651
VIX_t	6.57E-4	4.21E-4	0.1190	4.27E-4	0.1249	4.36E-4	0.1328	4.25E-4	0.1225
$\Delta r_{F_{2year},t}$	0.0197	0.0284	0.4900	0.0286	0.4922	0.0293	0.5024	0.0256	0.4425
$SPRETURNS_t$	-0.0007	1.57E-3	0.6410	1.67E-3	0.6614	1.71E-3	0.6697	1.50E-3	0.6270
$\mathbb{I}_{Baa,t-1}$	0.9921	5.90E-3	<2E-16	6.14E-3	<2E-16	6.25E-3	<2E-16	5.83E-3	<2E-16

TABLE A-13. Dependent variable: Corporate Bond Index $\mathbb{I}_{Baa,t}$, multiple linear regression model, OLS Estimates ($T = 952$; intercept not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{NW} stands for robust standard errors based on Newey and West (1987).

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{DK}	p-value
$CLOUDCOVER_t$	0.0472	0.0503	0.3475	0.0316	0.1354	0.0316	0.1354	0.0648	0.4664
$VISIBILITY_t$	0.0472	2.81E-5	0.3319	1.69E-5	0.1073	1.69E-5	0.1073	4.39E-5	0.5341
$TEMP_{DS,t}$	0.0291	0.0207	0.1607	0.0118	0.0134	0.0118	0.0134	0.0382	0.4469
$PRECIPITATION_t$	-0.0200	7.10E-3	0.0049	4.19E-3	1.85E-6	4.19E-3	1.85E-6	0.0158	0.2056
$BAROPRESS_t$	0.0017	7.63E-4	0.0298	3.75E-4	1.00E-5	3.75E-4	1.00E-5	4.49E-4	0.0002
$HUMIDITY_t$	-0.0044	0.0101	0.6662	3.61E-3	0.2260	3.61E-3	0.2260	0.0120	0.7146
$WINDSPEED_t$	0.0422	0.0396	0.2863	0.0207	0.0416	0.0207	0.0416	0.0641	0.5099
$TEMPDY_t$	-0.0161	0.0282	0.5676	0.0193	0.4041	0.0193	0.4041	0.0655	0.8056
SAD_t	-0.0426	0.2660	0.8727	0.3670	0.9076	0.3670	0.9076	0.6510	0.9478
$MONDAY_t$	1.0485	0.2840	0.0002	0.1200	<2.2E-16	0.1200	<2.2E-16	0.3170	0.0009
TM_{it}	0.3665	0.2650	0.1665	0.2750	0.1830	0.2750	0.1830	0.3011	0.2238
DVR_{it}	0.0558	0.0455	0.2202	0.0606	0.3573	0.0606	0.3573	0.0278	0.0450
ΔDD_{it}	13.3010	10.1000	0.1893	6.1900	0.0317	6.1900	0.0317	6.9200	0.0545
VIX_t	0.4901	0.0955	7.23E-15	0.0724	1.31E-11	0.0724	7.23E-15	0.0603	4.24E-16
$\Delta r_{F_{2year},t}$	-30.4840	12.7180	0.0165	3.1222	<2.2E-16	3.1222	<2.2E-16	4.1220	1.42E-13
$SPRETURNS_t$	2.0663	0.6063	0.0007	0.2657	7.53E-15	0.2657	7.53E-15	0.2799	1.57E-13
$s_{i,t-1}$	0.7545	0.0507	<2.2E-16	0.0361	<2.2E-16	0.0361	<2.2E-16	0.0273	<2.2E-16

TABLE A-14. Dependent variable: Corporate bond yield spreads s_{it} in basis points, fixed effects model, panel estimation method based on the Balestra and Varadharajan-Krishnakumar (1987) transformation ($N = 179$ bonds, $T = 952$; fixed effects not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are the White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007). Instruments: VIX_{t-1}, DAX_t, $NIKKEI_t$, $DVR_{i,t-1}$, $\Delta DD_{i,t-1}$, $SPRETURNS_{t-1}$, $\Delta r_{F_{2year},t-1}$. The exogenous/predetermined variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t, TM_{it}, $s_{i,t-1}$ and $MONDAY_t$.

