INVESTOR ATTENTION AND SENTIMENT

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Abstract

Investor sentiment and attention are often linked to the same non-economic events making it difficult to understand why and how asset prices are affected. This thesis disentangles these two potential drivers of market behaviour by studying how investors react to sports outcomes, weather conditions and merger and acquisition announcements.

Firstly, a new dataset of medals for major participating countries and sponsor firms over four Summer Olympic Games is analysed. Results show that although Olympic success does not lead to abnormal stock returns, subsequent market activity is reduced substantially. In the US, for example, trading volume (realised volatility) during Olympics is over 24% (46%) lower than usual while gold medal awards lead to a further decrease over the next trading day. These findings are in line with recent theories and evidence related to investor inattention but cannot easily be explained on the basis of sentiment. Analysis of data from online search volumes and surveys measuring investor sentiment, also suggest that the market impact of the Olympics is linked to changes in attention. I demonstrate that the statistical regularities can be exploited by simple volatility trading strategies in the US to produce significant risk adjusted profits.

Secondly, I study the relationship between weather and stock market activity using a new perspective that does not rely solely on investor mood. I argue that bad weather can increase the productivity of investors by making them more focused on trading and less concerned about other leisure activities. This allows me to explain the empirical finding of higher trading activity on rainy days for a sample of 33 international stock markets. In

line with previous literature, I confirm that particularly bad weather conditions which create inconvenience to market participants, such as snow, have the opposite effect by reducing productivity and trading volume. Finally, I find evidence that weather has a nonlinear effect on market activity.

Thirdly, I explore if the market reaction to M&As in the US is governed by attention or sentiment. I find that attention, as proxied by online abnormal search volume, decreases significantly before announcements and then increases dramatically on the event date. The high level of attention diminishes shortly after. I also investigate whether the abnormal search volume surrounding the event date affects stock prices. The results suggest that the resolved uncertainty before the announcement date is incorporated into price discovery shortly after the announcement as the learning capacity of investors constrains the information processing speed in a bid to adjust the investment decisions.

I would like to dedicate this thesis to my loving parents …

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Table of contents

List of figures

List of tables

Chapter 1

Introduction

1.1 Background and motivation

Since the seminal work of De Long et al. (1990), several papers argue that the behaviour of some investors deviates from the norm of full rationality which underlies the standard model of market efficiency. Whilst this literature takes several different directions (for a review see Barberis and Thaler, 2002; Shiller, 2003; Baker and Wurgler, 2007), I concentrate here on the work related to sentiment and attention. Although these two effects are treated separately, I show how they are related and focus on their joint investigation. A brief overview of each literature follows.

The interest in the role of sentiment, feelings, mood and emotions in business and finance stems from the seminal work of Kahneman and Tversky (1979). Research in this area builds on evidence from experimental psychology and economics and studies how investors are affected in the evaluation of information, risk, gains and future prospects. Investor sentiment is estimated in empirical studies using a variety of approaches (Baker and Wurgler, 2007). Direct measures involve posing questions to investors through surveys, such as those undertaken by the American Association of Individual Investors, Investors Intelligence, etc. General surveys of consumer confidence, such as the University of Michigan Consumer

Sentiment Index, are also sometimes used as they are known to have a close relationship to investor sentiment. Indirect proxies typically assume that sentiment is influenced through the psychological mechanism of "mood misattribution" (Ross, 1977). Simply put, sports success or sunny weather influence the mood of some investors and make them more optimistic. In turn, this makes them more willing to enter into long positions, which leads to higher returns in the short-run. The causal link between the actual events and the mood of investors is based on evidence from psychology which demonstrates, for example, that certain events influence the general mood in the population (Kavetsos and Szymanski, 2010; Dawson et al., 2014).

As noted by Edmans et al. (2007), the two principal approaches for indirectly measuring investor sentiment are based on continuous variables and a single event respectively. The continuous variables used include: weather conditions (Saunders Jr, 1993; Hirshleifer and Shumway, 2003; Symeonidis et al., 2010; Schmittmann et al., 2015), lunar cycles (Yuan et al., 2006) and market variables (e.g., performance, types of trading, derivatives positions; see Brown and Cliff, 2004). Event based studies use, for example, aviation disasters (Kaplanski and Levy, 2010b); changes to and from daylight saving (Kamstra et al., 2003) and holidays (Frieder and Subrahmanyam, 2004). Finally, another proxy for sentiment that is popular recently is based on the textual analysis of news (Tetlock, 2007; Loughran and McDonald, 2011; Ferris et al., 2013). Overall, the empirical evidence has shown that sentiment is associated with stock returns in an asymmetric manner according to which poor mood has a stronger effect (see, for example Edmans et al., 2007; Kaplanski and Levy, 2010a). Beyond the first moment, there is some controversy in the literature concerning the link between investor sentiment and market volatility. A comprehensive study by Symeonidis, Daskalakis, and Markellos (2010) demonstrates that good mood, as proxied by weather and environmental variables, is associated with increased volatility.

The exploration of attention in finance also stems from studies in psychology which deal with the limitations to rationality (Simon, 1957; Kahneman, 1973). Part of this literature concentrates on how limited attention influences judgements and memory and leads to behavioural biases such as the halo effect, the illusion of truth and magical thinking (Yantis, 1998). Another strand emphasises more the nature of attention as a scarce resource and studies how this is allocated in a positive or normative manner between all the different decisions and activities that investors are facing (Veldkamp, 2011). The work of Sims (2003) studies the limited attention of an economic agent as an information processing constraint and its implications in dynamic consumption choice. The arguments for the impact of attention in finance often draw from the vast “dual-task interference" literature in psychology which shows convincingly that humans cannot effectively complete two or more tasks simultaneously (Pashler, 1994). As Ehrmann and Jansen (2012) point out, attention may be inversely related to the complexity (Cohen and Frazzini, 2008), the quantity (Hirshleifer and Shumway, 2003), the time horizon (DellaVigna and Pollet, 2009) and non-saliency of the available information (Huberman and Regev, 2001). Moreover, attention may differ across time, countries and firms (Barber and Odean, 2008). Some of the empirical implications that are attributed to attention include the post-earnings announcement drift, the accrual anomaly, the profit anomaly (Hirshleifer et al., 2011), asset mispricing (Brown, 2014), and the reaction to stale news (Gilbert et al., 2012). In terms of empirical measurement, investor attention is proxied using variables such as distance to weekends (DellaVigna and Pollet, 2009), holidays (Jacobs and Weber, 2011), Google search volumes (Da et al., 2011), market maker activity (Corwin and Coughenour, 2008) and saliency of events (Barber and Odean, 2008).

Although there is growing empirical evidence about the importance of attention, few relevant theoretical frameworks exist. DellaVigna and Pollet (2009) develop a model of the response of stock prices to earnings announcements in which a proportion of investors is assumed to be distracted. The share of inattentive inventors amplifies the delayed response of prices to news about earnings. Peng and Xiong (2006) model a representative investor and solve for her optimal attention allocation in the presence of overconfidence. In this model attention is assumed to be fixed and is shown to endogenously lead to category-learning behaviour where investors tend to process more market rather than firm-related information. An interesting aspect of this model is that it allows for inattention but also for sentiment in the form of overconfidence. However, this overconfidence is assumed to affect only the cognitive capacity to process information rather than mood. Andrei and Hasler (2015) study the joint importance of endogenously determined investor attention and uncertainty and show how these drive risk premia and volatility. Increased attention in their model means that market-related news is informative and volatility increases while uncertainty is reduced. Although variance and risk premia of stock returns increase quadratically with attention and uncertainty, attention is a more powerful driver of volatility. Attention to news varies across time according to changes in the state of the economy but is under the direct control of the investor. Schmidt (2013) develops a model of rational attention according to which investors allocate more weight to market news over firm specific news when attention is scarce. He proxies attention scarcity on the basis of the intensity of sports-related search activity on Google. When attention is distracted by sports events, trading volumes are smaller, while volatility and synchronicity become higher. A novelty of the model against others in the rational attention literature (e.g., Sims, 2003; Peng and Xiong, 2006; Kacperczyk et al., 2014) is that attention can be allocated between leisure time, such as following sports, and, learning news which allows obtaining more precise signals for investment decisions.

1.2 Structure of the thesis

This remainder of the thesis has three parts. The first part (Chapter 2) examines the relationship between trading activity and sports performance at market and firm level. I concentrate on the direct link between sports outcomes, attention and sentiment respectively. The next part (Chapter 3) extends the research question proposed in Chapter 2 regarding the potentially joint effect of attention and sentiment through weather. This study investigates a new channel through which investors are affected by weather, which is typically believed to be a driver for investor sentiment. Finally, the last part (Chapter 4) reinforces the importance of attention in response to financial signals at a firm level by focusing on the information demand before, during and after mergers and acquisitions announcements. In particular, it explores the informativeness of abnormal search volume in relation to abnormal announcement returns of acquiring firms. The final part of the thesis provides a summary and conclusion of the research along with limitations and recommendations for future studies. The appendices provide additional test statistics and results to supplement the research output introduced in the empirical analyses.

Chapter 2

Is there an Olympic gold medal rush in the stock market?[1]

Oh enjoying the thrill of the chase is fine.

Craving the distraction of the game, I sympathize entirely.

But sentiment, sentiment is a chemical defect found in the losing side.

Sherlock Holmes, *A Scandal in Belgravia* (BBC, 2012)

2.1 Introduction

The central idea in this chapter is that major non-economic events, such as soccer matches, holidays or good weather, cannot be used as an indirect proxy of sentiment, as they also affect the attention of investors. Information and behavioural biases, such as those caused by sentiment, are reflected in asset prices only to the extent that investors pay attention to market-

[1]I thank Chris Brooks, Laura Veldkamp, Zhi Da, Jeffrey Wurgler, David Hirshleifer, Timothy Loughran, David-Jan Jansen, Daniel Andrei, George Kavetsos, John Ashton, Wolfgang Maennig, Alasdair Brown, Peter Dawson, Robert Hudson, Marc Jones and Thomas Gilbert for their comments on this chapter. I am also grateful for feedback from the participants of the Research in Behavioural Finance in Rotterdam, the 2014 Behavioural Finance Working Group Conference in London, the Behavioural Models and Sentiment Analysis Applied to Finance Conference in London and of research seminars at University of Edinburgh Business School and Norwich Business School.

related activities. In this sense, attention is a prerequisite for shifts in the mood of investors, a necessary but not sufficient condition for financial impact. If investors are distracted by the loss of the team they support, for example, the decline in their mood may not find its way into the stock market. What I may observe, however, is a reduction in market activity. My research sheds doubt on the unbiasness of non-economic events as proxies of investor behaviour and justifies a deeper investigation of the joint importance of sentiment and attention.[2] To this end, I analyse a new dataset of medal results over four Summer Olympic Games for eight major economies (US, UK, France, Australia, Netherlands, Germany, South Korea and Japan) and five multinational sponsoring firms (Coca Cola, McDonald's, Panasonic, Visa, and Samsung). I ask if the stock market impact of the Games and gold medals is due to a shift in the mood of investors or to a distraction of their attention. Results indicate that there is no significant statistical association between medal performance and abnormal returns over the next trading day. However, trading volumes and volatility are significantly lower during Olympic Games and are further reduced as a function of the gold medals won over the previous day. For example, for each gold medal won by the US, the trading volume in the S&P 500 firms is almost 3% less on the following day. For Germany and South Korea, this decrease is even higher at 6.7% and 7.3%, respectively. These statistical regularities can be exploited through simple volatility trading strategies in the US which produce positive profits in excess of those from a passive approach. My results are consistent with recent theories of investor attention, but cannot be explained on the basis of investor sentiment. I also show that Olympic Games have an impact on a more direct measure of investor attention based on online search volumes, but not on direct survey-based measures of investor sentiment. I

[2] It is surprising that this possibility has not been entertained yet in the financial literature, although it is an idea that has been popular since antiquity. For example, the phrase *panem et circenses* - bread and circuses, the latter having the meaning of public games and other of mass spectacles - is popular since Roman times as a figure of speech to describe how a major sports event can be used to appease a specific group of people by diverting their attention. The idea is still very popular, as exemplified by Hunger Games, the popular trilogy by Suzanne Collins which was recently turned into a movie.

conclude that in the case of Olympic Games, it is investor attention rather than mood that is driving the effect on the stock market.

My study follows De Long et al. (1990) and other researchers which argues that irrational investors may also exist in the market that are influenced by psychological and behavioural factors. I concentrate on two of these factors, investor sentiment and attention, for three main reasons. First, although a considerable amount of research is devoted to showing the significant empirical effects of these factors on financial markets, they are treated separately in the literature (examples for sentiment include Saunders Jr, 1993; Barberis et al., 1998; for attention see Barber and Odean, 2008; Peng and Xiong, 2006). Since attention and sentiment may have a similar impact on investors, a joint investigation of their importance is justified. For example, sentiment is often proxied on the basis of exogenous events, such as sports outcomes, which are considered to have a significant impact on the mood of investors (see Edmans et al., 2007). However, investor attention may also be significantly affected during these events which raises concerns about their unbiasness as sentiment proxies. Although not studied in this chapter, my results suggest more generally that the use of continuous variables for capturing investor sentiment, such as temperature or cloudiness, potentially suffer from the same problems. My research produces interesting new evidence about the validity of competing hypotheses and theoretical models of investor sentiment and attention. This allows us to better understand how economic agents operate within markets and if their motivation is more behavioural or rational. Second, my study is one of the few in the literature which examines the impact of sentiment and attention at both the market and firm level. In addition to increasing the robustness of the results, this is important since it is possible that effects are diluted at the aggregate level due to noise or heterogeneity between firms (Baker and Wurgler, 2007). Finally, correctly measuring the effects of sentiment and attention has practical implications for the design of superior event-driven investment strategies (Kaplanski and Levy, 2010a).

My previously unexplored dataset of Olympic Game medals offers advantages over existing data drawn from other sports, such as soccer matches and the Super Bowl, used by other studies. This is because the Olympic Games are more likely to affect significantly the behaviour of investors since they constitute the most globalised and important sports event in terms of national and corporate impact. This means that I can adopt different units of analysis which include developed and developing participating countries along with multinational sponsoring firms. For example, compared to the 2010 FIFA World Cup, which is another important sports event of comparable importance (Edmans et al., 2007; Ehrmann and Jansen, 2012), the 2012 Summer Olympics involved 204 countries (compared to 32 which qualified in the FIFA), 26 sports (1, soccer), 219.4 million TV viewers in the US (94.5 million), $13.6 billion in organising costs ($3.6 billion), $5.6 billion worth of advertising ($36 million) and $100 million for each of 11 partners worth of partner sponsorship deals (between $24 to $44 million for each one of 6 partners every year from 2007 to 2010) (data drawn from IOC and FIFA websites and various newspaper articles). For the 2008 Olympics, it is estimated that up to 4.7 billion viewers (or 70% of the world population) watched some part of the coverage (Press release, Nielsen Media Research, 8 September 2008). In the US alone, the London Olympics constitute the most-watched television event on NBC with an average of 31.1 million viewers and unprecedented traffic, consumption and engagement on digital platforms (NBC Press Release, 14 August 2012). The economic, social and political importance of the Olympics means that evidence about their effects on the stock market is highly relevant for organisers, policy makers and advisors. My findings concerning the impact of the Olympics on individual sponsor firms are particularly useful for managers in these firms but also for investors and market makers.

Within the sentiment literature, this study is related to an influential study by Edmans et al. (2007) that proposes sports results as an indirect investor mood proxy. The authors argue that losses in international games of soccer, cricket, rugby and basketball induce a negative mood which in turn leads to lower returns in the stock market over the next day. In line with the prospect theory of Kahneman and Tversky (1979), the effect of match results is asymmetric since wins are found not to affect returns. Further evidence of the economic significance of these results is presented by Kaplanski and Levy (2010a). At the firm level, Chang et al. (2012) show that National Football League (NFL) game losses lead to lower next-day returns for locally headquartered NASDAQ firms. The importance of sports sentiment for the stock market is also analysed in Super Bowl (US) by Krueger and Kennedy (1990), in soccer (UK) by Ashton et al. (2003), in horse-racing (Australia) by Worthington (2007), in rugby by Boyle and Walter (2003) and in cricket (India) by Mishra and Smyth (2010). Finally, Bernile and Lyandres (2011) and Palomino et al. (2009), show that investor sentiment is important for stock prices of publicly traded soccer clubs.

Within the attention literature, my study is related to Ehrmann and Jansen (2012) and Schmidt (2013) who use sports events to capture inattention amongst investors. Ehrmann and Jansen (2012) analyse high frequency data to show that market level trading volumes and co-movements with global stock returns are reduced during soccer matches and goals. In my research, rather than looking at what happens during sports events, I focus on the subsequent short term effect that these events have on stock market activity.

My study of data related to Olympic Games is not novel in the literature although my perspective is original. The economic, social and political significance of the Olympic Games has motivated researchers to examine their impact empirically for hosting countries (see the review by Kavetsos and Szymanski 2010) and sponsoring firms (Farrell and Frame, 1997; Miyazaki and Morgan, 2001; Hanke and Kirchler, 2013) but the evidence has been largely inconclusive. Several studies suggest that the Olympics may have "well-being", "feel-good" or "happiness" benefits stemming from attending events, volunteering, national pride, etc. For example, Kavetsos and Szymanski (2010) use a variety of major sporting events, including Olympics, to demonstrate significant feel-good effects in the short term for hosting countries. However, they also find that the association between national athletic success and happiness is statistically insignificant in their sample (further support to these results is given by Oxford Economics 2012). As emphasised by Kavetsos and Szymanski (2010) and Dawson et al. (2014), exploring the impact of Olympic Games on happiness is important since this is assumed as given by politicians and it is adopted as a primary policy objective. For example, one of the two strategic priorities that the Blair Government set out in the bidding for, and hosting, the London Olympics in 2012 was "*a sustainable improvement in success in international competition, particularly in the sports which matter most to the public, primarily because of the 'feel-good factor' associated with winning*" (DCMS/ Strategy Unit, 2002, p.12). Outside the Olympics, Palomino et al. (2009) are one of the few studies that examine sports sentiment and investor attention. They use a sample of listed British soccer teams and study the variation in stock prices conditional to match outcomes and betting odds. The evidence suggests that investor sentiment has an impact on prices while the effect of attention is less clear. Drawing more general conclusions from these results is limited by the sample used since it includes only 16 firms from one country over three years. Moreover, these firms are all from the sports industry where shareholders are likely to be also fans and are more prone to sentiment effects.

2.2 Hypothesis development

My hypotheses involve the effect of positive outcomes from major sports events on investor sentiment, attention and stock market activity. These are motivated by the literature reviewed in the previous section. First, I examine the direction of this effect on stock market activity, as measured by trading volume and volatility, respectively. Sports success is proxied in my study by the number of Olympic medals won by a particular country or sponsoring firm.

Hypothesis I. Sports success leads to a decrease in stock market activity.

The existing literature on the effect of sports events does not examine this particular hypothesis and focuses on interpretations that involve investor sentiment alone. I study the strength and nature of this effect by considering the possibility of both investor sentiment and attention. On the one hand, existing theories and evidence from an investor sentiment perspective suggest that sports success should have a weak or insignificant positive effect on stock market returns (see Edmans et al., 2007). However, it is not clear in the literature what the effect of sentiment is on trading volume and volatility (see Symeonidis et al., 2010). On the other hand, the literature on investor attention predicts a positive relationship between the level of investor attention and market activity (eg., see Andrei and Hasler, 2015 for a relevant theoretical justification; for relevant empirical evidence see Ehrmann and Jansen, 2012; Vlastakis and Markellos, 2012). In my particular empirical setting, there is evidence which implies that the general population and workers are significantly distracted. For example, in August 2008, when Olympics took place, the time spent watching TV by all UK viewers was 3,898 minutes (2.09 hours per day), compared to 3,418 minutes (1.83 hours per day) in 2007 (Ofcom, 2012), an increase in viewership by 14%. The same report notes survey evidence on the media intentions of UK consumers for the London 2012 Games which suggests that around one in four people in full time employment reported a priori that they are likely to watch or listen the events coverage at work (for evidence on other sports see also Lozano, 2011; Hagn and Maennig, 2008). In order to shed further light on the driving forces behind the market activity effect of sports events, I also examine how sport success affects direct measures of investor sentiment and attention, respectively:

Hypothesis II. Sports success has a positive effect on investor sentiment.

Hypothesis III. Sports success has a negative effect on investor attention.

In my study, I use the intensity of online search volumes for investment information in order to directly approximate information. Sentiment is proxied using responses from relevant surveys of market participants.

