Schmalenbach Journal of Business Research
https://doi.org/10.1007/s41471-021-00125-5

ORIGINAL ARTICLE

Does Weather Still Affect The Stock Market?

New Insights Into The Effects Of Weather On Returns, Volatility, And Trading Volume

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Abstract This paper examines the impact of weather phenomena on the German stock market, evaluating cloud cover, humidity, air pressure, precipitation, temperature, and wind speed as weather variables. We use stock market data (returns, trading volume, and volatility) from the DAX, MDAX, SDAX, and TecDAX for the period from 2003 to 2017 and show, with modern time-series (GARCH) models that air pressure is the only weather variable that exerts a potentially consistent effect on the stock market. Air pressure reduces the trading volume on the SDAX and TecDAX, and changes in air pressure lead to increases in returns on the DAX, MDAX and SDAX. The effects of the other weather variables show no clear pattern and are critically discussed. In addition, this article contains an overview of the historical research results on the effects of weather on stock markets.

Keywords Weather effects · Air pressure · GARCH

This paper was originally submitted and independently peer-reviewed at Schmalenbach Business Review, one of SBUR's predecessor journals. It has been accepted by the same Editor-in-Chief for publication in the successor journal SBUR.

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Published online: 10 December 2021

1 Introduction

In the first empirical investigation of the impact of weather phenomena on the stock market, Saunders (1993) indicated of the limits of classical capital market theory, showing a significant negative effect of clouds on the returns of North American equity indices. Motivated by this empirical finding, numerous studies with different study designs and overall inconclusive results followed (e.g., Bassi et al. 2013; Chang et al. 2008; Dowling and Lucey 2008; Frühwirth and Sögner 2015; Hirshleifer and Shumway 2003; Kamstra et al. 2003; Krämer and Runde 1997; Symeonidis et al. 2010). These studies confirming the effects of weather contradict the predictions of classical capital market theory but are consistent with behavioral science findings that identify the influence of mood on decision-making processes.

The theoretical basis for the existence of weather effects within stock markets is the assumption that there is an indirect functional chain of weather that influences investor mood, which in turn influences their decision-making processes (e.g., Bassi et al. 2013; Cao and Wei 2005; Frühwirth and Sögner 2015). If this indirect functional chain is operative to some extent and capital market anomalies in the form of weather effects actually exist, then these facts would lend support to theories of behavioral finance, an interdisciplinary field combining economics, psychology and sociology (Shiller 2003), while weakening the support for the efficient market hypothesis (Malkiel and Fama 1970).

There have been many empirical investigations into the effects of the capital market weather anomaly on the New York Stock Exchange (NYSE) (e.g., Saunders 1993 and Trombley 1997), New Zealand Stock Exchange (Keef and Roush 2002), Madrid Stock Exchange (Pardo and Valor 2003), London Stock Exchange (Apergis et al. 2016), Australian stock market (Worthington 2009), Korean stock market (Yoon and Kang 2009), Taiwanese stock market (Chang et al. 2006), Chinese stock market (Lu and Chou 2012), and German stock market (Klein 2005). These studies differ with regard to the stock market examined and the possible indices, weather variables, time period and statistical method used in the analysis.

For the German stock market, the weather capital market anomaly has not yet been exhaustively investigated. Overall, research gaps exist in terms of both content and methodology; the literature has not yet considered all important indices and all relevant weather variables simultaneously. Most studies, especially those on the German market, have analyzed only returns (Apergis et al. 2016; Cao and Wei 2005; Jacobsen and Marquering 2008; Klein 2005; Krämer and Runde 1997; Schneider 2014a). To our knowledge, no study has analyzed trading volumes, and only Dowling and Lucey 2008 investigated volatility.

From a statistical point of view, the usage of ordinary least squares (OLS) regression models for time-series data is insufficient in most cases due to heteroskedasticity problems and poor robustness. The majority of existing studies use only OLS regressions (exceptions include, e.g., Dougal et al. 2012; Symeonidis et al. 2010; Yoon and Kang 2009), which may explain the different outcomes of studies on weather anomalies in capital markets.

To address this shortcoming and provide more recent empirical evidence on weather anomalies in capital markets, we use generalized autoregressive conditional heteroskedastic (GARCH) time–series models and show, with data on German stock market indices (DAX, MDAX, SDAX, and TecDAX) covering August 2003 to July 2017, that weather has an impact on volatility and trading volume. The remainder of this paper is organized as follows. In the first section, we discuss the indirect functional chain linking weather, mood and decision-making. Then, we provide a literature review of the empirical results on a possible weather anomaly in capital markets. Thereafter, we briefly discuss the use of GARCH models for our analysis and present our results. Finally, we discuss the results and provide conclusions.

2 Theoretical Background and Hypotheses

The theoretical reasoning behind studies on the effect of weather on stock markets is the assumption of an indirect functional chain whereby weather influences investors' mood, which in turn influences their decision-making processes (e.g., Bassi et al. 2013; Cao and Wei 2005; Frühwirth and Sögner 2015). Mood is an affective state that can be influenced by external factors such as an individual's overall (biological) condition and health status. Weather can have an impact on these external factors and, thus, on mood. A study by Fletcher (1988) found that people reported increased joint pain, headaches, irritability, and nervousness in relation to exposure to Chinook winds in Canada. In addition, Guedj and Weinberger (1990) showed that weather can impact physical health, finding that changes in weather related to air pressure, temperature, and precipitation increased the pain sensitivity of rheumatism patients. Moreover, Jamison et al. (1995) obtained similar results. Other studies have focused on the effects of weather on mental health. Rosenthal et al. (1984) discovered, for example, a type of annually recurring depression in autumn or winter known as seasonal affective disorder (SAD). The symptoms of this disease change depending on the climate and latitude. Howarth and Hoffman (1984) identified a negative effect of humidity on concentration and a positive effect on tiredness, as well as a positive correlation between temperature and skepticism and a positive effect of sunshine on optimism. Recent studies by Denissen et al. (2008) and Kööts et al. (2011) have shown similar results and identified a negative impact of sunshine on tiredness. Schwarz and Clore (1983) observed that study participants generally thought more positively about their life on sunny days. The authors concluded that people use their current mood, here influenced by the weather, as a source of information for decision-making. Allen and Fischer (1978) observed that humidity influences mental efficiency, while Delyukov and Didyk (1999) showed that memory performance was impaired by aperiodic variations in air pressure. A meta-analysis of performance as a function of temperature was carried out by Pilcher et al. (2002) and found that both cold and hot temperatures generally have a negative influence on cognitive efficiency. Keller et al. (2005) obtained similar results and showed that high temperatures and high air pressure have a positive impact on memory performance and mental receptiveness. Thus, a variety of external factors related to weather have an impact on mood and ultimately influence decision-making.

The most commonly used models for explaining the influence of positive or negative affective states (which can be significantly influenced by weather) on (risk)

Table 1 Weather, the AIM, and the MMH

	Mood Maintenance Hypothesis (MMH)	Affect Infusion Model (AIM)
Positive affective state (good weather)	Risk-averse	Risk-seeking
Negative affective state (bad weather)	Risk-seeking	Risk-averse

behavior are Forgas' affect infusion model (AIM) (Forgas 1994, 1995) and Isen and Patrick's mood maintenance hypothesis (MMH) (Isen and Patrick 1983). However, these explanatory approaches differ in terms of their mechanisms of action and are therefore briefly presented below while also providing the basis for hypothesis development.

The MMH describes that individuals who are in a positive affective state try to maintain it (Isen and Simmonds 1978). Then, it follows that individuals in a negative affective state try to leave it (mood repair) to get back to a positive affective state (Cialdini et al. 1973). If this hypothesis is translated to risky situations, such as investment decisions in stock markets, then a positive affective state leads to risk-averse behavior and a negative affective state to risk-seeking behavior (Isen 2008). The AIM argues diametrically and can be described via affect priming and affect as information (Forgas 1995). Affect priming leads to a selective perception of information needed for decision-making; thus, the decision is indirectly influenced by the current affective state. Affect as information describes the adoption of the affective state as an evaluation criterion for decision-making. The affective state then possibly leads to a decision that corresponds to the affective state (Forgas 1994), which, for decisions under risk, results in risk-seeking behavior for positive affective states and risk-averse behavior for negative affective states. The following table shows the relationships involving weather as an affective state.

Forgas (1995) concluded that the impact of mood on decision-making processes is stronger for uncertain, riskier, and more abstract situations which applies to financial decisions (Frühwirth and Sögner 2015). Consequently, mood can influence investors' decision-making processes in a way that may impact the capital market. It is therefore reasonable to assume that weather might influence the capital market.

