Do investors save trading for a rainy day?

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Abstract

This paper studies the impact of weather on 31 countries stock index trading volumes, through the influence on investors attention. First, in our panel analysis we regress trading volumes on four weather variables (temperature, sky cloud cover, precipitation and snow). We find that precipitation and temperature are positively linked to trading volumes while snow has an opposite effect. And this relationship is also found to be nonlinear. We find that the trading volumes increase with low temperature and comfortable conditions whereas decrease with adverse weather conditions. For example, with 1 inch increase of snow leads to 2.82% decrease in trading volume of S&P 500. Second, we directly link weather effect to the measure of attention and sentiment. We find that the attention to the markets decreases with the increase of the temperature whereas weather appears has no impact on the weekly sentiment index of U.S. We propose attention as an alternative channel of weather effect entering the stock markets in addition to the weather sentiment. Lastly, we are able to explore the implications of weather effect and develop the economic application. The economic magnitude of the empirical results show an exploitable aggregate effect when the trading signals are based on 7 developed countries weather influence on U.S. market.

Keywords: Trading Activities, Weather, Attention, Sentiment

1 Introduction

A voluminous literature has examined the effect of weather variables, such as sunshine, lunar cycle and daylight savings on financial markets (for more details see Saunders Jr, 1993; Kamstra, Kramer, and Levi, 2009; Hirshleifer and Shumway, 2003; Saunders Jr, 1993; Goetzmann and Zhu, 2005; Loughran and Schultz, 2004). Most of the empirical studies report a positive relationship between good weather and stock market returns. This is explained by assuming that good weather creates a general upbeat mood which triggers more optimistic investment decisions. Motivated by recent research in psychology by Lee, Gino, and Staats (2014) who show that precipitation has a positive effect on individual productivity in three separate working environments, in this study, we seek an additional explanation of the weather effect on stock markets. Given that precipitation has been identified in the literature as the most important barrier to outdoor physical activities, we focus our investigation on the changes of attention in affecting trading activities as the additional explanation of weather effect. The proxy of productivity and unit of analysis is trading volume in major stock markets across 31 countries. In line with the existing literature on weather and finance, we control for the possible effect of sentiment by using cloudiness as a mood proxy. Motivated by Loughran and Schultz (2004), we also control for the negative effect of snow on trading activity which is associated with the inconvenience brought in urban environments by this particular weather condition.

Our major findings are summarised as follows: firstly, we conduct panel regression to find out whether trading behaviour will be significantly affected by the influence of weather while controlling for heterogeneity among the countries. This involves the danger to identify weather effects that may not really exist as the majority of trading takes place electronically, only a small proportion of the action on the floor of the stock exchange still has its place. We find that snow significantly reduces market trading volume while rain and temperature have the opposite effect. The weather impact on the stock markets also appears to be asymmetric and nonlinear. Low temperature increases trading volume, while as the temperature increases, the trading volume decreases as a result of an inactive trading activities due to distracted investors. Second, by using Google Search Volume Index (SVIs) as a direct measure of attention, we show for the first time that weather has a significant impact on investors' attention. Low temperature increases SVIs for a panel of total 16 markets under study. Lastly, both contemporaneous and lagged weather condition in seven developed countries have statistically significant impact on

U.S. market namely rain, cloud and temperature. By constructing a simple trading strategy, we find that the weather anomaly is also economically significant. The drivers of weather effect are complex and depend on the "true-feeling" of investors, country characteristics and level of weather conditions. The nature of the effects is multidimensional and is due to various reasons such as rational inattention, involuntary distraction, transportation problems or sentiment.

Our work contributes, more broadly, to a growing literature on the economics of attention. A large proportion of existing literature concentrates on the role of attention in asset price dynamics leaving no room for investor sentiment. For example, the attention literature investigates the effect of weekends when earnings are announced (DellaVigna and Pollet, 2009); the selective attention to favourable news and avoidance towards unfavourable information (Karlsson, Loewenstein, and Seppi, 2009); and the investors discrete choice depending on both action's true payoffs and prior beliefs (Matêjka, McKay, et al., 2015). We argue that sentiment may not be captured if investors are not attentive to the markets. Similarly, sentiment and attention can be present at stock markets simultaneously. Our study investigate the possibility that one exogenous factor could affect both investor attention and sentiment, therefore, focusing on either element would undermine the influence of another in investors' decision-making process. One noteworthy contribution of our study is that weather effect realisation on the financial market can also be explained by varying levels of attention and loss of productivity, rather than sentiment-based trading alone.

2 Literature review

One stream of behavioural finance literature investigates how the fluctuation of mood affects stock market performances. This group of studies focus on if asset prices are related to weather and environmental conditions, such as *seasonal affective disorder* (SAD) (Kamstra, Kramer, and Levi, 2003), lunar cycles (Yuan, Zheng, and Zhu, 2006; Kuo, Coakley, and Wood, 2010) and sunshine (Saunders Jr, 1993; Hirshleifer and Shumway, 2003). This line of literature is based on the psychological evidence which suggests that the weather affects mood (Keller, Fredrickson, Ybarra, Côté, Johnson, Mikels, Conway, and Wager, 2005), and mood, in turn, can affect the judgement and quality of decision-making (negative relation found by Au, Chan, Wang, and Vertinsky, 2003), and attitude towards risk (Kliger and Levy, 2003). In this context, weather is considered as a proxy of mood acting on asset prices with upbeat mood linked to more risktolerant behaviour, consequently, investors are more inclined to hold financial securities (Bassi, Colacito, and Fulghieri, 2013).

The relationship between weather and stock market returns has been the subject of an increasing number of empirical studies, however, the empirical evidence is rather inconclusive. An influential study by Saunders Jr (1993) finds that the returns on NYSE are negatively related to sky cloud cover in New York City with sunny days associated with a higher market return. The finding is further supported by Hirshleifer and Shumway (2003) who examine the relationship between morning sunshine in 26 cities where the leading stock exchanges are located. They conclude that the sunshine is strongly correlated with stock returns whereas snow and rain are irrelevant to the returns. Comparing with the significant relationship found between sunshine and stock returns, the evidence concerning the impact of other weather variables on stock markets is less clear. For example, Dowling and Lucey (2005) investigate the impact of precipitation on the Irish stock market and conclude that there is a negative but significant relationship between rain and stock returns. With regard to the temperature, the returns of nine international stock markets are investigated and a negative relation is found between stock returns and temperature (Cao and Wei, 2005). They argue that the negative correlation is due to investors' more risk-taking behaviour under low temperatures that leads to a higher return. The findings conclude that investors change the state of sentiment under high temperature given that the negative relation is slightly weaker in summer than winter. A more recent study by Chang, Chen, Chou, and Lin (2008) looks at the impact of weather on stock returns of NYSE and its trading activity. The findings suggest that more cloud is associated with not only lower returns but also higher volatility whereas temperature is irrelevant to intraday stock returns. In summary, these inconsistent results lead us to postulate that the impact of weather on investors may not be linear.

Despite the compelling evidence of weather effect on the stock markets, the way in which the market is affected remains unclear, especially when 77% of the trades take place electronically indoors nowadays (Schwartz, Byrne, and Colaninno, 2006, Chapter 1, page 8). Therefore, the weather-mood effect on stock market is questionable. In addition, if it is mood that drives the stock prices, why do different markets exhibit immense variability in reaction to the stimuli (e.g., see individual regression results from Hirshleifer and Shumway, 2003)? As a result, we seek an additional explanation of weather effect on the financial markets.

The literature related to impact of inattention in stocks' return-generating process has also discussed the potential influence of weather on investors attention (see Schmittmann, Pirschel, Meyer, and Hackethal, 2015, for more details). We then explore the impact of weather on affecting investors attention to the markets. As the stock returns may not be affected due to arbitrage, the variation of trading volume may give a more lucid picture of investment decisions. Loughran and Schultz (2004) investigate the link between weather and investor localised trading activities. They find little evidence that local cloud conditions affect trading volume or asset prices. However, the results show that extremely bad weather and religious holidays reduce trading volume significantly. Drawing from the above findings, we hypothesize that the reduced trading volume is caused by the lack of participation in markets.

If the above assumption holds, there should be a positive contemporaneous correlation between trading volume and volatility, the volatility should exhibit a similar movement as trading volume in response to weather shocks. Symeonidis, Daskalakis, and Markellos (2010) investigate how market volatility is affected by weather to capture the investors risk attitude in their investment activities. Their empirical results suggest that sky cloud cover is inversely related to various measures of stock market volatility. The evidence supports our assumption that the investors are less attentive to the market; whereas it contradicts the prevailing sentiment literature arguing that the bullish sentiment is negatively correlated with market volatility (Lee, Jiang, and Indro, 2002; Brown, 1999; Gervais and Odean, 2001). However, unlike Loughran and Schultz (2004), they find that extreme weather conditions do not offer additional explanatory power to the variations of market volatility. The interesting finding is inconsistent with the results from both sentiment and attention literature, which reinforces our assumption of a nonlinear relationship between weather and trading activities and the influence of inattention can potentially adds extra explanatory power to the mixed results.

Even though the weather effect may be driven by both attention and sentiment, in the existing literature, the two factors are often treated separately in their behavioural implications for the market movements. Therefore, we jointly study both factors in order to disentangle the respective impact on the trading behaviour and market performances.

It is intuitive that severe weather hampers the productivity that occurs outdoors (for example, Burke, Dykema, Lobell, Miguel, and Satyanath, 2014; Deschênes and Greenstone, 2012, in agriculture). Interestingly, it is also found that heat has large negative effects on productivity in office labour and manufacturing (for example, Jones and Olken, 2010, industrial output of trades). With regard to the stock market, a recent study by McTier, Tse, and Wald (2013) examines the U.S. stock market affected by influenza and finds evidence from 25 countries and 15 major international cities that an increase in the incidence of flu would coincide with a decrease in trading and return volatility. This finding suggests that the absence of key market participants reduces the production and flow of information.