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{DK}	p-value
$CLOUDCOVER_t$	-0.0188	0.0439	0.6678	0.0154	0.2216	0.0154	0.2216	0.0439	0.6678
$VISIBILITY_t$	1.34E-5	3.39E-5	0.6935	1.25E-5	0.2857	1.25E-5	0.2857	3.39E-5	0.6935
$TEMP_{DS,t}$	0.0265	0.0277	0.3391	8.20E-3	0.0012	8.20E-3	0.0012	0.0277	0.3391
$PRECIPITATION_t$	-0.0105	0.0130	0.4176	3.86E-3	0.0064	3.86E-3	0.0064	0.0130	0.4176
$BAROPRESS_t$	0.0008	9.71E-4	0.4018	3.83E-4	0.0338	3.83E-4	0.0338	9.71E-4	0.4018
$HUMIDITY_t$	0.0047	9.92E-3	0.6391	3.14E-3	0.1386	3.14E-3	0.1386	9.92E-3	0.6391
$WINDSPEED_t$	0.0185	0.0470	0.6939	0.0143	0.1975	0.0143	0.1975	0.0470	0.6939
$TEMPDY_t$	-0.0419	0.0420	0.3184	0.0160	0.0086	0.0160	0.0086	0.0420	0.3184
SAD_t	-0.0681	0.3950	0.8632	0.1900	0.7203	0.1900	0.7203	0.3950	0.8632
$MONDAY_t$	0.7289	0.2770	0.0085	0.0911	1.25E-15	0.0911	1.25E-15	0.2770	0.0085
TM_{it}	0.1327	0.1930	0.4927	0.1570	0.3985	0.1570	0.3985	0.1930	0.4927
DVR_{it}	0.0005	8.13E-3	0.9488	0.0127	0.9673	0.0127	0.9673	8.13E-3	0.9488
ΔDD_{it}	0.0538	0.0493	0.2751	0.0505	0.2866	0.0505	0.2866	0.0493	0.2751
VIX_t	0.3024	0.0389	7.23E-15	0.0378	1.21E-15	0.0378	1.21E-15	0.0389	7.23E-15
$\Delta r_{F_{2year},t}$	1.0237	2.2022	0.6420	1.4072	0.4669	1.4072	0.4669	2.2022	0.6420
$SPRETURNS_t$	0.4452	0.1438	0.0020	0.0422	$<$2.2E-16	0.0422	$<$2.2E-16	0.1438	0.0020
$s_{i,t-1}$	0.8648	0.0161	$<$2.2E-16	0.0189	$<$2.2E-16	0.0189	$<$2.2E-16	0.0161	$<$2.2E-16

TABLE A-15. Dependent variable: Corporate bond yield spreads s_{it} in basis points, LS estimates, fixed effects model, panel estimation method based on taking the within-transform ($N = 179$ bonds, $T = 952$; fixed effects not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are the White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007).