This relationship is also known as a capital market anomaly, which cannot be explained by classical capital market theory and thus provides a justification for the interdisciplinary behavioral finance approach, which combines economics, psychology, and sociology (e.g., Shiller 2003). While there are many capital market anomalies (e.g., Dimson 1988), the following paragraphs discuss only the weather anomaly in relation to returns, volatility, and trading volume.

2.1 Return

Saunders' first study on weather phenomena in capital markets (Saunders 1993) marked the beginning of a research trend that continues to this day. The empiri-

Table 2 Weather effects on returns

Author(s)	Cloud cover	Sunshine	Temperature	Precipitation	Wind	Air pressure	Humidity	Visual range	Snow
Saunders (1993)	▼								
Krämer and Runde (1997)	•			•		•	•		•
Keef and Roush (2002)	•		▼		▼				
Hirshleifer and Shumway (2003)	▼			•					•
Kamstra et al. (2003)*	▼		▲	▼					
Krivelyova and Robotti (2003)	•		•	•					
Pardo and Valor (2003)		•					•		
Loughran and Schultz (2004)	▼								
Tufan and Hamarat (2004)	•								
Cao and Wei (2005)	▼		▼						
Dowling and Lucey (2005)	•			▼			▲		
Goetzmann and Zhu (2005)	▼			•					•
Klein (2005)	▼	▲							
Chang et al. (2006)*	▼		▼				•		

Table 2 (Continued)

Author(s)	Cloud cover	Sunshine	Temperature	Precipitation	Wind	Air pressure	Humidity	Visual range	Snow
Keef and Roush (2007)	●		▼		●				
Chang et al. (2008)	▼		●	●	●				●
Dowling and Lucey (2008)*			▼	●	●				
Jacobsen and Marquering (2008)			▼						
Worthington (2009)		●	●	●	●		●		
Yoon and Kang (2009)*	▼		▼				▼		
Zadorozhna (2009)*	●		●	●	●	●	●	●	
Kang et al. (2010)*		●	▼				●		
Akhtari (2011)	▼								
Floros (2011)*			▼						
Lu and Chou (2012)	●		●	●	●	●	●	●	▼
Schneider (2014a)	●		●	●	●	▲	▼		
Frühwirth and Sögner (2015)	●		●	▲	●	●	●	●	
Goetzmann et al. (2015)	▼								
Apergis et al. (2016)		▼	▼	▼	▼		▼		

Table 2 (Continued)

Author(s)	Cloud cover	Sunshine	Temperature	Precipitation	Wind	Air pressure	Humidity	Visual range	Snow
Sariannidis et al. (2016)*					▲		▲		
Pizzutilo and Roncone (2017)	●		●	●	●	●	●	●	●
Positive effect (%)	0	20	5	7	8	17	14	0	0
Negative effect (%)	52	20	53	20	17	0	22	0	17
No effect (%)	48	60	42	73	75	83	64	100	83

● no significant effect, ▼ significant negative effect, ▲ significant positive effect, sources marked with * use GARCH cal results of the abovementioned studies, which consider returns as a dependent variable, are shown in the Table 2.

The table lists an effect only if a consistent direction of the effect has been identified in at least one model within a study. If different statistical methods have been applied, then the table reports the results of the regression analysis.

Cloudiness is by far the most frequently studied variable, followed by temperature and precipitation. For cloudiness and temperature, more than half of the studies found their negative impacts on returns. In contrast, the remaining studies could not detect any effect for the two variables on returns. For other weather variables, the majority of the studies showed no significant correlation. Air pressure has been one of the least studied weather variables, although it is the only weather phenomenon to which people are exposed inside buildings (Schneider 2014a).

The dominant statistical method used in these related studies is OLS regression, the majority of which have attempted to take into account the special nature of finance data by applying White or Newey-West standard errors to correct for bias in the results arising from heteroskedasticity problems. Only Chang et al. (2006); Dowling and Lucey (2008); Floros (2011); Kamstra et al. (2003); Kang et al. (2010); Sariannidis et al. (2016); Yoon and Kang (2009), and Zadorozhna (2009) used modern financial market econometrics in the form of GARCH models. Therefore, the possibility cannot be excluded that the effects identified in these studies that use traditional models are based on an insufficient data representation.

As previously described, weather impacts people's mood. The AIM and MMH provide different theoretical explanations for the impact of weather on the stock market. Empirical evidence can be found for both approaches, although the majority of the results favor the AIM. Good weather conditions positively influence mood, which in turn leads to a positive impact on stock returns (AIM). The predictions arising from this line of reasoning are in contrast to the findings of studies that reported a correlation between bad weather[1] and high returns (MMH). But differences can also be identified for the different weather variables. For example, most studies revealed a negative influence of temperature on returns, which might be explained by an increased willingness to take risks under certain weather conditions. According to this line of argument, cold temperatures lead to aggressive behavior, a greater willingness to take risks and, ultimately, increased returns. More pronounced risk-taking behavior in bad weather is in line with the results of Raghunathan et al. (2006), who observed riskier behavior among subjects who reported experiencing sadness (Raghunathan and Pham 1999). However, the different empirical results, the majority of which are in favor of the AIM over the MMH, do not allow for a clear theoretical positioning. According to the AIM and MMH, two competing hypotheses can be concluded.

Hypothesis 1a: Good (bad) weather conditions lead to higher (lower) returns on the German stock market (AIM).

[1] The climate in Germany belongs to the cool temperate climate zone, so bad weather represents an increase in cloud cover, fewer hours of sunshine, higher relative humidity, lower barometric pressure, more precipitation, lower temperature and higher wind speed.

Table 3 Weather effects on volatility

Author(s)	Volatility	Cloud cover	Sunshine	Temperature	Precipitation	Wind	Air pressure	Humidity	Visual range	Snow
Chang et al. (2008)		▲	●	▲		▲				●
Dowling and Lucey (2008)*				●	▲	▲				
Kang et al. (2010)*			●	▲				●		
Symeonidis et al. (2010)*	Historical	▼		▲	▼					
Symeonidis et al. (2010)*	Implicit	▼		▲	▲					
Symeonidis et al. (2010)*	Realized	●		▲	▲					
Lu and Chou (2012)		▼		●	▲	▲	●	▲	●	●
Frühwirth and Sögner (2015)	VIX	●		●	▲	●	●	●	●	
Pizzutilo and Roncone (2017)		●	●	●	●	●	●	●	●	●
Positive effect (%)		14	0	56	72	60	0	25	0	0
Negative effect (%)		43	0	0	14	0	0	0	0	0
No effect (%)		43	100	44	14	40	100	75	100	100

● no significant effect, ▼ significant negative effect, ▲ significant positive effect, sources marked with * use GARCH

Hypothesis 1b: Bad (good) weather conditions lead to higher (lower) returns on the German stock market (MMH).

In addition to absolute weather characteristics or absolute deviations from average weather conditions having an effect on people and their decisions, studies have also shown that changes in weather can have an effect on people's physical constitution (Guedj and Weinberger 1990; Jamison et al. 1995). In addition, Wang (2016) discovered a correlation at the investor level between worsening changes in weather and risk appetite, measured in terms of the number and size of transactions in the UK spread market (MMH). At the index level, Schneider (2014a) found significant effects of positive daily changes in air pressure on the returns of the TecDAX and FTSE (AIM). The analysis of changes in weather also shows no clear direction based on underlying theories, so we also provide two competing hypotheses.

Hypothesis 1c: Positive (negative) changes in weather lead to higher (lower) returns on the German stock market (AIM).

Hypothesis 1d: Negative (positive) changes in weather lead to higher (lower) returns on the German stock market (MMH).

2.2 Volatility

Stock market volatility is less commonly assessed in weather studies than are returns. Table 3 summarizes the results of the studies on this indicator.

With the exception of Chang et al. (2008); Frühwirth and Sögner (2015); Lu and Chou (2012), and Pizzutilo and Roncone (2017), the above studies used GARCH models. In studies concerning weather and volatility, the variables cloud cover, temperature, and precipitation were mostly used.

Poor weather conditions, such as high precipitation and wind, lead to increased volatility in stock markets (MMH). It is argued that volatility results from heterogeneity or divergences in investor opinions and expectations (Harris and Raviv 1993; Shalen 1993). Bad weather can cause divergences in mood among investors and thus increase stock market volatility (Chang et al. 2008).