2.3 Empirical analysis

2.3.1 Sample description

My sample covers four Summer Olympic Games (2000, 2004, 2008, 2012) and eight countries: United States of America, United Kingdom, France, Australia, Netherlands, Germany, Japan and South Korea (a full list of the variables and acronyms used in this study is given in Table 2.1). These countries are Olympic "superpowers" and consistently rank at the top positions in terms of the medal winning index over the sample period (a breakdown of medals is given in Table A.1 in the Appendix). It is important to study several countries since there is evidence that both sentiment (Jones et al., 2012) and attention (Ehrmann and Jansen, 2012) may have different effects across cultures. The US leads in terms of Olympic performance by winning 11.08% of total medals over the four games studied. The performance of these countries is stable over time as indicated by the fact that their total medal count proportion per year ranges between 34.76% and 43.05% (for the US it is 10.45%, 10.92%, 11.48% and 11.45% for 2000, 2004, 2008 and 2012 respectively). It is known from previous research that Olympic success at the country level is linked to economic performance (Bernard and Busse, 2004). So, it comes as no surprise that the countries in my sample are significant economic powers with stock markets that have an important role in the global environment. All countries, except for South Korea, can be clearly classified as developed (e.g., see 2014 MSCI market classification). South Korea is usually classified as an emerging market (e.g., in MSCI and Dow Jones Global Index), but sometimes appears as a developed market (e.g., in the Dow Jones Global Total Stock Market and S&P Global BMI indices). My sample also includes five firms which have been major (also known as worldwide) sponsors for the Summer Olympic Games throughout the period of study: Coca Cola, Visa, McDonald's, Panasonic and Samsung. The three first are listed on the New York Stock Exchange (NYSE) while Panasonic and Samsung are listed on the Tokyo Stock

Exchange and Korea Exchange, respectively. All firms are multinational corporations with a global consumer and investment base and a combined capitalisation of over half a trillion dollars on 1 August, 2012.

Table 2.1 Variable abbreviations and descriptions

Abbreviation	Description
US, UK, FRA, AUS, NLD, GER, KOR, JPN	Country label for United States of America, United Kingdom, France, Australia, Netherlands, Germany, South Korea, Japan
R	Stock market index logarithmic return (S&P 500:US, FTSE:UK,CAC:FRA, ASX:AUS, AEX:NLD, DAX:GER, KOSPI:KOR, NIKKEI:JPN)
Games	Dummy variable denoting the Olympic market period for each country
MSCI	Morgan Stanley stock market index for global stock funds in local currency
RV	Realised volatility estimate for each country
IV	Implied Volatility Index (VIX: US, VFTSE:UK, VCAC:FRA, SPAVIX: AUS, VAEX: NLD, VDAX: GER, VKOSPI: KOR, VXJ: JPN)
Med	Total Number of Medals
TMed	Total Number of medals from eight Countries
Gold	Number of Gold Medals
TGold	Total Number of Gold medals from eight Countries
Silver	Number of Silver Medals
TSilver	Total Number of Silver medals from eight Countries
Bronze	Number of Bronze Medals
TBronze	Total Number of Bronze medals from Eight Countries
Popular	Total Number of Medals from Popular Sports
TPopular	Total Number of Medals from Popular sports from eight Countries
KO, MCD, PC, VIS, SAM	Coca Cola, McDonald's, Panasonic, Visa, Samsung
VLM	Trading volume for each country in USD
SVI	Search Volume Index

For each country in my sample, I hand collect from a variety of online sources data on gold, silver and bronze medals won over the sample period.[3] My sample includes all of the 3,729 medals across 35 different sports won by the eight countries studied between 2000 and 2012. In addition to the overall results, I also study a subsample of medals from the five most popular sports according to the definition given by the International Olympic Committee (IOC). This definition is based on the number of visits to the pages of the IOC website for

[3]Crosschecks where performed across several websites in order to ensure the validity of the results for the Games of: 2000 (Pandora, Medaltally, CNN sports), 2004 (Yahoo sports, Telegraph), 2008 (Telegraph, BBC) and 2012 (London 2012 official website).

different sports from January 2004 to 11 February 2005 (see IOC Report to the 117th IOC Session from 24 May 2005).

Datastream is used to draw financial data. For each country I collect stock market variables, daily stock prices and trading volumes, related to a major basket index: S&P500 (US), FTSE (UK), CAC (FRA), ASX (AUS), AEX (NLD), DAX (GER), KOSPI (KOR) and NIKKEI (JPN). As in Edmans et al. (2007), I use total returns (assuming that dividends are reinvested) in local currency since I am primarily interested in the impact for domestic investors. The MSCI World Total Return (Net) Index is used to approximate the stock market return at a global level. I also gather daily observations on the following implied volatility indices: VIX (US), VFTSE (UK), VCAC (FRA), SPAVIX(AUS), VAEX(NLD), VDAX(GER), VKOSPI (KOR), VXJ (JPN). Daily measures of realised volatility on a simple 5-minute estimator are drawn from the Oxford-Man Institute website. Stock price and volume data for sponsor firms are collected for the five stocks under study.

Descriptive statistics of the logarithmic returns for the stock indices and firms under study are presented in Table 2.2. A first observation is that the average return over the whole sample (Mean) is lower than that over the period of the Olympic Games (Mean′) for all countries and firms, except one (SAM). However, none of these differences are statistically significant on the basis of a two-tailed t-test. This is a first indication that Olympic euphoria is not transmitted to the stock market.

The most (least) volatile market in the sample is South Korea (Australia) with an annualised daily standard deviation of 26.7% (16.9%). The descriptive statistics indicate clearly that unconditional standard deviation is much lower over the Olympic period for all but one country (South Korea) and three of the firms (KO, MCD and SAM). For example, the standard deviation of S&P 500 daily returns is 18.3% lower during the Olympic Games. A two-sided chi-squared test confirms that these differences are highly significant and not due to sample error. A further investigation of the effect on stock market activity indicates that

Table 2.2 Descriptive statistics of stock index and sponsor firm returns

Variable	Mean	Mean′	St.Dev	St.Dev′	Min	Max
MSCI	-1.09E-05	9.13E-04	0.0115	0.0094	-0.0733	0.0910
US	-1.56E-05	1.46E-03	0.0136	0.0094	-0.0947	0.1096
UK	-3.74E-05	1.12E-03	0.0131	0.0102	-0.0926	0.0938
FRA	-2.08E-04	9.50E-04	0.0159	0.0136	-0.0947	0.1059
AUS	8.92E-05	6.06E-04	0.0107	0.0091	-0.0870	0.0563
NLD	-2.30E-04	1.56E-03	0.0160	0.0100	-0.0959	0.1003
GER	1.84E-06	8.49E-04	0.0165	0.0119	-0.0743	0.1080
KOR	3.71E-04	9.53E-04	0.0168	0.0246	-0.1280	0.1128
JPN	-1.94E-04	7.69E-05	0.0159	0.0121	-0.1211	0.1323
KO	2.42E-04	2.83E-03	0.0135	0.0174	-0.1060	0.1303
MCD	4.83E-04	3.82E-03	0.0156	0.0178	-0.1371	0.0898
PC	-3.88E-04	4.38E-03	0.0211	0.0189	-0.2045	0.1739
VIS	9.80E-04	3.80E-03	0.0260	0.0174	-0.1467	0.2501
SAM	5.47E-04	2.57E-04	0.0246	0.0401	-0.1480	0.1398

Mean′ (St.Dev′) gives the average (standard deviation) of index returns during Olympic Games. The other summary statistics are estimated over the complete sample.

unconditional measures of implied volatility, realised volatility and trading volume tend to be significantly lower than average during the Olympic Games compared to the complete sample (see Table A.2 in the Appendix). For instance, the average implied and historical volatility is more than 30% lower for the countries studied. Average trading volume is over 20% (16%) less for countries (firms). These results suggest that whilst returns seem to be unaffected during Olympics, market activity is significantly less for all markets and all but one of the sponsor firms (SAM). However, since market activity may be significantly influenced by market conditions and calendar effects, a further investigation in a regression framework is undertaken in the following section.

2.3.2 Hypothesis I - The impact of Olympic medals on volatility and trading volumes

I follow the two-stage event study approach of Edmans et al. (2007) in investigating the effect of Olympic medals on returns, volatility and trading volume. In the first stage, I treat the series under investigation ($x_{i,t}$) in order to remove the effect of the market and calendar regularities:

$$x_{i,t} = \alpha_i + \beta_{i1}M_t + \beta_{i2}M_{t-1} + \beta_{i3}M_{t+1} + \beta_{i4}x_{i,t-1} + \beta_{i5}January_t + \beta_{i6}Monday_t + \varepsilon_{i,t} \quad (2.1)$$

Where $x_{i,t}$ is the series under investigation for country or firm i; $January_t$ and $Monday_t$ are calendar dummy variables. When analysing country (firm) returns as the dependent variable in regression (2.1), I include returns from the market portfolio proxy M_t (corresponding MSCI national index) as an additional control variable. In the case of volume and volatility, I only control for calendar effects using dummies for each month of the year. In the second stage I regress the estimated residuals from (2.1) against gold medals won by each country over the previous day:

$$\hat{\varepsilon}_{i,t} = b_{i1}Gold_{i,t-1} + b_{i2}Games + u_{i,t} \quad (2.2)$$

Where $Gold_{i,t-1}$ is the number of gold medals won by country i over the previous trading day. If gold medals are won when the market is closed, these medals are aggregated in order to capture a compound effect on attention. I also include a dummy ($Games_t$) in order to capture any systematic effects that may occur over the whole Olympic period. When analysing sponsor firm returns, I use the number of medals at a national level (in the country where the firm is listed) and the total number for the eight countries analysed. This allows us to investigate effects at a local and global level. In addition to gold medals, I estimate the regressions using silver, bronze and total medals (sum of gold, silver and bronze) along with medals won in the five most popular sports (including gold, silver, bronze and total medals). Following Kaplanski and Levy (2010a), in addition to looking at the effect of medals for each one of the eight countries and five firms, I also look at the collective effect that the total number of medals for all countries has on the US stock market. These different ways of measuring sports success and impact add robustness to my analysis and shed more light on my hypotheses.

In line with the previous literature, I find that success in terms of Olympic medals is not significantly related to stock returns at the market and sponsor firm level (results show in Table A.3, Appendix). The nature of the sports I am studying and my dataset means that only success can be directly measured for most sports. For example, for soccer, which involves two teams it may be possible to identify a winner and loser during the final but for the marathon the silver medal may not be considered a failure. Since betting odds data are not readily available for Olympic Games, I attempt an analysis of the unexpected element in the medals using the average number of medals per country for each sport over the sample period as an estimate of the expected result. Specifically, I first calculate for each sport the likelihood (p_1) for each country of winning a medal as the percentage of medals the country won divided by the total number of medals awarded. Then for each Olympic event, I calculate for each sport the actual number of medals won by each country (p_2). The difference between p_1 and p_2 gives a proxy for the surprise element. This will be positive (negative) if the country wins a larger proportion of total medals than expected for each sport compared to what it won overall over the complete sample of four Games. Rather than using the total number of medals, this calculation can be done also on the basis of gold medals only. For example, in Archery the US won in 2000 (over the four games) a total of two medals (three medals over four games), none of which was gold. Therefore, the surprise is zero for gold medals. The total number of medals in Archery is twelve for each Olympic game so the overall proportion of medals won by the US over the sample of four Olympics is 6.25% ($3 \div (4 \times 12)$). The actual proportion of medals won in 2000 is 16.67% ($2 \div 12$) so there is a positive surprise for that event which is 10.42% (16.67%-6.25%) for total medals. This allows us to measure positive and negative surprises and assess any asymmetry in the impact of sports performance. I repeat the regression analysis using surprise-weighted medal results. The results once again suggest that Olympic performance is not linked to stock returns (results shown in Table A.4, Appendix). Conclusions are comparable even if I allow for an asymmetric effect of positive and negative surprises in the test regression (2.2).

I turn next to the analysis of market activity for the countries and firms studied. The results in Table 2.3 confirm my descriptive analysis and indicate an inverse relationship between the number of gold medals and trading volume over the next day for all countries and firms, except for Japan. In other words, the results confirm the effect of attention on trading volume. In all cases, except UK, Australia, Japan, Coca Cola and Panasonic, the relationship is statistically significant at the 10% level. Comparable results are obtained for the alternative measures of success. As expected, gold medals appear to have a more significant impact on volume compared to silver medals with the average coefficient b_1 in regression (2.2) being on average higher in magnitude for the countries studied (-0.0507 for gold compared to -0.0454 and -0.0345 for silver and bronze, respectively).

Similar conclusions are reached from the analysis of realised and implied volatility indices shown in Table 2.4. The relationship is correctly signed in all regressions but one (Australia) and is statistically significant at the 10% level in most cases. Results are highly significant for the US, Germany and Netherlands. The magnitude of the coefficient for each individual country is small, implying a marginal effect. However, the collective impact of all countries on the US stock market is significant and substantial in magnitude, with each additional gold medal decreasing realised volatility by almost 20%. Comparable results

Table 2.3 The impact of Olympic medals on trading volumes

Market	Gold	Med	Silver	Bronze	Popular
US	-0.0295***	-0.0107**	-0.0261**	-0.0195	-0.0163**
	(-3.2868)	(-2.3947)	(-2.0221)	(-1.5511)	(-2.0899)
UK	-0.0213	-0.0125	-0.0399	-0.0392	-0.0206
	(-1.2370)	(-1.3052)	(-1.1575)	(-1.3203)	(-0.8659)
FRA	-0.0925**	-0.0260**	-0.0385	-0.0377	0.0248
	(-2.3349)	(-2.2352)	(-1.2257)	(-1.2743)	(0.8487)
AUS	-0.0116	-0.0145	-0.0552**	-0.0098	0.0127
	(-0.2269)	(-0.8224)	(-2.0808)	(-0.2357)	(0.7230)
NLD	-0.1109***	-0.0445**	-0.1081**	0.0283	0.0034
	(-3.2309)	(-2.2635)	(-2.7234)	(0.8392)	(0.0569)
GER	-0.0668**	-0.0282***	-0.0506**	-0.0792***	-0.0803**
	(-2.4668)	(-3.0729)	(-1.9726)	(-4.1994)	(-2.1302)
KOR	-0.0732**	-0.0279**	-0.0205	-0.0832**	0.0792**
	(-2.2068)	(-2.0196)	(-0.7913)	(-2.1555)	(2.1852)
JPN	0.0006	-0.0133	-0.0241	-0.0353	-0.0279
	(0.0187)	(-0.8373)	(-1.4652)	(-1.1187)	(-1.4280)
TUS	-0.0088***	-0.0029***	-0.0083***	-0.0078**	-0.0066**
	(-2.9044)	(-2.7868)	(-2.7695)	(-2.4863)	(-2.3002)
KO	-0.0263	-0.0059	-0.0072	-0.0062	-0.0103
	(-1.6396)	(-0.7676)	(-0.3652)	(-0.2664)	(-0.8877)
MCD	-0.0685***	-0.0243**	-0.0522*	-0.0543*	-0.0296*
	(-2.9348)	(-2.2204)	(-1.7193)	(-1.7522)	(-1.9214)
PC	-0.0175	-0.0037	0.0084	-0.0233	-0.0090
	(-0.4280)	(-0.1919)	(0.1850)	(-0.3841)	(-0.3112)
VIS	-0.0321**	-0.0137**	-0.0398*	-0.0245	-0.0228***
	(-1.9561)	(-2.0623)	(-1.7351)	(-1.1889)	(-2.6573)
SAM	-0.0940**	-0.0177	0.0160	-0.0310	-0.0302
	(-2.1648)	(-1.3993)	(0.4523)	(-0.5591)	(-0.3126)
Firm	**TGold**	**TMed**	**TSilver**	**TBronze**	**TPopular**
KO	-0.0059	-0.0018	-0.0052	-0.0043	-0.0047
	(-1.0296)	(-0.8668)	(-0.8610)	(-0.6930)	(-0.8321)
MCD	-0.0182**	-0.0067***	-0.0198***	-0.0200**	-0.0147**
	(-2.3855)	(-2.6167)	(-2.8151)	(-2.5096)	(-2.1734)
PC	-0.0057	-0.0021	-0.0073	-0.0055	-0.0024
	(-0.4012)	(-0.4795)	(-0.6207)	(-0.4190)	(-0.1955)
VIS	-0.0115**	-0.0040**	-0.0113*	-0.0112**	-0.0117**
	(-2.1506)	(-2.1526)	(-1.9923)	(-2.1589)	(-2.1477)
SAM	-0.0079***	-0.0025**	-0.0060*	-0.0078**	-0.0086***
	(-2.7386)	(-2.4729)	(-1.8609)	(-2.3051)	(-3.2735)

This table gives the value of the coefficients b_{i1} in regression (2.2) *with trading volume as the dependent variable in* (2.1)*, 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. When TUS is used, it is the total number of medals for all eight countries, the trading volume corresponds to the US. When analysing firms, the number of medals and volume correspond to the market where the firm is listed. I also use the total number of medals for the eight countries analysed in order to capture a more global effect of medals on firms which may result from international exposure.*

(shown in Table 2.5) are obtained if historical volatility is analysed using a GJR GARCH(1,1) model (Glosten et al., 1993):

$$\sigma_{i,t}^2 = \omega_i + \varphi_{i1}\mu_{i,t-1}^2 + \varphi_{i2}\sigma_{i,t-1}^2 + \varphi_{i3}\mu_{i,t-1}^2 I_{i,t-1} + \delta_i MED_{i,t} \tag{2.3}$$

$$\textit{where } I_{i,t-1} = 0 \textit{ if } \mu_{i,t-1} \geq 0 \textit{ and } I_{i,t-1} = 1 \textit{ if } \mu_{i,t-1} < 0$$

For all firms and countries studied, a negative relationship is found between gold medals and historical volatility over the next day and it is statistically significant in most cases (including US, UK, FRA, JPN, TUS and four of the companies studied).

The final step in the analysis is to examine if the statistical regularities uncovered are economically significant. In line with the literature (Kaplanski and Levy, 2010a), I investigate the US since this is by far the largest market in my sample. Although results for returns are statistically insignificant they are correctly signed (see Table A.3 in Appendix), which motivates us to examine economic significance. VIX futures and S&P 500 futures contracts are used as underlying assets for trading volatility and returns, respectively.[4] For VIX futures a cost of $1.2 is assumed per contract side (estimate from CBOE for April 2013). For the S&P 500 futures the cost was assumed at $3.80 per round-trip transaction (estimate from CME, effective February 26, 2014). Trading signals are constructed on the basis of medals awarded since the previous working day. Four different medal results are considered: total number of US gold medals, total number of US gold medals in popular sports, total number of gold medals across all countries and total number of gold medals across all countries in popular sports. The results of various active trading strategies against passive strategies for the VIX and S&P500 are presented in Table 2.6. The number of contracts per trade was determined on the basis of gold medals won over the previous day. So, if US won four gold medals over one day, then according to the first strategy four VIX contracts are shorted. In

[4]VIX futures started to trade on 26 March 2004. In order to extend this series so that it covers complete sample of four Olympic games, I used VIX spot data for the period between 15 September 2000 and 2 October 2000 as a proxy of the futures series.