Following this line of thought, the paper by Cachon, Gallino, and Olivares (2012) is more relevant to our study because they investigate the impact of weather on manufacturing industry which happens indoors and presumably occurs in the presence of air conditioning. They use weekly production data from 64 automobile plants in the U.S. over a ten-year period and find that adverse weather conditions, such as excess heat and rain, lead to a significant reduction in production. The magnitude of effect varies from location to location. They also find the weather shocks increase the volatility of production. In contrast to the conclusion drawn by Lee et al. (2014), where the good weather is viewed as a distraction whilst bad weather increases productivity, it is concluded that "a blizzard can disrupt production" because of worker absenteeism. The latest study shows that interruptions and other distractions consume 28% of the day for the knowledge worker thereby diminishing efficiency and productivity. The overall distraction cost is $588 billion per annum in the United States alone (Spira and Feintuch, 2005). Taken together the above findings, good weather is treated as a potential distraction for outdoor and leisure activities resulting in a loss of productivity. Adverse weather can also be a distraction as, for example, workers may be late at work due to the disruption of transportation, or leave early, or absenteeism. As a result, the trading volume may be affected by both good and bad weather conditions due to lack of attention or changing risk perceptions.

3 Hypothesis formulation

Summarizing the growing literature of weather effects on global stock markets, currently there is no general agreement on how the stock market is affected by the condition of weather. Some papers even doubt if a weather effect truly exists or simply it is a form of data manipulation (see Jacobsen and Marquering, 2008; Kamstra et al., 2009; Jacobsen and Marquering, 2009; Pizzutilo and Roncone, 2016, for full details). However, the findings from the psychological literature are compelling and the mixed results on stock market returns are significant enough to raise the question whether the influence is channelled through various mechanisms, which may be nonlinear. In labour economics, it argues that labour productivity increases during raining days as workers substitute leisure time with more time at work. New psychological findings further confirm that bad weather increases individual productivity by eliminating potential distractions from good weather (Lee et al., 2014). Whereas conventionally, bad weather leads to a negative mood and hence impairs executive functions. These two contradictory conclusions also motivate our study to consider both attention and mood as potential drivers of investors trading behaviour.

By using trading volume, we are not only able to investigate investor behaviour mechanism, but also help to understand the performance of return volatility because of well documented positive correlation between volatility and volume (Gallant, Rossi, and Tauchen, 1992). Furthermore, we focus on trading volume rather than returns since the former will capture more trading and information activity whereas the reaction to the shock may be unnoticeable in the returns process (Andersen, 1996) which could draw misleading conclusions. There are two further advantages of using trading volume to understand the psychological and cognitive trading behaviour. In one respect, motivated by sentiment literature, the change in beliefs and overconfidence affect the trading volume (Shefrin, 2008). This means that trading volume is able to capture the investors sentiment if weather affects investors' mood. In a second respect, information processing capacity is conditional on investors attention allocation to the stock market or distraction from weather related events, therefore, the change in trading volume is in response to the arrival of new information (Sims, 2003; Andersen, 1996). From these two perspectives, the theoretical nature of trading volume emphasises the changes in investors' beliefs associated with new information.

To summarise the above arguments, we can develop the following hypotheses:

Hypothesis I. Good (bad) weather conditions, such as lack of rain, that increase (decrease) the salience and attractiveness of outdoor options, will decrease (increase) the productivity of market participants and will lead to lower (higher) levels of trading activity.

Hypothesis II. The effect of weather on productivity and trading activity is nonlinear and depends on the level of weather variables and their interaction.

Similar hypotheses are examined in a different empirical setting using survey and laboratory data by Lee et al. (2014). In addition to rain, as a possible productivity driver, the authors control for the effect of other variables such as temperature and visibility. Moreover, the nonlinear effect of weather is also considered through linear and quadratic terms as productivity could be higher with either low or high temperature, for example.

4 Data

This section will describe the weather and stock market data variables, the methodologies that are used to pre-process data and their basic statistical properties.

4.1 Weather variables

Following much of the literature on the economic and financial effect of weather, we include four weather variables in the sample: sky cloud cover (CLOUD), precipitation (RAIN), snow (SNOW) and temperature (TEMP). We obtain the weather data from National Climatic Data Centre (NCDC, data available at `http://www.ncdc.noaa.gov/cdo-web/`). This database includes hourly summaries of weather variables from different observation stations. We use the observations from major airports near 31 cities for consistency of measurement across the globe. These chosen cities are the host cities of major stock exchanges.

Sky cloud cover is one of the weather variables under investigation to capture sentiment. Recent empirical evidence suggests that clouds are inversely related to stock market returns due to its influence on mood. Market index returns tend to be higher during sunny days as opposed to cloudier days (Hirshleifer and Shumway, 2003; Chang et al., 2008). The cloud cover, is recorded hourly on a 10-point scale as: Clear (0), Scattered(1-4), Broken(5-7), Overcast(8), Obscured (9) and Partial Obscuration (10). We first eliminate errors and missing values. Then we compute for each day the daily cloud cover by taking the average value from 6.00 to 16.00 so that it roughly corresponds with the work-hour. The purpose of using the pre-market hours is to investigate the potential weather effect on investors mood before the trading activity and also effects related to commuting (Hirshleifer and Shumway, 2003; Loughran and Schultz, 2004).

Precipitation, as a potential deterrence for outdoor activities is included in our weather variables in order to investigate the attention side of effect from weather. We use daily total rainfall or melted snow during the day to explore the aggregated effect from the rainfall.

Temperature and snow have been found to have a significant relation to market returns and trading activity (e.g., see Cao and Wei, 2005; Loughran and Schultz, 2004) so we include both in the study. Temperature refers to the mean temperature for the day in Fahrenheit degrees to tenths while overall depth of snow is expressed in inches to tenths.

The raw data is then deseaonalised as frequently done in the weather literature in finance to capture the weather shocks. So, we first compute the historical mean of each weather variable for each calendar week in the sample and then we subtract this mean from the daily weather value to obtain the seasonally-adjusted weather values.

Table 1 summarises the description of the weather variables used in the study.

Table 1. Description of weather variables

Weather Variable	Description
TEMP	Mean temperature for the day in degrees Fahrenheit to tenths (.1 Fahrenheit); deseasonalise it by subtracting weekly mean (5 days a week) of whole sample period from mean temperature for the day (TEMP).
RAIN	Total precipitation (rain and/or melted snow) reported during the day in inches and hundredths (.01 inches); deseasonalise the daily precipitation by same method as described above.
SNOW	Snow depth in inches to tenths (.1 inches); deseasonalise the daily snow depth using same method as above.
CLOUD	Average hourly sky cover data from 6.00 to 16.00 (from 0 as clear to 10 as partial obscuration); deseasonalise sky cloud cover as above.

Descriptive statistics of the weather variable under consideration for individual countries shown in Table 2 indicate considerable heterogeneity in the sample.

Table 2. Descriptive statistics of raw weather variables for individual cities

	Market	Mean	Obs.	S.D	C.V.	Skew.	Kurt.
	Amsterdam						
Temperature		51.3644	3074	11.2595	0.2192	-0.2225	2.4542
Precipitation		0.0857	3074	0.1859	2.1688	4.2124	28.1501
Snow		0.0192	3074	1.0659	55.4437	55.4166	3072.0000
Sky Cloud Cover		4.7141	3074	1.9445	0.4125	-0.4568	2.4895
	Athens						
Temperature		65.7288	3187	13.9537	0.2123	-0.0183	1.9994
Precipitation		0.0002	3187	0.0080	49.2959	55.0448	3072.6870
Snow		0.0000	3187	0.0000	.	.	.
Sky Cloud Cover		3.4017	3180	2.1353	0.6277	0.1400	2.0412
	Buenos Aires						
Temperature		64.4000	2557	9.6639	0.1501	-0.0701	2.0839
Precipitation		0.1152	2557	0.4301	3.7337	7.3162	77.4721
Snow		0.0000	2557	0.0000	.	.	.
Sky Cloud Cover		3.3802	2529	2.5541	0.7556	0.3492	1.8617
	Bangkok						
Temperature		84.2494	2932	2.9968	0.0356	-0.7036	4.8951

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Table 2 – continued from previous page							
	Market	**Mean**	**Obs.**	**S.D.**	**C.V.**	**Skew.**	**Kurt.**
Precipitation		0.2040	2932	0.5098	2.4990	4.4034	30.7240
Snow		0.0000	2932	0.0000	.	.	.
Sky Cloud Cover		5.4699	2932	1.5350	0.2806	-0.6691	2.5844
	Brussels						
Temperature		51.5648	3325	11.6654	0.2262	-0.2074	2.5022
Precipitation		0.0837	3325	0.2237	2.6742	10.9446	202.1705
Snow		0.0725	3325	1.2572	17.3311	43.9326	2184.4150
Sky Cloud Cover		4.5212	3325	1.5483	0.3425	-0.5116	2.6743
	Copenhagen						
Temperature		48.5982	3251	12.2926	0.2529	-0.0725	2.0253
Precipitation		0.0553	3251	0.1493	2.6973	6.8435	81.1222
Snow		0.2772	3251	2.9872	10.7762	30.6367	1084.2850
Sky Cloud Cover		4.7815	3249	1.7498	0.3660	-0.5662	2.4382
	Dublin						
Temperature		48.6111	3287	12.2584	0.2522	-0.0773	2.0372
Precipitation		0.0553	3287	0.1485	2.6861	6.8412	81.6352
Snow		0.2711	3287	2.9610	10.9235	31.0687	1110.7940
Sky Cloud Cover		5.3216	3287	1.3188	0.2478	-0.6714	2.8166
	Frankfurt						
Temperature		47.8327	3181	13.3252	0.2786	-0.1266	2.3487
Precipitation		0.1520	3181	0.3718	2.4467	4.9918	42.0384
Snow		0.0404	3181	0.4102	10.1468	11.9057	156.5448
Sky Cloud Cover		5.2258	3109	1.7104	0.3273	-0.7485	3.3971
	Helsinki						
Temperature		43.3173	3181	16.9586	0.3915	-0.3389	2.5728
Precipitation		0.0721	3181	0.1699	2.3556	5.7804	67.5330
Snow		2.8575	3181	6.6500	2.3272	2.6409	9.1261
Sky Cloud Cover		5.0464	3179	1.7411	0.3450	-0.5561	2.3962
	Hong Kong						
Temperature		75.6554	3205	9.6759	0.1279	-0.6593	2.5085
Precipitation		0.1936	3205	0.6524	3.3706	5.9477	49.0080
Snow		0.0000	3205	0.0000	.	.	.
Sky Cloud Cover		3.7979	3205	1.6807	0.4425	-0.0186	2.1792
	Istanbul						
Temperature		60.3185	2265	13.8746	0.2300	-0.0686	1.9043
Precipitation		0.0538	2265	0.1569	2.9133	4.6695	31.4031
Snow		0.0528	2265	0.8914	16.8823	35.6670	1488.2930
Sky Cloud Cover		3.1381	2265	2.0360	0.6488	0.0447	1.8498
	Johannesburg						
Temperature		61.4829	2813	7.8339	0.1274	-0.5245	2.7712
Precipitation		0.0762	2813	0.2208	2.8968	4.4348	27.7443
Snow		0.0000	2813	0.0000	.	.	.
Sky Cloud Cover		2.6550	2794	1.8235	0.6868	0.2409	2.4897
	Kuala Lumpur						
Temperature		82.2827	3203	2.0904	0.0254	-0.0409	2.7130
Precipitation		0.3068	3203	0.6312	2.0571	5.4203	78.7145
Snow		0.0000	3203	0.0000	.	.	.
Sky Cloud Cover		6.0832	3194	0.2705	0.0445	4.0382	32.0739
	London						