There is also a diametrically opposed argument that could explain a positive correlation between good weather and volatility (AIM), such as high temperature. Good weather could create a positive mood among investors and consequently increase trading activities, that may have an influence on the volatility (Brown 1999). The effects for cloudiness are also attributable to AIM and show reduced volatility as cloudiness increases. In summary, the empirical results show a nearly balanced distribution between effects attributable to AIM and MMH. Thus, we offer the following hypotheses:

Hypothesis 2a: Good (bad) weather conditions lead to higher (lower) volatility on the German stock market (AIM).

Hypothesis 2b: Bad (good) weather conditions lead to higher (lower) volatility on the German stock market (MMH).

Table 4 Weather effects on trading volume

Author(s)	Cloud cover	Sunshine	Temperature	Precipitation	Wind	Air pressure	Humidity	Visual range	Snow
Loughran and Schultz (2004)									▼
Goetzmann and Zhu (2005)	●								
Chang et al. (2008)	●		●	●	●				●
Hasan and Subhani (2011)			●		●	●	●		
Lu and Chou (2012)	●		▲	●	▲	●	●	●	●
Schmittmann et al. (2015)	▲		▼	●		▼			
Wang (2016)	▲		▼	▼	●	▼			
Pizzutilo and Roncone (2017)	●		●	●	●	●	●	●	
Positive effect (%)	33		17	0	20	0	0	0	0
Negative effect (%)	0		33	20	0	40	0	0	33
No effect (%)	67		50	80	80	60	100	100	67

● no significant effect, ▼ significant negative effect, ▲ significant positive effect

2.3 Trading Volume

Another dependent variable considered in studies on weather and capital markets is trading volume, with the results shown in Table 4. As in the cases of returns and volatility, the observed studies present a mixed picture with regard to the significance and direction of the effects.

One possible reason for the heterogeneous results is that the trading volume variable is operationalized differently across the listed studies. For example, the studies by Goetzmann and Zhu (2005) and Wang (2016) used data at the individual and investor levels, whereas Loughran and Schultz (2004) and Chang et al. (2008) formed portfolios for individual companies. The remaining studies were based on aggregated index trading volumes.

Two possible arguments could explain the effects of weather on trading volume. First, it is possible that when weather conditions are good, professional investors substitute working hours with free time (Connolly 2008), and private investors use their free time for activities other than trading. Second, poor weather conditions might increase the risk appetite of investors and thus their willingness to invest in equity markets. Both arguments propose a consistent effect of weather on trading volume in line with the MMH. Good weather conditions lead to a substitution between trading and different activities, and bad weather conditions lead to a higher risk appetite, which in turn leads to higher trading volume. Even if the argumentation seems conclusive, the empirical results do not show a clear direction in favor of the MMH, and additionally, the number of empirical results is limited thus far. At the same time, it is conceivable that good weather conditions lead to an increase in trading volume (AIM). Thus, we also propose competing hypotheses according to the AIM and MMH for trading volume:

Hypothesis 3a: Good (bad) weather conditions lead to a higher (lower) trading volume on the German stock market (AIM).

Hypothesis 3b: Bad (good) weather conditions lead to a higher (lower) trading volume on the German stock market (MMH).

3 Empirical Analysis

3.1 Data

Market data for several German stock indices (DAX, MDAX, SDAX, and TecDAX) were collected from Thomson Reuters Eikon (formerly Datastream). Trading volume was measured as turnover by volume for the DAX, MDAX, and SDAX and as turnover by value for the TecDAX due to data restrictions in the Thomson Reuters Eikon database. Due to these data restrictions, the time series for trading volume in the TecDAX was shorter and contained 2,144 observations compared to 3,565 observations for all other index and variable combinations. Control variables were also included, which were dummy variables for Monday (Wang et al. 1997), January

Table 5 Variables and their descriptions

TUR: turnover by volume for DAX, MDAX, SDAX, and turnover by value for TecDAX	
TUR*: first difference of the natural logarithm of TUR	
SKC: daily ∅ cloud cover (0=clear sky, 8=completely overcast)	
TEMP: daily ∅ temperature in degrees Celsius	
RET: daily returns $R = \ln(P_t/P_{t-1})$	VOL: volatility
HUM: daily ∅ relative humidity in %	PRESS: daily ∅ air pressure in hPa
PREC: daily ∅ precipitation in mm	WIND: daily ∅ wind speed in m/s
$SKC^* = SKC_t - \varnothing SKC_{CW}$	$\Delta SKC = SKC_t - SKC_{t-1}$
$HUMI^* = HUMI_t - \varnothing HUMI_{CW}$	$\Delta HUMI = HUMI_t - HUMI_{t-1}$
$PRESS^* = PRESS_t - \varnothing PRESS_{CW}$	$\Delta PRESS = PRESS_t - PRESS_{t-1}$
$PREC^* = PREC_t - \varnothing PREC_{CW}$	$\Delta PREC = PREC_t - PREC_{t-1}$
$TEMP^* = TEMP_t - \varnothing TEMP_{CW}$	$\Delta TEMP = TEMP_t - TEMP_{t-1}$
$WIND^* = WIND_t - \varnothing WIND_{CW}$	$\Delta WIND = WIND_t - WIND_{t-1}$
MON, JAN, DEC: dummy variables for Monday, January, December	
Halloween: dummy variable for every day from May to October	
DJIA: daily returns on the DJIA	
TURN: dummy variable for the turn-of-the-month effect	

CW=calendar week, DJIA=Dow Jones Industrial Average

and December (Agrawal and Tandon 1994; Gultekin and Gultekin 1983), and the 'Sell in May and go away strategy' named the Halloween anomaly (Bouman and Jacobsen 2002). Furthermore, the previous day's yield on the Dow Jones Industrial Average (DJIA) was included as a variable (Drozdz et al. 2001). The DJIA returns were calculated on the basis of the performance index; the German indices were also calculated based on the total return system. Additionally, we added a dummy variable to capture any possible turn-of-the-month effect in the data (Zwergel 2010). For the weather, we used data from the Climate Data Center (CDC) of the German Weather Service. The data were for the period from August 2003 to August 2017 in Frankfurt (Station-ID 01420). Frankfurt is Germany's financial center; as Germany is relatively small compared to the US or China, it ensures that a large proportion of domestic investors are exposed to the weather in Frankfurt or to similar weather conditions (Schneider 2014a,b). Schneider (2014a) showed, for example, that air pressure conditions are highly correlated across Germany. Similar results were found by Klein (2005), who found high correlations of sunshine duration and cloudiness between major German cities. Therefore, the weather in Frankfurt is a good proxy for that in other German cities.

The selected weather variables were sky cover, temperature, precipitation, air pressure, humidity and wind speed. Sunshine was not selected due to multicollinearity with cloud cover. To account for seasonal weather patterns, we followed Hirshleifer and Shumway (2003) and calculated the average value of each weather variable for a particular calendar week over the whole dataset. Each daily observation was subtracted by the corresponding weekly mean. This method ensured that the variable being measured was the impact of abnormal weather conditions on stock markets. Table 5 summarizes the variables and their descriptions.

3.2 Descriptives

To test for the normality of the stock market data, we used the Jarque-Bera test. The return, trading volume, and volatility data were not normally distributed, suggesting that the residuals of subsequent regressions would not be normally distributed either. Hence, we used robust standard errors for the significance tests. Autocorrelation in the data was assessed by means of the Ljung-Box (LB) Q test. A significant test result indicated the presence of autocorrelation or the absence of white noise. Moreover, the test results indicated autocorrelation and the existence of volatility clusters. The difference stationarity of the stock market data was tested with the augmented Dickey-Fuller (ADF) test and trend-stationarity with the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. If stationarity was present, then the ADF test should be statistically significant, and the KPSS test should not. These results indicated nonstationarity for turnover by volume and value time series, and thus, we transformed the corresponding values using the first difference of the natural logarithm. Regarding the test results, we assumed that the time series were stationary. Table 6 shows the descriptives of the weather variables, and Tables 7 and 8 show the stock market descriptives and the rest of the results.