Table 2.4 The impact of Olympic medals on realised (RV) and implied (IV) volatility

	Market	Gold	Med	Silver	Bronze	Popular
RV	US	-6.47E-06**	-2.53E-06**	-5.99E-06*	-5.91E-06	-2.45E-06
		(-2.1323)	(-2.0395)	(-1.7369)	(-1.3332)	(-1.2905)
	UK	-2.36E-06	-1.39E-06	-2.90E-06	-5.58E-06*	-2.87E-06
		(-0.7723)	(-1.0375)	(-0.7094)	(-1.7421)	(-0.4832)
	FRA	-6.25E-06	-2.40E-06	-8.91E-06	1.17E-06	-2.95E-06
		(-1.4008)	(-1.1503)	(-1.6189)	(0.1994)	(-0.5169)
	AUS	2.63E-05***	6.79E-06***	7.96E-06**	1.90E-05***	-2.00E-07
		(9.6316)	(4.9323)	(2.3015)	(4.2385)	(-0.0471)
	NLD	-2.28E-05***	-1.28E-05**	-2.49E-05**	-5.21E-06	1.36E-05
		(-2.5821)	(-2.4951)	(-2.4186)	(-0.6886)	(0.9854)
	GER	-2.81E-05***	-5.78E-06*	-6.80E-06	-8.90E-06	-2.29E-05*
		(-3.0275)	(-1.8760)	(-0.5948)	(-0.8131)	(-1.8108)
	KOR	-9.58E-06	-3.14E-06	3.85E-07	-1.09E-05**	-1.13E-05
		(-1.5441)	(-1.1492)	(0.0889)	(-2.1591)	(-0.9621)
	JPN	-5.54E-06	-1.75E-06	-4.84E-06*	1.70E-07	-6.68E-06*
		(-1.6395)	(-0.8195)	(-1.9455)	(0.0281)	(-1.8929)
	TUS	-1.98E-06**	-6.51E-07**	-1.95E-06**	-1.70E-06*	-1.27E-06*
		(-2.0685)	(-2.1270)	(-2.2833)	(-1.8213)	(-1.9168)
IV	US	-8.91E-06***	-3.38E-06**	-7.03E-06*	-9.13E-06**	-4.40E-06**
		(-3.0842)	(-2.4034)	(-1.8103)	(-2.1787)	(-2.2181)
	UK	-8.36E-06*	-4.61E-06**	-1.36E-05**	-1.42E-05**	-3.82E-06
		(-1.8607)	(-2.0813)	(-2.1143)	(-2.1526)	(-0.3880)
	FRA	-2.16E-05***	-7.69E-06***	-1.24E-05***	-1.41E-05*	2.23E-06
		(-3.9424)	(-3.3655)	(-2.6772)	(-1.6977)	(0.3070)
	AUS	1.51E-06	-3.39E-06	-9.14E-06	-8.92E-06	2.07E-05**
		(0.1003)	(-0.7430)	(-1.1965)	(-0.8987)	(2.2783)
	NLD	-5.10E-05***	-2.74E-05***	-3.39E-05**	-2.42E-05	-6.54E-06
		(-2.8760)	(-2.6227)	(-2.1781)	(-1.4977)	(-0.5624)
	GER	-2.14E-05**	-9.56E-06***	-1.96E-05**	-2.52E-05***	-2.26E-05**
		(-2.4126)	(-3.0823)	(-2.3725)	(-3.9920)	(-2.3239)
	KOR	-9.76E-06*	-4.05E-06**	-5.19E-06	-1.01E-05**	-1.03E-05
		(-1.8971)	(-2.1672)	(-1.0934)	(-2.2775)	(-0.8131)
	JPN	-7.46E-06	-8.24E-06***	-1.65E-05**	-1.54E-05***	-1.41E-05***
		(-1.1308)	(-3.1641)	(-2.4126)	(-2.8441)	(-3.5145)
	TUS	-2.79E-06***	-9.30E-07***	-2.53E-06**	-2.74E-06***	-1.63E-06**
		(-2.7072)	(-2.6617)	(-2.5109)	(-2.6383)	(-2.0250)

*This table gives the value of the coefficients b_{i1} in regression (2.2) with realised and implied volatility as the dependent variable in regression (2.1), 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. When TUS is used, which is the total number of medals for all eight countries, the realised and implied volatility correspond to the US.*

Table 2.5 The impact of Olympic medals on historical volatility

Market	Gold	Total	Silver	Bronze	Popular
US	-1.70E-05***	-4.48E-07**	-1.25E-06***	-1.58E-06***	-6.35E-07***
	(-269.6852)	(-2.3188)	(-10.4413)	(-9.1287)	(-4.8870)
UK	-2.30E-06***	-1.06E-05***	-3.69E-06***	-3.09E-06***	-4.91E-06***
	(-26.3963)	(-13.8386)	(-10.8105)	(-9.7972)	(-13.1744)
FRA	-7.47E-05***	-1.33E-06*	-4.30E-05	-5.07E-05**	-5.07E-06
	(-13.9220)	(-1.7493)	(-1.0983)	(-2.3294)	(-1.5266)
AUS	-2.40E-05	-3.90E-07	-1.30E-06***	-1.01E-06**	-1.73E-06***
	(-0.5358)	(-1.5621)	(-7.7394)	(-2.2150)	(-3.0274)
NLD	-1.34E-06	-1.33E-06	-3.60E-06	-7.50E-06***	-2.91E-06
	(-0.4772)	(-1.486)	(-1.4505)	(-4.3284)	(-0.9002)
GER	-2.58E-06	-9.73E-07**	-3.40E-06	-2.44E-06	-5.83E-06***
	(-1.0510)	(-2.0099)	(-1.9150)	(-1.5405)	(-2.7802)
KOR	-1.37E-06	-3.50E-05***	-2.57E-05	-5.90E-07	-1.48E-05
	(-0.2689)	(-3.1789)	(-0.6330)	(-0.0889)	(-0.9604)
JPN	-4.96E-06*	-1.53E-06	-2.65E-06	-4.09E-06	-3.27E-06
	(-1.7052)	(-1.3138)	(-0.6314)	(-1.3425)	(-1.2054)
TUS	-5.90E-06***	-1.30E-07	-4.15E-06***	-3.98E-07*	-3.30E-07
	(-3.5149)	(-1.5684)	(-3.2830)	(-1.7927)	(-1.2111)
KO	-2.12E-06***	-8.30E-07	-1.44E-06	-2.45E-06***	-1.29E-06***
	(-7.4879)	(-1.2252)	(-0.8865)	(-5.3442)	(-3.7863)
MCD	-2.23E-06***	-3.28E-06***	-2.00E-06**	-2.60E-06**	-5.46E-06***
	(-7.0519)	(-6.9751)	(-1.9558)	(-2.3589)	(-2.9376)
PC	-9.93E-05**	-4.30E-05***	-3.70E-06	-5.97E-05***	-8.46E-05
	(-2.5060)	(-10.1986)	(-0.3402)	(-2.6036)	(-1.3147)
VIS	-6.51E-05***	-2.69E-06**	-9.51E-06*	-8.76E-06	-4.28E-06***
	(-7.0712)	(-2.0945)	(-1.6587)	(-1.4022)	(-7.8150)
SAM	3.50E-06	-1.22E-08	-4.34E-06	3.14E-07	-7.52E-06
	(0.2543)	(-0.0023)	(-0.3206)	(0.0160)	(-0.1626)
Firm	**TGold**	**TMed**	**TSilver**	**TBronze**	**TPopular**
KO	-7.40E-07	-2.43E-07	-7.22E-07	-6.40E-07	-5.52E-07
	(-1.2302)	(-1.4399)	(-1.0816)	(-0.9330)	(-0.9381)
MCD	-3.83E-06	-1.06E-06***	-3.56E-06***	-6.66E-07***	-7.00E-06***
	(-1.5002)	(-2.7367)	(-9.4940)	(-2.7669)	(-5.6443)
PC	3.15E-08	1.32E-08	4.35E-08	4.20E-08	-6.47E-06***
	(0.0381)	(0.0552)	(0.0526)	(0.0508)	(-17.9240)
VIS	-2.37E-05***	-5.25E-06***	-2.30E-06**	-2.46E-06***	-7.19E-06***
	(-12.19923)	(-36.06726)	(-2.2985)	(-2.9433)	(-8.0901)
SAM	7.72E-09	-5.10E-09	-6.42E-08	1.18E-08	-9.12E-08
	(0.0061)	(-0.0133)	(-0.0496)	(0.0089)	(-0.0880)

*This table gives the value of the GJR GARCH (1,1) coefficients δ_i in model (2.3). Numbers in brackets correspond to z-statistic values. 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. When TUS is used, it is the total number of medals for all eight countries, the historical volatility corresponds to the US. When analysing firms, the number of medals and historical volatility correspond to the market where the firm is listed. I also use the total number of medals for the eight countries analysed in order to capture a more global effect of medals on firms which may result from international exposure.*

the case of the S&P 500 strategies, a long position in futures contracts is taken for each gold medal won. All trading positions last only for one day. The results suggest that all volatility trading strategies are highly profitable and superior to a passive approach. For example, taking a short VIX contract for each US Gold medal won, leads to an average daily return of 1.79% with a total of 156 contracts, 60.98% of which are profitable. Overall, the trading strategies allow similar conclusions to those drawn on the basis of the statistical analysis. So, the impact of medals on volatility is significant from both a statistical and economic perspective. The same does not hold for the impact of medals on returns since they do not lead to any significant profits.

Table 2.6 Economic significance of results: VIX and S&P 500 futures trading strategies

	Strategy	**Daily Return**	**Contracts**	**Profitable Trades**
VIX	US Gold Medals	1.79%	156	60.98%
	US Popular Gold Medals	1.48%	106	60.98%
	Total Gold Medals	4.28%	483	62.79%
	Total Popular Gold Medals	1.96%	179	61.90%
	Buy & Hold	-0.09%	4	50.00%
	Sell & Hold	0.09%	4	50.00%
S&P 500	US Gold Medals	-0.36%	156	56.10%
	US Popular Gold Medals	-0.28%	106	56.10%
	Total Gold Medals	-1.56%	483	55.81%
	Total Popular Gold Medals	-0.46%	179	57.14%
	Buy & Hold	-0.01%	4	50.00%
	Sell & Hold	0.01%	4	50.00%

2.3.3 Hypothesis II and III - The impact of Olympic medals on investor sentiment and attention

In this section I examine the association between the Olympic Games and alternative measures of sentiment and attention. For sentiment I am limited by the availability of data and analyse only the US using five different measures: the Michigan Consumer Sentiment Index, the Wurgler sentiment index, the Dow Jones Economic Sentiment Indicator (ESI), the IPSOS Global Primary Consumer Sentiment Index (PCSI) and the American Association of Individual Investors Investor Sentiment Survey (AAII).[5] The first four are recorded at a monthly interval while the last is in weekly frequency. I perform my analysis over the complete sample available and over subsamples in order to examine the stability of the results.

I deseasonalise all indices using a regression against a monthly dummy in order to remove any calendar regularities. I then create dummies for the Olympic periods which I regress against the deseasonalised indices. The correspondence is not always perfect since Olympic Games do not cover only one or a whole calendar month. I include a dummy for each month if the Olympics cover at least two weeks over that month. In the case of the AAII sentiment index, I regress it against the number of medals won, by the US and all countries, over the same and the previous week. Results for the monthly indices and the weekly index are given

[5]The Michigan Consumer Sentiment Index is based on a monthly telephone survey of a minimum of 500 interviewees. It is based on the balance between favourable vs unfavourable responses on 50 core questions concerning views on the financial situation of the interviewees and the economy in general (for a detailed description see Lemmon and Portniaguina, 2006; Schmeling, 2009). The Wurgler sentiment index is based on six sentiment proxies which involve information with respect to closed-end fund discounts, equity share turnover, first day returns on IPOs, IPO volumes, equity share in new issues and the dividend premium (see Baker and Wurgler, 2007). The Dow Jones ESI indicator is based on the relative sentiment of text references to the US economy on the basis of 15 major daily newspapers (see Vázsonyi, 2010). The IPSOS index measures consumer sentiment is based on the composite response of consumers to 11 questions across 24 countries. The questions are about current and future economic conditions, intentions and expectations, consumer confidence, job security and investments in the future (see http://im.thomsonreuters.com/solutions/content/ipsos-primary-consumer-sentiment-index/). Finally, the AAII indicator measures sentiment though a weekly survey of individual investors with respect to their bullish, bearish, or neutral on the stock market over the next six months (see Brown and Cliff, 2004).

in Table 2.7 and Table 2.8, respectively. In all cases, the Olympics appear to have a positive impact on monthly sentiment but this link is statistically insignificant. For the weekly index, the effect of medals on sentiment tends to be negative over the same week and positive in the week after the medals won but again no relationship is significant. In line with the literature, these results suggest that the Olympic Games and successes do not lead to stronger bullish sentiment amongst consumers and investors.

Table 2.7 Impact of Olympic Games on monthly sentiment indicators for US

Index	**Sample**	**Coefficient**
Michigan	1952-2012	1.6042
		(0.4009)
	1984-2012	-1.3057
		(-0.2764)
	2000-2012	1.7240
		(0.2082)
Wurgler	1965-2010	0.1474
		(0.5539)
	1984-2010	0.2713
		(1.1774)
	2000-2010	0.3980
		(1.4766)
ESI	1990-2012	0.3419
		(0.0730)
PCSI	2002-2012	1.6052
		(0.4299)

*This table gives the value of the regression coefficients between various sentiment indicators and dummies denoting months during which Olympics take place. 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.*

Finally, I investigate if the Olympic Games have an impact on investor attention for the countries in my sample. I use a direct measure of attention, the Search Volume Index (SVI) which is based on the intensity of queries on Google (see also Da et al., 2011; Vlastakis and Markellos, 2012). Specifically, I investigate market-wide attention on the basis of SVIs for queries related to different index names. For example, I use the SVI of “S&P 500" in

Table 2.8 Impact of Olympic Games and performance on the weekly AAII sentiment for US

US	Med_t	$Gold_t$	$Silver_t$	$Bronze_t$	$Popular_t$
	-0.0014 (-0.4860)	-0.0024 (-0.3236)	-0.0096 (-1.4471)	0.0078 (0.7201)	-0.0068 (-1.3156)
	Med_{t-1}	$Gold_{t-1}$	$Silver_{t-1}$	$Bronze_{t-1}$	$Popular_{t-1}$
	0.0011 (0.4763)	0.0031 (0.5023)	0.0055 (0.7311)	-0.0025 (-0.4756)	0.0035 (0.9552)
Aggregate	$TMed_t$	$TGold_t$	$TSilver_t$	$TBronze_t$	$TPopular_t$
	-0.0008 (-0.9053)	-0.0024 (-1.1321)	-0.0014 (-0.5541)	-0.0023 (-0.8110)	-0.0050 (-1.3483)
	$TMed_{t-1}$	$TGold_{t-1}$	$TSilver_{t-1}$	$TBronze_{t-1}$	$TPopular_{t-1}$
	0.0005 (0.7621)	0.0017 (0.9411)	0.0013 (0.5752)	0.0015 (0.6878)	0.0022 (1.0762)

*This table gives the value of the regression coefficients between sentiment and medals during the same week (t) and the previous week (t-1), 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.*

order to measure the market attention for US. Raw SVIs are logarithmically transformed and deseasonalised using dummies for each month of the year. I then examine the relationship between investor attention and Olympic performance by regressing my SVIs on medals. The results in Table 2.9 clearly suggest that the attention of investors inversely depends on the number of medals won over the previous day for the stock markets under study. The coefficients are correctly signed in all cases except for France, whereas the estimates are statistically insignificant for France and Japan. Moreover, I obtain similar results if I use number of medals from the same day rather than previous days (see Table A.5 in Appendix).

Overall, the results reject my second hypothesis and lend support to my third hypothesis. Combined with the results and discussion in the previous section, the analysis suggests that the significant impact of Olympic success on market activity is the result of investor inattention rather than a shift in mood.

Table 2.9 Impact of Olympic Medals over previous day on investor attention measured by Google SVI

Market	**Gold**	**Med**	**Silver**	**Bronze**	**Popular**	**Surprise**
US	-0.0652**	-0.0275**	-0.0585*	-0.0963***	-0.0377***	-0.9420
	(-2.4727)	(-2.3706)	(-1.8138)	(-2.8875)	(-2.7616)	(-1.2810)
UK	-0.1590***	-0.0788***	-0.1093**	-0.2067***	-0.1913**	-0.1847
	(-5.1366)	(-4.0962)	(-2.5352)	(-3.6956)	(-2.2801)	(-0.2157)
FRA	-0.0415	0.0086	0.0595	0.0053	0.0236	-0.1781
	(-0.1183)	(0.0709)	(0.3564)	(0.0239)	(0.1012)	(-0.0572)
AUS	-0.1122***	-0.0615***	-0.1190***	-0.1536***	-0.0708**	1.7402**
	(-3.4351)	(-3.3762)	(-2.7703)	(-3.4737)	(-2.5638)	(2.6691)
NLD	-0.1023***	-0.0597**	-0.0612	-0.1112**	-0.1326***	1.2210
	(-2.6119)	(-2.4549)	(-1.4822)	(-1.9838)	(-2.8939)	(0.7937)
GER	-0.0530	-0.0292**	-0.0531	-0.0782**	-0.0390	-0.8908**
	(-1.4282)	(-1.9954)	(-1.5174)	(-2.0302)	(-1.1295)	(-2.5325)
JPN	-0.0514	-0.0730	-0.2293*	-0.1333	-0.0936	0.7331
	(-0.4962)	(-1.0739)	(-1.8560)	(-1.1939)	(-0.8704)	(0.3351)

*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.*

2.4 Conclusions

This chapter analyses two potential drivers of investment behaviour, sentiment and attention, by investigating the Summer Olympic performance for eight participating countries and five sponsoring firms. The results show that medals have a negative impact on trading volumes and volatility which is statistically and economically significant. These findings are in line with theories of attention but cannot be explained easily on the basis of sports sentiment. Furthermore, I find a positive relationship between medals and a direct measure of investor inattention for all sample countries. However, no significant link was found between Olympics and investor sentiment on the basis of five different indicators. I conclude that Olympic Games and medals affect the attention of investors but not their mood.

The recommendation of this chapter is that researchers should focus more on “attention” when analysing “sentiment”. I study investor inattention and sentiment in the context of sports events and performance. However, another empirical setting which is widely used in the behavioural finance literature is related to the weather and environmental conditions. It could be that the positive impact of sunny weather on returns is related also to investor inattention rather than mood. This possibility is first discussed in Symeonidis et al. (2010) as an alternative rational explanation for the negative impact of poor weather on volatility. The literature suggests that the impact of weather on market activity is likely to be complex. Goetzmann and Zhu (2005) report that in order to beat the rush, market participants tend to leave early on rainy days which could have a negative effect on impact due to less time devoted to work. However, Connolly (2008) show that workers tend to work longer hours during rainy days (see also Hagn and Maennig, 2008). Loughran and Schultz (2004) show that trading volume is lower during blizzards in a city due to travel and weather disruptions. Zivin and Neidell (2014) show the effect of daily temperature shocks on the allocation of time to labor as well as leisure activities. Lee et al. (2014) use arguments from cognitive psychology along with field and lab data to show that bad weather increases productivity by eliminating potential cognitive distractions related to good weather. Hamermesh et al. (2008) argue that daylight and time zones can induce temporal coordination of economic activities and affect timing. More research is justified in order to better understand the interaction of investor attention and sentiment in financial market.

Chapter 3

Do investors save trading for a rainy day?[1]

3.1 Introduction

A voluminous literature has examined the effect of weather variables, such as sunshine, cloudiness, rain and snow on financial markets (for more details see Saunders Jr, 1993; Kamstra et al., 2009; Hirshleifer and Shumway, 2003; Saunders Jr, 1993; Goetzmann and Zhu, 2005; Loughran and Schultz, 2004)). Most of the empirical studies report a positive link between good weather and stock market returns. This is explained by using behavioural finance arguments which in essence suggest that good weather creates a general positive mood and optimism which in turn affects investment decisions. In the present study I seek an additional possibility about the effect of weather on stock markets. This is motivated by recent research in psychology by Lee et al. (2014) who show that precipitation has a positive relation to productivity of individuals in three separate working environments. The focus is on precipitation as this has been identified in the literature as the most important barrier to

[1] I thank Lazaros Symeonidis and Stephen Dorling for the comments on earlier version of the chapter. I also thank the participants in the conference on Recent Development in Financial Econometrics and Empirical Finance, and ICAEW Research Colloquium for their feedback.

outdoor physical activities. The proxy of productivity and unit of analysis is trading activity in major stock markets across 31 countries. In line with the previous literature on weather and finance, I control for the possible effect of sentiment by using cloudiness as a mood proxy. Motivated by Loughran and Schultz (2004), I 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.

3.2 Literature review

3.2.1 Weather, investor mood and stock return

One stream of behavioural finance literature investigates how the fluctuation of mood affects stock market performances. To be more specific, this group of studies focus on if asset prices are related to weather and environmental conditions, such as *seasonal affective disorder* (SAD) (Kamstra et al., 2003), lunar cycles (Yuan et al., 2006; Kuo et al., 2010) and sunshine (Saunders Jr, 1993; Hirshleifer and Shumway, 2003). This line of literature is based on empirical evidence in psychology which dictates that the weather affects mood (Keller et al., 2005), and mood, in turn, can affect the judgement and quality of decision-making (negative relation found by Au et al., 2003), and risk aversion (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 risk-tolerant behaviour with investors being more inclined to hold financial securities (Bassi et al., 2013).

The relationship between weather and stock market returns has been the subject of an increasing number of empirical studies but empirical evidence is somewhat inconclusive. An influential study by Saunders Jr (1993) finds that the returns on the NYSE are negatively related to sky cloud cover in New York City with sunny days associated with a higher return. The finding is further confirmed 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 market returns. Comparing with findings on the significant relationship between sunshine and stock returns, the evidence concerning the impact of other weather variables on market performance 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, Cao and Wei (2005) investigate whether stock market returns are related to temperature for nine international stock markets. They find that stock returns are negatively related to temperature as investors are more risk-taking resulting from low temperatures. Results are slightly weaker in summer than in the winter, and overall there is a statistically significant negative relationship between temperature and market returns. A more recent study by Chang et al. (2008) looks at the impact of weather on stock returns of NYSE and its trading activity and the findings suggest that more cloud is associated with not only lower returns but also higher volatility. On the other hand, they find temperature is irrelevant to intraday stock returns.

Along this line of literature, an interesting paper by Schmittmann et al. (2015) finds that good weather has a positive impact on investors mood, and subsequently investors are more active in buying over selling behaviour. This finding supports sentiment literature which suggests that good mood inversely affects investor risk aversion so that participants are inclined to buy more. The paper also finds that retail investors trade more during days with bad weather compared to days with good weather. The reason is that the opportunity cost for spending time on trading when weather is good is higher.

Even though a certain relationship between weather and stock returns is supported by large amount of empirical results, the way in which the market is affected by non-economic factors remains unclear, especially when 82% of the trades take place electronically indoors nowadays. The argument that mood is the carrier bringing the weather effect into market performance is questionable. If it is the mood mechanism that influences investment decisions, why do different markets exhibit different levels of response (e.g., see individual regression results from Hirshleifer and Shumway, 2003)? These mixed results and unanswered questions motivate my research to seek an alternative explanation of weather generated anomalies.

3.2.2 Weather, attention, trading Volume

Loughran and Schultz (2004) test the connection between the weather and investor behaviour by focusing on localised trading activities. They find little evidence that local cloud conditions affect trading volume or asset prices. However, they find that extremely bad weather and religious holidays do reduce trading volume significantly. Their findings do not corroborate earlier findings of a negative relationship between cloud cover and stock returns, but do shift the focus from prices and return to trading activity. As the stock returns may not be affected due to arbitrage, the variation of volume may give a more lucid picture of investment decisions. However, Goetzmann and Zhu (2005) argue that the volume is an inaccurate way of observing individual investor trading activities, because the volume at aggregate level may not fully capture both the buy & sell side of activities. They use local trading records for five major US cities to explore the relationship between liquidity and weather for individual investors and again they find there is no significant difference in buy or sell behaviour on cloudy days compared to the sunny days for individuals. As a result, they propose an alternative interpretation of weather effect on NYSE spread. According to this argument, the change of weather affects risk aversion of market-makers rather than individual investors and this leads to a pattern of liquidity change on NYSE.