Variable	$\boldsymbol{\beta}$	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{DK}	p-value
$CLOUDCOVER_t$	0.0194	0.0234	0.4072	0.0077	0.0119	0.0077	0.0119	0.0234	0.4072
$VISIBILITY_t$	-1.58E-5	1.69E-5	0.3487	5.12E-6	0.0020	5.12E-6	0.0020	1.69E-5	0.3487
$TEMP_{DS,t}$	0.0164	0.0223	0.4631	0.0049	0.0009	0.0049	0.0009	0.0223	0.4631
$PRECIPITATION_t$	2.92E-4	6.67E-3	0.9650	0.0018	0.8719	0.0018	0.8719	0.0067	0.9650
$BAROPRESS_t$	4.86E-4	5.27E-4	0.3563	1.47E-4	9.18E-4	1.47E-4	9.18E-4	0.0005	0.3563
$HUMIDITY_t$	-0.0126	0.0044	0.0037	2.90E-3	1.34E-5	2.90E-3	1.34E-5	0.0044	0.0037
$WINDSPEED_t$	0.0115	0.0246	0.6407	0.0082	0.1636	0.0082	0.1636	0.0246	0.6407
$TEMPDY_t$	-0.0047	0.0279	0.8654	0.0058	0.4143	0.0058	0.4143	0.0279	0.8654
SAD_t	-4.0953	5.4039	0.4486	1.2417	0.0010	1.2417	0.0010	5.4039	0.4486
$CLOUDCOVER_{t-1}$	7.84E-4	0.0246	0.9746	0.0052	0.8799	0.0052	0.8799	0.0246	0.9746
$VISIBILITY_{t-1}$	1.38E-5	1.50E-5	0.3579	3.75E-6	2.44E-4	3.75E-6	2.44E-4	0.0000	0.3579
$TEMP_{DS,t-1}$	0.0264	0.0212	0.2125	7.21E-3	2.45E-4	7.21E-3	2.45E-4	0.0212	0.2125
$PRECIPITATION_{t-1}$	0.0048	0.0063	0.4460	1.04E-3	3.52E-6	1.04E-3	3.52E-6	0.0063	0.4460
$BAROPRESS_{t-1}$	0.0006	0.0005	0.2605	1.96E-4	3.29E-3	1.96E-4	3.29E-3	0.0005	0.2605
$HUMIDITY_{t-1}$	-0.0059	0.0048	0.2225	1.24E-3	2.06E-6	1.24E-3	2.06E-6	0.0048	0.2225
$WINDSPEED_{t-1}$	0.0064	0.0221	0.7726	0.0048	0.1863	0.0048	0.1863	0.0221	0.7726
$TEMPDY_{t-1}$	-0.0354	0.0272	0.1925	0.0106	8.59E-4	0.0106	8.59E-4	0.0272	0.1925
SAD_{t-1}	4.3953	5.3975	0.4155	1.2439	4.11E-4	1.2439	4.11E-4	5.3975	0.4155
$MONDAY_t$	-0.9099	0.1486	9.37E-10	0.1944	2.88E-6	0.1944	2.88E-6	0.1486	9.37E-10
VIX_t	1.7796	0.2387	9.29E-14	0.3765	2.30E-6	0.3765	2.30E-6	0.2387	9.29E-14
VIX_{t-1}	-1.7906	0.2392	7.36E-14	0.3795	2.39E-6	0.3795	2.39E-6	0.2392	7.36E-14
$\Delta r_{F_{2year},t}$	-0.9514	0.1076	<2.2E-16	0.2613	2.72E-4	0.2613	2.72E-4	0.1076	<2.2E-16
$\Delta r_{F_{2year},t-1}$	0.0105	0.0452	0.8157	0.0156	0.4980	0.0156	0.4980	0.0452	0.8157
$STR_{i,t-1}$	-0.0191	0.0243	0.4314	0.0133	0.1515	0.0133	0.1515	0.0243	0.4314

TABLE A-16. Dependent variable: Stock returns STR_{it} in percentage terms, fixed effects model, panel estimation method based on the Balestra and Varadharajan-Krishnakumar (1987) transformation ($N = 23$ stocks, $T = 952$; fixed effects and Fama-French factor loadings not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are the White (1980) adjusted standard errors, SE_{HC3} provides a refinement (see Croissant and Millo, 2008). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007). Instruments: DAX_t, $NIKKEI_t$, VIX_{t-1}, $\Delta r_{F_{2year},t-1}$, VIX_{t-2}, $\Delta r_{F_{2year},t-2}$. The exogenous/predetermined 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 $j = 0, 1$, $STR_{i,t-1}$ and $MONDAY_t$.