Table 6 Descriptives of weather variables

RAW	WIND	PREC	SKC	PRES	TEMP	HUMI
n	3565	3565	3565	3565	3565	3565
Min	0	0	0	965.42	−11.00	36.00
Max	12.80	50.20	8.00	1,031.28	29.80	100.00
Median	2.90	0	5.80	1,003.58	11.40	75.00
Mean	3.27	1.58	5.32	1,003.52	11.23	73.77
Sd	1.52	3.75	2.00	8.35	7.53	12.96
Deseasonalized	WIND*	PREC*	SKC*	PRES*	TEMP*	HUMI*
n	3565	3565	3565	3565	3565	3565
Min	−3.67	−2.26	−6.33	−41.74	−13.32	−32.76
Max	9.28	48.41	3.55	27.06	10.43	34.53
Median	−0.32	−1.37	0.53	0.43	0.05	−0.11
Mean	−0.01	−0.07	0.02	−0.03	0.14	−0.10
Sd	1.50	3.74	1.90	8.26	3.55	9.91
Daily change	ΔWIND	ΔPREC	ΔSKC	ΔPRES	ΔTEMP	ΔHUMI
n	3565	3565	3565	3565	3565	3565
Min	−7.10	−50.10	−6.30	−23.80	−8.50	−31.71
Max	7.20	50.20	7.30	23.40	7.90	39.00
Median	0	0	0	−0.12	0.1	−0.29
Mean	0.01	−0.04	0.03	−0.01	0.03	−0.11
Sd	1.44	4.82	1.84	5.15	2.12	8.88

Cloudiness (SKC) is measured from 0 = clear sky to 8 = completely overcast.

Table 7 Descriptives of stock market data I

Variable	Mean	Sd	Jarque Bera
RET_{DAX}	0.00035	0.01341	5,545.1***
RET_{MDAX}	0.00053	0.01352	4,328.1***
RET_{SDAX}	0.00044	0.01062	6,711.4.3***
RET_{TECDAX}	0.00045	0.01493	4,116.9***
TUR_{DAX}	118,852.28	50,727.35	11,910.85***
TUR_{MDAX}	18,064.70	8,656.94	113,001.90***
TUR_{SDAX}	1,976.94	2,290.92	17,232.79***
TUR_{TECDAX}	140.63	87.30	3,348.98***

Signif. codes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 8 Descriptives of stock market data II

Variable	Ljung-Box Q(5)	Ljung-Box Q(10)	Ljung-Box Q(20)	ADF	KPSS
RET_{DAX}	15.60**	20.70*	40.57**	−15.31***	0.05
RET_{MDAX}	33.64***	40.84***	51.09***	−15.59***	0.09
RET_{SDAX}	78.16***	82.42***	109.92***	−13.11***	0.14
RET_{TECDAX}	41.23***	43.77***	56.55***	−14.76***	0.09
TUR_{DAX}	4,926.21***	7,907.77***	12,455.62***	−6.90***	3.5417***
TUR_{MDAX}	5,974.95***	10,245.81***	16,829.46***	−6.33***	3.91***
TUR_{SDAX}	11,081.81***	20,219.52***	37,327.57***	−5.53***	17.82***
TUR_{TECDAX}	5,223.63***	9,352.30***	16,129.67***	−4.74***	7.26***
TUR^*_{DAX}	648.13***	698.88***	793.26***	−22.09***	0.003
TUR^*_{MDAX}	475.84***	525.60***	624.58***	−21.22***	0.005
TUR^*_{SDAX}	454.04***	465.00***	485.16***	−20.91***	0.02
TUR^*_{TECDAX}	429.33***	282.03***	310.92***	−17.69***	0.04

Signif. codes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

3.3 Model

Stock market returns have specific characteristics that cannot be adequately represented by classical time-series models or simple OLS regressions. These characteristics include leptokurtic distributions, higher-order autocorrelations and volatility clusters. The autoregressive conditional heteroskedasticity (ARCH) models introduced by Engle (1982) can handle time series with these specific characteristics and assume that conditional variance is a function of the available information from previous periods. In this way, the error term varies over time. To model financial time series, ARCH models have been replaced by GARCH models, which allow for a more parsimonious specification. Classic ARCH or GARCH models assume a symmetrical effect of positive and negative errors on volatility. According to this assumption, both good and bad news should have symmetrical effects on the variation in the data. However, this assumption often does not stand up to empirical scrutiny for certain capital market data. In the case of stock returns, for example, it has been observed that volatility reacts more sensitively to falling prices or bad news than to rising prices or good news, respectively. This asymmetrical reaction of volatility is called the leverage effect (Black 1976) and is considered in the exponential GARCH (E-GARCH) model proposed by Nelson (1991) and the threshold GARCH (T-GARCH or GJR-GARCH) model proposed by Glosten et al. (1993).

Indeed, our dataset displayed the abovementioned characteristics. The LB test revealed strong autocorrelation in the returns and trading volume series, and the data showed volatility clustering. As a result, and following other studies (e.g., Chang et al. 2006; Floros 2011; Kang et al. 2010, and Yoon and Kang 2009), we applied GARCH models to capture this volatility clustering and to consider heteroskedasticity in the estimation (Bollerslev 1986).

To investigate the relationship between stock returns and abnormal weather conditions, we chose a linear autoregressive (AR(2)) model with the GJR-GARCH(1,1) process from Glosten et al. (1993). In all models, following good empirical research practices, we applied Bollerslev-Wooldridge error terms from the maximum likelihood estimation, which were robust to conditional nonnormality (Zivot 2009).

$$\begin{aligned}\mathrm{RET}_{i,t} &= \mathrm{mu}_{i,0} + w_1\mathrm{RET}_{i,t-1} + w_2\mathrm{RET}_{i,t-2} + w_3\mathrm{WIND}^*{}_t + w_4\mathrm{PREC}^*{}_t + \\ & w_5\mathrm{SKC}^*{}_t + w_6\mathrm{PRES}^*{}_t + w_7\mathrm{TEMP}^*{}_t + w_8\mathrm{HUMI}^*{}_t + w_9\mathrm{DJIA}_{t-1} + w_{10}\mathrm{MON} + \\ & w_{11}\mathrm{DEC} + w_{12}\mathrm{Halloween} + w_{13}\mathrm{JAN} + w_{14}\mathrm{TURN} + w_{15}\mathrm{TUR}^* + \epsilon_{i,t},\end{aligned} \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}(\alpha_i + \gamma d_{t-1})\epsilon_{t-1}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2. \tag{2}$$

Eq. (1) includes autoregressive processes to correct for the autocorrelation of returns. In addition, the weather and control variables are included as explanatory variables. The error term ϵ_t is a zero-mean white noise process and is normally distributed. Eq. (2) gives the specification of the conditional variance of σ_t^2 at time t, where α represents the lagged squared residuals and can be interpreted as the news coefficient, with higher values implying that more recent news has a greater impact. β is the conditional variance of previous periods, showing the impact of past variance, and $\alpha + \beta$ measures the persistence of volatility (Bollerslev 1986).

The GJR specification allows for an asymmetric impact of bad and good news on conditional variance. The leverage effect γ is considered via the dummy variable d, where $d_t = 1$ if $\epsilon_t < 0$ and $d_t = 0$ otherwise. In this way, good and bad news can have different impacts on conditional volatility. Good news ($\epsilon_t \geq 0$) has an impact of α_i, while bad news ($\epsilon_t < 0$) has an impact of $\alpha + \gamma$. If γ is significant and positive leverage exists, then bad news increases volatility. For $\gamma = 0$, the model is reduced to a symmetric GARCH model. The nonnegativity constraint is satisfied if $\alpha_0 > 0$, $\alpha_i + \gamma > 0$, $\beta_j > 0$.

A similar model with a GJR-GARCH(1,1) process is adopted to assess the relationship between stock returns and daily changes in weather.

$$\mathrm{RET}_{i,t} = \mathrm{mu}_{i,0} + w_1\mathrm{RET}_{i,t-1} + w_2\mathrm{RET}_{i,t-2} + w_3\Delta\mathrm{WIND}_t + w_4\Delta\mathrm{PREC}_t + w_5\Delta\mathrm{SKC}_t + w_6\Delta\mathrm{PRES}_t + w_7\Delta\mathrm{TEMP}_t + w_8\Delta\mathrm{HUMI}_t + w_9\mathrm{DJIA}_{t-1} + w_{10}\mathrm{MON} + w_{11}\mathrm{DEC} + w_{12}\mathrm{Halloween} + w_{13}\mathrm{JAN} + w_{14}\mathrm{TURN} + w_{15}\mathrm{TUR}^* + \epsilon_{i,t}. \tag{3}$$

To analyze the relationship between stock volatility and weather factors, we selected the linear autoregressive (AR) model with the E-GARCH(1,1) process from Nelson (1991) because it avoided nonnegativity constraints for the parameters in the variance equation, which now include weather and control variables. The logarithmic function of the conditional variance (Eq. 5) ensures that the variance is positive. E-GARCH models, like for GJR-GARCH processes, can capture asymmetry in the volatility.

$$\mathrm{RET}_{i,t} = \mathrm{mu}_i + \rho_i \mathrm{RET}_{i,t} + \epsilon_{i,t}. \tag{4}$$

$$\ln(\sigma^2_{i,t}) = \alpha_0 + \alpha_i + g(z_{t-1}) + \beta_i \ln\sigma^2_{i,t-1} + \sum_{k=1}^{l} m_{ik} M_{ik,t}, \tag{5}$$

$$\text{with } g(z_{t-1}) = \Theta\left[\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right] - E\left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-j}}. \tag{6}$$

Eq. (5) assumes that returns follow an AR(1) process with drift, analogous to the series in Symeonidis et al. (2010). M represents the weather and control variables. In equation (6), γ shows the sign and leverage effect, Θ indicates the size effect, and β displays the persistence.