As the volatility is a direct measure to capture the investors attitude towards risk, Symeonidis et al. (2010) investigate the relationship between weather and market volatility in order to further understand its implication for risk management. Considering a positive contemporaneous correlation between trading volume and volatility, the volatility should behave similarly as trading volume in response to weather shocks. Unexpectedly, their empirical results suggest that sky cloud cover is inversely related to various measures of stock market volatility, whereas the prevailing sentiment literature claims that the bullish shifts in sentiment are negatively correlated with market volatility Lee et al. (2002); Brown (1999); Gervais and Odean (2001). These inconsistent empirical studies further motivate me to investigate the trading activity in relation to weather by looking beyond the arguments involving investor mood.

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 influence 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, 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 (see Keller et al., 2004). In labour economics, it has been argued that labour productivity increases during raining days as workers substitute leisure time with more time at work. New psychological findings suggest that bad weather increases individual productivity by eliminating potential distractions from good weather (Lee et al., 2014). This finding is somewhat contrary to conventional wisdom that bad weather causes a negative mood and hence impairs executive functions. This finding also motivates my study to consider both attention and mood as potential drivers of investors trading behaviour.

In addition to the evidence of weather effect from the psychology literature, the roles of attention and mood in economics and financial markets have also been widely discussed. Both factors are considered as constraints to rational investment decision making. A comprehensive recent survey of the psychological basis for mood influencing the perception of risk is discussed by Loewenstein et al. (2001). In this paper, a "*risk-as-feeling*" model is developed to act as a descriptive model of decision making under conditions of risk and uncertainty. Specifically, they concentrate on how decision making under the influence of emotion deviates from rational or optimal decision making. Attention to the financial information and irrelevant news also affects the degree of risk aversion on current evaluation and future outlook of the investment portfolio. In this context, the attention is seen as a risk, namely "*attention-induced*" risk, with respect to deriving the utility of information during the investors decision making process (Karlsson et al., 2009; Andrei and Hasler, 2015). Therefore, both mood and attention play a role in affecting investors risk perceptions, and subsequently, market behaviour.

Furthermore, attention and mood not only affect investors attitude towards risk and asset assessment, they could also interchangeably dominate the decision-making conditions, which makes it even more difficult to identify the mechanism that ultimately determines investor trading activities. Emotion can be overridden by deliberate attention which will enhance the information process ability, at the same time, the irrelevant but salient stimuli which draw investors attention may also cause emotional bias (Simon, 1982; Kahneman, 2003). Yet, in the existing literature, they are often treated separately when it comes to study the their behavioural implication for the financial market. Consequently, it is simply biased to attribute weather-market anomaly to either attention or mood since these two conditions frequently interact with each other and it is hard to observe and determine at which point one is in dominance. Therefore, I jointly study both factors in order to disentangle the respective impact on the trading behaviour and market performances.

By studying the weather impact on trading volume, I am 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 et al., 1992). Furthermore, I 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 means that misleading conclusions could be drawn. There are two further advangtages of using trading volume to understand the psychological and cognitive trading behaviour. In one respect, motivated by sentiment literature, the process governing the rate of change in belief ensues the trading volume, while overconfidence serves to amplify the effects of representativeness in generating trading volume (Shefrin, 2008). This means that trading volume is able to capture the investors sentiment if investors perspectives are under influence of weather-induced mood. In a second respect, information processing capacity is conditional on investors attention allocation to market securities or distraction from weather related events., and 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 emphasizes that it stems from changes in investor beliefs associated with new information.

3.2.3 Weather, absenteeism, productivity

It is apparent that severe weather should hamper the productivity of work that occurs outdoors (for example, Burke et al., 2014; Deschênes and Greenstone, 2012, in agriculture). Rather, findings in office labour productivity and manufacturing suggest that heat has large negative effects for productivity (for example, Jones and Olken, 2010, industrial output of trades). In terms of productivity in stock market, a recent study by McTier et al. (2013) examines the US stock market effects of 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 information flows and the production of information which is consistent with greater absenteeism implying less information production.

The study by Cachon et al. (2012) is more interesting to me because they investigate the impact of weather on manufacturing which happens indoors and presumably occurs in the presence of air conditioning. They use weekly production data from 64 automobile plants in the US 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 distraction whilst bad weather is regarded as an encouragement to work more, it is concluded that "a blizzard can disrupt production" because of worker absenteeism while it is unclear the extent to which automobile companies are aware of the impact of weather on their productivity with regard to the cognitive functioning. In addition to the finding of the disruptive weather on manufacturing productivity, 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). Together with the findings in Lee et al. (2014), which treat good weather as a potential distraction for outdoor and leisure activities and result 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 productivity of investors measured by trading volume will be affected.

3.3 Hypothesis formulation

Taken together, the arguments from the previous section lead us to 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.

3.4 Empirical analysis

The next subsection will describe the weather and stock market datasets used, how these are pre-processed and what are their basic statistical properties. The following subsection presents and discusses the results of the empirical analysis.

3.4.1 Sample description

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

I use sky cloud cover as one of the weather variables, as recent empirical evidence suggests that it is strongly 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 variable of 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). I first eliminated errors and missing values. Then I computed for each day the daily cloud cover by taking the average of the data from 6.00 to 16.00 so that it roughly corresponds with the work and trading day. The purpose of using the pre-market hours is to investigate the potential weather effect on investor's mood before the trading activity and also effects related to commuting (Hirshleifer and Shumway, 2003; Loughran and Schultz, 2004).

In addition to sky cloud cover, precipitation is another weather variable proposed in the literature, yet with arguable results. Even though Hirshleifer and Shumway (2003) find that rain is unrelated to market returns after controlling for cloud cover, Dowling and Lucey (2005) use above average rainfall in the study and find a significant and negative impact on equity returns for the Irish market. Moreover, Lee et al. (2014) have argued that this variable has an effect on worker productivity. Motivated by these findings, I use daily total rainfall or melted snow in the study to investigate 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 I 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.

After the raw data collection, I deseaonalise the weather time series as frequently done in the weather literature in finance to capture the weather shocks. So, I first compute the historical mean of each weather variable for each calendar week in the sample and then I subtract this mean from the daily weather value to obtain the seasonally-adjusted weather values.

Table 3.1 summarizes the description of the weather variables used in the study.

Table 3.1 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 3.2 indicates considerable heterogeneity in the sample.

Table 3.2 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

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Table 3.2 – continued from previous page							
	Market	Mean	Obs.	S.D.	C.V.	Skew.	Kurt.
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
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						

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Table 3.2 – continued from previous page

	Market	Mean	Obs.	S.D.	C.V.	Skew.	Kurt.
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

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Table 3.2 – continued from previous page

	Market	Mean	Obs.	S.D.	C.V.	Skew.	Kurt.
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						
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

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Table 3.2 – continued from previous page

	Market	Mean	Obs.	S.D.	C.V.	Skew.	Kurt.
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

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Table 3.2 – continued from previous page							
	Market	**Mean**	**Obs.**	**S.D.**	**C.V.**	**Skew.**	**Kurt.**
	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
	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

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Table 3.2 – continued from previous page

	Market	Mean	Obs.	S.D.	C.V.	Skew.	Kurt.
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						

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Table 3.2 – continued from previous page

	Market	Mean	Obs.	S.D.	C.V.	Skew.	Kurt.
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

I now turn to trading volume which is my main dependent variable under study against which I 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 I use the value of shares traded as a measure of trading activity in each city and draw the relevant data from Bloomberg.

I investigate 33 markets corresponding to 31 cities weather where the stock exchanges are listed. For the US, I include the S&P 500, NASDAQ composite and Dow Jones Industrial

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

$$\hat{V}_{it} = logV_{it} - (\hat{a}_i + \hat{b}_{it}) \tag{3.1}$$

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

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 3.3 presents descriptive statistics of filtered trading volume under study. Again I 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 3.4, confirm that the stationary has been achieved.

Table 3.3 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

Table 3.4 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.*

3.4.2 Results

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

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

$$\upsilon_{it} = \alpha_i + \beta_{i1}TEMP_{it} + \beta_{i2}RAIN_{it} + \beta_{i3}SNOW_{it} + \beta_{i4}CLOUD_{it} + \varepsilon_{it} \tag{3.2}$$

Where υ_{it} are the transformed trading volume values for market i at time t. In line with the empirical literature in this area, I find some significant relationship with mixed coefficient signs. Specifically, the results show that temperature has significant impact on 10 out 33 markets whilst the positive or negative relationship is mixed. For eight countries I 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 3.5 reports full details of the results for the whole sample. The overall results suggest a weak indication that cloud and snow are inversely related to trading volume. In this regard, the results of sky cover are in line with the mood literature which postulates that more cloud is linked to a downward mood and, thereby, leads to a less active trading behaviour. The results for snow are consistent with the findings by Loughran and Schultz (2004) suggesting that it causes disruption for investors, while the impact is less clear for precipitation and temperature.

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 et al., 2013). Then, I use panel regression methodology to control for heterogeneity problem cross the countries and climate zones. This is also justified by the descriptive statistics which show a large variation between the markets under study.

Table 3.5 Regression analysis of the weather effect on trading volume for individual markets

	TEMP	**RAIN**	**SNOW**	**CLOUD**
AMS	0.0030	0.0434	0.0113***	-0.0047
	(1.3540)	(0.8934)	(5.9213)	(-1.0548)
ATH	0.0034	3.0744***		-0.0022
	(0.6553)	(6.0964)		(-0.2054)
BAI	-0.0028	-0.0301		-0.0006
	(-0.9205)	(-1.1249)		(-0.1298)
BKK	-0.0008	0.0141		-0.0455***
	(-0.1076)	(0.6383)		(-3.8945)
BRU	-0.0016	-0.0047	-0.0091**	-0.0047
	(-0.7158)	(-0.1230)	(-2.2479)	(-0.7229)
COP	0.0065**	0.0925	-0.0016	-0.0120**
	(2.3121)	(1.5250)	(-0.7754)	(-2.1585)
DUB	0.0129***	0.1606**	-0.0044	-0.0024
	(3.4128)	(2.1233)	(-1.3191)	(-0.2891)
FRK	0.0007	0.0313	-0.0471**	0.0067
	(0.3816)	(1.2800)	(-2.4228)	(1.2445)

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Table 3.5 – continued from previous page

	TEMP	RAIN	SNOW	CLOUD
HEL	0.0017	0.1076**	-0.0122***	-0.0049
	(0.8178)	(1.9649)	(-3.8893)	(-0.7704)
HKG	-0.0016	0.0005		0.0018
	(-0.4381)	(0.0320)		(0.1989)
IST	0.0008	0.0055	0.0087*	0.0013
	(0.3667)	(0.1069)	(1.9278)	(0.2768)
JOH	0.0002	0.0403		-0.0076
	(0.1026)	(1.0394)		(-1.1848)
KLU	-0.0308***	-0.0176		-0.0503
	(-4.1825)	(-1.2590)		(-1.3151)
LDN	0.0070***	0.0392	0.0267*	0.0488***
	(2.9051)	(1.1573)	(1.8255)	(7.0725)
MAD	-0.0026	0.1072		-0.0060
	(-0.9543)	(1.4454)		(-1.0107)
MIL	0.0017	0.0421***		-0.0052
	(0.6361)	(4.9976)		(-1.1356)
MNL	0.0108	-0.0301**		0.0119
	(1.2952)	(-2.2335)		(1.3412)
OSL	0.0059*	0.0600	-0.0104	0.0116
	(1.8868)	(0.9145)	(-1.5651)	(1.2734)
PAR	-0.0021	0.0626	-0.1024**	-0.0013
	(-1.1357)	(1.2478)	(-2.4468)	(-0.2813)
SEO	-0.0003	-0.0022	-0.0060	-0.0027

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Table 3.5 – continued from previous page

	TEMP	RAIN	SNOW	CLOUD
	(-0.1640)	(-0.1858)	(-0.2437)	(-0.8534)
SIN	0.0123**	0.0012		-0.0084
	(2.5322)	(0.0890)		(-0.5160)
SPL	-0.0067***	0.0542***		-0.0076
	(-2.8136)	(2.6155)		(-1.6217)
STG	-0.0110***	-0.0113		-0.0078**
	(-3.5955)	(-0.1477)		(-1.9724)
STK	0.0036**	-54.8943***		0.0035
	(2.1530)	(-4.9987)		(0.7716)
SYD	0.0006	-0.0160	-0.3257***	0.0031
	(0.3158)	(-0.6624)	(-5.3019)	(0.8159)
TKY	0.0004	-0.0100		0.0056
	(0.1243)	(-0.6961)		(1.1730)
TPI	-0.0035	0.0067		-0.0038
	(-1.5097)	(0.5424)		(-0.7027)
TRT	0.0002	0.0242	-0.0016	-0.0062**
	(0.1500)	(0.7170)	(-0.2321)	(-2.2803)
VIE	0.0003	0.0832	-0.0034	-0.0335***
	(0.0892)	(0.9310)	(-0.2376)	(-2.7620)
ZUR	0.0010	0.0679*	-0.0185	-0.0122
	(0.4383)	(1.6735)	(-0.9420)	(-1.6450)
NQ	0.0036***	0.0006	-0.0220***	-0.0058**
	(2.7872)	(0.0421)	(-3.8916)	(-2.4008)

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Table 3.5 – continued from previous page

	TEMP	RAIN	SNOW	CLOUD
DJ	0.0009	0.0192	-0.0127**	-0.0036*
	(0.8158)	(1.4460)	(-2.2441)	(-1.7140)
SP	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 in the next step of the analysis, I conduct a panel regression test with fixed-effects for 31 markets (S&P500 is used for the US market). Based on recent developments in the climate-economics literature, I investigate the weather shock on financial market using the panel regression method by relying on deviations from averages:

$$\upsilon_{it} = \gamma + \delta W_{it} + \mu_i + e_{it} \tag{3.3}$$

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 3.6 show that snow is inversely related to volume 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 as the outdoor distractions are less appealing while snow reduces trading volume by causing inconvenience to investors.

Table 3.6 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 (3.3) *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 better understand the disruptive effect of weather as a driver of trading activity I also investigate the effect on worker absences for the US. Specifically, I 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 the bad weather. The absence is recorded on a monthly interval dated back to 1990. I regress raw weather value and filtered weather variables on logarithmic values of absences and results are presented in Table 3.7. The results of the raw weather regression clearly suggest that rain, snow and low temperature increase absences. By using filtered weather as regressor, only rain and low temperature show a significant impact on the increase of absences. So the results show that bad weather has an adverse effect on productivity.

Table 3.7 Regression analysis of the effect of weather on absences for US

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 I 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.

3.4.2.2 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 especially 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 within stock market.

First, I conduct quantile estimation for individual countries. The results, given in Table B.1 and B.2 show mixed results of an asymmetric effect. For example, the top 10% of snow in Copenhagen 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, I control for unobserved individual heterogeneity by quantile analysis in panel data.

Following recent development on quantile regression for panel data, (Koenker, 2004), I 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).

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

$$Q_{yit}(\tau|x_{it}) = \alpha_i + x_{it}'\beta(\tau) \quad t = 1,\ldots,m_i, \;\; i = 1\ldots,n. \tag{3.4}$$

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. Thereby, the weather vector of fixed-effects coefficients are penalized by a penalty term, shrinking these coefficients towards zero.

The results from Table 3.8 suggest that intercepts of the model 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 decreases when it is sunny, and snowy (τ=0.1); while volume increases when there is more rain and a low temperature. 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,

Table 3.8 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 (3.4). *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. It provides panel fixed-effect regression for 31 markets, condition on five different quantiles.*

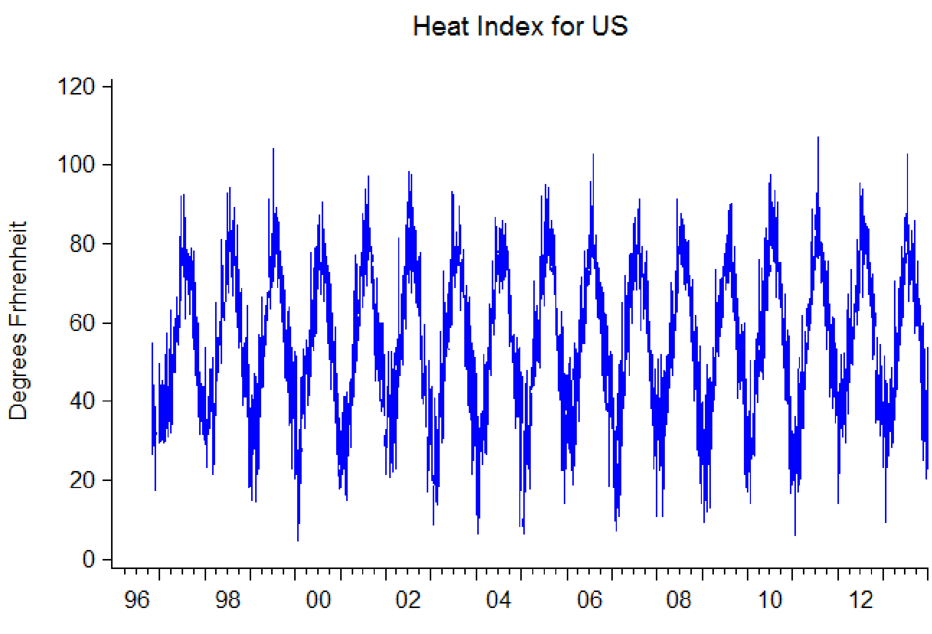
suggesting that considerable volume of rainfall increases productivity, that is, trading volume, by eliminating potential distraction from good weather (Lee et al., 2014; Connolly, 2008).

I 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 et al. (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, I use the heat index widely reported in the United States so as to see the impact of "real-feel" 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:

$$\begin{aligned} HI = & -42.379 + 2.04901523 * T + 10.14333127 * RH - .22475541 * T * RH \\ & - .00683783 * T * T - .05481717 * RH * RH + .00122874 * T * T * RH \\ & + .00085282 * T * RH * RH - .00000199 * T * T * RH * RH \end{aligned} \tag{3.5}$$

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 US is graphically depicted in Figure 3.1.

Fig. 3.1 Heat index for US



In order to further explore the asymmetric impact of heat on trading volume, I also include higher order terms of the Heat Index (HI) in the regression. The results are shown in Table 3.9. 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,

Table 3.9 Regression analysis of the effect of heat index on trading volume for US

	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.*

trading volume starts to increase at descending rate as the weather condition becomes a distraction for leisure and outdoor activities so that the productivity is weakened; whilst the heat reaches a caution level, the investors opt to focus more on trading and volume increases again.

Motivated by the asymmetric heat impact on trading volume for US, I also investigate whether temperature has an asymmetric impact on the panel data of 31 countries.[2] I follow the same fixed-effects method as in model (3.3) which can be written as:

$$\upsilon_{it} = \theta + \kappa_1 W_{it} + \kappa_2 TEMP^2_{it} + \xi_i + \psi_{it} \tag{3.6}$$

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 spatial characteristics, whether observed or unobserved, disentangling the shock from many possible sources of omitted variable bias.

[2]The relative humidity data is not available for the rest of countries in the sample other than US, so that the Heat Index can only be constructed for US. Therefore, I use a similar variable “temperature” to reflect HI in the panel regression.

The results from equation (3.6) are presented in Table 3.10. The impact from rain, snow and temperature are consistent with panel regression in Section 3.4.2.1, which suggests that rain and temperature increase productivity whereas snow has a significant and negative impact 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 I include $TEMP^3$ in the model, unlike the heat index results, it shows an insignificant impact on trading volume. For this result, I understand that the effect is so marginal that the sample heterogeneity may debilitate this marginal effect.

Table 3.10 Fixed-effects panel regression of asymmetric 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 (3.3) 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.*

3.4.2.3 Effect of weather on attention and sentiment

I now examine the link between weather and direct measures of sentiment and attention. For sentiment, I am limited by the availability of data for all 31 countries so that I use the American Association of Individual Investors Investor Sentiment Survey (AAII) for US [3] between 1996 to 2013.

In the analysis of the AAII sentiment index, I regress it on US weather using contemporaneous and lagged values. Results for the weekly AAII index are given in Table 3.11. In all cases, I find that there is no significant weather effect on investor sentiment for the US.

Table 3.11 Regression analysis of the effect of weekly weather on sentiment for US

	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

I 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 et al., 2011; Vlastakis and Markellos, 2012). Due to the quality and availability of SVIs for all 31 market index queries, I only conduct panel regression

[3] 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 index. The AAII indicator measures sentiment though a weekly survey of individual investors with respect to their bullish, bearish, or neutral on the stock market over the next six months (see Brown and Cliff, 2004).

analysis for 13 out of 31 countries.[4] Specifically, I investigate market-wide attention on the basis of SVIs for queries related to different index names. For example, I use the SVI of query for "S&P 500" in order to measure the market attention for US. Raw daily SVIs are logarithmically transformed and deseasonalised using dummies for each month of the year. I then examine the relationship between investor attention and weather by regressing the SVIs on weather variables. The results in Table 3.12 clearly suggest that the temperature has negative effect on SVIs, which is to say that attention decreases with the increase of the temperature. I find that all three weather variables rain, snow and cloud have no significant impact on investor attention for the panel of 13 cities.

Table 3.12 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

In general, the weather condition is found to have no significant impact on investor sentiment for US whilst investor attention is only negatively related to temperature.