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Table 2 – continued from previous page							
	Market	**Mean**	**Obs.**	**S.D.**	**C.V.**	**Skew.**	**Kurt.**
Temperature		52.5938	6859	9.9824	0.1898	-0.0426	2.3891
Precipitation		0.0671	6859	0.1929	2.8745	23.4776	1108.3730
Snow		0.0213	6859	0.3385	15.8920	51.5324	3454.1060
Sky Cloud Cover		5.0089	6759	1.8561	0.3706	-0.5189	2.7083
	Madrid						
Temperature		58.9591	3272	14.4069	0.2444	0.1234	1.8613
Precipitation		0.0369	3272	0.1306	3.5370	6.0300	55.8754
Snow		0.0000	3272	0.0000	.	.	.
Sky Cloud Cover		3.1858	3264	2.0010	0.6281	0.1795	2.1243
	Milan						
Temperature		54.5911	2648	14.9693	0.2742	-0.0911	1.8804
Precipitation		0.1892	2648	0.8395	4.4363	7.6778	75.7473
Snow		0.0000	2648	0.0000	.	.	.
Sky Cloud Cover		3.6820	2636	2.4020	0.6524	0.2884	2.0823
	Manila						
Temperature		82.3009	3186	2.6839	0.0326	0.0706	2.9161
Precipitation		0.0552	3186	0.4211	7.6284	19.2439	537.7364
Snow		0.0000	3186	0.0000	.	.	.
Sky Cloud Cover		4.9103	3186	1.8271	0.3721	0.2211	1.7039
	Oslo						
Temperature		41.7553	3039	15.8836	0.3804	-0.3168	2.4066
Precipitation		0.0943	3039	0.2346	2.4883	6.6385	89.1102
Snow		1.6018	3039	4.5899	2.8654	3.3010	13.9773
Sky Cloud Cover		5.3974	3026	1.8477	0.3423	-0.3457	2.2609
	Paris						
Temperature		53.6363	3221	12.1579	0.2267	-0.1244	2.3901
Precipitation		0.0630	3221	0.1455	2.3087	4.2647	27.2580
Snow		0.0243	3221	0.2108	8.6722	12.0900	173.5793
Sky Cloud Cover		5.0499	3216	1.7941	0.3553	-0.7682	2.9300
	Seoul						
Temperature		54.6597	2976	17.5479	0.3210	-0.2672	1.9353
Precipitation		0.1495	2976	0.5669	3.7930	7.3052	72.0550
Snow		0.0688	2976	0.4850	7.0483	10.9945	169.1263
Sky Cloud Cover		3.8475	2972	2.7111	0.7047	0.0823	1.6775
	Singapore						
Temperature		82.0179	1516	2.1303	0.0260	-0.2277	2.7510
Precipitation		0.2457	1516	0.5715	2.3258	5.0435	46.0852
Snow		0.0000	1516	0.0000	.	.	.
Sky Cloud Cover		5.6745	1516	0.5270	0.0929	-0.5225	5.3089
	New York						
Temperature		54.7294	4531	16.1378	0.2949	-0.1511	2.0739
Precipitation		0.1233	4531	0.3425	2.7768	5.2994	43.8771
Snow		0.2633	4531	1.4368	5.4573	8.8498	103.0157
Sky Cloud Cover		4.7809	4528	2.4898	0.5208	-0.1797	1.7014
	São Paulo						
Temperature		68.2452	3217	6.3177	0.0926	-0.2935	2.7037
Precipitation		0.1175	3217	0.4040	3.4370	7.8789	109.5381
Snow		0.0000	3217	0.0000	.	.	.
Sky Cloud Cover		4.4988	3214	2.3308	0.5181	-0.3877	2.1132
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Table 2 – continued from previous page

	Market	Mean	Obs.	S.D.	C.V.	Skew.	Kurt.
	Santiago						
Temperature		58.7045	2194	9.3425	0.1591	-0.0434	1.9652
Precipitation		0.0180	2194	0.1090	6.0460	10.4139	152.0586
Snow		0.0000	2194	0.0000	.	.	.
Sky Cloud Cover		2.6927	2185	2.7383	1.0169	0.6173	1.9104
	Stockholm						
Temperature		44.9137	3263	14.9612	0.3331	-0.1698	2.3031
Precipitation		0.0000	3263	0.0002	57.1227	57.0964	3261.0000
Snow		0.0000	3263	0.0000	.	.	.
Sky Cloud Cover		4.0754	3103	1.9461	0.4775	-0.4704	2.4744
	Sydney						
Temperature		65.2918	3067	7.6383	0.1170	0.0313	2.1794
Precipitation		0.0973	3067	0.3073	3.1580	5.9398	50.2108
Snow		0.0004	3067	0.0217	55.3805	55.3534	3065.0000
Sky Cloud Cover		3.9253	3063	1.9200	0.4891	-0.1423	2.0638
	Tokyo						
Temperature		61.6300	3253	13.6753	0.2219	0.0283	1.8186
Precipitation		0.1734	3253	0.5033	2.9033	5.4820	45.8773
Snow		0.0000	3253	0.0000	.	.	.
Sky Cloud Cover		5.1233	3253	2.1545	0.4205	-0.4094	2.1384
	Taipei						
Temperature		74.4153	2979	9.6176	0.1292	-0.3397	2.1132
Precipitation		0.2201	2943	0.5674	2.5780	4.3849	27.7228
Snow		0.0000	2979	0.0000	.	.	.
Sky Cloud Cover		5.8455	2979	1.8543	0.3172	-0.5675	2.1910
	Toronto						
Temperature		48.8006	3202	17.0258	0.3489	-0.2178	2.1842
Precipitation		0.0791	3202	0.2080	2.6287	4.8548	39.9749
Snow		0.7281	3193	2.0224	2.7778	3.5244	16.3272
Sky Cloud Cover		3.5359	3203	2.9688	0.8396	0.1979	1.4812
	Vienna						
Temperature		51.6642	3221	15.2754	0.2957	-0.1822	2.1255
Precipitation		0.0629	3221	0.1767	2.8087	5.7499	51.3582
Snow		0.2312	3221	1.3850	5.9912	15.5332	368.9210
Sky Cloud Cover		4.8814	3218	1.7105	0.3504	-0.4756	2.4220
	Zurich						
Temperature		49.8563	3020	13.8736	0.2783	-0.1176	2.1400
Precipitation		0.1062	3020	0.2485	2.3396	4.2965	29.6531
Snow		0.1600	3020	0.7080	4.4247	6.5361	56.8718
Sky Cloud Cover		4.7906	3020	1.7172	0.3584	-0.4470	2.4666
	Total						
Temperature		58.4525	104698	16.9764	0.2904	-0.2557	2.4409
Precipitation		0.1061	104662	0.3690	3.4775	9.5521	169.9314
Snow		0.2228	104689	1.8305	8.2141	17.5953	611.2066
Sky Cloud Cover		4.5333	104236	2.1801	0.4809	-0.3689	2.2138

4.2 Productivity measure

We now turn to trading volume which is our main dependent variable under study against which we shall test the hypotheses. Aggregate turnover, which is defined as the total number of shares traded divided by the total number of shares outstanding, is considered in the literature as a natural measure of trading activity (Campbell and Wang, 1993; Stickel and Verrecchia, 1994; Lo and Wang, 2000). So we use the turnover as a measure of productivity in each city and draw the relevant data from Bloomberg.

We investigate 33 market indices corresponding to 31 cities weather where the stock exchanges are listed. For the U.S., we include the S&P 500, NASDAQ composite, and Dow Jones Industrial Average. We collect daily observations from each market excluding holidays and weekends. The period ranges from 2001 to 2013 for 29 markets, which are the earliest available data for volume, with exception for FTSE 100 and S&P 500 which start from 1986 and 1996, respectively.

After collecting the raw data, we apply three transformations. First, following Lo and Wang (2000), as share turnover is highly persistent with strong autocorrelation, we apply log-linear detrending to induce stationarity. Second, as after the detrending process the data still contain periodic components, we remove the calendar regularities by regression against monthly dummies. Lastly, in order to reduce the effect of possibly spurious outliers, we winsorise the deseasonalised and detrended data by limiting 1% of the extreme values in the sample, and we denote as υ_{it}. More specifically, the process can be expressed below:

$$\hat{V}_{it} = logV_{it} - (\hat{a}_i + \hat{b}_{it}) \tag{1}$$

$$\hat{V}_{it} = c_{i0} + c_{i1}Jan_{it} + c_{i2}Feb_{it} + c_{i3}Mar_{it} + \dots, + c_{i11}Nov_{it} + \nu_{it}$$

Where V_{it} is the raw share turnover for each market index i at time t, $\hat{V}_{it}$ is logarithmic linear detrended volume, the residuals ν_{it} from deseasonalised $\hat{V}_{it}$ are winsorised at 98% percentile denoting as υ_{it}. Table 3 presents descriptive statistics of filtered trading volume under study. Again we can observe a large variation in the location and dispersion of the distributions under study for different markets. The results of standard unit root tests on the transformed data, shown in Table 4, confirm that the stationary has been achieved.