Variable	β	SE	p-value	SE_{HC0}	p-value	SE_{HC3}	p-value	SE_{HC4}	p-value
$CLOUDCOVER_t$	-0.0056	0.0053	0.2854	0.0053	0.2912	0.0053	0.2912	0.0053	0.2912
$VISIBILITY_t$	1.46E-6	3.89E-6	0.7069	3.72E-6	0.6944	3.72E-6	0.6944	3.72E-6	0.6944
$TEMP_{DS,t}$	0.0015	0.0043	0.7381	0.0039	0.7077	0.0039	0.7077	0.0039	0.7077
$PRECIPITATION_t$	2.01E-3	1.74E-3	0.2455	0.0015	0.1737	0.0015	0.1737	0.0015	0.1737
$BAROPRESS_t$	2.36E-4	1.07E-4	0.0282	0.0001	0.0754	0.0001	0.0754	0.0001	0.0754
$HUMIDITY_t$	-5.82E-4	1.00E-3	0.5621	0.0011	0.5939	0.0011	0.5939	0.0011	0.5939
$WINDSPEED_t$	-0.0069	0.0056	0.2171	0.0071	0.3299	0.0071	0.3299	0.0071	0.3299
$TEMPDY_t$	-0.0070	0.0062	0.2561	0.0057	0.2155	0.0057	0.2155	0.0057	0.2155
SAD_t	-4.1284	1.1761	0.0004	1.0821	0.0001	1.0821	0.0001	1.0821	0.0001
$CLOUDCOVER_{t-1}$	0.0073	0.0053	0.1708	0.0051	0.1581	0.0051	0.1581	0.0051	0.1581
$VISIBILITY_{t-1}$	9.74E-6	3.79E-6	0.0101	3.84E-6	0.0111	3.84E-6	0.0111	3.84E-6	0.0111
$TEMP_{DS,t-1}$	1.76E-4	4.32E-3	0.9676	0.0042	0.9667	0.0042	0.9667	0.0042	0.9667
$PRECIPITATION_{t-1}$	2.76E-3	1.49E-3	0.0648	8.20E-4	7.76E-4	0.0008	0.0008	0.0008	0.0008
$BAROPRESS_{t-1}$	-1.79E-4	1.15E-4	0.1190	1.26E-4	0.1577	0.0001	0.1577	0.0001	0.1577
$HUMIDITY_{t-1}$	-0.0010	0.0010	0.2908	5.81E-4	0.0716	0.0006	0.0716	0.0006	0.0716
$WINDSPEED_{t-1}$	0.0046	0.0056	0.4086	0.0047	0.3318	0.0047	0.3318	0.0047	0.3318
$TEMPDY_{t-1}$	-0.0004	0.0062	0.9470	0.0073	0.9552	0.0073	0.9552	0.0073	0.9552
SAD_{t-1}	4.1327	1.1713	0.0004	1.0859	0.0001	1.0859	0.0001	1.0859	0.0001
$MONDAY_t$	-0.0013	0.0281	0.9642	0.0275	0.9634	0.0275	0.9634	0.0275	0.9634
VIX_t	0.0010	0.0161	0.9492	0.0247	0.9668	0.0247	0.9668	0.0247	0.9668
VIX_{t-1}	0.0019	0.0160	0.9065	0.0254	0.9409	0.0254	0.9409	0.0254	0.9409
$\Delta r_{F_{2year},t}$	0.0083	0.0135	0.5410	0.0085	0.3284	0.0085	0.3284	0.0085	0.3284
$\Delta r_{F_{2year},t-1}$	-0.0219	0.0127	0.0841	0.0127	0.0845	0.0127	0.0845	0.0127	0.0845
$STR_{i,t-1}$	0.0030	0.0056	0.6015	0.0106	0.7805	0.0106	0.7805	0.0106	0.7805

TABLE A-17. Dependent variable: Stock returns STR_{it} in percentage terms, LS Estimates, fixed effects model, panel estimation method based on taking the within-transform ($N = 23$ stocks, $T = 952$; fixed effects and Fama-French factor loadings not reported). SE stands for the standard errors without using any robust adjustment. SE_{HC0} are the White (1980) adjusted standard errors, SE_{HC3} and SE_{HC4} provide refinements (see Croissant and Millo, 2008).