3.4.2.4 Economic significance: A weather-based volatility trading strategy for US

Considering that the US market attracts a large number of international traders, I am motivated to investigate if the average weather condition in G7 countries is linked to trading volume

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

Table 3.13 Impact of G7 weather on trading volume for US

	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)

in the US market. So I construct a G7 weather index by taking the average weather values of seven countries. I 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 time in New York. The impact of G7 countries weather condition on the US trading volume is presented in Table 3.13. Both G7 rain and temperature significantly increase S&P 500 trading volume on the day and the following day while cloud reduces volume significantly.

Based on the collective weather effect from G7 weather conditions on US trading volumes, I seek to explore the economic implications of these results. Table 3.13 shows that more rain and less cloud increase trading volume of S&P 500 significantly; even though temperature also has a positive effect on trading volume, I consider that the marginal profit from trading on temperature may not cover the transaction cost, therefore, my trading signal is based on rain and sky cloud cover.

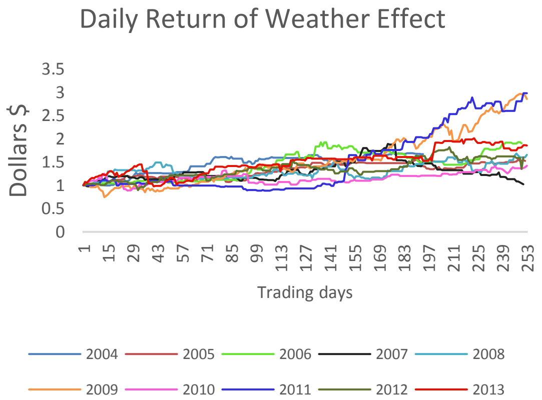
VIX futures contracts are used as underlying assets for trading volatility. For VIX futures a cost of $1.2 is assumed per contract side (estimate from CBOE for April 2013). Trading signals are constructed on the basis of rain fall volume from excessive rain. First, I calculate weekly means from the previous year; then I subtract the weekly mean from each daily value, so that I establish a benchmark for excessive rainfall. If the current value is above the value for the previous year, then I take a long position. I take the raw data of G7 rain index as the basis of the trading signal. Hypothetically, I invest \$1 dollar at the beginning of the year and trade through the whole year based on volumes of rainfall and cloud cover. By using the simple long and short trading strategy, I can profit from the weather in 9 out of 10 years, except for 2007, result shown in Table 3.14.

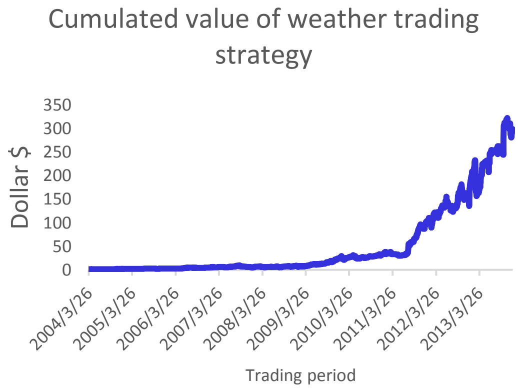
Table 3.14 Annualised return from VIX futures trading strategy

Year	Buy&Hold	Short/Long	
	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

The cumulative return from the trading strategy is depicted in Figure 3.2.

Fig. 3.2 The value of $1 invested from 2004-2013





3.5 Conclusions

Psychological evidence claims that rainy days yield higher productivity by reducing potential outdoor distractions. In this study, I examine the relationship between weather conditions and trading volumes for 33 stock exchanges from 2000 to 2013. I 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 decision condition changes, so does the trading activity. In conclusion, investors are more productive during the rainy days as the outdoor distractions are eliminated. However, in line with previous research I find that snow causes inconvenience for the investors to attend work and this results in a decreased trading volume. When the rainfall reaches a disruptive point, it also reduces work efficiency. 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 my findings is a simple trading strategy based on the volume pattern in the US market with respect to the average weather in G7 countries. I use VIX future contracts as underlying assets for trading volatility and take long or short position based on adverse weather conditions from 2004 to 2013. After I take out of transaction costs, I benefit in nine out of ten years in my 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.

Chapter 4

Hot information in high demand: mergers and acquisitions announcements

4.1 Introduction

The objective of this chapter is to further investigate the relationship between investor attention/sentiment and trading behaviour/asset prices at the firm level. While in the previous two chapters, I examined the effects of sets of events that are not directly related to stock markets (Olympic Games and weather conditions), here I focus on events initiated by firms. In particular, I study how investor attention and information demand changes around Merger and Acquisition (M&A) announcements. I am also interested in how these changes are affected by firm characteristics and whether they can explain post-announcement returns.

My framework is related to two strands in the financial literature. The first strand studies the concept of attention allocation to firm-specific and market-wide news. Rational attention allocation is considered as a pre-requisite for seeking financial information related to corporate events. In particular, investor attention can affect equilibrium trading volume and asset pricing (Sicherman et al., 2014). The second strand develops around the hypothesis that while the management of a firm is primarily rational, markets and investors may not be fully rational (e.g. Shleifer and Vishny, 2003). In this case, managers learn from the markets and make strategic announcements which serve their objectives. On the other hand, investors' reaction to these announcement may be driven by sentiment. This chapter aims to extend both literatures by separating the role of investor attention from that of sentiment to the reaction to M&A deals announcements. In this context, I again use the Google Search Volume Indices (SVIs) to quantify investor's attention and demand for information and investigate how these vary around M&A announcements as well as whether they affect post-announcement returns.

The contribution of this chapter is threefold. First, I provide strong evidence of the existence of an information-dependent utility at the level of the individual investor. In particular, I show that information demand significantly decreases before the actual announcement date while it significantly increases on the first two days after the announcement. This is because uncertainty resolves as the announcement approaches and this reduces demand for information. However, the announcement corresponds to a new information shock and generates new demand for information. Second, I find that information demand is typically lower for larger firms which are usually more transparent and are associated with higher information supply. Third, I offer an additional way to explain the abnormal returns around M&A announcements as I show that information demand has a positive and significant impact on the acquiror's post-announcement returns. Equivalently, the quicker the uncertainty about the deal is resolved, the lower post-announcement returns will be. This result is robust after controlling for a proxy of the market sentiment. As such, it supports the view that the market reaction to M&As is primarily driven by rational factors rather than sentiment and is consistent with the literature which studies the rational allocation of attention and its connection to the price discovery process.

4.2 Literature review and hypothesis formulation

In the M&A literature, empirical evidence shows that acquirors' cumulative abnormal returns (CARs) around the announcement date are close to zero or negative (Jensen and Ruback, 1983). On the contrary, target firm's shareholders earn significantly positive excess returns. For example, Andrade et al. (2001) show that in a sample of 3,688 mergers between 1973 and 1998, target firms gain 23.8% in the window beginning 20 days before the acquisition announcement and ending on the announcement day. Acquiring firms lose 3.8% over the same interval, and the combined value change is statistically insignificant. A set of firm characteristics and the form of payment appear to play an important role in the underperformance of M&As from the acquirors' perspective. Indicatively, Rau and Vermaelen (1998) find that acquirors earn a statistically and significantly negative 4% return relative to size and book-to-market benchmarks in the first three years after the merger. Similar findings are also documented by Agrawal and Jaffe (2000). Moeller et al. (2004) analyse a large sample of more than 10,000 deals and find evidence of a size effect: on average, acquirors' CARs are positive and significant (around 1.5%) but, the larger the deal, the smaller (or more negative) the CAR becomes. Furthermore, Malmendier and Tate (2008) find that the average announcement effect for the acquiring firm is -29 basis points with the reaction to cash bids being significantly positive and the reaction to stock bids being significantly negative.

Several arguments have been proposed in the literature to explain the market reaction to M&As with the most popular explanation being the managerial hubris hypothesis (Roll, 1986) and the synergy hypothesis (Mitchell and Mulherin, 1996).[1] On one hand, the hubris hypothesis argues that managers may engage in acquisitions to satisfy their personal aims. Rosen (2006) argues that shareholders could disengage themselves from this value-destroying behaviour, however, on the other hand, the synergy hypothesis, prominently represented by Mitchell and Mulherin (1996), argues that the M&A activities could be the result of industrial

[1] See Harford (2005); Andrade et al. (2001) for more details on the behavioural theory and the neoclassical theory in mergers and acquisitions.

and technological shocks. Similar studies draw on the theory of rational expectations and market efficiency under which stock prices reflect the discounted value of future profits, and adjust rapidly to reflect new public information. In this context, the reaction of the merging entities and their competitors at the announcement of a deal can serve as a proxy for the expected future profits from the transaction. If a merger is expected to create value, merging companies' stock prices should increase, otherwise they should fall.

Despite the enormous effort made in the literature to decipher the market response to M&A announcements, the investors' trading behaviour and their decision-making process in connection with mergers performance have received little attention. An important issue that remains unresolved is the extent to which investors react rationally around M&A announcements. In this context, recent literature suggests that price changes to a corporate announcement can be affected by investor sentiment (Shleifer and Vishny, 2003; Rosen, 2006). For example, M&A abnormal returns could result from investors becoming pessimistic (optimistic) with regard to mergers performance during periods of economic downturn (upturn). Shleifer and Vishny (2003) develop a model which explains that the reason for the documented size effect and payment effect in acquisitions is that the market absorbs investors' rational expectations as well as their sentiments. Moreover, Rau and Vermaelen (1998) study long-term performance of the acquiring firms after the M&A announcements and find that low book-to-market firms underperform high book-to-market firms. This is because low book-to-market firms are considered as "glamour" stocks, and they are more likely to strengthen the management and investors' belief in future performance and returns (Lakonishok et al., 1994).

On the other hand, investors attention allocation and learning capacity affect their consumption behaviour and price dynamics. Peng (2005) studies the learning process of a representative investor with a capacity (or attention) constraint and finds that investors preempt in the firm's information disclosure and smooth out the responses of stock prices. This effect is particularly strong for large firms since more attention allocated to larger firms lead to less announcement surprises. Hou (2007) shows that slow information diffusion is a leading cause of the lead-lag effect in stock returns, and limited attention associated learning capacity may be the reason for the delayed information incorporation. Cohen and Frazzini (2008) test the impact of the attention constraints on the predictability of stock returns and find that stock prices do not instantaneously incorporate financial news due to information processing constraints. These lagged trading patterns are considered to be exploitable, which leads to monthly alphas of over 150 basis points by a long-short equity strategy.

In this chapter, I differentiate from the aforementioned literature and examine, under the learning capacity constraint, a rational perspective of the behaviour of investors around deal announcements. I particularly focus on the concepts of attention allocation and information demand around M&A deals. My motivation stems from the empirical evidence which suggests that new information is incorporated into prices before the announcement dates due to anticipation and speculation. In this context, I expect information demand to fall as the M&A announcement date approaches and to increase on the date in response to the information shock generated from the announcement. However, as existing evidence uses indirect information proxies of investor attention which are usually based on stock prices, volatility and volume (Augustin et al., 2014), it is still unclear when the investors pay attention to public information and how they react to new information about M&As. My analyses help resolve this issue by directly testing the following hypothesis:

Hypothesis I. Information demand increases on the event date in response to the corresponding information shock. In contrast, information demand decreases when the announcement date is approaching as the uncertainty about the deal is resolved.

As, high M/B firms are believed to reflect overconfidence amongst investors, so I can use the M/B ratio as a proxy of the sentiment when testing the above hypothesis. In that way, I am able to isolate the effect of sentiment from investor attention.

In spite of aforementioned compelling evidence concerning the learning constraint on asset prices, its impact on acquiring firms' returns to M&A announcement has not been studied. In the context of M&A literature, Lambrecht (2004) studies the timing of acquisition under the assumption that investors have complete information. The results suggest that increased uncertainty leads to an increased investment threshold, which causes a higher execution cost resulting in a higher output price, therefore, the cumulative returns increase accordingly. Conversely, more uncertainty resolved leads to a less surprising announcement, and a lower expected price, subsequently, I expect a decrease in cumulative returns. Looking from a relaxed information environment, when facing learning capacity constraint,Andrei and Hasler (2015) find that improvement of uncertainty implies an increase in fundamental and current consumption because future consumption is expected to be larger, and investors wish to smooth consumption over time. Hence the demand for the stock decreases, implying a drop in the price.

Therefore, if *Hypothesis I* holds, I can assume that reduced search volume implies an improved uncertainty in price valuation, *vice versa*. Considering the attention and information constraint, investors consume time to process and incorporate new information into their decisions (Peng, 2005), stock prices that incorporate the disclosure shock will exhibit a delay in reflecting re-assessed fundamental value due to learning capacity constraints. Moreover, the empirical evidence by Hou (2007) also suggests that slow incorporation of new information cause lead-lag effects on stock returns. Subsequently, in the second stage of my empirical analysis I investigate the explanatory power of abnormal information demand in connection with the M&A abnormal returns. The flattened abnormal search volume suggests more resolved uncertainties, so that the surprise element is weakened by publicly-available information. Even though there is still an increase in fundamental value, the improved uncertainty and investors' smoothing consumption behaviour are constitute to a drop in price and negative returns as results. Thereby, my second hypothesis can be expressed as follows:

Hypothesis II. Abnormal information demand before the M&A announcement dates is positively related to post-announcement abnormal returns.

4.3 Data description

4.3.1 Sample description

I obtain daily Google Search Volume (SVI) for the S&P 500 constituents for the years 2006 to 2014. I follow Drake et al. (2012) and use S&P 500 firms because these firms are among the largest in the U.S. economy, and as such, they are more likely to have search data available from Google at a daily level. Following Vlastakis and Markellos (2012), I identify a S&P 500 stock by using its company name. There are two reasons for using the company name rather than its ticker name as recommended by Da et al. (2011). First, some ticker names, such as “T”,“CAT” cannot be accurately identified as a particular company; second, I want to capture a more generalised demand for information that goes beyond financial information. For example, investors may be interested in company products, operation efficiency, company history, etc., and it is possible that these information demands are also incorporated into their investment decisions. I further find that 42 of the S&P 500 firms have no values of SVIs for the entire sample period. As such, I excluded these firms from my sample.

I focus on the firms that have M&As announced between 2006 and 2014, as reported in Thomson Reuters Eikon. I narrow the M&A deals by using four criteria: 1) all the acquiring firms are in the S&P 500; 2) the status of both targets and acquirors is public firms; 3) the transaction value is at least $1 million; 4) both participants in the M&A are not financial firms because their high leverage ratios distort my operating performance measures. An additional reason is that financial firms are closely regulated, which may constrain their ability to invest and to manipulate accruals. I also exclude utility firms as these firms operate under special regulations.

In order to perform my event study, I assume that the date of the announcement of an M&A deal is the event day. The event window that I consider in my analysis starts two (five) days prior to the announcement date and ends two (five) days after announcement ([-2,+2],[-5,+5]). I choose this five-day and ten-day windows around the announcement by following Fuller et al. (2002) and Drake et al. (2012). I have also used a three-day window, as in Bouwman et al. (2009), and the results are qualitatively similar.

4.3.2 Information demand: abnormal Google Search Volume

To understand the variability of the investors' information demand around the announcement of an M&A deal, I employ abnormal Google SVIs (ASVI). These are calculated for firm i on day t as the raw SVI for the same day of the week k minus the average raw SVI in the prior 10 weeks. I consider this definition in order to remove the influence of potential day-of-the-week effects, as search volume is considerably lower on weekends than it is on weekdays. Following Da et al. (2011), I use the natural logarithm of 1+ASVI to normalise the distribution of ASVI (ASVI'). Also, in order to make cross-sectional comparisons, I investigate whether abnormal search volume around event dates varies with specific firm characteristics (i.e. size and M/B). This interest is motivated by the existing literature which suggests that size and sentiment affect acquiring firms' announcement returns as discussed in section 4.2. I average abnormal search volumes (ASVI) over particular windows and I append the variable name to specify the window over which the variables are measured. For example, ASVI[-5,-1] denotes that abnormal search volume is averaged over the five-day period ending one day before the deal announcement date. The event windows under study are up to ten days around the deal announcement.

4.3.3 Dependent variable: M&A abnormal returns

To build the dependent variable for my tests, I use the return to the acquiring firm as market reaction towards announcements, which reflects the investors valuation assessment to the announcement of a deal. In particular, my proxy for the market reaction is the short run cumulative abnormal announcement return (CAR) of the acquiror's stock around the first public announcement. For example, the five-day event window is measured as two days prior to the announcement until two days after the announcement.

I apply the event study methodology (MacKinlay, 1997) to calculate the effect of the deal announcement on stock prices. I use a one factor model "market model" to compute abnormal returns. This model accounts for variation in the market and thereby eliminates a potential bias in the returns related to changes in the market which are not directly related to the takeover. The abnormal return on a distinct day within the event window represents the difference between the actual stock return ($r_{i,t}$) on that day and the expected returns, calculated as:

$$E(r_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i r_{m,t}, \tag{4.1}$$

where the security specific parameters $\hat{\alpha}_i$ and $\hat{\beta}_i r_{m,t}$ are calculated using an estimation window of 30 days and event window of 5 days [2]. The abnormal return and the sample cumulative abnormal announcement return can be then calculated as:

$$\begin{aligned} AR_{i,t} &= r_{i,t} - E(r_{i,t}) \\ \widehat{CAR}(t_1,t_2) &= \sum_{t=-2}^{2} \widehat{AR_{i,t}} \end{aligned} \tag{4.2}$$

[2] I use the same methodology in the case of ten-day event windows.

4.3.4 Other variables

In addition to ASVI, I also include a set of explanatory variables to identify other firm-specific factors that may affect investors' information demand in order to isolate the information demand strictly related to the M&A announcement. First, the means of payment is an important factor known to affect abnormal return, so I use dummy variables to account for deals financed with stock, cash or mixed. Second, I consider the total assets, as measures of accounting performance that can be affected by both the method of payment and the accounting method. If the acquiror chooses different accounting methods, the book value of assets will also affect the net income. Therefore, I use the ranking of total assets as another control variable. Third, the size of the firm is also controlled in the model. In particular, I use the ranking of market capitalisation of acquiring firms as one control variable. Fourth, I consider the relative size *logrelsize*, which captures the relative importance of the acquisition and is defined as the logarithm of the transaction value at the time of the acquisition announcement divided by the acquiror's market value of equity 30 days prior to the announcement date. Finally, the financial strength of the acquiring firm is also taken into account, and this is expressed by the market-to-book ratio. As high book-to-market ratio is linked to higher short-run CARs (Lang et al., 1989), it is a good proxy that controls investors sentiment. The definition of these variables is presented in Table 4.1.

4.3.5 Descriptive statistics

The sample consists of 658 completed acquisitions announced during 2006-2014 available from Eikon. Table 4.2 reports,the summary statistics of the deals, the summary statistics of the abnormal return under each payment method at the announcement date and the percentage of deals that are paid by cash, stock or mix of both. Cash payment is the dominant financing method, which accounts for 64% of the overall payment compared with 34% of mixed financing.

Table 4.1 Definition of variables

Variable	Description
ASVI'[.]	The natural logarithm of 1+the average value of ASVI_it estimated over windows [-2,-1], [0,+2] ; [-5,-1], [0,+5]
ASVI_it	The average value of raw Google Search Volume Index (SVI) for a given day *t* minus the average SVI for the same weekday over the past 10 weeks, scaled by the average SVI for the same weekday over the past 10 weeks
AR[0]	Abnormal return estimated on the day of announcement by using market model in Section 4.3.3.
CAR[.]	The abnormal return estimated over four windows, [-5,-1], [-2,-1], [0, +2], [0,+5]. Abnormal returns are calculated by using market model that are described in Section 4.3.3.
M/B	Market-to-book value, ratio of market value of equity to book value of equity;
Rank of M/B	Percentile ranks of market-to-book ratio, taking values between 0 and 1;
Rank of size	Percentile ranks of market capitalisation, taking values between 0 and 1;
Rank of assets	Percentile ranks of total assets, taking values between 0 and 1;
Logrelsize	The logarithm of the transaction value at the time of the acquisition announcement divided by the acquiror's market value of the equity 30 days prior to the announcement date;
Cash	The payment has the form of cash.
Stock	The payment has the form of stock.
Mix	The payment method is a mix of stock and cash or other type of financing.
Deal size	Transaction value expressed in million dollars.

Table 4.2 Summary statistics for M&A deals

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB
					Mix			
AR[0]	0.0032	1.88E-05	0.2765	-0.1922	0.0372	2.0565	22.2543	3650.329
Deal size	2709.243	690	130298	10	10085.74	10.1646	120.838	134649.5
								Obs. 226 (34%)
					Cash			
AR[0]	0.0026	0.0006	0.1494	-0.0845	0.0204	1.1737	11.9178	1491.695
Deal size	607.6247	200	18040	1	1455.463	6.9337	67.3249	75955.45
								Obs. 421 (64%)
					Stock			
AR[0]	-0.0002	0.0003	0.0482	-0.0974	0.0389	-1.3487	4.6834	4.6339
Deal size	722.0909	175	4446	5	1331.702	2.2407	6.7984	15.8175
								Obs. 11 (2%)

Table 4.3 reports descriptive statistics for the variables used in the empirical tests described in the next section. I find that the mean abnormal search volume two days after the announcement (ASVI'[0,+2]) is 0.0180. As a result, the abnormal search volume is 1.3% higher than the average information demand over the whole sample period. Also, the average search volume over five days before the announcement (ASVI'[-5,-1]) is 1.5% greater than average search volume over the entire sample period. With regards to the abnormal search volume at the M&A announcement dates, the ASVI[0] is 5.9% higher than average search volume over the whole sample period.