Table 3. Descriptive Statistics of stock market trading volume

Index	Location	Obs.	Mean	S.D.	C.V.	Skew.	Kurt.
AEX	Amsterdam (AMS)	3074	0.0014	0.3837	278.2792	0.4140	3.3370
ASE	Athens (ATH)	3188	-0.0005	0.7617	-1498.9210	0.0342	2.2306
MERVAL	Buenos Aires (BAI)	2558	0.0031	0.4938	158.4356	-0.1944	2.8095
SET	Bangkok (BKK)	2935	0.0006	0.5037	797.7829	0.0016	3.1078
BEL 20	Brussels (BRU)	3325	0.0023	0.4402	190.6760	0.0738	2.6910
KFX	Copenhagen (COP)	3251	0.0010	0.4277	449.1210	0.1128	2.5893
DJIA	New York (DJ)	3521	0.0017	0.2694	159.7136	0.3765	3.1007
IESQ 20	Dublin (DUB)	3287	0.0035	0.5920	169.9906	0.2361	2.7506
DAX	Frankfurt (FRK)	3181	-0.0003	0.4088	-1540.7510	0.6088	3.1511
OMX Helsinki	Helsinki (HEL)	3181	0.0008	0.4688	569.6283	0.4674	2.8031
Hang Seng Index	Hong Kong (HKG)	3205	0.0009	0.5027	568.6865	0.6624	3.1932
BIST 30	Istanbul (IST)	2265	0.0018	0.3212	181.9431	-0.2838	3.0181
FTSE/JSE	Johannesburg (JOH)	2817	0.0043	0.3622	84.2887	-0.1630	3.0750
FTSE Bursa Malaysia KLCI	Kuala Lumpur (KLU)	3203	0.0004	0.4829	1112.0070	0.3806	2.8708
FTSE 100	London (LDN)	6859	0.0008	0.5880	711.8085	-0.1546	2.0588
IBEX 35	Madrid (MAD)	3272	0.0001	0.4698	5393.1650	0.2076	2.5641
FTSE MIB	Milan (MIL)	2648	0.0006	0.3717	639.0565	0.2129	2.7003
PSEi Index	Manila (MNL)	3189	0.0001	0.4914	4123.8360	0.0429	3.1683
NASDAQ	New York (NQ)	3052	0.0017	0.2910	170.8583	0.3111	2.8825
OSEAX	Oslo (OSL)	3039	0.0004	0.6496	1773.8050	0.0480	2.1101
CAC 40	Paris (PAR)	3221	0.0026	0.3643	141.3732	0.2817	3.1204
KOSPI	Seoul (SEO)	2977	0.0002	0.3554	1676.5520	0.0790	2.3026
FTSE ST All-Share	Singapore (SIN)	1516	0.0013	0.2883	228.1310	-0.1459	2.9982
S&P 500	New York (SP)	4531	0.0009	0.4208	459.2224	-0.4012	2.7985
BOVESPA	São Paulo (SPL)	3217	0.0010	0.3918	393.2249	-0.0279	2.8288
IPSA	Santiago (STG)	2194	0.0010	0.4139	414.4218	0.0894	2.9327
OMX Stockholm 30	Stockholm (STK)	3263	0.0002	0.3693	1613.3700	0.0583	2.8295
S&P ASX 200	Sydney (SYD)	3068	0.0007	0.3579	485.4716	-0.0186	2.8800
Nikkei 225	Tokyo (TKY)	3253	0.0010	0.4516	474.3718	0.3322	2.3381
TAIEX	Taipei (TPI)	2983	0.0006	0.3579	563.3495	-0.0793	2.6842
S&P TSX Composite	Toronto (TRT)	3204	0.0014	0.3605	259.7298	-0.2167	3.2703
ATX	Vienna (VIE)	3221	-0.0002	0.7697	-4166.8130	0.2065	2.0448
Swiss Market Index	Zurich (ZUR)	3020	0.0001	0.4251	4381.3410	0.5705	3.0298
	Total	104718	0.0010	0.4669	446.7966	0.1237	3.2533

This table reports summary statistics of the trading volumes for 31 cities where the stock exchange is located. Among which, we use three indices data for New York city consisting of Dow Jones Industrial Average, S&P 500 and NASDAQ composite. S.D. is standard deviation, C.V. is coefficient of variation.

Table 4. Stationarity analysis of stock market trading volume

	ADF			Phillips-Perron		
	none	const.	c, trend	none	const.	c, trend
AMS	-0.409	-3.8058***	-4.3526***	-0.5306	-28.5024***	-30.7279***
ATH	-0.2042	-3.9537***	-3.9911***	-0.292	-18.1830***	-18.3009***
BAI	-0.0248	-7.0587***	-7.0632***	-0.3103	-36.5514***	-36.5421***
BKK	0.0564	-3.9779***	-5.6658***	0.4142	-8.9821***	-18.3885***
BRU	-0.0443	-3.4842***	-4.4647***	-0.3497	-22.6735***	-35.8285***
COP	-0.0197	-3.5161***	-4.0290***	-0.1337	-26.6039***	-31.0922***
DUB	-0.224	-2.9862**	-3.4850**	-0.5682	-37.1564***	-39.7746***
FRK	-0.1293	-4.1697***	-4.1589***	-0.342	-36.0001***	-36.0139***
HEL	-0.3595	-3.2050**	-3.6285**	-0.4573	-29.7827***	-33.1567***
HKG	0.1459	-2.2627	-4.5660***	0.2223	-8.1676***	-23.7763***
IST	0.0951	-4.0644***	-7.3515***	0.3939	-17.1020***	-29.0935***
JOH	0.2240	-2.9865**	-7.6345***	-0.0489	-17.2961***	-35.2758***
KLU	0.0217	-4.2708***	-6.7032***	0.0695	-11.8328***	-25.2367***
LDN	0.3416	-2.2995	-2.5300	-0.0002	-11.9577***	-31.5519***
MAD	-0.1577	-5.3215***	-5.6183***	-0.3183	-30.9617***	-33.6643***
MIL	-0.1659	-3.6367***	-4.3745***	-0.3746	-21.5366***	-24.3362***
MNL	0.2099	-1.9873	-6.4748***	0.3262	-10.0160***	-39.8402***
OSL	0.0203	-2.4779	-2.3777	0.0546	-8.5587***	-8.4025***
PAR	-0.3955	-4.6506***	-4.7401***	-0.4993	-36.8620***	-37.1448***
SEO	-0.1694	-3.4277***	-4.4845***	-0.306	-8.2412***	-16.0565***
SPL	0.5573	-1.6883	-3.9939***	0.5045	-7.9615***	-34.3972***
SIN	-0.2447	-7.6182***	-8.0340***	-0.2991	-23.1231***	-23.7210***
STG	0.1395	-5.7559***	-7.1009***	0.0656	-38.4040***	-41.0902***
STK	-0.2888	-5.1500***	-5.1966***	-0.3416	-35.4123***	-35.7346***
SYD	0.1249	-3.2998**	-3.7663**	-0.271	-27.7135***	-36.1060***
TKY	0.3304	-2.7949*	-3.1576*	0.3696	-11.4369***	-15.0179***
TPI	-0.2746	-5.8289***	-5.8737***	-0.4077	-18.7077***	-18.8087***
TRT	-0.0386	-2.4152	-5.4655***	-0.1662	-30.5067***	-39.3935***
VIE	-0.0583	-2.8473*	-2.9500	-0.403	-11.9829***	-15.1870***
ZUR	-0.1936	-3.1579**	-3.2893*	-0.1914	-29.8621***	-30.5388***
SP	0.1061	-3.4269**	-3.4571**	0.0975	-21.9653***	-21.9710***
DJ	-0.6859	-4.9786***	-8.1574***	-0.5805	-30.2725***	-46.3489***
NQ	-0.4728	-4.8835***	-5.8447***	-0.6522	-20.3203***	-26.4982***

*ADF and Phillips-Perron refer to augmented Dickey-Fuller test and Phillips-Perron test for a unit root (Dickey and Fuller, 1979; Phillips and Perron, 1988). ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively.*

5 Empirical Results

5.1 Hypothesis I.: Does bad weather increase trading activity?

We first take the classic approach in the literature (Saunders Jr, 1993; Hirshleifer and Shumway, 2003; Dell, Jones, and Olken, 2014; Symeonidis et al., 2010), estimating simple regressions by ordinary least squares separately for each market in the sample. Specifically, we estimate the parameters of the regression as follows:

$$\upsilon_{it} = \alpha_i + \beta_{i1} TEMP_{it} + \beta_{i2} RAIN_{it} + \beta_{i3} SNOW_{it} + \beta_{i4} CLOUD_{it} + \epsilon_{it} \quad (2)$$

Where υ_{it} are the transformed trading volume values for market i at time t. In line with the empirical literature in this area, we find some significant relationship with mixed signs of coefficient. Specifically, the results show that temperature has a significant impact on 10 out 33 markets whilst the positive or negative relationship is mixed. For eight countries we find that trading volumes are affected by precipitation. Trading volumes increase significantly with rainfall in six out of eight markets whereas negative impact of rain is found in Manila and Stockholm markets. In general, snow has an adverse influence on the trading volumes except for Istanbul, London and Amsterdam. As for sky cloud cover, the results show that seven out of thirty-three markets are negatively affected by sky cover except for London. Table 5 reports full details of the results for the whole sample. The overall results suggest a weak link that cloud and snow are inversely related to trading volume. In this regard, the results of sky cover are in line with the sentiment literature which postulates that more cloud is associated with a downward mood and, thereby, leads to a less active trading. The results for snow are consistent with the findings by Loughran and Schultz (2004) suggesting that it causes disruption for investors, whilst the impact of precipitation and temperature is less conclusive in the results.

However, the simple regression estimation faces potential omitted variable bias and problems related to over-controlling. More importantly, this form of estimation is best for assessing the long-term historical effect of weather rather than to focus on the contemporary effect of climate on economic activity (Auffhammer, Hsiang, Schlenker, and Sobel, 2013). Therefore, we use panel regression to control for heterogeneity across the countries and climate zones. This is also justified by the descriptive statistics showing a large variation of variables between the markets under study.