The impact of weather on trading volume was tested with several models. Based on (unreported) tests (namely, LBQ statistics and an Engle's ARCH test), a linear AR(5) model with the GJR-GARCH(1,1) process was identified as the most appropriate model. The weather and control variables were regressed against the first difference of the logarithmized trading volume (TUR*). The variance equation conformed to the return models.

$$\mathrm{TUR}^*_{i,t} = \mathrm{mu}_{i,0} + \sum_{l=1}^{5} z_{il}\mathrm{TUR}^*_{il,t} + h_1\mathrm{WIND}^*_t + h_2\mathrm{PREC}^*_t + h_3\mathrm{SKC}^*_t + h_4\mathrm{PRES}^*_t + h_5\mathrm{TEMP}^*_t + h_6\mathrm{HUMI}^*_t + h_7\mathrm{RET}_{i,t-1} + h_8\mathrm{DJIA}_{t-1} + h_9\mathrm{MON} + h_{10}\mathrm{DEC} + h_{11}\mathrm{Halloween} + h_{12}\mathrm{JAN} + h_{13}\mathrm{TURN} + \epsilon_{i,t}. \tag{7}$$

3.4 Regression Diagnostics and Robustness

For maximum-likelihood-based procedures, the quality of the model fit was determined by means of the Akaike and Bayesian information criteria (AIC and BIC,

Table 9 Regression diagnostics: ARCH-LM test

	ARCH-LM test		
	ARCH Lag[3]	ARCH Lag[5]	ARCH Lag[7]
RET_{DAX}	0.50000	1.44000	2.31500
RET_{MDAX}	0.60880	2.91540	3.47590
RET_{SDAX}	0.00649	0.02014	0.30375
RET_{TecDAX}	0.43950	1.65740	2.21660
ΔRET_{DAX}	0.29890	1.11630	1.47910
ΔRET_{MDAX}	0.81600	3.38600	4.04400
ΔRET_{SDAX}	0.50000	1.44000	2.31500
ΔRET_{TecDAX}	0.51400	1.66000	2.31800
VOL_{DAX}	0.38770	0.67800	0.78430
VOL_{MDAX}	0.55720	1.87930	2.60890
VOL_{SDAX}	0.04046	2.63291	3.29208
VOL_{TecDAX}	0.38360	5.36110†	7.16380†
TUR^*_{DAX}	0.63850	0.82830	0.91440
TUR^*_{MDAX}	0.87660	0.92040	1.68400
TUR^*_{SDAX}	0.10730	0.89200	2.30540
TUR^*_{TecDAX}	1.94900	3.91600	8.88100*

Note: ΔRET: regression with changes in weather
Signif. codes: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

respectively), which are mainly used for model selection and the detection of overfitting and thus are not relevant for our purposes. To test for the existence of residual heteroskedasticity, we used the Lagrange multiplier (LM) test proposed by Engle (1982). Nonsignificant test results indicated homoscedastic residuals. Table 9 shows the ARCH-LM test results for different lag parameters. With the exception of lag 7 for turnover by volume on the TecDAX, all test results were nonsignificant. Accordingly, we could assume homoscedastic residuals. The autocorrelation of the residuals was tested by means of the LB test with different lags and with standardized and squared standardized residuals (Table 10). The LB test on standardized residuals evaluated the dependence of the first moments with a time lag. The LB test on the squares of standardized residuals, similar to the ARCH-LM test, evaluated the dependence of the second moments with a time lag.

The clearly significant results for the turnover-by-volume model for the DAX, MDAX, SDAX, and TecDAX reflected an autocorrelation problem that was already present upon model selection (see Sect. 3.3) and could not be completely resolved by our AR(5) model. However, all further changes to the model specification (e.g., a higher number of lags and the multiple differentiation of trading volume) did not lead to an improvement but, in fact, worsened the diagnostic values. Therefore, we retained the GJR-GARCH(1,1) AR(5) model. The LB test on the squares of standardized residuals and the ARCH-LM test showed no problems. In summary, the regression diagnostics showed the good usability of the models, even if there were autocorrelation problems for the turnover-by-volume model.

Table 10 Regression diagnostics: LB test

	LB test (ϵ_t/σ_t)			LB test $(\epsilon_t/\sigma_t)^2$		
	Lag[1]	Lag[5]	Lag[9]	Lag[1]	Lag[5]	Lag[9]
RET_{DAX}	0.03151	0.43471	1.87715	0.02683	3.22962	4.20941
RET_{MDAX}	0.14820	0.71850	2.09850	0.26220	1.51610	3.09490
RET_{SDAX}	0.18570	0.96970	1.72670	0.00019	0.98106	1.60406
RET_{TecDAX}	0.01437	0.36005	0.82740	0.05361	1.22115	2.47688
ΔRET_{DAX}	0.03402	0.37079	1.63298	0.04475	3.27127	4.28241
ΔRET_{MDAX}	0.15550	0.62770	2.06780	0.25240	1.64940	3.49520
ΔRET_{SDAX}	0.22090	1.00760	1.77860	0.00007	1.02777	1.75085
ΔRET_{TecDAX}	0.01309	0.39370	0.85401	0.06416	1.17048	2.45924
VOL_{DAX}	0.08579	0.80823	3.28666	1.32800	1.90400	2.53100
VOL_{MDAX}	3.55500†	7.13200***	12.76700***	0.77310	1.77530	3.22150
VOL_{SDAX}	1.89400	1.98900	2.80600	1.13100	2.74400	4.49000
VOL_{TecDAX}	4.99900*	5.03300***	6.05000*	2.60000	4.61800	9.81900†
TUR^*_{DAX}	1.51000	20.42000***	28.85000***	0.84570	1.69770	2.01980
TUR^*_{MDAX}	0.34480	55.04910***	75.04070***	2.53000	4.71500	5.71800
TUR^*_{SDAX}	0.74870	44.48750***	57.31300***	3.74700†	4.19000	5.66500
TUR^*_{TecDAX}	0.61260	39.72400***	51.84830***	0.10860	2.17470	7.19200

We tested the robustness of the results in two ways. First, we removed all outliers from the data and then recalculated the GARCH models. The results remained constant, even with the outliers excluded. Another robustness test was carried out to vary the distribution assumption of the GARCH specification. For this, the models were computed with the generalized error distribution (GED) and Student's t distribution, instead of the normal distribution we used for our calculations. Except for the results for trade volume, the effects changed only slightly, even after varying the distribution assumptions. One reason for the lack of robustness in trade volume could be the heteroscedasticity problem discussed earlier. Therefore, we saw no evidence of a lack of robustness in the results. We can provide the comprehensive robustness results upon request.

3.5 Results

The results are presented in detail in Tables 16–19 in the appendix and in concise form in Tables 11–14 in this section. For the interpretation of the results, we used only the abridged tables.