4.4 Empirical analysis

In this section, I set up a series of models that examine the relationship between abnormal search volume and M&A announcement dates and examine how information demand varies in the pre-event period, announcement date and post-event period. I also examine the extent to which cross-sectional determinants explain variation of search volume around the event dates. Finally, I investigate the explanatory power of changes in search volume for acquiring firm's abnormal returns. Collectively, my analysis aims to shed light on the investor attention

Table 4.3 Descriptive statistics

	Mean	Std. Dev.	Median	Max.	Min.	Skewness	Kurtosis
CAR[0,+5]	0.0019	0.0484	0.0005	0.2791	-0.3016	0.2106	10.2155
CAR[0,+2]	0.0034	0.0371	0.0017	0.2188	-0.1822	0.4443	10.6688
CAR[-2,-1]	0.0006	0.0200	-0.0002	0.0841	-0.0937	0.2229	6.1847
CAR[-5,-1]	0.0008	0.0339	0.0008	0.2200	-0.1529	0.4907	7.1994
ASVI'[0,+5]	-0.0043	0.1710	0.0140	0.4830	-1.3666	-2.3340	15.0558
ASVI'[0,+2]	0.0180	0.1725	0.0286	0.6092	-1.3875	-2.1875	15.6613
ASVI'[-2,-1]	-0.0410	0.2481	-0.0023	0.8011	-1.5150	-1.7627	10.0612
ASVI'[-5,-1]	-0.0451	0.2251	-0.0019	0.7507	-1.6966	-2.4881	14.7410
Deal Size	1316.7840	6114.7540	312.0000	130298	1.0000	16.3836	321.9865
Logrelsize	-4.3590	1.8657	-4.2990	2.1108	-10.8691	-0.2213	3.6423
Rank of Assets	0.4570	0.2815	0.4583	0.9902	0.0000	0.1079	1.8474
Rank of Size	0.5157	0.2916	0.5262	0.9996	0.0000	-0.0579	1.7560
Rank of M/B	0.5250	0.2937	0.5471	1.0000	0.0000	-0.1063	1.7754
Rank of deal	0.4733	0.3742	0.5000	1.0000	0.0000	0.0756	1.5729
Observations	654						

This table reports summary statistics for information search volume over different event windows and control variables. The sample consists of 654 observations for S&P 500 firms over the period from 2006 to 2014.

allocation around the M&A announcement date and could help explain the announcement effect for acquiring firms.

4.4.1 Relationship between M&As announcements and ASVIs

Managers of a firm will consider carefully the consequences of any disclosure for the stock price of the firm, and they will strategically make an M&A announcement. For this reason, in the short run (five-day and ten-day event window in my study), I consider the M&A announcement to be the main shock of news disclosure for the interested investors; thus, observed abnormal search volumes (ASVI) can be primarily attributed to this news. Hence, in my first model setting, I regress daily abnormal search volume on the indicator variable of the M&A deal announcement dates and the control variables that are based on information from financial reports and the market. I estimate the model using the full time-series of daily Google search data for my sample of S&P 500 firms. The purpose of the estimation is to investigate the relationship between acquisition announcement and information demand (attention allocation).

The first model can be written as:

$$ASVI_{i,t} = \alpha_0 + \alpha_1 Acquisition\ Announcement[.]_{i,t} + \alpha_n Controls + \varepsilon_{i,t}, \tag{4.3}$$

where:

$ASVI_{i,t}$: Google SVI on day t for firm i minus the average Google SVI for the same firm and weekday over the previous 10 weeks, all scaled by the average Google SVI for the same firm and weekday over the previous 10 weeks;

$Acquisition\ Announcement[.]_{i,t}$: Dummy variable set equal to one on day t before, or after, if firm i makes an acquisition announcement and to zero otherwise (i.e. event days[-5,-1],[0],[+1,+5]);

$Controls$: A set of control variables including $rank\ of\ market\text{-}to\text{-}book\ ratio$, $rank\ of\ assets$ and $rank\ of\ size$.

In model (4.3), I include acquisition announcement dates to identify the magnitude of abnormal search volume during, before and after the M&A announcement date. My set of control variables helps us account for the potential influence from other firm-specific factors, including the financial strength of the acquiring firm expressed by market-to-book ratio (M/B), the size of the company by using market capitalisation and accounting performance by using total assets.

Table 4.4 reports the estimation results for equation (4.3). I find that abnormal search volume in the pre-event announcement period is significantly and negatively related to the event date, whereas during and after the announcement dates, the search volume is significantly higher than the average search volume. The abnormal high demand of information diminishes five days after the actual announcement. These findings support *Hypothesis I* that the uncertainty resolves as we get closer to the event date, as the available information is being consumed and incorporated into prices before the acquisition announcement. When the firm makes the announcement, new information shocks lead the investors to demand more information to resolve the uncertainty in relation to the deal. Gradually, the abnormal search volume dissolves as the information of the M&A is consumed.

Table 4.4 The abnormal information demand surrounding the acquisition announcements

	abnormal search volume around announcement dates				
	Announcement				
	[-5,-1]	[-2,-1]	[0]	[+1,+2]	[+1,+5]
ASVI	-0.0283***	-0.0264***	0.0596***	0.0164***	0.0034
	(-6.4777)	(-3.7847)	(7.7180)	(2.6766)	(0.8091)
Control	Yes	Yes	Yes	Yes	Yes
Observation	413,972	413,972	413,972	413,972	413972
Adjust R^2	0.0666	0.0665	0.0666	0.0665	0.0665

This table reports the results of abnormal search volume surrouding the takeover announcement from equation (4.3). *The dependent variable is the abnormal level of search volume (ASVI) for a firm's name for each day at various event windows. t-statistics are presented in brackets. The sample consists of S&P 500 firms from 2006 to 2014. Variable definitions are provided in Table 4.1. *,**,*** indicate statistical significance at 10%, 5% and 1% level, respectively.*

4.4.2 Cross-sectional differences in the timing of investor demand around M&A announcements

In this section, I explore whether firm-specific characteristics affect the patterns of search volume around deals announcements by examining the extent to which differences in the cross-section of firms influence those patterns. Given the large literature which documents that the firm characteristics could affect information demand, I investigate abnormal search volume around M&As announcements using ranks of two popular cross-sectional attributes: firm size and financial strength. I identify firms as being high versus low in a particular attribute by using the highest percentile amongst whole sample firms. My model in this case can be expressed as:

$$
\begin{aligned}
ASVI_{i,t} = \beta_0 + \beta_1 Announcement[.]_{i,t} + \beta_2 Attribute_{i,t} \\
+ \beta_3 (Announcement[.]_{i,t} \times Attribute_{i,t}) + \beta_n Controls,
\end{aligned} \tag{4.4}
$$

where:

$Announcement[.]_{i,t}$: event-day indicator variables set equal to one during the days before, during and after (i.e. event days [-2,-1], [-5,-1],[0],[+1,+2], [+1,+5]), and zero otherwise;

$Attribute_{i,t}$: one of two indicators variables defined as follows:

$Large\ firms$: indicator variable set equal to one if the market value of the firm is in the highest 10% of the sample and to zero otherwise;

$Glamour\ firms$: indicator variable set equal to one if the financial strength of the firm is in the highest 10% of the sample and to zero otherwise;

Controls: a set of control variables including $rank\ of\ deal\ size$, $rank\ of\ assets$ and $rank\ of\ market\text{-}to\text{-}book\ ratio$.

Table 4.5 reports the estimation results of firm size effects for equation (4.4). Even though my results are consistent with the previous section, I find that the size of the firm has a negative effect on the abnormal search volume. My interpretation is that the cost of acquiring information for large firms is relatively low given that large firms' information is more accessible and transparent compared to small firms. This result is also confirmed when I replace the large firm dummy to the small firm dummy (lowest 10% of market value). In this case, the signs of the interaction between small firms and announcement date are positive before and during the announcement, suggesting that investors demand more information for small firms.[3] This finding is supported by the existing literature which reports that return premiums for small firms are higher than large firms to compensate the information

[3]The results are reported in Table C.2 in the Appendix

Table 4.5 The impact of firms size on the timing of information demand around M&A announcement

	Daily Abnormal Search Volume				
	(1)	(2)	(3)	(4)	(5)
Large firms	-0.0015	-0.0016*	-0.0014	-0.0015	-0.0015
	(-1.4615)	(-1.6741)	(-1.4315)	(-1.4888)	(-1.4781)
Announcement[-5,-1]	-0.0295***				
	(-6.0494)				
[-5,-1]*large firms	0.0068				
	(0.6227)				
Announcement[-2,-1]		-0.0327***			
		(-4.1918)			
[-2,-1]*large firms		0.0321*			
		(1.8615)			
Announcement[0]			0.0379***		
			(3.1132)		
[0]*large firms			-0.0497**		
			(-2.5430)		
Announcement[+1,+2]				0.0208***	
				(3.0667)	
[+1,+2]*large firms				-0.0231	
				(-1.4568)	
Announcement[+1,+5]					0.0054
					(1.1545)
[+1,+5]*large firms					-0.0095
					(-0.8796)
Controls	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	413,038	413,038	413,038	413,038	413,038
Adjusted R^2	0.0666	0.0665	0.0665	0.0665	0.0665

This table reports the results of firm size effect from equation (4.4). *The dependent variable is the abnormal level of Google search volume for a firm i for each day t. t-statistics are presented in brackets. The sample consists of S&P 500 firms from 2006 to 2014. Variable definitions are provided in Table 4.1. *,**,*** indicate statistical significance at 10%, 5% and 1% level, respectively.*

acquisition costs (Moeller et al., 2004). However, these results are not significant in several cases. This is because my sample only includes S&P 500 firms, which are generally large.

I next investigate the relationship between information demand and investor sentiment (proxied by the M/B ratio). Specifically, I examine if investors demand more information for glamour firms (high M/B ratio) than value firms (low M/B ratio) [4]. According to Shleifer and Vishny (2003), high M/B firms are overvalued by the market and investor sentiment may be the reason for the misvaluation. The empirical evidence also suggests that around the announcement of the acquisition, glamour bidders experience higher abnormal returns than value bidders (Rau and Vermaelen, 1998). Therefore, around an M&A announcement for a glamour firm, if the investors are driven by sentiment, the information demand for glamour and value firms will be significantly different. In other words, by looking at the impact of glamour firms on the abnormal search volume, I am able to examine if bullish sentiment attracts more attention and demand of information from investors. To this end, I have repeated the tests from equation (4.4) and report the following results:

Table 4.6 reports the estimation results for potential sentiment effect. I find that abnormal search volume around announcement dates shows the same pattern as in first section. The pre-announcement search is negatively related to announcement dates whereas the search volume increases during and after actual announcement. However, the interaction term is not significant in this estimation. Overall, the results give further evidence in support of *Hypothesis I*: the information demand change around the announcement date is driven by the uncertainty of the value of the deal rather than sentiment.

[4] Barber and Odean (2008) point out that investors may limit their search to stocks meeting specific criteria that attract their attention.

Table 4.6 The impact of firms value status on the timing of information demand around M&A announcement

	Daily Abnormal Search Volume				
	(1)	(2)	(3)	(4)	(5)
Glamour firms	-0.0003	-0.0004	-0.0005	-0.0004	-0.0005
	(-0.2628)	(-0.4148)	(-0.4835)	(-0.4146)	(-0.4815)
Announcement[-5,-1]	-0.0245***				
	(-5.2965)				
[-5,-1]*glamour firms	-0.0353**				
	(-2.5001)				
Announcement[-2,-1]		-0.0240***			
		(-3.2697)			
[-2,-1]*glamour firms		-0.0217			
		(-0.9506)			
Announcement[0]			0.0282**		
			(2.3403)		
[0]*glamour firms			0.0081		
			(0.3273)		
Announcement[+1,+2]				0.0184***	
				(2.8472)	
[+1,+2]*glamour firms				-0.0190	
				(-0.9468)	
Announcement[+1,+5]					0.0032
					(0.7036)
[+1,+5]*glamour firms					0.0033
					(0.2410)
Controls	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	413,038	413,038	413,038	413,038	413,038
Adjusted R^2	0.0666	0.0665	0.0665	0.0665	0.0665

This table reports the results of the impact of firm value status on the timing of abnormal search volume from equation (4.4). *The dependent variable is the abnormal level of Google search volume for a firm i for each day t. t-statistics are presented in brackets. The sample consists of S&P 500 firms from 2006 to 2014. Variable definitions are provided in Table 4.1. *,**,*** indicate statistical significance at 10%, 5% and 1% level, respectively.*

4.4.3 The impact of abnormal search volume on the market response to M&A announcements

In this section, I examine whether abnormal search volume can explain announcement abnormal returns. My main hypothesis is that abnormal pre-announcement search have a positive relation to post-announcement abnormal returns. To investigate whether abnormal information demand is associated with the price discovery of M&A announcement, I perform my analysis on four event windows: [-2,-1], [0,2]; [-5,-1], and [0,+5]. I test whether the relationship between pre-announcement abnormal search volumes and the subsequent abnormal returns is stronger when pre-announcement search volume is relatively higher. Specifically, I estimate the following model:

$$\begin{aligned} CAR[.] = \gamma_0 + \gamma_1 ASVI'[.] + \gamma_2 Deal\ attributes + \gamma_3 (Deal\ attributes\ \times\ ASVI'[.]) \\ + \gamma_n Controls + \varepsilon \end{aligned} \tag{4.5}$$

Where,

CAR[.] = the abnormal return over various event windows; e.g. CAR[-5,-1] denotes the abnormal return starts five days before the announcement and end one day before the announcement;

ASVI'[.] = The natural logarithm of 1+the average value of $ASVI_{i,t}$ estimated over various windows; e.g. ASVI'[-5,-1] denotes the normalised abnormal search volume starts five days before the announcement and ends one day before the announcement;

Deal attributes = payment methods including cash, stock and mix; logrelsize;

Controls = a set of control variables, including *rank of size*, *rank of market-to-book ratio* and *rank of assets*.

Table 4.7 reports the estimation results for equation (4.5). The two panels respectively report the impact of deal characteristics on abnormal returns during two event windows

[-2,-1] and [-5,-1]. The heading of each column denotes the abnormal return by different payment methods and deal size. In columns (1), (2), (3) and (4) from the upper half of the table, I report the results using the normalised abnormal search volume for the event window [-2,-1] (ASVI'[-2,-1]) as the variable of interest; and in the lower half of the table, I present the results for the event window [-5,-1] (ASVI'[-5,-1). I also include the control variables and the interactions of the abnormal search volume with the deal properties in all regressions.

In Table 4.7, column (1), I find that the coefficient for ASVI'[-2,-1] is positively and significantly related to the cumulative abnormal return at [0,+2]. The interaction term of the abnormal search volume with the deal relative size is also positive and significant in connection to post-announcement abnormal return. These results suggest that, when investors search for more information for large deals in the period prior to the announcement, the search volume information is translated into new information and incorporated into price changes with a delay. In column (3), I find the results for cash payment are similar to (1). On the other hand, as the results in column (2) indicate, the interaction of the abnormal search volume with the stock as payment method is not significantly related to the abnormal return, even though the lead-lag abnormal return effect still holds and payment in the form of stock leads to a negative abnormal return. This indicates that investors are not particularly interested in searching for more information when the stock is used for payment. Insignificant but positive coefficient for the interaction is lastly observed for the case for mixed payment of cash and stock as shown in column (4). Finally, when the event window is extended to [-5,-1], the coefficients of the interactions are insignificant.

Overall, the results support *Hypothesis II*, suggesting that pre-announcement abnormal search volume is associated with post-announcement abnormal returns. As I have controlled for investor sentiment using the M/B ratio, my results suggest that investor attention is a strong driver of negative CARs after the announcement. This is in line with information-dependent utility hypothesis, suggesting that pre-empted information is used to resolve valuation uncertainty and price discovery.

I also repeat the above analysis for different event windows to examine whether lagged abnormal search volume is associated with abnormal returns at [0,+5]. The results are reported in Table C.1 in Appendix C and are qualitatively similar to the case CAR[0,+2], but less significant, as the effect of information demand changes dissipates with time.

4.4.4 Alternative explanations

When I interpret the results, I am also aware that the underlying psychology of information demand and trading decisions conditional on information is very different. For example, abnormal search volume may be associated with a realisation utility burst as gains and losses are almost certain or interact with fluctuations in investor confidence (Daniel et al., 1998; Gervais and Odean, 2001; Peng and Xiong, 2006), while paying attention (and mentally focusing) may reinforce their sentiment driven utility burst. In this study, I do not separate their motives of demanding information surrounding the event dates. On the contrary, I investigate the outcome of abnormal information demand and its impact on the price discovery of the announcement shock.

The another noticeable factor in M&A announcement is the anticipation effect that affects investors' searching behaviour for information. Billett and Qian (2008) find that the market anticipates future acquisition deals based on CEO acquisition targets and earn abnormal returns because of the increased probability that they will be targets themselves. In my study, the anticipation effect is not controlled in the model so that I cannot rule out that the increased abnormal information demand is the result of a complete shock; otherwise it could also be the consequence of predicted acquisition.

Table 4.7 The relationship between abnormal returns, deal size, payment method and abnormal search

	CAR[0,+2]			
	(1)	(2)	(3)	(4)
ASVI'[-2,-1]	0.0006**	0.0101	0.0391*	0.0113
	(2.3146)	(0.7834)	(1.8220)	(0.6057)
ASVI'[-2,-1]*Logrelsize	0.0002**			
	(2.5143)			
Logrelsize	0.0055**			
	(2.4327)			
ASVI'[-2,-1]*Stock		−0.1120		
		(1.2826)		
Stock		−0.1390***		
		(−4.7817)		
ASVI'[-2,-1]*Cash			0.0004***	
			(3.3846)	
Cash			0.0098	
			(0.2196)	
ASVI'[-2,-1]*mix				0.0144
				(0.4860)
Mix				0.0025
				(0.3301)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Observation	654	654	654	654
Adjusted R^2	0.3561	0.3572	0.3893	0.3236
ASVI'[-5,-1]	0.0716**	0.0224	0.0571**	0.0206
	(2.1208)	(1.5439)	(2.0140)	(1.1583)
ASVI'[-5,-1]*Logrelsize	0.0099			
	(1.3653)			
Logrelsize	0.0047**			
	(2.2697)			
ASVI'[-5,-1]*Stock		−0.0965		
		(−1.3041)		
Stock		−0.1441***		
		(−4.7761)		
ASVI'[-5,-1]*Cash			−0.0371	
			(−1.1104)	
Cash			0.0099	
			(1.2336)	
ASVI'[-5,-1]*Mix				0.0195
				(0.5352)
Mix				0.0028
				(0.3603)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Observation	655	655	655	655
Adjusted R^2	0.3036	0.3035	0.3098	0.3084

This table reports the results of relationship between the abnormal return, abnormal search volume and deal characteristics from equation (4.5). *The dependent variable is the cumulative abnormal return at period [0,+2]. t-statistics are presented in brackets. The sample consists of S&P 500 firms from 2006 to 2014. Variable definitions are provided in Table 4.1. *,**,*** indicate statistical significance at 10%, 5% and 1% level, respectively.*

4.5 Conclusions

By using Google search volume as a proxy for information demand and attention allocation, I set up a series of models that investigate the relationship between the timing of investors information demand and M&A announcement, and the extent to which investor demand for information. First, I investigate the relationship between abnormal search volume and M&A announcement dates and examine how information demand varies in the pre-event period, announcement date and post-event period. Next, I examine the extent to which cross-sectional determinants explain variation of search volume around the event dates. I also investigate the explanatory power of changes in search volume in acquiring firms' abnormal returns. Collectively, these analyses shed light on investors attention allocation for information in order to resolve price valuation uncertainties surrounding the M&A announcement date and provide more understanding in explaining the announcement effect for acquiring firms.

I provide empirical evidence on the nature and timing of investor information demand surrounding corporate event announcement dates. I find that the acquiring firms' price changes are in relation to the abnormal search volume before the actual announcement dates. Overall, my findings are summarised as follows: first, I find that investor information demand increases significantly when it is at the announcement date and the abnormal high demand diminishes two days after the announcement date. Second, I find that the pre-announcement abnormal search volume decreases for large firms, where the acquiror's information is more accessible and the information cost to resolve more uncertainties is low. Third, my results show that abnormal search volume prior to the announcement contains useful information and is translated into price discovery in a delay after the actual announcement dates. In general, I conclude that pre-announcement abnormal search volume is useful to explain the post-announcement price changes of the acquiring firms; and this positive relationship can be partially explained by relative deal size and payment method.

In this study, I am not able to distinguish the impact between large firms and small firms on the abnormal search volume because my entire sample is S&P 500 firms, which makes the firm size difference negligible. In future research, I could include more random public firms in order to examine whether firm size affects abnormal search volume. Moreover, I could also extend my study to the target firms by looking at acquiring firms and target firms simultaneously; then, I could understand better how investors make use of information and whether abnormal search volume is also related to target firm characteristics.

Chapter 5

Conclusions

5.1 Conclusions of the thesis

This thesis investigates the role of investor attention and sentiment in the financial markets by performing three empirical studies. First, it examines the impact of significant sports events on stock performance at the market and firm level in order to distinguish the market effects of inattention from those of sentiment. Second, it studies the influence of weather on investor attention and sentiment and how this translates to changes on investor trading activity and stock market performance. Finally, it examines how investors allocate their attention around the announcement of mergers and acquisitions and how their attention before the announcements affects post-announcement stock prices.