Table 5. Regression analysis of the weather effect on trading volume for individual markets

	TEMP	**RAIN**	**SNOW**	**CLOUD**
Amsterdam	0.0030	0.0434	0.0113***	-0.0047
	(1.3540)	(0.8934)	(5.9213)	(-1.0548)
Athens	0.0034	3.0744***		-0.0022
	(0.6553)	(6.0964)		(-0.2054)
Buenos Aires	-0.0028	-0.0301		-0.0006
	(-0.9205)	(-1.1249)		(-0.1298)
Bangkok	-0.0008	0.0141		-0.0455***
	(-0.1076)	(0.6383)		(-3.8945)
Brussels	-0.0016	-0.0047	-0.0091**	-0.0047
	(-0.7158)	(-0.1230)	(-2.2479)	(-0.7229)
Copenhagen	0.0065**	0.0925	-0.0016	-0.0120**
	(2.3121)	(1.5250)	(-0.7754)	(-2.1585)
Dublin	0.0129***	0.1606**	-0.0044	-0.0024
	(3.4128)	(2.1233)	(-1.3191)	(-0.2891)
Frankfurt	0.0007	0.0313	-0.0471**	0.0067
	(0.3816)	(1.2800)	(-2.4228)	(1.2445)
Helsinki	0.0017	0.1076**	-0.0122***	-0.0049
	(0.8178)	(1.9649)	(-3.8893)	(-0.7704)
Hong Kong	-0.0016	0.0005		0.0018
	(-0.4381)	(0.0320)		(0.1989)
Istanbul	0.0008	0.0055	0.0087*	0.0013
	(0.3667)	(0.1069)	(1.9278)	(0.2768)
Johannesburg	0.0002	0.0403		-0.0076
	(0.1026)	(1.0394)		(-1.1848)
Kuala Lumpur	-0.0308***	-0.0176		-0.0503
	(-4.1825)	(-1.2590)		(-1.3151)
London	0.0070***	0.0392	0.0267*	0.0488***

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Table 5 – continued from previous page				
	TEMP	**RAIN**	**SNOW**	**CLOUD**
	(2.9051)	(1.1573)	(1.8255)	(7.0725)
Madrid	-0.0026	0.1072		-0.0060
	(-0.9543)	(1.4454)		(-1.0107)
Milan	0.0017	0.0421***		-0.0052
	(0.6361)	(4.9976)		(-1.1356)
Manila	0.0108	-0.0301**		0.0119
	(1.2952)	(-2.2335)		(1.3412)
Oslo	0.0059*	0.0600	-0.0104	0.0116
	(1.8868)	(0.9145)	(-1.5651)	(1.2734)
Paris	-0.0021	0.0626	-0.1024**	-0.0013
	(-1.1357)	(1.2478)	(-2.4468)	(-0.2813)
Seoul	-0.0003	-0.0022	-0.0060	-0.0027
	(-0.1640)	(-0.1858)	(-0.2437)	(-0.8534)
Singapore	0.0123**	0.0012		-0.0084
	(2.5322)	(0.0890)		(-0.5160)
São Paulo	-0.0067***	0.0542***		-0.0076
	(-2.8136)	(2.6155)		(-1.6217)
Santiago	-0.0110***	-0.0113		-0.0078**
	(-3.5955)	(-0.1477)		(-1.9724)
Stockholm	0.0036**	-54.8943***		0.0035
	(2.1530)	(-4.9987)		(0.7716)
Sydney	0.0006	-0.0160	-0.3257***	0.0031
	(0.3158)	(-0.6624)	(-5.3019)	(0.8159)
Tokyo	0.0004	-0.0100		0.0056
	(0.1243)	(-0.6961)		(1.1730)
Taipei	-0.0035	0.0067		-0.0038
	(-1.5097)	(0.5424)		(-0.7027)
Toronto	0.0002	0.0242	-0.0016	-0.0062**

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Table 5 – continued from previous page				
	TEMP	**RAIN**	**SNOW**	**CLOUD**
	(0.1500)	(0.7170)	(-0.2321)	(-2.2803)
Vienna	0.0003	0.0832	-0.0034	-0.0335***
	(0.0892)	(0.9310)	(-0.2376)	(-2.7620)
Zurich	0.0010	0.0679*	-0.0185	-0.0122
	(0.4383)	(1.6735)	(-0.9420)	(-1.6450)
Nasdaq	0.0036***	0.0006	-0.0220***	-0.0058**
	(2.7872)	(0.0421)	(-3.8916)	(-2.4008)
Dow Jones	0.0009	0.0192	-0.0127**	-0.0036*
	(0.8158)	(1.4460)	(-2.2441)	(-1.7140)
S&P500	0.0005	0.0099	-0.0135	-0.0038
	(0.2910)	(0.5460)	(-1.2635)	(-1.2489)

*This table gives the value of the coefficients b_{i1} in regression with deseasonalised and detrended trading volume as the dependent variable and deseaonslised weather as independent variables, respectively. Numbers in brackets correspond to t-statistics. Heteroskedasticity and autocorrelation consistent standard errors are estimated using the Newey and West (1987) approach. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively.*

So next step of analysis, we run panel regression with fixed-effects for 31 markets (S&P500 is used for the U.S. market) in order to observe deviations from averages to investigate weather shock on market performances:

$$\upsilon_{it} = \gamma + \delta W_{it} + \mu_i + e_{it} \tag{3}$$

Where W_{it} represents a vector containing the weather variables. The fixed effects for the spatial areas, μ_i, absorb fixed spatial characteristics, whether observed or unobserved, disentangling the shock from many possible sources of omitted variable bias.

The results in Table 6 show that snow is inversely related to volumes whilst temperature and rain have significant and positive effect on trading volumes when deseasonalised weather variables are used as regressors. Temperature appears to be irrelevant when raw value is used in the regression. This finding is consistent with the study by Fruehwirth and Sögner (2012) suggesting that only temperature contains a strong seasonality and deseasonalistion is necessary. The results of rain and snow support the findings by Lee et al. (2014) and Loughran and Schultz (2004), suggesting that investors are more productive during the rainy days when more time is allocated to work while snow reduces trading volume by causing inconvenience to investors.

Table 6. Fixed-effects panel regression analysis of the weather effect on trading volume

Filtered	**Coefficient**	**Raw**	**Coefficient**
TEMP	0.0014**	TEMP	-1.41E-05
	(2.5278)		(-0.0405)
RAIN	0.0138***	RAIN	0.0128***
	(3.2688)		(3.1844)
SNOW	-0.0091***	SNOW	-0.0071***
	(-6.2829)		(-6.8734)
CLOUD	0.0005	CLOUD	0.0002
	(0.4837)		(0.2122)
Constant	0.0026	Constant	0.0027
	(0.4715)		(0.1240)
Observations	97615	Observations	97626
Adjusted R^2	0.0009	Adjusted R^2	0.0005

*This table gives the value of the coefficients δ in regression (3) with deseasonalised and detrended trading volume as the dependent variable, and deseaonslised weather and raw weather as independent variables respectively. Heteroskedasticity and autocorrelation consistent standard errors are estimated using the Newey and West (1987) approach. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively. 'Filtered' column provides panel fixed-effect regression for 31 markets with filtered weather variables; 'Raw' columns provides panel fixed-effect regression for 31 markets with raw weather variables.*

In order to further understand the disruptive effect of weather as a driver of trading activity We also investigate the impact of bad weather on employee absences for the U.S. Specifically, we use absence data from the Labor Force Statistics of the Current Population Survey from the U.S. Bureau of Labor Statistics, as a measure of loss of productivity. The data provide the number of full-time employees from non-agricultural industries that are either absent or work less than full time due to a bad weather. The absence is recorded on a monthly interval dated back to 1990. We regress raw weather values and filtered weather variables on logarithmic values of absences and results are presented in Table 7. The results of the raw weather regression clearly suggest that rain, snow and low temperature increase absences. By using filtered weather as independent variables, only rain and low temperature show a significant impact on the increase of absences. So this group of results show that bad weather has an adverse effect on productivity.

From the above two panel regressions, we find that the rain and temperature have inconsistent impact on the trading volumes and productivity represented by the absence rate.

We contemplate that extreme weather conditions such as excessive rainfall, low temperature and snow may cause disruption in transportation leading to a loss of productivity whilst bad weather (such as rainy days) eliminates distraction and improves productivity. Thereby, this set of results motivate our next test Hypothesis II. suggesting that the impact of weather may be nonlinear and asymmetric.

Table 7. Regression analysis of the effect of weather on absences for U.S.

Filtered	**Coefficient**	**Raw**	**Coefficient**
RAIN	1.7862*	RAIN	2.0587***
	(1.7614)		(2.6243)
CLOUD	0.0716	CLOUD	0.0737
	(0.6904)		(1.3103)
SNOW	0.2011	SNOW	0.3140***
	(1.2670)		(3.4001)
TEMP	-0.0631**	TEMP	-0.0269***
	(-2.4147)		(-6.4439)
Constant	5.7291***	Constant	6.5058***
	(79.2192)		(14.8923)
Observations	216	Observations	216
Adjusted R^2	0.1199	Adjusted R^2	0.4805

The right half of table gives the results for logarithmic absence and raw weather. If we calculate the elasticity of the absences on weather change, the absences are very sensitive to rain fall, snow and temperature. In particular, 1% increase in rain results in 3% increase in absences whereas 1% drop in temperature increases 1.04% absences.

5.2 Hypothesis II.: Is the effect of weather on trading activity nonlinear?

The literature has often found a nonlinear relationship between climate and the economic outcome of interest, with extremely warm temperatures being particularly important. Although this is more related to agriculture, the recent findings in indoor manufacturing activity encourage us to explore the potential nonlinearity of weather effect on stock markets.

First, we conduct quantile estimation for individual countries. The results, given in Table A1 and A2 show mixed results of an asymmetric effect. Taking Copenhagen market as an example, a large amount of snow (top 10%) reduces trading volume significantly whilst the bottom 10% of snow has no impact on trading volume. In order to further explore the asymmetric effect between volume and weather, we control for unobserved market heterogeneity by using quantile analysis in the panel data.

Following recent development on quantile regression for panel data, (Koenker, 2004), we estimate directly a vector of individual weather effects. The fixed-effects estimator is based on minimizing a weighted sum of 5 ordinary quantile regression objective functions corresponding to a selection of 5 values of τ, (0.1, 0.25, 0.5, 0.75 and 0.9).

We will consider the following model for the conditional quantile functions of the response of the tth observation on the ith individual country y_{it}.

$$Q_{yit}(\tau|x_{it}) = \alpha_i + x_{it}'\beta(\tau) \quad t = 1, \ldots, m_i, \;\; i = 1 \ldots, n. \tag{4}$$

where x_{it} is a vector of independent weather variables, depend on the quantile, τ, for all quantiles τ is in the interval (0,1). Fixed effect α is a pure location shift effect on the conditional quantiles of response, implying that the conditional distribution for each country's volume has the same shape, but different locations as long as the α's are different. The effects of the weather variables, x_{it} are permitted to depend upon the quantile, τ, of interest, but the α's do not. The parameter $\beta(\tau)$ estimation increases the variability of the estimates of the covariate effect, but shrinkage of these effects towards a common value helps to reduce this additional variability.