Variable	$\boldsymbol{\beta}$	SE_{DK}	p-value
$CLOUDCOVER_t$	-0.0178	0.0140	0.2023
$VISIBILITY_t$	1.06E-5	8.68E-6	0.2206
$TEMP_{DS,t}$	-0.0145	0.0110	0.1867
$PRECIPITATION_t$	-0.0002	0.0036	0.9477
$BAROPRESS_t$	2.54E-5	2.06E-4	0.9018
$HUMIDITY_t$	0.0082	0.0028	0.0036
$WINDSPEED_t$	-0.0030	0.0159	0.8511
$TEMPDY_t$	-0.0136	0.0153	0.3749
SAD_t	-2.3634	3.2906	0.4726
$CLOUDCOVER_{t-1}$	0.0043	0.0144	0.7644
$VISIBILITY_{t-1}$	5.24E-6	7.96E-6	0.5100
$TEMP_{DS,t-1}$	-0.0123	0.0119	0.3012
$PRECIPITATION_{t-1}$	0.0025	0.0028	0.3668
$BAROPRESS_{t-1}$	-0.0006	0.0002	0.0005
$HUMIDITY_{t-1}$	0.0022	0.0025	0.3896
$WINDSPEED_{t-1}$	0.0056	0.0119	0.6391
$TEMPDY_{t-1}$	0.0067	0.0178	0.7073
SAD_{t-1}	2.1325	3.2767	0.5152
$MONDAY_t$	0.3880	0.0828	2.84E-6
VIX_t	-0.7913	0.1128	2.50E-12
VIX_{t-1}	0.8060	0.1126	8.90E-13
$\Delta r_{F_{2year},t}$	0.7564	0.0836	$<$2.2E-16
$\Delta r_{F_{2year},t-1}$	-0.0184	0.0251	0.4626
$STR_{i,t-1}$	0.0042	0.0153	0.7834

TABLE A-18. Dependent variable: Stock returns STR_{it} in percentage terms, fixed effects model, panel estimation method based on the Balestra and Varadharajan-Krishnakumar (1987) transformation; $\hat{\beta}_{Mi} := \left[\hat{\beta}_{FFi}\right]_{(1)} \leq 1$ subsample ($N = 9$ stocks, $T = 952$; fixed effects and Fama-French factor loadings not reported). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007). Instruments: DAX_t, $NIKKEI_t$, VIX_{t-1}, $\Delta r_{F_{2year},t-1}$, , VIX_{t-2}, $\Delta r_{F_{2year},t-2}$. The exogenous/predetermined 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 $MONDAY_t$.