In particular, Chapter 2 analyses how sentiment and attention are related to investment behaviour by investigating the market effects of the Summer Olympic Games for eight participating countries and five sponsoring firms. In this context, I employ a new dataset of daily medals awarded over the Olympic Games. I find that medals negatively affect both volatility and trading volumes in a statistically and economically significant manner. For example, US trading volume (realised volatility) during Olympics is more than 24% (61%) lower than comparable periods in years when Games do not take place. Each gold medal leads to a further decrease in volume of nearly 3% on average over the trading day following the award. I extend my analysis to determine whether this result can be explained on the basis of investor attention or sports sentiment. To this end, I document that medals have a positive relationship with a direct measure of investor inattention for all sample countries. In contrast, my analysis shows that there are no significant links between Olympics and investor sentiment as this is measured by five different indicators. Overall, I conclude that Olympic Games affect the attention of investors but not their mood.

In Chapter 3, I study the connection between weather conditions and stock market activity for 31 stock exchanges in the period of 2000-2013. My hypothesis is that rainy days can enhance investor attention to market trading by making the outdoor leisure activities less appealing. I empirically confirm that rain and temperature positively affect trading activity, and the weather-volume relationship is nonlinear. I also find that particularly bad weather conditions, such as snow, reduce trading volume as they generate inconvenience to investors and other market participants. These results are robust to fixed effects and asymmetries. Finally, I show that the documented relationship between weather and volatility can be used to create a profitable trading strategy which employs volatility futures.

In Chapter 4, I use Google searches as a proxy for information demand and attention allocation in order to investigate how investor information demand changes around M&A announcements. I find that investor information demand significantly increases before the announcement date and falls two days after the announcement date. Abnormal search volume is smaller for large firms, where the acquiror's information is more accessible and the information cost to resolve potential uncertainties is low. Finally I show that post-announcement acquiring firms' price changes are positively related to the abnormal search volume before the actual announcement dates. As such, abnormal information search volume prior to the announcement contains useful information of the price changes of the acquiring firms. This connection can be partially explained by the relative deal size and payment method. My results in this chapter evince that post-acquisition returns can be partially explained by rational attention allocation.

Overall, this thesis extends the literature in the fields of investor attention and sentiment in several important ways. First, it highlights the importance of the joint treatment of attention and sentiment in the context of addressing trading patterns in the financial markets. Second, it shows that specific patterns of investor behaviour that are typically examined in the context of sentiment can be rationally explained through the concept of investor attention. Third, it shows that investor attention and sentiment results in stock market patterns that can be exploited by specific trading strategies. I expect that the thesis will generate a new strand in the literature that will examine the effect of investor attention on market patterns which, up to now, have been considered to stem from investor sentiment changes.

5.2 Limitations and future research

I now discuss the limitations of my analyses in each chapter of this thesis which could be resolved by future research. Starting with Chapter 2, one limitation is that I estimate distraction by adding up all the medals from the previous working day during the Olympic Games period. However, the eight countries typically receive more than one medal during the day. In this sense, I assume that every medal carries the same weight of distraction, hence, the sum of the medals over the previous workday may be over-extrapolated (under-) as a measure of distraction. Also, I assume that the medals from the previous workday is a distraction for next day's trading performance, whereas this inattention may last for more than one day. Finally, in future research, I could use alternative measures of investor attention, such as account logon activity during the event period.

In Chapter 3, I investigate the impact of weather on investors trading behaviour by including four weather variables as regressors. However, in this study, I do not consider the interactions between the weather variables, except for heat. This could be achieved in future research. Also, I do not fully account for the fact that investors in the region may not participate in their local stock markets. This is especially relevant for mature markets, where many investors are international players. Although I take *home bias* into consideration, it is possible that the observed pattern of behaviour change is under-represented.

In Chapter 4, investor sentiment is proxied by the acquiring firms market-to-book ratio. This assumes that the misvaluation of the stock price is the projection of investor sentiment. However, a large market-to-book ratio could simply be that fundamental price changes fall outside of the company's accounting period when the new information is not recorded. In this sense, my results of information demand for glamour firms are subject to the choice of accounting periods and methods. Another limitation in this chapter is that I use firms from the S&P 500 index that are typically large market capitalisation firms. Future research could extend my analysis to smaller firms. Finally, I could investigate the role of the information demand for target firms in M&As.

Appendix A

Is there an Olympic gold medal rush in the stock market?

Table A.1 Allocation of medals across countries and years

		Total	US		UK		FRA		AUS		NLD		GER		KOR		JPN		Sum	
2000	Subtotal	928	97	10.45%	28	3.02%	38	4.09%	58	6.25%	25	2.69%	57	6.14%	28	3.02%	18	1.94%	349	37.61%
	Gold	300	39	13.00%	11	3.67%	13	4.33%	16	5.33%	12	4.00%	14	4.67%	8	2.67%	5	1.67%	118	39.33%
	Silver	300	25	8.33%	10	3.33%	14	4.67%	25	8.33%	9	3.00%	17	5.67%	9	3.00%	8	2.67%	117	39.00%
	Bronze	328	33	10.06%	7	2.13%	11	3.35%	17	5.18%	4	1.22%	26	7.93%	11	3.35%	5	1.52%	114	34.76%
2004	Subtotal	925	101	10.92%	30	3.24%	33	3.57%	49	5.30%	22	2.38%	48	5.19%	30	3.24%	37	4.00%	350	37.84%
	Gold	300	35	11.67%	9	3.00%	11	3.67%	17	5.67%	4	1.33%	14	4.67%	9	3.00%	16	5.33%	115	38.33%
	Silver	300	39	13.00%	9	3.00%	9	3.00%	16	5.33%	9	3.00%	16	5.33%	12	4.00%	9	3.00%	119	39.67%
	Bronze	325	27	8.31%	12	3.69%	13	4.00%	16	4.92%	9	2.77%	18	5.54%	9	2.77%	12	3.69%	116	35.69%
2008	Subtotal	958	110	11.48%	47	4.91%	41	4.28%	46	4.80%	16	1.67%	41	4.28%	31	3.24%	25	2.61%	357	37.27%
	Gold	302	36	11.92%	19	6.29%	7	2.32%	14	4.64%	7	2.32%	16	5.30%	13	4.30%	9	2.98%	121	40.07%
	Silver	303	38	12.54%	13	4.29%	16	5.28%	15	4.95%	5	1.65%	10	3.30%	10	3.30%	6	1.98%	113	37.29%
	Bronze	353	36	10.20%	15	4.25%	18	5.10%	17	4.82%	4	1.13%	15	4.25%	8	2.27%	10	2.83%	123	34.84%
2012	Subtotal	918	104	11.45%	65	7.16%	34	3.74%	35	3.85%	20	2.20%	44	4.85%	28	3.08%	38	4.19%	368	40.53%
	Gold	302	46	15.23%	29	9.60%	11	3.64%	7	2.32%	6	1.99%	11	3.64%	13	4.30%	7	2.32%	130	43.05%
	Silver	306	29	9.48%	17	5.56%	11	3.59%	16	5.23%	6	1.96%	19	6.21%	8	2.61%	14	4.58%	120	39.22%
	Bronze	310	29	9.35%	19	6.13%	12	3.87%	12	3.87%	8	2.58%	14	4.52%	7	2.26%	17	5.48%	118	38.06%
Sum	Subtotal	3729	412	11.08%	170	4.57%	146	3.93%	188	5.06%	83	2.23%	190	5.11%	117	3.15%	118	3.17%	1424	38.30%
	Gold	1204	156	12.96%	68	5.65%	42	3.49%	54	4.49%	29	2.41%	55	4.57%	43	3.57%	37	3.07%	484	40.23%
	Silver	1209	131	10.84%	49	4.05%	50	4.14%	72	5.96%	29	2.40%	62	5.13%	39	3.23%	37	3.06%	469	38.82%
	Bronze	1316	125	9.50%	53	4.03%	54	4.10%	62	4.71%	25	1.90%	73	5.55%	35	2.66%	44	3.34%	471	35.81%
	TotalP		270		38		33		92		23		45		11		49		561	

Table A.2 Descriptive statistics of volatility and trading volume for markets and sponsor Firms

	Market/Firms	Mean	Mean′	△%	St.Dev	St.Dev′	△%	Min	Max
RV	US	1.43E-04	7.70E-05	-46.15%	2.93E-04	7.32E-05	-75.03%	7.75E-07	4.55E-06
	UK	1.01E-04	6.11E-05	-39.50%	1.87E-04	5.20E-05	-72.19%	4.63E-07	4.86E-06
	FRA	1.65E-04	1.14E-04	-30.91%	2.72E-04	8.24E-05	-69.70%	5.12E-07	4.07E-06
	AUS	8.23E-05	9.93E-05	20.66%	1.01E-04	4.55E-05	-55.00%	1.03E-03	3.14E-06
	NLD	1.45E-04	8.23E-05	-43.24%	2.31E-04	5.50E-05	-76.20%	3.62E-07	3.81E-06
	GER	2.08E-04	1.38E-04	-33.65%	3.41E-04	1.47E-04	-56.92%	5.88E-07	5.14E-06
	KOR	1.34E-04	8.04E-05	-40.00%	2.49E-04	3.41E-05	-86.32%	5.94E-07	9.92E-06
	JPN	1.16E-04	7.26E-05	-37.41%	1.78E-04	5.48E-05	-69.21%	3.23E-07	7.00E-06
IV	US	2.30E-04	1.36E-04	-40.87%	2.44E-04	3.35E-05	-86.29%	2.59E-03	3.88E-05
	UK	2.81E-04	1.39E-04	-50.53%	2.55E-04	5.02E-05	-80.31%	2.42E-03	3.39E-05
	FRA	3.06E-04	1.86E-04	-39.22%	3.18E-04	3.73E-05	-88.27%	2.62E-03	4.06E-05
	AUS	2.23E-04	2.60E-04	16.59%	2.31E-04	1.91E-05	-91.73%	2.46E-03	3.29E-05
	NLD	2.93E-04	1.80E-04	-38.57%	2.87E-04	4.03E-05	-85.94%	3.16E-03	7.95E-05
	GER	3.13E-04	1.85E-04	-40.89%	3.00E-04	2.96E-05	-90.15%	2.75E-03	5.39E-05
	KOR	3.01E-04	2.07E-04	-31.23%	2.39E-04	4.66E-05	-80.49%	1.77E-03	5.87E-05
	JPN	3.21E-04	2.12E-04	-33.96%	3.11E-04	4.90E-05	-84.23%	3.32E-03	5.28E-05
	KO	2.03E-04	2.23E-04	9.85%	1.80E-04	1.66E-04	-7.78%	3.83E-05	1.70E-03
	MCD	2.99E-04	2.74E-04	-8.36%	2.18E-04	1.60E-04	-26.61%	5.03E-05	1.99E-03
	VIS	4.82E-04	4.01E-04	-16.80%	4.08E-04	2.15E-04	-47.30%	1.15E-04	3.71E-03
VLM	US	1232.5124	923.8914	-25.04%	396.4508	322.5794	-18.63%	258.2406	2952.6387
	UK	1393.7986	997.2136	-28.45%	496.6419	278.7584	-43.87%	67.5300	4447.2013
	FRA	125.1974	101.1539	-19.20%	52.8434	53.9192	2.04%	9.8138	573.0802
	AUS	1996.2364	1418.6349	-28.93%	695.2893	406.4552	-41.54%	133.9206	6178.6970
	NLD	112.2627	97.8186	-12.87%	41.4396	25.6114	-38.20%	7.8820	527.8209
	GER	117.3076	101.2470	-13.69%	54.9798	46.2057	-15.96%	12.7747	494.0122
	KOR	445.1536	310.6129	-30.22%	208.7039	62.3072	-70.15%	136.3290	2379.2940
	JPN	1074.5700	878.3106	-18.26%	477.3712	404.9427	-15.17%	158.1884	4157.1940
	KO	15.4998	12.4266	-19.83%	8.3102	4.3270	-47.93%	124.1738	2.1474
	MCD	6.8410	5.8958	-13.82%	3.9658	4.6117	16.29%	86.9818	1.2809
	PC	0.3080	0.2140	-30.54%	0.2734	0.1719	-37.13%	3.4421	0.0180
	VIS	7.3752	4.8930	-33.66%	6.3481	2.9256	-53.91%	84.3883	1.0873
	SAM	0.5541	0.7269	31.19%	0.3137	0.6196	97.50%	3.2843	0.1369

Mean′ (St.Dev′) gives the average (standard deviation) of variables when Olympic Games take place in the sample. The other summary of statistics estimated over the complete sample. The △% columns give the percentage difference between then first and second moment during the complete period and the Olympics, respectively. Australia only contains realised volatility data for the Game of 2008. All volumes figures are expressed in millions of dollars.

Table A.3 Impact of Olympic medals on the returns at market and firm level

Market	**Gold**	**Med**	**Silver**	**Bronze**	**Popular**
US	-0.0002*	-5.71E-05	-0.0001	-9.46E-05	-6.63E-05
	(-1.8486)	(-1.3834)	(-1.4369)	(-0.5864)	(-0.9089)
UK	0.0003	0.0001**	0.0009	-5.32E-05	0.0010*
	(1.3812)	(2.1575)	(0.1806)	(-0.1917)	(1.9137)
FRA	0.0016***	0.0006***	0.0009	0.0015***	0.0025***
	(2.6510)	(2.9330)	(1.3822)	(3.9204)	(4.7558)
AUS	0.0001	5.63E-05	0.0003	-3.11E-05	-0.0004
	(0.2343)	(0.3221)	(0.6708)	(-0.0604)	(-0.6996)
NLD	0.0008	0.0007*	0.0019***	0.0012	5.33E-05
	(0.7294)	(1.6947)	(3.0003)	(0.9951)	(0.1093)
GER	0.0004	0.0003**	0.0008	0.0009***	0.0007
	(0.7295)	(2.3577)	(1.4913)	(4.0761)	(1.1883)
KOR	-0.0006	-0.0003	-0.0008	-0.0010	0.0050***
	(-0.6922)	(-0.6643)	(-0.3869)	(-0.6785)	(2.9557)
JPN	0.0001	0.0004	0.0002	0.0016***	0.0005
	(0.1262)	(1.5240)	(0.3455)	(3.3061)	(1.5895)
MSCI	-2.60E-05	-1.11E-05	-5.19E-05	-1.93E-05	-7.92E-06
	(-0.3265)	(-0.4412)	(-0.6766)	(-0.2886)	(-0.1202)
TUS	-1.18E-04	-4.38E-05	-1.43E-04	-1.25E-04	-7.63E-05
	(-1.1870)	(-1.4264)	(-1.6574)	(-1.4441)	(-0.9292)
Firms	**TGold**	**TMed**	**TSilver**	**TBronze**	**TPopular**
KO	1.76E-04	7.67E-05	3.14E-04	1.69E-04	2.31E-04
	(0.8522)	(0.9224)	(1.0798)	(0.6790)	(0.9439)
MCD	-2.03E-04	-5.91E-05	-1.64E-04	-1.44E-04	-1.70E-05
	(-1.4720)	(-1.0944)	(-0.9613)	(-0.8365)	(-0.0580)
PC	1.25E-04	5.56E-05	2.18E-04	1.35E-04	-7.90E-06
	(0.4182)	(0.5638)	(0.7875)	(0.4719)	(-0.0301)
VIS	1.76E-04	4.84E-05	4.10E-05	1.88E-04	3.53E-06
	(1.4028)	(1.0566)	(0.2579)	(1.5630)	(0.0195)
SAM	4.40E-05	2.19E-05	9.83E-05	4.59E-05	1.95E-04
	(0.3339)	(0.4602)	(0.6941)	(0.3048)	(1.3494)

The table gives the value of the coefficients b_{i1} in regression (2.2) *with return as the dependent variable in regression* (2.1). *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 1%, 5% and 10% level respectively. When TUS is used, which is the total number of medals for all eight countries, the returns correspond to U.S.*

Table A.4 Impact of surprise-weighted Olympic medals on returns, volume, realised volatility (RV) and implied volatility (IV)

Market	Return	Volume	RV	IV
US	0.0036	-0.3430	2.05E-05	-1.29E-04**
	(0.5864)	(-1.1319)	(0.1630)	(-2.0831)
UK	-0.0028	-0.2729	-2.1E-05	-7.19E-05
	(-0.4793)	(-0.7538)	(-0.5106)	(-0.9984)
FRA	0.0068	-1.1991**	-0.0001	-2.37E-04***
	(0.3287)	(-2.1905)	(-0.8351)	(-2.7249)
AUS	0.0137	0.1830	0.0005***	4.44E-04**
	(1.5174)	(0.2072)	(3.9368)	(2.3269)
NLD	0.0050	-1.7609**	-0.0005***	-8.83E-04**
	(0.2318)	(-2.3369)	(-2.6505)	(2.0963)
GER	0.0215	-1.3864***	-0.0003**	-2.66E-04**
	(0.9239)	(-3.0436)	(-2.0876)	(-2.0670)
KOR	-0.0799	-1.9971**	-4.9E-05	-7.49E-05
	(-1.5646)	(-2.2443)	(-0.5787)	(-0.5378)
JPN	0.0139	-1.5170	-0.0001	-5.12E-04
	(0.6374)	(-0.9733)	(-0.6697)	(-1.4141)

*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 1%, 5% and 10% level respectively.*

Table A.5 Contemporaneous impact of Olympic medals on investor attention measured by Google SVI

Market	**Med**	**Gold**	**Silver**	**Bronze**	**Popular**	**Surprise**
US	-0.0283**	-0.0652**	-0.0681**	-0.0896***	-0.0336**	-1.5239**
	(-2.4954)	(-2.3965)	(-2.1881)	(-2.8154)	(-2.3911)	(-2.0223)
UK	-0.0920***	-0.1799***	-0.2236***	-0.1857***	-0.2678***	-0.2722
	(-5.3560)	(-6.3929)	(-4.3220)	(-3.9488)	(-2.6022)	(-0.3349)
FRA	0.0094	-0.0151	0.0499	0.0034	0.0236	0.0155
	(0.0767)	(-0.0443)	(0.2842)	(0.0153)	(0.0997)	(0.0052)
AUS	-0.0648***	-0.1486***	-0.1128***	-0.1528***	-0.0855***	1.6990*
	(-4.5461)	(-5.4215)	(-3.066)	(-4.1620)	(-2.9657)	(2.0371)
NLD	-0.0699***	-0.1442*	-0.1416***	-0.0580*	-0.1959**	1.1646
	(-3.3886)	(-1.8796)	(-3.2822)	(-1.8575)	(-2.2605)	(1.0271)
GER	-0.0246*	-0.0394	-0.0436	-0.0724*	-0.0428	-1.3331***
	(-1.6719)	(-1.0463)	(-1.3651)	(-1.8760)	(-0.9746)	(-4.9106)
JPN	-0.0917	-0.0670	-0.2304*	-0.2041**	-0.1279	0.4726
	(-1.3947)	(-0.6284)	(-1.8218)	(-2.2516)	(-1.2806)	(0.2232)

*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 1%, 5% and 10% level respectively.*

Appendix B

Do investors save trading for a rainy day?

Table B.1 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)

Continued on next page

Table B.1 – continued from previous page

	TEMP	RAIN	SNOW	CLOUD	Constant
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)
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***

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Table B.1 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
	(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)
SYD	0.0020	0.0197	0.0761	-0.0030	-0.4357***
	(0.8589)	(0.6302)	(1.4229)	(-0.5839)	(-46.6793)

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Table B.1 – continued from previous page

	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
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 B.2 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***

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Table B.2 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
	(-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***
	(-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)

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Table B.2 – continued from previous page

	TEMP	RAIN	SNOW	CLOUD	Constant
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***
	(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***

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Table B.2 – continued from previous page					
	TEMP	**RAIN**	**SNOW**	**CLOUD**	**Constant**
	(-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***
	(-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.*

Appendix C

Hot information in high demand: mergers and acquisitions announcement

Table C.1 The relationship between lagged abnormal return and abnormal search volume during various event window

CAR[0,+5]		CAR[0,+5]	
ASVI'[-5,-1]	0.0774	ASVI[-2,-1]	0.0454
	(1.4219)		(0.9834)
ASVI'[-5,-1] *Logrelsize	0.0111	ASVI[-2,-1]*Logrelsize	0.0013
	(0.9547)		(0.1041)
Logrelsize	0.0097***	Logrelsize	0.0097***
	(2.6730)		(2.6857)
ASVI'[-5,-1]	0.0189	ASVI[-2,-1]	0.0236
	(0.7515)		(1.0805)
ASVI'[-5,-1]*Stock	-0.2401*	ASVI[-2,-1]*Stock	-0.2669*
	(-1.8859)		(-1.8002)
Stock	-0.1925***	Stock	-0.1795***
	(-3.6864)		(3.6094)
ASVI'[-5,-1]	0.0301	ASVI[-2,-1]	0.0214
	(0.6422)		(0.6046)
ASVI'[-5,-1]*Cash	-0.0134	ASVI[-2,-1]*Cash	0.0088
	(-0.2405)		(0.1857)
Cash	0.0145	Cash	0.0150
	(1.1454)		(1.2060)
Control	Yes	Control	Yes
Observation	655	Observation	654

This table reports the results of cumulative abnormal returns at different event windows from equation (4.5)*. The dependent variable is the abnormal level of Google searh volume for a firm's name for each day. t-statistics are presented in brackets. The sample consists of S&P 500 firms from 2006 to 2014. Variable definitions are provided in Table 4.1. *,**,*** indicates statistical significance at 10%, 5% and 1% level respectively.*

Table C.2 The impact of small firms on the timing of information demand around M&A announcement

	Daily Abnormal Search Volume				
	(1)	(2)	(3)	(4)	(5)
Small firms	0.0006	0.0007	0.0007	0.0008	0.0008
	(0.5577)	(0.6121)	(0.6161)	(0.6898)	(0.7127)
Announcement[-5,-1]	-0.0285***				
	(-6.3732)				
[-5,-1]*Small firms	0.0056				
	(0.2696)				
Announcement[-2,-1]		-0.0265***			
		(-3.7156)			
[-2,-1]*Small firms		0.0048			
		(0.1448)			
Announcement[0]			0.0269**		
			(2.2707)		
[0]*Small firms			0.0443		
			(1.1805)		
Announcement[+1,+2]				0.0174***	
				(2.7754)	
[+1,+2]*Small firms				-0.0219	
				(-0.7027)	
Announcement[+1,+5]					0.0046
					(1.0619)
[+1,+5]*Small firms					-0.0245
					(-1.1833)
Controls	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	413,038	413,038	413,038	413,038	413,038
Adjusted R^2	0.0666	0.0665	0.0665	0.0665	0.0665

This table reports the results of firm size effect of small firms from equation (4.4)*. The dependent variable is the abnormal level of Google searh volume for a firm's name for each day. t-statistics are presented in brackets. The sample consists of S&P 500 firms from 2006 to 2014. Variable definitions are provided in Table 4.1. *,**,*** indicates statistical significance at 10%, 5% and 1% level respectively.*

References

Agrawal, Anup, and Jeffrey F. Jaffe, 2000, *Advances in Mergers and Acquisitions*, volume 1 (Elsevier Science Inc).