Table 8. Quantile fixed-effects panel regression analysis of the weather effect on trading volume

	τ(0.1)	**τ(0.25)**	**τ(0.5)**	**τ(0.75)**	**τ(0.9)**
TEMP	0.0019*	0.0009	0.0006	0.0020	0.0020
	(1.7953)	(1.2950)	(0.8639)	(1.5744)	(1.4900)
RAIN	0.0089	0.0183***	0.0136**	0.0124	0.0218
	(1.1394)	(2.7708)	(2.4409)	(1.5329)	(1.5856)
SNOW	-0.0082	-0.0055	-0.0084***	-0.0126***	-0.0074
	(-0.6336)	(-0.8930)	(-2.7973)	(-2.8061)	(-1.5381)
CLOUD	0.0087	0.0021	-0.0010	-0.0029	-0.0046
	(1.0580)	(0.6017)	(-0.4239)	(-1.1687)	(-1.6442)
Constant	-0.5692***	-0.3019***	-0.0213***	0.3087***	0.6338***
	(-21.2607)	(-26.5211)	(-4.2190)	(18.8612)	(21.6138)

*This table gives the value of the coefficients β in regression (4). ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively. It provides panel fixed-effect regression for 31 markets, condition on five different quantiles.*

The results of intercepts showing in the Table 8 suggest that the country unobserved characteristics are significant, which is the estimated conditional quantile function of the each trading volume under the influence of weather conditions when τ is 0.1, 0.25, 0.5, 0.75, and 0.9. It suggests that trading volume increases when there is more rain (τ=0.25, and 0.5) and a low temperature (τ=0.1). If the value of snow is above the average, the trading volume decreases significantly. The result for rain is in line with existing attention literature, suggesting that considerable volume of rainfall increases productivity, that is, trading volume, by eliminating potential distraction from good weather (Lee et al., 2014; Connolly, 2008).

Other than asymmetric effect, we also consider the nonlinear effect of weather by examining indices which involve interactions between variables to capture the "true feeling" on humans (e.g., see Shi and Skuterud, 2015), for example, heat index has been studied by geographers interested in identifying the ideal climate for particular tourism-related activities. De Freitas, Scott, and McBoyle (2008) distinguish between three facets of weather: thermal, aesthetic and physical, where physical elements such as rain and strong winds, tend to nullify the effect of thermal sensation and aesthetic features of the weather. To capture thermal sensation, we use the heat index widely reported in the United States to capture the "real-feel" impact of temperature. The computation of the index is a refinement of a result obtained by multiple regression analysis carried out by Rothfusz (1990). Specifically, the heat index is calculated as:

$$\begin{aligned} HI = {} & -42.379 + 2.04901523 * T + 10.14333127 * RH - .22475541 * T * RH \\ & -.00683783 * T * T - .05481717 * RH * RH + .00122874 * T * T * RH \\ & +.00085282 * T * RH * RH - .00000199 * T * T * RH * RH \end{aligned} \tag{5}$$

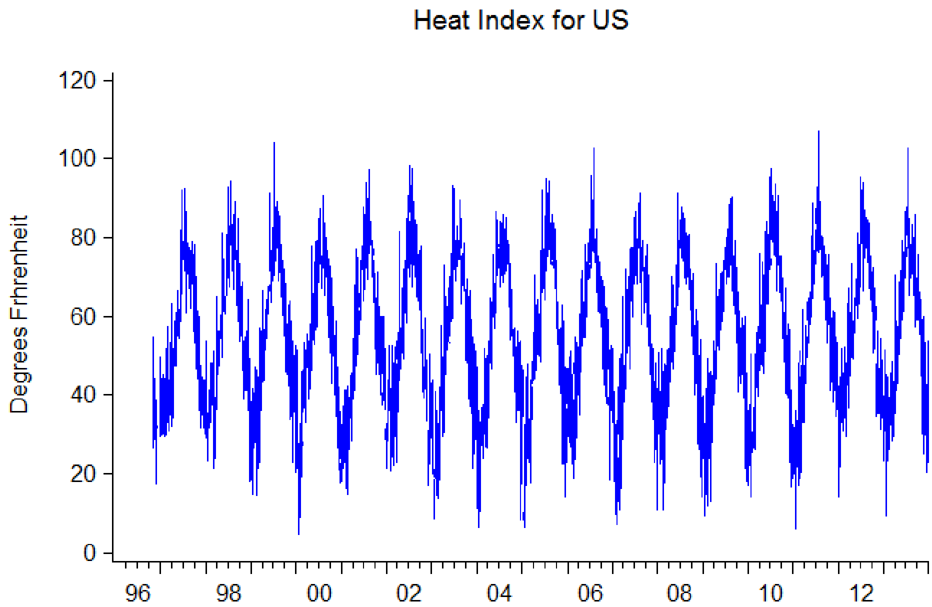
where T is temperature in degrees Fahrenheit and RH is relative humidity in percent. HI is the heat index expressed as an apparent temperature in degrees Fahrenheit. Adjustments also have been made when the temperature is below 80 degree Fahrenheit. The heat index for the U.S. is graphically depicted in Figure 1.

Table 9. Regression analysis of the heat effect on trading volume for U.S.

	Coefficient			
	(1)	(2)	(3)	(4)
HI(-1)	0.0008***			
	(3.2092)			
HI		0.0008***	-0.0007	1.0632***
		(3.1734)	(-0.5679)	(62.9410)
HI^2			0.0003***	-0.0197***
			(3.4755)	(-34.5129)
HI^3				0.0001***
				(24.6167)

*This table gives the value of the coefficients of heat index on trading volume. Heteroskedasticity and autocorrelation consistent standard errors are estimated using the Newey and West (1987) approach. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively. Columns (1), (2) and (3) report the results of filtered heat index and volume; column (4) reports the results of raw heat index on logarithmic volume.*

Figure 1. Heat index for U.S.



In order to further explore the nonlinear impact of heat on trading volume, we also include higher order terms of the Heat Index (HI) in the regression. The results are shown in Table 9. Given that heat index is above 80 degree Fahrenheit, the trading volume decreases with more desirable weather for outdoor activities; whilst the heat reaches a caution level, the investors opt to focus more on trading and volume increases again.

Motivated by the characteristics of heat impact on trading volume for U.S., we too investigate whether temperature has the similar effect on the panel data of 31 countries.[1] We follow the same fixed-effects method as in model (3) which can be written as:

$$\upsilon_{it} = \theta + \kappa_1 W_{it} + \kappa_2 TEMP_{it}^2 + \xi_i + \psi_{it} \tag{6}$$

Where W_{it} represents a vector containing weather variables, $TEMP^2$ is included to test the quadratic relationship between temperature and trading volume. The fixed effects for the spatial areas, ξ_i, absorb fixed country characteristics.

The results from equation (6) are presented in Table 10. The impact from rain, snow and temperature are consistent with panel regression in Section 5.1, which suggests that rain and temperature increase productivity whereas snow has a significant and negative impact

[1]The relative humidity data is not available for the rest of countries in the sample other than U.S., so that the Heat Index can only be constructed for U.S. Therefore, we use a similar variable "temperature" to reflect HI in the panel regression of 31 markets.

on trading volume. When squared temperature is included in the model of using raw weather values, the results are comparable to the heat index analysis. The trading volume increases with the temperature as weather improves working condition so that the productivity is enhanced; but as it increases, trading volume starts to decrease as the improved weather condition becomes a distraction for leisure and outdoor activities so that the trading volume is reduced. However, when we include $TEMP^3$ in the model, unlike the heat index results, it shows an insignificant impact on trading volume. For this result, we understand that the effect is so marginal that the sample heterogeneity may debilitate this marginal effect.

Table 10. Fixed-effects panel regression of nonlinear weather effect on trading volume

Filtered	**Coefficient**	**Raw**	**Coefficient**
RAIN	0.0139***	RAIN	0.0118***
	(3.3036)		(2.9375)
CLOUD	0.0004	CLOUD	-0.0005
	(0.3685)		(-0.5198)
SNOW	-0.0091***	SNOW	-0.0055***
	(-6.2735)		(-5.7983)
TEMP	0.0014**	TEMP	0.0046***
	(2.3955)		(4.1993)
$TEMP^2$	-7.64E-05	$TEMP^2$	-4.34E-05***
	(-1.3128)		(-4.5237)
Constant	0.0046	Constant	0.1022***
	(0.8147)		(-3.1819)
Observations	97615	Observations	97615
Adjusted R^2	0.0009	Adjusted R^2	0.0011

*This table gives the value of the coefficients δ in regression (3) with deseasonalised and detrended trading volume as the dependent variable, and deseaonslised weather and raw weather as independent variables respectively. Heteroskedasticity and autocorrelation consistent standard errors are estimated using the Newey and West (1987) approach. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively. 'Filtered' column provides panel fixed-effect regression for 31 markets with filtered weather variables; 'Raw' columns provides panel fixed-effect regression for 31 markets with raw weather variables.*

5.3 Effect of weather on attention and sentiment

We now examine the link between weather and direct measures of sentiment and attention. For sentiment, we are limited by the availability of data for all 31 countries so that we use the American Association of Individual Investors Investor Sentiment Survey (AAII) for U.S. [2]

[2] The IPSOS Global Primary Consumer Sentiment Index (PCSI) is available for 16 countries(see `http://im.thomsonreuters.com/solutions/content/ipsos-primary-consumer-sentiment-index/`), however, it is a monthly indicator which may not be able to timely capture the weather effect in their indices. The AAII indicator measures sentiment though a weekly survey of individual investors with respect to their bullish, bearish, or neutral expectations on the stock market over the next six months (see Brown and Cliff, 2004).

between 1996 to 2013.

In the analysis of the AAII sentiment index, we regress it on U.S. weather using contemporaneous and lagged values. Results for the weekly AAII index are given in Table 11. In all cases, we find that there is no significant weather effect on investors' sentiment for the U.S. under study.

Table 11. Regression analysis of the effect of weekly weather on investors' sentiment for U.S.