Variable	$\boldsymbol{\beta}$	SE_{DK}	p-value
$CLOUDCOVER_t$	0.0493	0.0612	0.4199
$VISIBILITY_t$	-6.02E-5	4.12E-5	0.1438
$TEMP_{DS,t}$	0.0723	0.0569	0.2040
$PRECIPITATION_t$	0.0077	0.0173	0.6555
$BAROPRESS_t$	0.0012	0.0010	0.2421
$HUMIDITY_t$	-0.0409	0.0116	0.0004
$WINDSPEED_t$	0.0398	0.0652	0.5415
$TEMPDY_t$	-0.0016	0.0727	0.9828
SAD_t	-8.8259	16.2420	0.5869
$CLOUDCOVER_{t-1}$	-0.0056	0.0624	0.9282
$VISIBILITY_{t-1}$	5.10E-6	3.87E-5	0.8950
$TEMP_{DS,t-1}$	0.0882	0.0555	0.1123
$PRECIPITATION_{t-1}$	0.0117	0.0159	0.4629
$BAROPRESS_{t-1}$	0.0021	0.0011	0.0658
$HUMIDITY_{t-1}$	-0.0235	0.0124	0.0592
$WINDSPEED_{t-1}$	0.0103	0.0559	0.8541
$TEMPDY_{t-1}$	-0.0764	0.0734	0.2979
SAD_{t-1}	9.9843	16.1960	0.5376
$MONDAY_t$	-2.0990	0.3652	9.31E-9
VIX_t	4.0894	0.5600	3.03E-13
VIX_{t-1}	-4.1832	0.5660	1.56E-13
$\Delta r_{F_{2year},t}$	-3.5364	0.3803	<2.2E-16
$\Delta r_{F_{2year},t-1}$	0.0189	0.1452	0.8965
$STR_{i,t-1}$	-0.0696	0.0561	0.2146

TABLE A-19. Dependent variable: Stock returns STR_{it} in percentage terms, fixed effects model, panel estimation method based on the Balestra and Varadharajan-Krishnakumar (1987) transformation; $\hat{\beta}_{Mi} = \left[\hat{\beta}_{FFi}\right]_{(1)} > 1$ subsample ($N = 14$ stocks, $T = 952$; fixed effects and Fama-French factor loadings not reported). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007). Instruments: DAX_t, $NIKKEI_t$, VIX_{t-1}, $\Delta r_{F_{2year},t-1}$, VIX_{t-2}, $\Delta r_{F_{2year},t-2}$. The exogenous/predetermined 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 $MONDAY_t$.

Variable	$\boldsymbol{\beta}$	SE_{DK}	p-value
$CLOUDCOVER_t$	0.1141	0.1067	0.2850
$VISIBILITY_t$	-2.95E-5	5.21E-5	0.5713
$TEMP_{DS,t}$	0.0358	0.0435	0.4109
$PRECIPITATION_t$	-0.0241	0.0193	0.2129
$BAROPRESS_t$	0.0013	0.0012	0.2432
$HUMIDITY_t$	-0.0061	0.0162	0.7065
$WINDSPEED_t$	0.0509	0.0854	0.5509
$TEMPDY_t$	0.0073	0.0789	0.9264
SAD_t	0.2403	0.7164	0.7374
$CLOUDCOVER_t{\cdot}\mathbf{1}_{AAA_{it}}$	0.1502	0.1754	0.3918
$VISIBILITY_t{\cdot}\mathbf{1}_{AAA_{it}}$	2.50E-5	3.73E-5	0.5035
$TEMP_{DS,t}{\cdot}\mathbf{1}_{AAA_{it}}$	-0.0201	0.0347	0.5631
$PRECIPITATION_t{\cdot}\mathbf{1}_{AAA_{it}}$	0.0113	0.0132	0.3897
$BAROPRESS_t{\cdot}\mathbf{1}_{AAA_{it}}$	0.0013	0.0014	0.3354
$HUMIDITY_t{\cdot}\mathbf{1}_{AAA_{it}}$	-0.0274	0.0300	0.3609
$WINDSPEED_t{\cdot}\mathbf{1}_{AAA_{it}}$	-0.0907	0.0802	0.2583
$TEMPDY_t{\cdot}\mathbf{1}_{AAA_{it}}$	-0.0461	0.0531	0.3851
$SAD_t{\cdot}\mathbf{1}_{AAA_{it}}$	-1.2651	0.9753	0.1945
$CLOUDCOVER_t{\cdot}\mathbf{1}_{BBB_{it}}$	-0.6944	0.2328	0.0029
$VISIBILITY_t{\cdot}\mathbf{1}_{BBB_{it}}$	-0.0006	0.0005	0.2735
$TEMP_{DS,t}{\cdot}\mathbf{1}_{BBB_{it}}$	0.4362	0.3304	0.1867
$PRECIPITATION_t{\cdot}\mathbf{1}_{BBB_{it}}$	0.0569	0.1451	0.6949
$BAROPRESS_t{\cdot}\mathbf{1}_{BBB_{it}}$	0.0131	0.0076	0.0825
$HUMIDITY_t{\cdot}\mathbf{1}_{BBB_{it}}$	-0.1368	0.1261	0.2781
$WINDSPEED_t{\cdot}\mathbf{1}_{BBB_{it}}$	1.2745	0.7804	0.1024
$TEMPDY_t{\cdot}\mathbf{1}_{BBB_{it}}$	-0.6920	0.4392	0.1151
$SAD_t{\cdot}\mathbf{1}_{BBB_{it}}$	1.7307	3.6273	0.6333
$MONDAY_t$	1.4563	0.3878	0.0002
TM_{it}	-0.1162	0.3336	0.7275
DVR_{it}	0.1309	0.0447	0.0034
ΔDD_{it}	25.7020	13.3950	0.0550
VIX_t	0.3016	0.0609	7.41E-7
$\Delta r_{F_{2year},t}$	-51.1620	6.2579	2.99E-16
$SPRETURNS_t$	2.8703	0.4769	1.77E-9
$s_{i,t-1}$	0.8602	0.0171	<2.2E-16