In contrast to the findings of traditional studies, here, we could not observe a sunshine or cloud cover effect. One reason for this might be that almost all former studies identifying a sunshine or cloud cover effect adopted classic OLS or time-series models, which cannot accurately represent stock market data, as they are characterized by autocorrelation and volatility clustering. As a consequence, it cannot be ruled out that the significant results detected in the prior literature might be spurious. Only Yoon and Kang (2009) used a model that was appropriate for capital market data, namely, a GJR model, to identify a significant impact of cloud cover on

Table 11 Regression results overview: Returns

Weather variables	DAX	MDAX	SDAX	TecDAX
WIND*				
PREC*				
SKC*				
PRES*			▲	
TEMP*				
HUMI*				
$DJIA_{t-1}$	▲	▲	▲	▲
MON	▼			
DEC				
Halloween				
JAN		▲	▲	▲
TURN		▲	▲	▲
TUR*	▼	▼	▼	

▼ significant negative effect, ▲ significant positive effect

Table 12 Regression results overview: Changes in weather and returns

Weather variables	DAX	MDAX	SDAX	TecDAX
ΔWIND				
ΔPREC				
ΔSKC				
ΔPRES	▲	▲	▲	
ΔTEMP	▲	▲		
ΔHUMI				
$DJIA_{t-1}$	▲	▲	▲	▲
MON				▲
DEC				
Halloween			▼	
JAN		▲	▲	▲
TURN		▲		▲
TUR*		▼	▼	

▼ significant negative effect, ▲ significant positive effect

stock returns in Korea in the period prior to the Asian financial crisis (1990–1997); however, this impact disappeared in the post-crisis period (1998–2006).

In total, 8 significant effects could be found that could be assigned to the theoretical construct of the AIM and 3 significant effects in connection with the MMH. These findings can be taken as a weak indication that good weather leads to risk-seeking behavior and that bad weather to risk-averse behavior in the stock market. A more detailed discussion is provided in Sect. 4.

Table 13 Regression results overview: Volatility

Weather variables	DAX	MDAX	SDAX	TecDAX
WIND*			▼	
PREC*				
SKC*				▲
PRES*				
TEMP*				
HUMI*				▼
MON	▲		▲	▲
DEC				
Halloween	▼	▼		
JAN	▼			
TURN				
TUR*	▲	▲	▲	▲

▼ significant negative effect, ▲ significant positive effect

Table 14 Regression results overview: Trading volume

Weather variables	DAX	MDAX	SDAX	TecDAX
WIND*				
PREC*				
SKC*				
PRES*			▼	▼
TEMP*				
HUMI*				
$RET_{i\,t-1}$		▼		
$DJIA_{t-1}$				
MON	▼	▼		▼
DEC	▲	▼	▼	
Halloween	▲			▲
JAN	▲	▲		▲
TURN		▲		▲

▼ significant negative effect, ▲ significant positive effect

3.6 Returns

The results mainly showed no weather effects in any of the German stock markets when the dependent variable was returns. There was only a statistically significant effect of air pressure on SDAX returns. Thus, good weather conditions may have a positive effect on returns (AIM), but the predominantly missing effects point to a rejection of H1a and H1b.

In addition, we modeled the effect of daily changes in weather on returns and found more significant effects. If air pressure increases, then the returns of the DAX, MDAX and SDAX increase (AIM). Only for the TecDax does no significant correlation with air pressure appear. In addition, our results show positive effects of a temperature improvement on the DAX and MDAX (AIM). In contrast to the literature (see Table 2), which found mainly negative effects on returns from temperature increases, an increase in temperature in the German market leads to a positive effect on returns, which can be attributed to the temperate climate in Germany, in that a rising temperature represents a positive change in weather, whereas in Asian markets, for example, a rise in temperature tends to denote a worsening of the weather. Given these effects of the changes in weather in terms of air pressure and temperature, this indicates the confirmation of H1c. However, since the effects are not consistently observable across the large and small indices and since other weather influences are absent, we also cannot confirm H1c.

3.7 Volatility

Among the weather variables, we observed three statistically significant effects (see Table 13). Wind speed reduced the volatility of the SDAX (AIM), and relative humidity reduced the volatility of the TecDAX (AIM). Thus, bad weather conditions may have had a negative effect on volatility, which is indicative of risk-averse behavior and thus attributable to the AIM. In contrast, cloud cover had a positive impact on TecDAX volatility, which is attributable to the MMH. Since there were no weather effects for the DAX and MDAX and only 3 contradictory effects for the SDAX and TecDAX, we could not confirm H2a or H2b.

3.8 Trading volume

The regression results show significant negative effects of air pressure on trading volume for the SDAX and TecDAX. A rise in air pressure could be associated with good weather, which leads to decreased trading (MMH). These effects are in line with H3b, which posited that good weather conditions lead to a lower trading volume. However, since we did not observe effects from any of the other variables, the existing effects could be shown for only the SDAX and TecDAX, and there were still some autocorrelation problems for the analysis of trading volume (see Sect. 3.4), we were not able to confirm H3b.

3.9 GARCH vs. OLS

The majority of past empirical weather anomaly studies used OLS regression. However, this was not adequate in most cases due to heteroskedasticity issues, even when controlling for heteroskedasticity using White or Newey-West standard errors. Our literature review showed that for returns, for example, not even one-third of the studies used modern financial econometrics for empirical analysis (see also Sect. 2).

How serious an influence the choice of method has on the results can be shown by a comparative analysis. A calculation of our models with OLS using White estimators led to completely different results compared to those identified using the GARCH model. The following Table shows an overview of the GARCH and OLS

Table 15 Regression results overview: GARCH vs. OLS

	Weather variables	DAX	MDAX	SDAX	TecDAX
Return	PRES*			▲	
	ΔPRES	▲	▲	▲	
	ΔTEMP	▲	▲		
	ΔSKC	△			
Trading Volume	PRES*			▼	▼
	WIND*	△			
	SKC*			▽	
	PRES*	▽	▽	▽	
	TEMP*	▽	▽	▽	
	HUMI*			▽	

▼ significant negative effect GARCH, ▲ significant positive effect GARCH, ▽ significant negative effect OLS, △ significant positive effect OLS

results. If there is interest in the detailed regression tables, they can be provided upon request.

Table 15 shows that only one significant effect is detectable with OLS regression for the impact of weather on returns. For changes in weather, the results showed a positive influence of sky cover on the DAX. The GARCH model, conversely, identified one positive effect of air pressure on returns in the SDAX and five positive effects of changes in air pressure and temperature on the DAX, MDAX and SDAX. The analysis of trading volume also showed that OLS regression provided a completely different picture of these relationships. Although the GARCH model showed only two negative effects of air pressure on trading volume for the SDAX and TecDAX, OLS regression showed one positive effect of wind on trading volume and eight negative effects of sky cover, air pressure, temperature and humidity for the DAX, MDAX and SDAX.

These different results make it clear that the choice of method has a significant impact on the results or that the violation of application requirements of econometric models for the detection of financial market anomalies can lead to incorrect conclusions. At the same time, it is of great importance to consider which control variables are used. In particular, month effects (e.g., Halloween effect and Monday, January, and December dummies) should be controlled; otherwise, they could be incorrectly assigned to weather.

4 Conclusions

This study attempts to answer the question of whether there are indeed effects of weather on stock markets. The application of modern time-series regressions to data from the most important German stock indices shows a mixed picture, and thus, this question cannot be answered conclusively. As we mentioned in the results section, we do not regard isolated significant effects of weather variables as an indication of a significant capital market anomaly. This applies, in particular, to the effects of weather on volatility (the negative effect of wind on the SDAX, the positive effect of clouds on the TecDAX, and the negative effect of humidity on the TecDAX).

However, the effect of air pressure shows more consistent results for the various key figures and capital markets. We find a positive effect of air pressure on the returns of the SDAX but not on those of the TecDAX. At the same time, trading volume decreases on the SDAX and TecDAX as air pressure increases. These results show, on the one hand, that air pressure is an important weather variable to be considered and, on the other hand, that the effects of investor mood may be particularly relevant for small-capitalization indices (Baker and Wurgler 2006; Klein 2005; Lee et al. 2002; Schneider 2014a; Statman et al. 2006). Therefore, it may be reasonable to have a higher proportion of domestic investors in small caps compared to blue chips. However, the analysis of the changes in air pressure and temperature also shows effects on the returns of larger indices such as the DAX and MDAX. This finding contradicts the assumption that only the proportion of domestic investors makes the effects of weather detectable. Rather, the strength of the weather influence also seems to play a role. One explanation for the effects on the DAX and MDAX could accordingly be that changes in weather have a stronger influence on people's health and behavior than does the weather itself, and thus, the proportion of domestic investors as an explanation for the effects of weather on the stock market moves into the background.

However, the divergence between the results in the literature and those of this study may also be due to methodological reasons. For example, it is noticeable that some authors use fewer control variables and OLS regression, and thus, their results are only comparable to a limited extent. The comparison of the GARCH model and OLS regression (see Table 15 and Sect. 3.9), for example, shows no OLS effects for air pressure and temperature and thus shows absolutely opposite results based on the method used. This finding shows that a comparison of the studies is questionable when using different financial market econometrics.