	AAII		AAII
$RAIN_t$	-0.0459	$RAIN_{t-1}$	-0.0430
	(-1.2579)		(-1.2280)
$CLOUD_t$	0.0058	$CLOUD_{t-1}$	2.74E-05
	(1.2695)		(0.0054)
$SNOW_t$	-0.0098	$SNOW_{t-1}$	-0.0035
	(-1.2448)		(-0.5773)
$TEMP_t$	-0.0017	$TEMP_{t-1}$	-0.0017
	(-1.0140)		(-1.0629)
Constant	0.0751***	Constant	0.0753***
	(5.8901)		(5.8893)
Observations	937	Observations	936
Adjusted R^2	0.0015	Adjusted R^2	-0.0014

*The table gives the value of slope coefficient for deseaonslised weather variables on sentiment AAII index at time t and $t-1$. Heteroskedasticity and autocorrelation consistent standard errors are estimated using the Newey and West (1987) approach. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively.*

We then examine if the weather shock affects investor attention by using a direct measure of attention, the Search Volume Index (SVI) which is based on the intensity of queries on Google search (see also Da, Engelberg, and Gao, 2011; Vlastakis and Markellos, 2012). Due to the quality and availability of SVIs for all 31 market index queries, we only conduct panel regression analysis for 13 out of 31 countries.[3] Specifically, we investigate market-wide attention on the basis of SVIs for queries related to different index names. For example, we use the SVI of query for "S&P 500" in order to measure the market attention for U.S. Raw daily SVIs are logarithmically transformed and deseasonalised using dummies for each month of the year. We then examine the relationship between investor attention and weather by regressing the SVIs on weather variables. The results in Table 12 clearly suggest that the temperature has negative effect on SVIs, which is to say that attention decreases with the increase of the temperature. We find that all three weather variables rain, snow and cloud have no significant impact on

[3]The 13 cities include Bangkok, Frankfurt, Hong Kong, Istanbul, Johannesburg, London, Madrid, Paris, Singapore, New York, Sydney, Tokyo, and Toronto.

investor attention for the panel of 13 cities.

Table 12. Fixed-effects panel regression analysis of the weather effect on Google SVI

	SVI		SVI
$TEMP_t$	-0.0018***	$TEMP_{t-1}$	-0.0017***
	(-4.7710)		(-4.5176)
$RAIN_t$	-0.0005	$RAIN_{t-1}$	0.0022
	(-0.1000)		(0.4218)
$SNOW_t$	-0.0015	$SNOW_{t-1}$	-0.0026
	(-0.5706)		(-0.9284)
$CLOUD_t$	0.0014	$CLOUD_{t-1}$	0.0001
	(1.4045)		(0.12085)
Constant	0.1793***	Constant	0.1791***
	(101.8661)		(101.7529)
Observations	29047	Observations	29047
Adjusted R^2	0.210071	Adjusted R^2	0.210271

*The table gives the value of slope coefficient for weather variables on 13 markets' daily SVIs at time t and $t-1$. Heteroskedasticity and autocorrelation consistent standard errors are estimated using the Newey and West (1987) approach. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively.*

In general, the weather condition is found to have no significant impact on investors' sentiment for U.S. whilst investors' attention is only negatively related to temperature.

5.4 Economic significance: A weather-based volatility trading strategy for U.S.

Considering that the U.S. market attracts a large number of international traders, we are motivated to investigate whether the weather condition in The Group of Seven (G7) countries is linked to the trading volume in the U.S. market. So we construct a G7 weather index by taking an average weather values of the seven countries. We take the weather value of a country at t if it shares the same time zone as New York (Toronto), and take the weather value of a country at $t-1$ if the time zone is ahead of the time in New York. The impact of G7 countries weather condition on the U.S. trading volume is presented in Table 13. Both rain and temperature of G7 countries increase S&P 500 trading volume significantly on the day and the following day while cloud reduces volume significantly.

Based on the collective effect of weather conditions in G7 countries on the U.S. trading volumes, we seek to explore the economic implications of these results. Table 13 shows that more rain and less cloud increase trading volume of S&P 500 significantly; even though temperature also has a positive effect on the trading volume, we consider that the marginal profit from

Table 13. Impact of G7 weather condition on trading volume for U.S.

	S&P 500		S&P 500
G7 $RAIN_t$	0.2541***	G7 $RAIN_{t-1}$	0.2682***
	(5.5362)		(6.0114)
G7 $CLOUD_t$	-0.0331***	G7 $CLOUD_{t-1}$	-0.0312***
	(-4.5207)		(-4.1605)
G7 $SNOW_t$	0.0129	G7 $SNOW_{t-1}$	0.0096
	(0.4206)		(0.3144)
G7 $TEMP_t$	0.0075**	G7 $TEMP_{t-1}$	0.0076**
	(2.1092)		(2.1220)
Constant	0.0005	Constant	0.0007
	(0.0298)		(0.0391)

*The table gives the results for filtered volume index of S&P 500 and average weather values of G7 countries at time t and $t-1$. Heteroskedasticity and autocorrelation consistent standard errors are estimated using the Newey and West (1987) approach. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively.*

trading on temperature may not cover the transaction cost, therefore, our trading signal is based on rain and sky cloud cover and excludes temperature.

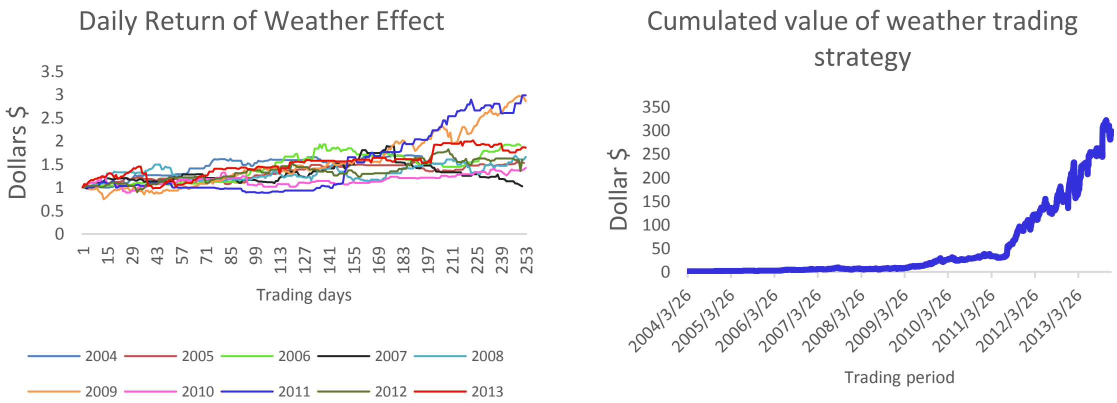
VIX futures contracts are used as underlying assets for trading volatility. For VIX futures, a cost of $1.2 is assumed per contract side (estimate from CBOE for April 2013). Trading signals are constructed on the basis of excessive rain. First, we calculate weekly average from the previous year; then we subtract the weekly mean from daily value, so that we establish a benchmark for excessive rainfall. If the current value is above the value of the previous year, then we take a long position. In our trading strategy, we use the raw weather data of G7 countries to establish our trading signal. Hypothetically, we invest $1 dollar at the beginning of the year and trade through the whole year based on excessive rainfall and cloud cover. By using the simple long and short trading strategy, we can profit from the weather in 9 out of 10 years, except for 2007, our active trading strategy cannot beat the passive buy&hold benchmark. The details of the results are shown in Table 14.

The cumulative return from the trading strategy is depicted in Figure 2.

Table 14. Annualised return from trading VIX futures

Year	Buy&Hold Benchmark	Short/Long Strategy	
	Annualised Return	Annualised Return	Sharpe
2004	-36.50%	134.19%	4.01
2005	-7.84%	77.11%	2.66
2006	-0.34%	120.09%	2.97
2007	88.24%	18.95%	0.36
2008	81.76%	111.76%	1.83
2009	-45.36%	145.33%	2.75
2010	-12.23%	72.83%	1.50
2011	37.62%	253.97%	3.97
2012	-30.95%	92.10%	1.58
2013	-17.22%	141.18%	2.20

Figure 2. The value of $1 invested from 2004-2013



6 Conclusions

Psychological evidence claims that rainy days yield higher productivity by reducing potential outdoor distractions. In this study, we examine the relationship between weather conditions and trading volumes for 33 stock exchanges from 2000 to 2013. We find that precipitation and temperature are positively related to trading volume while snow has a negative effect. This weather-volume relationship is also found to be nonlinear. When physical elements such as rain interact with thermal sensation such as temperature, the weather influence changes, so does the trading activity. In conclusion, investors are more productive during the rainy days as the outdoor distractions are eliminated. However, when the rainfall reaches a disruptive level, it also increases absences and reduces trading volumes. In line with previous research, we find that snow causes inconvenience for the investors to attend work and this results in a decreased trading volume. The trading volume increases with the heat as the environment becomes more comfortable and less disruptive so that the productivity is enhanced. But at the higher heat level, trading volume starts to increase at a descending rate as the weather condition becomes a distraction for leisure and outdoor activities so that the productivity is weakened.

The main practical implication of our findings is a simple trading strategy to exploit weather effect based on the results of G7 countries on the trading volume in the U.S. market. We use VIX future contracts as underlying assets for trading volatility and take long or short position based on rain and cloud from 2004 to 2013. After we take out of transaction costs, we benefit from nine out of ten years in the sample compared to a simple buy & hold strategy. If the hypothesized $1 dollar was invested, the value at the end of 2013 investment would be $298.

One of the potential developments in future research could be a model construction of possible interaction between investor sentiment and attention leading to a non-linear transition between the two states, so as to identify the characteristics of trading activity at each state, therefore, we are able to translate the cognitive bias into cost function for the purpose of predicting future price movement as a complementary indicator in addition to sentiment index.