TABLE A-20. Dependent variable: Corporate bond yield spreads s_{it} in basis points, fixed effects model, panel estimation method based on the Balestra and Varadharajan-Krishnakumar (1987) transformation (N = 179 bonds, T = 952; fixed effects not reported). SE_{DK} robust standard errors account for possible spatial and serial correlation (see Driscoll and Kraay, 1998, Hoechle, 2007). Instruments: VIX_{t-1}, DAX_t, $NIKKEI_t$, $DVR_{i,t-1}$, $\Delta DD_{i,t-1}$, $SPRETURNS_{t-1}$, $\Delta r_{F_{2year},t-1}$. The exogenous/predetermined variables are $CLOUDCOVER_t$, $VISIBILITY_t$, $TEMP_{DS,t}$, $PRECIPITATION_t$, $BAROPRESS_t$, $HUMIDITY_t$, $WINDSPEED_t$, $TEMPDY_t$, SAD_t, TM_{it}, $s_{i,t-1}$, $MONDAY_t$ and the weather variables times the corresponding rating indicators.

A-6 Measurements of Selected Variables Used

variable	measure	approximate range
$CLOUDCOVER_t$		$0 - 8$
$VISIBILITY_t$	meters (m)	$960 - 16000$
$PRECIPITATION_t$	mm	$0 - 124$
$TEMP_{DS,t}$	degree Celsius	$-11 - 15$
$HUMIDITY_t$	%	$24 - 100$
$BAROPRESS_t$	Hectopascals	$984 - 1040$
$WINDSPEED_t$	meters per second	$0.8 - 14$
$TEMP_{DY,t}$	degree Celsius	$-11 - 15$
SAD_t		-0.433 - 0.433
VIX_t		$10 - 45$
DD_{it}		$1.5 - 7.5$
TM_{it}	years	$1 - 12$
r_{Fit}	% per year	$1.2 - 5.1$
$\Delta r_{F_{2year},t}$	%points	$-0.26 - 0.26$
$SPRETURNS_t$	%	$-4 - 5$
STR_{it}	%	$-49 - 25$
s_{it}	basis points	$22 - 823$
DVR_{it}	decimal number	$0 - 1$
$\mathbb{I}_{Aaa,t}$	% per year	$4.76 - 6.62$
$\mathbb{I}_{Baa,t}$	% per year	$5.64 - 8.05$

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