Nevertheless, no uniform picture of this situation emerges. Changes in air pressure have a positive effect on the returns of the DAX, MDAX and SDAX, but not on those of the TecDAX. At the same time, it is difficult to explain why changes in temperature have a positive effect on the DAX and MDAX, but not on the SDAX and TecDAX. Accordingly, our results show no empirical evidence that small caps are more vulnerable to the effects of weather than are blue chips due to more local investors. We therefore conclude that changes in weather lead to the most empirically meaningful results in this study. However, the results are not completely conclusive and further research is needed in this area with a focus on changes in weather. In addition, there should be more focus on the composition of the indices and the type of investors to better explain the effects of weather.

When the results are viewed against the background of the AIM or the MMH, a clear positioning for the AIM emerges. A total of eleven statistically significant effects can be demonstrated, eight of which can be attributed to the AIM. If we exclude the results for trading volumes, then since the heteroscedasticity problem could not be completely solved for these models, only one effect for volatility (see Table 18) can be assigned to the MMH and all others to the AIM. Our results should therefore be taken as further empirical evidence for the effects of the AIM.

This empirical study provides added scientific value because it includes a systematic presentation of the state of the art on the effects of weather in capital markets and thus provides directions for future research. In addition, this work fills a gap in the research on the German stock market. No other study has examined the German market so comprehensively, and all relevant weather variables are included in this analysis. Furthermore, this work is not limited to the analysis of returns but also examines volatility and trading volume. Finally, a methodical research gap is bridged. With the application of GARCH models, this empirical work is based on the state of the art methodology in the analysis of stock markets.

Even though the focus of this paper is not on the application of weather trading strategies, the identified correlations could be used for this purpose. Thus, the results may have economic relevance and be exploited by traders, even if this approach is often questioned due to the various historical empirical results (see Sect. 2). Not much literature exists in this regard, although some authors have shown successful weather strategies. In one famous paper, Hirshleifer and Shumway (2003) tested a weather-induced trading strategy and were able to increase the Sharpe ratio[2], including transaction costs, for a hypothetical investor. Kamstra et al. (2003) showed that a pro-SAD strategy (the reallocation of 100 percent of the portfolio twice a year at the fall and spring equinoxes) leads to an annual average excess return of 7.9 percent compared to a neutral strategy. In a recent preprint, Dong and Tremblay (2020) reported that a global weather-based hedge strategy produced a mean annual return of 15.2 percent compared to mean world index return of 3.1 percent corresponding to a Sharpe ratio of 0.462 relative to 0.005 for the world index. They used premarket weather conditions—sunshine, wind, rain, snow, and temperature—for their calculations. Thus, it might be possible to make profits on the German stock market by using weather strategies that mainly take into account changes in weather and air pressure.

In contrast to the added value of this work, we also note its limitations, which at the same time delineate future research needs. International investors are not influenced by the weather in Germany; thus, despite the mostly insignificant results for the DAX and MDAX, there could be effect of weather on these markets. The second limitation is the inadequate mapping of the models for trading volume. It cannot be ruled out that the identified effects are based on deficits in terms of study design. Accordingly, the replication of this study with the help of another model is advisable.

However, weather-related strategies apply to higher-frequency trades, and thus, transaction costs must be very small for such trading strategies to pay off. Rather, Hirshleifer and Shumway (2003) viewed their empirical results as evidence of psychological effects to which investors are inevitably exposed and of which they should be aware. We also interpret our results as an indication of the existence of effects on stock markets that cannot be rationally explained. Future

[2] The analysis of the Sharpe ratio involves certain difficulties and should be critically reviewed, as the Sharpe ratio is only a meaningful measure under the assumption of a normal distribution which is usually not the case with returns (Bernardo and Ledoit 2000; Hodges 1998).

research should focus more on the consequences of the effects of weather, especially those of changes in weather and the impact of air pressure.

Appendix

Tables

Table 16 Regression results: Returns

	Dependent variable: Returns			
	(1) DAX	(2) MDAX	(3) SDAX	(4) TecDAX
mu	0.00020	0.00010	0.00023	−0.00112**
	(0.00021)	(0.00024)	(0.00023)	(0.00035)
AR(1)	−0.19815***	−0.11236***	0.00219	−0.08674**
	(0.04716)	(0.02284)	(0.02199)	(0.02642)
AR(2)	−0.05180**	−0.05900**	0.01880	−0.00253
	(0.01891)	(0.01874)	(0.01892)	(0.02344)
WIND*	0.00003	0.00002	−0.00009	−0.00019
	(0.00010)	(0.00010)	(0.00009)	(0.00018)
PREC*	−0.00002	0.00000	0.00001	0.00002
	(0.00004)	(0.00004)	(0.00003)	(0.00007)
SKC*	0.00007	0.00008	0.00009	0.00013
	(0.00015)	(0.00010)	(0.00008)	(0.00018)
PRES*	0.00002	0.00002	0.00003†	−0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
TEMP*	0.00000	0.00001	−0.00002	−0.00005
	(0.00008)	(0.00004)	(0.00003)	(0.00006)
HUMI*	−0.00002	−0.00002	−0.00001	−0.00003
	(0.00002)	(0.00002)	(0.00002)	(0.00003)
$DJIA_{t-1}$	0.80892***	0.69043***	0.42723***	0.70909***
	(0.03427)	(0.04082)	(0.03023)	(0.04042)
MON	−0.00076†	−0.00053	0.00023	0.00110
	(0.00045)	(0.00039)	(0.00032)	(0.00068)
DEC	0.00053	0.00043	0.00013	−0.00077
	(0.00052)	(0.00050)	(0.00045)	(0.000075)
Halloween	−0.00007	0.00016	−0.00017	0.00056
	(0.00037)	(0.00026)	(0.00026)	(0.00044)
JAN	0.00045	0.00145**	0.00169***	0.00263**
	(0.00045)	(0.00052)	(0.00049)	(0.00100)
TURN	0.00023	0.00087**	0.00125***	0.00272***
	(0.00038)	(0.00033)	(0.00029)	(0.00064)
TUR*	−0.00519†	−0.00243†	−0.00147†	0.00005
	(0.00307)	(0.00141)	(0.00085)	(0.00099)
α_0	0.00000	0.00000	0.00000***	0.00000
	(0.00002)	(0.00001)	(0.00000)	(0.00001)
α_1	0.03605	0.05016*	0.04801**	0.06732***

Table 16 (Continued)

	Dependent variable: Returns			
	(1) DAX	(2) MDAX	(3) SDAX	(4) TecDAX
	(0.19188)	(0.02066)	(0.01663)	(0.01551)
β_1	0.91591**	0.87972***	0.84139***	0.89010***
	(0.28294)	(0.05192)	(0.01094)	(0.03428)
γ_1	0.06553	0.08885	0.12298***	0.05119
	(0.12399)	(0.08041)	(0.02979)	(0.03649)
AIC	−6.53160	−6.50450	−6.84010	−5.88340
BIC	−6.49690	−6.46980	−6.80540	−5.83180

Note: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 17 Regression results: Returns and weather changes

	Dependent variable: Returns			
	(1) DAX	(2) MDAX	(3) SDAX	(4) TecDAX
mu	0.00017	0.00011	0.00025	−0.00113***
	(0.00022)	(0.00024)	(0.00023)	(0.00035)
AR(1)	−0.20166***	−0.11201***	0.00273	−0.08707***
	(0.05118)	(0.02272)	(0.02178)	(0.02635)
AR(2)	−0.05151**	−0.05494**	0.02352	−0.00231
	(0.01977)	(0.01880)	(0.01859)	(0.02338)
ΔWIND	0.00003	0.00010	−0.00011	−0.00004
	(0.00013)	(0.00012)	(0.00010)	(0.00019)
ΔPREC	−0.00002	0.00002	−0.00001	0.00007
	(0.00003)	(0.00003)	(0.00003)	(0.00005)
ΔSKC	0.00016	−0.00008	−0.00002	0.00003
	(0.00011)	(0.00009)	(0.00007)	(0.00015)
ΔPRES	0.00005†	0.00008**	0.00005*	−0.00001
	(0.00003)	(0.00003)	(0.00003)	(0.00006)
ΔTEMP	0.00015*	0.00014†	−0.00010	0.00004
	(0.00007)	(0.00008)	(0.00006)	(0.00012)

Table 17 (Continued)