Appendix: Sample Statistics and Additional Results

Table A1. Quantile regression analysis of the weather effect on trading volume for individual market

	TEMP	RAIN	SNOW	CLOUD	Constant
AMS	0.0015	-0.0787	0.0194***	0.0072	-0.4208***
	(0.8818)	(-1.8155)	-17.0665	(1.4803)	(-48.5319)
ATH	0.0109*	4.7990***		0.0423***	-0.9873***
	(2.4899)	(14.7853)		(3.6290)	(-50.4698)
BAI	-0.0078	-0.0493		-0.0014	-0.6187***
	(-1.8732)	(-1.3026)		(-0.1717)	(-31.7829)
BKK	-0.0006	0.0163		-0.0549**	-0.6334***
	(-0.0593)	(0.3563)		(-3.2444)	(-33.0664)
BRU	-0.0012	0.0137	-0.0398***	-0.0031	-0.5448***
	(-0.5490)	(0.1727)	(-8.4457)	(-0.3446)	(-43.6233)
COP	0.0058	-0.0217	0.0032	-0.0160	-0.5309***
	(1.6917)	(-0.2114)	(1.0041)	(-1.7316)	(-35.0764)
DJ	0.0002	0.0129	-0.0113	-0.0007	-0.3282***
	(0.2446)	(0.8168)	(-1.8911)	(-0.2875)	(-56.4050)
DUB	0.0055	-0.0293	-0.0050	0.0032	-0.6968***
	(1.7215)	(-0.3145)	(-1.3468)	(0.2471)	(-45.0592)
FRK	0.0000	-0.0145	-0.0300	0.0036	-0.4417***
	(0.0178)	(-0.5136)	(-1.0900)	(0.6209)	(-48.6404)
HEL	0.0042*	0.1029	0.0023	-0.0073	-0.5379***
	(2.5224)	(1.6591)	(0.9910)	(-0.9626)	(-47.7359)
HKG	0.0030	0.0125		0.0073	-0.5964***
	(1.2130)	(0.6494)		(0.9127)	(-52.9793)
IST	0.0012	0.0433	0.0207**	-0.0022	-0.4058***
	(0.4160)	(0.4975)	(3.2328)	(-0.2914)	(-31.3669)
JOH	0.0017	-0.0126		-0.0059	-0.4243***
	(0.5720)	(-0.1756)		(-0.5656)	(-31.0755)

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Table A1 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
KLU	0.0178**	-0.0037		0.1361**	-0.5726***
	(2.7019)	(-0.1889)		(2.7543)	(-44.3619)
LDN	0.0036	-0.0661	0.0521**	0.0809***	-0.7540***
	(1.8633)	(-1.6662)	(2.8194)	(14.4818)	(-77.0032)
MAD	0.0004	0.0946		-0.0125*	-0.5773***
	(0.1609)	(1.2221)		(-2.0833)	(-52.5868)
MIL	0.0030	0.0581***		-0.0076	-0.4533***
	(1.1686)	(3.8162)		(-1.3854)	(-38.2256)
MNL	0.0204	0.0201		0.0290*	-0.5855***
	(1.9526)	(0.9887)		(2.1414)	(-35.4282)
NQ	0.0030*	-0.0011	-0.0195**	-0.0009	-0.3462***
	(2.4506)	(-0.0566)	(-2.9754)	(-0.2888)	(-46.4044)
OSL	-0.0003	0.0007	-0.0274***	0.0172*	-0.8531***
	(-0.1592)	(0.0082)	(-7.9818)	(2.0576)	(-59.5619)
PAR	-0.0002	0.0087	-0.0258	-0.0062	-0.4180***
	(-0.1120)	(0.1350)	(-0.6319)	(-1.1859)	(-47.1072)
SEO	0.0018	0.0113	0.0206	-0.0030	-0.4726***
	(1.1290)	(0.8368)	(1.0257)	(-0.8873)	(-53.3720)
SIN	0.0258**	0.0429		0.0007	-0.3637***
	(3.2084)	(1.8525)		(0.0213)	(-23.9046)
SP	0.0038	-0.0295	-0.0203	0.0032	-0.5329***
	(1.9511)	(-0.8107)	(-1.7736)	(0.5932)	(-46.0221)
SPL	-0.0094**	0.0233		-0.0029	-0.4944***
	(-2.8255)	(0.8343)		(-0.3980)	(-37.1507)
STG	-0.0125**	0.0606		-0.0154*	-0.5192***
	(-3.2948)	(0.5578)		(-2.4770)	(-34.5882)
STK	0.0016	-18.1373		0.0019	-0.4401***
	(0.8221)	(-1.6368)		(0.2796)	(-36.7904)

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Table A1 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
SYD	0.0020	0.0197	0.0761	-0.0030	-0.4357***
	(0.8589)	(0.6302)	(1.4229)	(-0.5839)	(-46.6793)
TKY	0.0041	0.0282		0.0103*	-0.5512***
	(1.7032)	(1.3176)		(2.0500)	(-51.7069)
TPI	-0.0017	0.0199		-0.0104	-0.4624***
	(-0.6078)	(1.1143)		(-1.6064)	(-42.1023)
TRT	0.0010	-0.0026	-0.0228***	-0.0033	-0.4292***
	(0.5296)	(-0.0461)	(-3.3522)	(-0.7931)	(-39.9447)
VIE	-0.0044*	-0.0132	0.0031	-0.0270**	-0.9698***
	(-1.9711)	(-0.1626)	(0.3368)	(-2.8014)	(-63.8798)
ZUR	0.0008	-0.0405	0.0114	-0.0029	-0.4821***
	(0.4597)	(-0.9961)	(0.8970)	(-0.4561)	(-52.2538)

*This table gives the value of the quantile regression at bottom 10% with deseasonalised and detrended trading volume as the dependent variable and deseaonslised weather as independent variables, respectively. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively.*

Table A2. Quantile regression analysis of the weather effect on trading volume for individual market

	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
	TEMP	RAIN	SNOW	CLOUD	Constant
AMS	0.0075*	0.2271*	0.0056	-0.0209*	0.5278***
	(2.2638)	(2.3205)	(1.8966)	(-2.3670)	(28.6813)
ATH	0.0023	1.8819		-0.0322**	1.0354***
	(0.6138)	(1.5513)		(-3.0718)	(53.2512)
BAI	-0.0056	0.0062		0.0089	0.6483***
	(-1.3147)	(0.1391)		(1.2502)	(37.1926)
BKK	-0.0056	-0.0139		-0.0749***	0.6531***
	(-0.7891)	(-0.4803)		(-4.9709)	(40.1927)
BRU	-0.0022	0.0902*	-0.0128**	-0.0139	0.5988***

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Table A2 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
	(-0.9541)	(2.1622)	(-3.2447)	(-1.5681)	(43.7320)
COP	0.0085**	0.1310	-0.0060***	-0.0044	0.5841***
	(3.0826)	(1.0392)	(-3.3937)	(-0.4705)	(41.7898)
DJ	0.0014	0.0101	-0.0242***	-0.0014	0.3498***
	(0.9127)	(0.3897)	(-3.7953)	(-0.3548)	(39.2807)
DUB	0.0230***	0.2424	-0.0075**	-0.0212	0.8170***
	(5.5089)	(1.8662)	(-3.0439)	(-1.4431)	(39.8664)
FRK	0.0022	0.0787*	-0.0894**	0.0107	0.6229***
	(0.8770)	(2.1542)	(-2.8709)	(1.1004)	(39.0270)
HEL	-0.0016	-0.0273	-0.0255***	0.0063	0.6470***
	(-0.6601)	(-0.2634)	(-7.1952)	(0.5478)	(36.7813)
HKG	-0.0153**	-0.0265		0.0125	0.7212***
	(-2.6017)	(-0.6835)		(0.8267)	(30.2437)
IST	-0.0000	0.0130	-0.0017	0.0124*	0.4141***
	(-0.0217)	(0.1699)	(-0.3601)	(2.1089)	(41.4537)
JOH	-0.0027	0.0548		-0.0018	0.4910***
	(-1.0980)	(0.9435)		(-0.2341)	(45.2304)
KLU	-0.0892***	-0.0648*		-0.2030*	0.6674***
	(-8.7857)	(-2.1895)		(-2.5239)	(36.9749)
LDN	0.0023	0.2383***	-0.0036	-0.0039	0.7558***
	(1.5067)	(8.5871)	(-0.4440)	(-0.9905)	(96.4803)
MAD	-0.0063*	0.1665		-0.0081	0.6427***
	(-2.4433)	(1.6112)		(-1.0590)	(48.8021)
MIL	0.0002	0.0541**		-0.0180**	0.5163***
	(0.0549)	(3.2291)		(-2.7620)	(36.3401)
MNL	-0.0004	-0.0670		-0.0243*	0.6533***
	(-0.0367)	(-1.5312)		(-2.1137)	(39.7008)
NQ	0.0072***	0.0129	-0.0321***	-0.0061	0.3950***

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Table A2 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
	(3.4335)	(0.3295)	(-3.7103)	(-1.0928)	(30.0988)
OSL	0.0100***	-0.0164	0.0055*	0.0050	0.9089***
	(5.5236)	(-0.2973)	(2.0134)	(0.5925)	(64.0625)
PAR	-0.0032	0.1213	-0.2045**	0.0023	0.5135***
	(-1.3431)	(1.1807)	(-2.6774)	(0.2790)	(37.5291)
SEO	0.0003	-0.0205	-0.0111	0.0009	0.4742***
	(0.1502)	(-0.8564)	(-0.6341)	(0.1729)	(40.7606)
SIN	0.0116	-0.0157		-0.0009	0.3707***
	(1.2167)	(-0.5882)		(-0.0272)	(23.2813)
SP	-0.0003	-0.0011	-0.0098*	-0.0057	0.5208***
	(-0.2829)	(-0.0506)	(-2.0299)	(-1.7998)	(69.3288)
SPL	-0.0096**	0.0541*		-0.0155*	0.5108***
	(-3.2766)	(2.0674)		(-2.2855)	(39.3363)
STG	-0.0104*	-0.0502		0.0008	0.5436***
	(-2.0180)	(-0.3804)		(0.1090)	(30.7418)
STK	0.0029	-111.4706***		0.0057	0.5145***
	(1.7337)	(-14.6431)		(0.9707)	(46.6373)
SYD	0.0045	-0.0400	-0.7298***	0.0110	0.4757***
	(1.8383)	(-1.1544)	(-9.9898)	(1.8692)	(48.0144)
TKY	0.0013	-0.0178		-0.0061	0.6690***
	(0.4663)	(-0.8082)		(-1.0083)	(59.1435)
TPI	-0.0057*	-0.0102		-0.0074	0.4634***
	(-2.1805)	(-0.5689)		(-1.0505)	(43.1982)
TRT	-0.0022	-0.0028	0.0049	-0.0077*	0.4773***
	(-1.5065)	(-0.0615)	(0.8082)	(-2.1694)	(48.0309)
VIE	0.0058**	0.1090	-0.0183	-0.0284***	1.0992***
	(2.7821)	(1.4218)	(-1.1414)	(-3.3873)	(83.4696)
ZUR	-0.0012	0.2257***	-0.0465	-0.0249*	0.6188***

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Table A2 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
	(-0.3769)	(3.6368)	(-1.1827)	(-2.0252)	(34.5259)

*This table gives the value of the quantile regression at top 10% with deseasonalised and detrended trading volume as the dependent variable and deseaonslised weather as independent variables, respectively. ***,**,* denote statistical significance at the 1%, 5% and 10% level respectively.*

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