Andersen, Torben G, 1996, Return volatility and trading volume: An information flow interpretation of stochastic volatility, *Journal of Finance* 51, 169–204.

Andrade, Gregor, Mark Mitchell, and Erik Stafford, 2001, New evidence and perspectives on mergers, *Journal of Economic Perspectives* 103–120.

Andrei, Daniel, and Michael Hasler, 2015, Investor attention and stock market volatility, *Review of Financial Studies* 28, 33–72.

Ashton, John K, Bill Gerrard, and Robert Hudson, 2003, Economic impact of national sporting success: evidence from the London Stock Exchange, *Applied Economics Letters* 10, 783–785.

Au, Kevin, Forrest Chan, Denis Wang, and Ilan Vertinsky, 2003, Mood in foreign exchange trading: Cognitive processes and performance, *Organizational Behavior and Human Decision Processes* 91, 322–338.

Auffhammer, Maximilian, Solomon M Hsiang, Wolfram Schlenker, and Adam Sobel, 2013, Using weather data and climate model output in economic analyses of climate change, *Review of Environmental Economics and Policy* 7, 1–18.

Augustin, Patrick, Menachem Brenner, and Marti G Subrahmanyam, 2014, Informed options trading prior to m&a announcements: Insider trading?

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–151.

Barber, Brad M, and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Barberis, Nicholas, and Richard Thaler, 2002, A survey of behavioral finance, *National Bureau of Economic Research Working Paper Series* No. 9222.

Bassi, Anna, Riccardo Colacito, and Paolo Fulghieri, 2013, 'o sole mio: An experimental analysis of weather and risk attitudes in financial decisions, *Review of Financial Studies* 26, 1824–1852.

Bernard, Andrew B, and Meghan R Busse, 2004, Who wins the olympic games: Economic resources and medal totals, *Review of Economics and Statistics* 86, 413–417.

Bernile, Gennaro, and Evgeny Lyandres, 2011, Understanding investor sentiment: the case of soccer, *Financial Management* 40, 357–380.

Billett, Matthew T, and Yiming Qian, 2008, Are overconfident CEOs born or made? Evidence of self-attribution bias from frequent acquirers, *Management Science* 54, 1037–1051.

Bouwman, Christa HS, Kathleen Fuller, and Amrita S Nain, 2009, Market valuation and acquisition quality: Empirical evidence, *Review of Financial Studies* 22, 633–679.

Boyle, Glenn, and Brett Walter, 2003, Reflected glory and failure: International sporting success and the stock market, *Applied Financial Economics* 13, 225–235.

Brown, Alasdair, 2014, Information processing constraints and asset mispricing, *Economic Journal* 124, 245–268.

Brown, Gregory W, 1999, Volatility, sentiment, and noise traders, *Financial Analysts Journal* 55, 82–90.

Brown, Gregory W, and Michael T Cliff, 2004, Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1–27.

Burke, Marshall, John Dykema, David B Lobell, Edward Miguel, and Shanker Satyanath, 2014, Incorporating climate uncertainty into estimates of climate change impacts, *Review of Economics and Statistics* .

Cachon, Gerard, Santiago Gallino, and Marcelo Olivares, 2012, Severe weather and automobile assembly productivity.

Campbell, John Y, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 108, 905–939.

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

Chang, Shao-Chi, Sheng-Syan Chen, Robin K. Chou, and Yueh-Hsiang Lin, 2008, Weather and intraday patterns in stock returns and trading activity, *Journal of Banking and Finance* 32, 1754–1766.

Chang, Shao Chi, Sheng Syan Chen, Robin K. Chou, and Yueh Hsiang Lin, 2012, Local sports sentiment and returns of locally headquartered stocks: A firm-level analysis, *Journal of Empirical Finance* 19, 309–318.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *Journal of Finance* 63, 1977–2011.

Connolly, Marie, 2008, Here comes the rain again: Weather and the intertemporal substitution of leisure, *Journal of Labor Economics* 26, 73–100.

Corwin, Shane A, and Jay F Coughenour, 2008, Limited attention and the allocation of effort in securities trading, *Journal of Finance* 63, 3031–3067.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *Journal of Finance* 66, 1461–1499.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839–1885.

Dawson, Peter, Paul Downward, and Terence C Mills, 2014, Olympic news and attitudes towards the Olympics: a compositional time-series analysis of how sentiment is affected by events, *Journal of Applied Statistics* 41, 1307–1314.

DCMS/ Strategy Unit, 2002, Game plan: A strategy for delivering government's sport and physical activity objectives, Technical report, Department for Culture, Media and Sport/ Strategy Unit.

De Freitas, C.R., Daniel Scott, and Geoff McBoyle, 2008, A second generation climate index for tourism (cit): specification and verification, *International Journal of Biometeorology* 52, 399–407.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.

Dell, M., B. Jones, and B. Olken, 2014, What do we learn from the weather? the new climate-economy literature, *Journal of Economic Literature* 53, 740–798.

DellaVigna, Stefano, and Joshua M Pollet, 2009, Investor inattention and friday earnings announcements, *Journal of Finance* 64, 709–749.

Deschênes, Olivier, and Michael Greenstone, 2012, The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: reply, *American Economic Review* 102, 3761–3773.

Dickey, David A., and Wayne A. Fuller, 1979, Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association* 74, 427–431.

Dowling, Michael, and Brian M Lucey, 2005, Weather, biorhythms, beliefs and stock returns-some preliminary irish evidence, *International Review of Financial Analysis* 14, 337–355.

Drake, Michael S, Darren T Roulstone, and Jacob R Thornock, 2012, Investor information demand: Evidence from google searches around earnings announcements, *Journal of Accounting Research* 50, 1001–1040.

Edmans, Alex, Diego Garcia, and Øyvind Norli, 2007, Sports sentiment and stock returns, *Journal of Finance* 62, 1967–1998.

Ehrmann, Michael, and David-Jan Jansen, 2012, The pitch rather than the pit: investor inattention during FIFA world cup matches, *European Central Bank, Working Paper* .

Farrell, Kathleen Anne, and W Scott Frame, 1997, The value of olympic sponsorships: who is capturing the gold?, *Journal of Market-Focused Management* 2, 171–182.

Ferris, Stephen P, Qing Hao, and Min-Yu Liao, 2013, The effect of issuer conservatism on IPO pricing and performance, *Review of Finance* 17, 993–1027.

Frieder, Laura, and Avanidhar Subrahmanyam, 2004, Nonsecular regularities in returns and volume, *Financial Analysts Journal* 60, 29–34.

Fruehwirth, Manfred, and Leopold Sögner, 2012, Does the sun shine really shine on the financial markets?, working paper.

Fuller, Kathleen, Jeffry Netter, and Mike Stegemoller, 2002, What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions, *Journal of Finance* 57, 1763–1793.

Gallant, A Ronald, Peter Eric Rossi, and George Tauchen, 1992, Stock prices and volume, *Review of Financial studies* 5, 199–242.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1–27.

Gilbert, Thomas, Shimon Kogan, Lars Lochstoer, and Ataman Ozyildirim, 2012, Investor inattention and the market impact of summary statistics, *Management Science* 58, 336–350.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779–1801.

Goetzmann, William N, and Ning Zhu, 2005, Rain or shine: where is the weather effect?, *European Financial Management* 11, 559–578.

Hagn, Florian, and Wolfgang Maennig, 2008, Employment effects of the football World Cup 1974 in Germany, *Labour Economics* 15, 1062–1075.

Hamermesh, Daniel S, Caitlin Knowles Myers, and Mark L Pocock, 2008, Cues for timing and coordination: Latitude, letterman, and longitude, *Journal of Labor Economics* 26, 223–246.

Hanke, Michael, and Michael Kirchler, 2013, Football championships and jersey sponsors' stock prices: an empirical investigation, *European Journal of Finance* 19, 228–241.

Harford, Jarrad, 2005, What drives merger waves?, *Journal of Financial Economics* 77, 529–560.

Hirshleifer, David, Sonya S Lim, and Siew Hong Teoh, 2011, Limited investor attention and stock market misreactions to accounting information, *Review of Asset Pricing Studies* 1, 35–73.

Hirshleifer, David, and Tyler Shumway, 2003, Good day sunshine: Stock returns and the weather, *Journal of Finance* 58, 1009–1032.

Hou, Kewei, 2007, Industry information diffusion and the lead-lag effect in stock returns, *Review of Financial Studies* 20, 1113–1138.

Huberman, Gur, and Tomer Regev, 2001, Contagious speculation and a cure for cancer: A nonevent that made stock prices soar, *Journal of Finance* 56, 387–396.

Jacobs, Heiko, and Martin Weber, 2011, The trading volume impact of local bias: Evidence from a natural experiment, *Review of Finance* 16, 867–901.

Jacobsen, Ben, and Wessel Marquering, 2008, Is it the weather?, *Journal of Banking and Finance* 32, 526–540.

Jacobsen, Ben, and Wessel Marquering, 2009, Is it the weather? response, *Journal of Banking and Finance* 33, 583–587.

Jensen, Michael C, and Richard S Ruback, 1983, The market for corporate control: The scientific evidence, *Journal of Financial Economics* 11, 5–50.

Jones, Benjamin F., and Benjamin A. Olken, 2010, Climate shocks and exports, *American Economic Review* 100, 454–459.

Jones, Marc V, Pete Coffee, David Sheffield, Marc Yangüez, and Jamie B Barker, 2012, Just a game? changes in English and Spanish soccer fans' emotions in the 2010 World Cup, *Psychology of Sport and Exercise* 13, 162–169.

Kacperczyk, Marcin T, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, A rational theory of mutual funds' attention allocation, *NYU Working Paper No. 2451/28347* .

Kahneman, Daniel, 1973, *Attention and effort*, Prentice-Hall series in experimental psychology (Prentice-Hall, New Jersey).

Kahneman, Daniel, 2003, Maps of bounded rationality: Psychology for behavioral economics, *American Economic Review* 1449–1475.

Kahneman, Daniel., and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.

Kamstra, Mark J, Lisa A Kramer, and Maurice D Levi, 2003, Winter blues: A sad stock market cycle, *American Economic Review* 93, 324–343.

Kamstra, Mark J, Lisa A Kramer, and Maurice D Levi, 2009, Is it the weather? comment, *Journal of Banking and Finance* 33, 578–582.

Kaplanski, Guy., and Haim. Levy, 2010a, Exploitable predictable irrationality: The FIFA world cup effect on the U.S. stock market, *Journal of Financial and Quantitative Analysis* 45, 535–553.

Kaplanski, Guy, and Haim Levy, 2010b, Sentiment and stock prices: The case of aviation disasters, *Journal of Financial Economics* 95, 174–201.

Karlsson, Niklas, George Loewenstein, and Duane Seppi, 2009, The ostrich effect: Selective attention to information, *Journal of Risk and Uncertainty* 38, 95–115.

Kavetsos, Georgios, and Stefan Szymanski, 2010, National well-being and international sports events, *Journal of Economic Psychology* 31, 158–171.

Keller, Klaus, Benjamin M Bolker, and David F Bradford, 2004, Uncertain climate thresholds and optimal economic growth, *Journal of Environmental Economics and Management* 48, 723–741.

Keller, Matthew C, Barbara L Fredrickson, Oscar Ybarra, Stéphane Côté, Kareem Johnson, Joe Mikels, Anne Conway, and Tor Wager, 2005, A warm heart and a clear head the contingent effects of weather on mood and cognition, *Psychological Science* 16, 724–731.

Kliger, Doron, and Ori Levy, 2003, Mood-induced variation in risk preferences, *Journal of Economic Behavior & Organization* 52, 573–584.

Koenker, Roger, 2004, Quantile regression for longitudinal data, *Journal of Multivariate Analysis* 91, 74–89.

Krueger, Thomas M, and William F Kennedy, 1990, An examination of the super bowl stock market predictor, *Journal of Finance* 45, 691–697.

Kuo, Jing-Ming, Jerry Coakley, and Andrew Wood, 2010, The lunar moon festival and the dark side of the moon, *Applied Financial Economics* 20, 1565–1575.

Lakonishok, Josef, Andrei Shleifer, and Robert W Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Lambrecht, Bart M, 2004, The timing and terms of mergers motivated by economies of scale, *Journal of Financial Economics* 72, 41–62.

Lang, Larry HP, RenéM Stulz, and Ralph A Walkling, 1989, Managerial performance, tobin's q, and the gains from successful tender offers, *Journal of Financial Economics* 24, 137–154.

Lee, Jooa Julia, Francesca Gino, and Bradley R Staats, 2014, Rainmakers: Why bad weather means good productivity, *Journal of Applied Psychology* 99, 504–513.

Lee, Wayne Y., Christine X. Jiang, and Daniel C. Indro, 2002, Stock market volatility, excess returns, and the role of investor sentiment, *Journal of Banking and Finance* 26, 2277–2299.

Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer confidence and asset prices: Some empirical evidence, *Review of Financial Studies* 19, 1499–1529.

Lo, Andrew W, and Jiang Wang, 2000, Trading volume: definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 13, 257–300.

Loewenstein, George F, Elke U Weber, Christopher K Hsee, and Ned Welch, 2001, Risk as feelings., *Psychological Bulletin* 127, 267–286.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? textual analysis, dictionaries, and 10-ks, *Journal of Finance* 66, 35–65.

Loughran, Tim, and Paul Schultz, 2004, Weather, stock returns, and the impact of localized trading behavior, *Journal of Financial and Quantitative Analysis* 39, 343–364.

Lozano, Fernando A, 2011, The flexibility of the workweek in the United States: evidence from the FIFA World Cup, *Economic Inquiry* 49, 512–529.

MacKinlay, A Craig, 1997, Event studies in economics and finance, *Journal of Economic Literature* 13–39.

Malmendier, Ulrike, and Geoffrey Tate, 2008, Who makes acquisitions? ceo overconfidence and the market's reaction, *Journal of Financial Economics* 89, 20–43.

McTier, Brian C, Yiuman Tse, and John K Wald, 2013, Do stock markets catch the flu?, *Journal of Financial and Quantitative Analysis* 48, 979–1000.

Mishra, Vinod, and Russell Smyth, 2010, An examination of the impact of India's performance in one-day cricket internationals on the Indian stock market, *Pacific-Basin Finance Journal* 18, 319–334.

Mitchell, Mark L, and J Harold Mulherin, 1996, The impact of industry shocks on takeover and restructuring activity, *Journal of Financial Economics* 41, 193–229.

Miyazaki, Anthony D, and Angela G Morgan, 2001, Assessing market value of event sponsoring: corporate olympic sponsorships, *Journal of Advertising Research* 41, 9–16.

Moeller, Sara B, Frederik P Schlingemann, and René M Stulz, 2004, Firm size and the gains from acquisitions, *Journal of Financial Economics* 73, 201–228.

Newey, Whitney K, and Kenneth D West, 1987, A simple, positive semidefinite, heteroskedasticity and autocorrelation consistent covariance-matrix, *Econometrica* 55, 703–708.

Ofcom, 2012, The London 2012 Olympic Games: media consumption, Technical report, Office of Communications.

Oxford Economics, 2012, The economic impact of London 2012 Olympic & Paralympic Games, Technical report, Oxford Economics.

Palomino, Frederic, Luc Renneboog, and Chendi Zhang, 2009, Information salience, investor sentiment, and stock returns: The case of British soccer betting, *Journal of Corporate Finance* 15, 368–387.

Pashler, Harold, 1994, Dual-task interference in simple tasks: data and theory, *Psychological Bulletin* 116, 220–244.

Peng, Lin, 2005, Learning with information capacity constraints, *Journal of Financial and Quantitative Analysis* 40, 307–329.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Phillips, Peter C. B., and Pierre Perron, 1988, Testing for a unit root in time series regression, *Biometrika* 75, 335–346.

Rau, P Raghavendra, and Theo Vermaelen, 1998, Glamour, value and the post-acquisition performance of acquiring firms, *Journal of Financial Economics* 49, 223–253.

Roll, Richard, 1986, The hubris hypothesis of corporate takeovers, *Journal of Business* 197–216.

Rosen, Richard J, 2006, Merger momentum and investor sentiment: The stock market reaction to merger announcements, *Journal of Business* 79, 987–1017.

Ross, Lee, 1977, The intuitive psychologist and his shortcomings: Distortions in the attribution process, in Berkowitz Leonard, ed., *Advances in experimental social psychology*, volume 10, 173–220 (Academic Press, New York).

Rothfusz, Lans P, 1990, The heat index equation, *Fort Worth, Texas: National Oceanic and Atmospheric Administration, National Weather Service, Office of Meteorology* 90–23.

Saunders Jr, Edward M, 1993, Stock prices and wall street weather, *American Economic Review* 83, 1337–1345.

Schmeling, Maik, 2009, Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16, 394–408.

Schmidt, Daniel, 2013, Investors' attention and stock covariation: Evidence from Google sport searches, *Working paper, INSEAD* .

Schmittmann, Jochen M., Jenny Pirschel, Steffen Meyer, and Andreas Hackethal, 2015, The impact of weather on German retail investors, *Review of Finance* 19, 1143–1183.

Shefrin, Hersh, 2008, *A behavioral approach to asset pricing* (Academic Press).

Shi, Jingye, and Mikal Skuterud, 2015, Gone fishing! reported sickness absenteeism and the weather, *Economic Inquiry* 53, 388–405.

Shiller, Robert J, 2003, From efficient markets theory to behavioral finance, *Journal of Economic Perspectives* 17, 83–104.

Shleifer, Andrei, and Robert W Vishny, 2003, Stock market driven acquisitions, *Journal of Financial Economics* 70, 295–311.

Sicherman, Nachum, George Loewenstein, Duane Seppi, and Stephen Utkus, 2014, Financial attention, *Working paper* .

Simon, Herbert A, 1957, *Models of man; social and rational.* (Wiley, New York).

Simon, Herbert Alexander, 1982, *Models of bounded rationality: Empirically grounded economic reason*, volume 3 (MIT press).

Sims, Christopher A, 2003, Implications of rational inattention, *Journal of Monetary Economics* 50, 665–690.

Spira, Jonathan B, and Joshua B Feintuch, 2005, *The cost of not paying attention: How interruptions impact knowledge worker productivity* (Basex New York, NY).

Stickel, Scott E, and Robert E Verrecchia, 1994, Evidence that trading volume sustains stock price changes, *Financial Analysts Journal* 57–67.

Symeonidis, Lazaros, George Daskalakis, and Raphael N Markellos, 2010, Does the weather affect stock market volatility?, *Finance Research Letters* 7, 214–223.

Tetlock, Paul C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139–1168.

Vázsonyi, Miklós, 2010, Overview of quantitative news interpretation methods applied in financial market predictions, *Social and Management Sciences* 17, 17–29.

Veldkamp, Laura L, 2011, *Information choice in macroeconomics and finance* (Princeton University Press, New Jersey).

Vlastakis, Nikolaos, and Raphael N Markellos, 2012, Information demand and stock market volatility, *Journal of Banking and Finance* 36, 1808–1821.

Worthington, Andrew C, 2007, National exuberance: A note on the Melbourne Cup effect in Australian stock returns, *Economic Papers* 26, 170–179.

Yantis, Steven, 1998, Control of visual attention, in H. Pashler, ed., *In Attention*, 223–256 (University College London Press, London).

Yuan, Kathy, Lu Zheng, and Qiaoqiao Zhu, 2006, Are investors moonstruck? lunar phases and stock returns, *Journal of Empirical Finance* 13, 1–23.

Zivin, Joshua Graff, and Matthew Neidell, 2014, Temperature and the allocation of time: Implications for climate change, *Journal of Labor Economics* 32, 1–26.