	Dependent variable: Returns			
	(1) DAX	(2) MDAX	(3) SDAX	(4) TecDAX
ΔHUMI	−0.00001	0.00002	0.00002	0.00001
	(0.00003)	(0.00002)	(0.00002)	(0.00003)
$DJIA_{t-1}$	0.81088***	0.69164***	0.42620***	0.70727***
	(0.03562)	(0.04161)	(0.02967)	(0.04017)
MON	−0.00071	−0.00055	0.00024	0.00111†
	(0.00046)	(0.00039)	(0.00032)	(0.00067)
DEC	0.00058	0.00044	0.00016	0.00092
	(0.00051)	(0.00053)	(0.00045)	(0.000075)
Halloween	−0.00005	0.00016	−0.00020***	0.00055
	(0.00039)	(0.00026)	(0.00026)	(0.00043)
JAN	0.00043	0.00149**	0.00164***	0.00262**
	(0.00047)	(0.00054)	(0.00048)	(0.00101)
TURN	0.00022	0.00085*	0.00122	0.00275***
	(0.00037)	(0.00033)	(0.00028)	(0.00064)
TUR*	−0.00499	−0.00249†	−0.00146†	0.00004
	(0.00338)	(0.00145)	(0.00085)	(0.00100)
α_0	0.00000	0.00000	0.00000***	0.00000
	(0.00002)	(0.00001)	(0.00000)	(0.00001)
α_1	0.03650	0.04792*	0.04814**	0.06916***
	(0.21032)	(0.02055)	(0.01709)	(0.01574)
β_1	0.91645**	0.88097***	0.84004***	0.88824***
	(0.30526)	(0.05554)	(0.01103)	(0.03309)
γ_1	0.06375	0.09110	0.12579***	0.05088
	(0.12809)	(0.08513)	(0.02960)	(0.03651)
AIC	−6.53390	−6.50660	−6.84110	−5.88340
BIC	−6.49920	−6.47190	−6.80640	−5.83180

Note: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 18 Regression results: Volatility

	Dependent variable:			
	Volatility with volume-in-variance equation			
	(1) DAX	(2) MDAX	(3) SDAX	(4) TecDAX
mu	0.00042**	0.0094**	0.00087***	0.00056†
	(0.00014)	(0.00033)	(0.00017)	(0.00031)
AR(1)	−0.00349	0.00877	0.10628***	0.00954
	(0.02069)	(0.01881)	(0.01958)	(0.02013)
α_0	−0.22203***	−0.15157	−0.46537***	−0.19817***
	(0.01594)	(0.14186)	(0.02691)	(0.04232)
γ_1	−0.12170***	−0.09208	−0.12008***	−0.08117***
	(0.01023)	(0.00625)	(0.01335)	(0.01461)
β_1	0.97859***	0.98820***	0.95801***	0.98813***
	(0.00004)	(0.00625)	(0.00349)	(0.00456)
θ_1	0.11443***	0.12182	0.20703***	0.15135**
	(0.00828)	(0.10306)	(0.03509)	(0.04956)
WIND*	0.00004	−0.00143	−0.01514*	−0.00106
	(0.00401)	(0.00495)	(0.00739)	(0.00618)
PREC*	−0.00193	−0.00024	0.00284	−0.00109
	(0.00294)	(0.00267)	(0.00384)	(0.00333)
SKC*	−0.00074	0.00359	0.00778	0.01237*
	(0.00461)	(0.00629)	(0.00761)	(0.00548)
PRES*	−0.00014	0.00013	−0.00001	0.00090
	(0.00059)	(0.00072)	(0.00094)	(0.00075)
TEMP*	−0.00034	0.00015	0.00055	0.00048
	(0.00115)	(0.00130)	(0.00203)	(0.00178)
HUMI*	0.00041	−0.00084	−0.00153	−0.00198†
	(0.00078)	(0.00074)	(0.00145)	(0.00102)
MON	0.18945*	0.25553	0.32875***	0.45734***
	(0.07749)	(0.44165)	(0.09603)	0.09020
DEC	−0.00604	−0.00539	0.00313	−0.01273
	(0.01241)	(0.01109)	(0.01980)	(0.01375)
Halloween	−0.01210*	−0.01084*	−0.01183	−0.00645
	(0.00508)	(0.00517)	(0.00995)	(0.00700)
JAN	−0.02035†	−0.00692	0.01128	−0.00551
	(0.01167)	(0.01699)	(0.01537)	(0.01631)
TURN	0.01228	−0.00698	0.03835	0.05099
	(0.02540)	(0.02556)	(0.03039)	(0.03300)
TUR*	1.70391***	3.58181***	1.59778***	1.45453***
	(0.32530)	(0.27553)	(0.27670)	(0.15343)
AIC	−6.19510	−6.29490	−6.70970	−5.76950
BIC	−6.16390	−6.26370	−6.67840	−5.72310

Note: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 19 Regression results: Trading volume

	Dependent variable: Trading volume			
	(1) DAX	(2) MDAX	(3) SDAX	(4) TecDAX
mu	0.00056	0.01503***	0.00314***	0.01509**
	(0.00368)	(0.00148)	(0.00215)	(0.00584)
AR(1)	−0.50976***	−0.49175***	−0.48986***	−0.43599***
	(0.03141)	(0.02186)	(0.02168)	(0.02454)
AR(2)	−0.36948***	−0.39787***	−0.33565***	−0.35732***
	(0.03803)	(0.02174)	(0.02040)	(0.02599)
AR(3)	−0.24913***	−0.30784***	−0.25519***	−0.27982***
	(0.03579)	(0.02229)	(0.02040)	(0.02198)
AR(4)	−0.16559***	−0.19782***	−0.16929***	−0.17665***
	(0.03310)	(0.01975)	(0.02060)	(0.02130)
AR(5)	$-0.06498^{\dagger}$	−0.09145***	−0.08252***	−0.11651***
	(0.03456)	(0.01757)	(0.01724)	(0.01994)
WIND*	0.00024	0.00049	0.00018	0.00173
	(0.00114)	(0.00071)	(0.00095)	(0.00280)
PREC*	0.00015	−0.00021	−0.00003	−0.00145
	(0.00053)	(0.00036)	(0.00060)	(0.00128)
SKC*	0.00125	−0.00067	0.00062	−0.00174
	(0.00163)	(0.00084)	(0.00103)	(0.00280)
PRES*	0.00004	−0.00001	$-0.00031^{\dagger}$	−0.00115*
	(0.00018)	(0.00013)	(0.00016)	(0.00051)
TEMP*	0.00010	0.00018	0.00033	0.000040
	(0.00042)	(0.00023)	(0.00036)	(0.00090)
HUMI*	−0.00020	0.00017	−0.00012	−0.00007
	(0.00027)	(0.00014)	(0.00018)	(0.00047)
$RET_{i\,t-1}$	−0.10550	−0.27366*	−0.24372	0.03802
	(0.20635)	(0.11008)	(0.16476)	(0.32362)
$DJIA_{t-1}$	−0.39163	−0.22907	0.08651	0.16994
	(0.25766)	(0.16479)	(0.20008)	(0.43807)
MON	−0.08152***	−0.08125***	−0.00827	−0.16362***
	(0.00784)	(0.00582)	(0.00763)	(0.01902)
DEC	0.01974**	−0.00844**	−0.00612*	−0.00409
	(0.00696)	(0.00308)	(0.00309)	(0.00872)
Halloween	0.01296***	−0.00052	−0.00138	0.01169*
	(0.00292)	(0.00117)	(0.00169)	(0.00475)
JAN	0.02009***	0.00965***	0.00350	0.04237**
	(0.00588)	(0.00276)	(0.00369)	(0.01392)
TURN	0.00703	0.00955***	−0.00068	0.02423*
	(0.00505)	(0.00283)	(0.00416)	(0.01084)
α_0	0.00223**	0.00256*	0.00020***	0.01111***
	(0.00079)	(0.00106)	(0.00006)	(0.00331)

Table 19 (Continued)

	Dependent variable: Trading volume (1) DAX	(2) MDAX	(3) SDAX	(4) TecDAX
α_1	0.10456	0.08036*	0.03042***	0.04723*
	(0.08518)	(0.03197)	(0.00801)	(0.02186)
β_1	0.73153***	0.69093***	0.96280***	0.80632***
	(0.08889)	(0.09688)	(0.00069)	(0.04620)
γ_0	0.08853	0.02972	−0.00334	0.06008†
	(0.09467)	(0.03968)	(0.01744)	(0.03502)
AIC	−1.38460	−1.62480	−0.98812	0.43754
BIC	−1.34470	−1.58480	−0.94816	0.49692

Note: † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

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