Matthew C. Chang (Taiwan)

Do cats and dogs eat grass before a rain? Analysis of weather effects on order submissions and order imbalances

Abstract

Using a database of Taiwan Stock Exchange Capitalization Weighted Index Futures (TXF) that allows to identify the investor type for an order submission, this study investigates the relationship between weather and both order submissions and order imbalances by investor type. The paper analyzes investors' order imbalances from a behavioral perspective of weather effects other than any particular individual's sentiment. In particular, the period under study, which covers the duration of dot-com bubble and financial tsunami, enables us to obtain the significant insight of the influence of weather on economic and financial decisions of individual and institutional investors during historically calm and panic periods. In sum, although weather does not significantly affect market and limit order imbalances of both individual and institutional investors, order imbalances of individual and institutional investors are differently influenced by weather during financial crises. The findings of this paper indicate the necessity for future study on individual investors' abnormal behaviors during financial crises.

Keywords: weather effects, market orders and limit orders, order imbalances, individual and institutional investors.
JEL Classification: G14, G15.

Introduction

Many market anomalies, including January Effect (see e.g., Thaler, 1987; Seyhun, 1988; Haugen and Jorion, 1996) and Weekend Effect (see e.g., French, 1980; Lakonishok and Maberly, 1990; Abraham and Ikenberry, 1994) challenge Efficient Market Hypothesis[1] in recent years. Furthermore, researchers in finance find that many abnormal phenomena are due to people's behavior, including Disposition Effect (see e.g., Shefrin and Statman, 1985; Shapira and Venezia, 2001), Overconfidence (see e.g., Shefrin and Statman, 1994; Kahneman and Riepe, 1998), and House Money Effect (see e.g., Thaler and Johnson, 1990; Frino et al., 2008).

In particular, many studies demonstrate that weather has influence on assets' returns. For example, Saunders (1993) concludes that security markets are, to some degree, irrational by rejecting the null hypothesis that stock prices are not systematically affected by weather. Hirshleifer and Shumway (2003) conclude that fully rational price setting is difficult to reconcile with their findings that morning sunshine in the city of a country's leading stock exchange is strongly significantly correlated with stock returns. Although their conjecture for the abnormal relationship between weather and returns seems to be reasonable, they do not find direct evidence to explain the relationship by people's behaviors.

On the other hand, investors' order submissions directly determine order imbalances, and both theoretical and empirical studies indicate that order imbalances are responsible for asset returns (Kyle, 1985; Sias, 1997; Chordia and Subrahmanyam, 2004; Schlag and Stoll, 2005). Thus, order imbalances contain information as asset prices adjust to the release of information. In particular, Easley et al. (1998) and Chordia and Subrahmanyam (2004) argue that order imbalances are more informative than reported volumes because the former can bear a more meaningful relation to the direction and magnitude of asset returns.

In establishing a theoretical microstructure, researchers skillfully deal with this problem by imposing one of two common assumptions about investors' order submissions. The first assumption is that informed investors submit market orders and uninformed investors submit limit orders (e.g., Glosten, 1994; Seppi, 1997). The alternative assumption is that limit orders are submitted by patient investors, who expect better transaction prices as a tradeoff for non-execution risk and offer liquidity to impatient investors, who submit market orders to look for immediate execution. In addition, some research studies (e.g., Ranaldo, 2004; Foucault et al., 2005) classify investors according to their patience, i.e. eager investors are apt to submit aggressive orders while patient investors are apt to submit less aggressive orders. Thus, order submissions likely rely on information (e.g., Glosten, 1994; Seppi, 1997), as well as investors' patience or urgency (e.g., Harris, 1998; Ranaldo, 2004; Foucault et al., 2005).

Moreover, some studies demonstrate that order imbalances from different investor types play different roles. For example, Lee et al. (2004) conclude that all investor types are successful *de facto* market makers on the Taiwan Stock Exchange (TWSE), a purely order-driven market. In addition, large domestic institutions are the most informed investors, while large individuals are noise or liquidity investors on the TWSE. Boehmer and Wu

[1] See Fama (1970) for a review.

(2008) investigate the relationship between price returns and order imbalances for the stocks listed on the NYSE by investor types. They show that individuals, specialists, and other market makers appear to provide liquidity to actively trading institutions, and institutional non-program imbalances have predictive power for next-day returns. Although traditionally individual investors are regarded as less informed and more sentimental, and institutional investors are regarded as more informed and professional, some recent research studies (Barber et al., 2009; Kaniel et al., 2008) point out that individual investors can be correct in trading. To the best of my knowledge, these studies do not include any direct perspective related to investors' behaviors. That said, research demonstrates that asset returns are affected by weather, and some studies show that order imbalances by investor types differently affect asset returns (e.g., Lee et al., 2004; Boehmer and Wu, 2008; Barber et al., 2009).

In this study, I analyze investors' order submissions and order imbalances from a behavioral perspective affected by weather other than any particular individual's sentiment. This approach is interesting because studies demonstrate weather affects assets' returns (Saunders, 1993; Hirshleifer and Shumway, 2003), but no study finds direct evidence to explain the relationship by investor's behaviors. The unique data set from Taiwan Futures Exchange (TAIFEX) allows us to identify order submissions from individual and institutional investors, enabling us to explore individual and institutional investors' submission behavior. On the whole, I control for the effect of asset returns and investigate the relationship between weather and order imbalances.

Furthermore, the period under study, which covers the duration of dot-com bubble and financial tsunami, allows us to better understand whether weather differently affects individual and institutional investors during financial crises. First, the dot-com bubble was a historical speculative bubble covering roughly 1997-2000 during which stock markets in many countries experienced their equity value rise rapidly from growth in the Internet sector and related fields. The period was marked by the start-ups of a group of innovative Internet-based companies commonly referred to as dot-coms. However, the stock prices also raised sharply as long as the existent companies added an "e-" prefix to their names and/or a ".com" to the end. The dot-com bubble burst on March 10, 2000, when the NASDAQ Composite index, peaked at daily close 5,048.62, more than double its value just a year ago. On March 20, 2000, however, the NASDAQ Composite index lost more than 10 percent from its peak. Second, many economists consider the financial crisis of 2007-2008 is the worst financial crisis since the Great Depression of the 1930s. It resulted in the threat of total collapse of large financial institutions and melting down stock market capitalization around the world. The active phase of the crisis, which manifested as a liquidity crisis, can be dated from August 7, 2007, when BNP Paribas terminated withdrawals from three hedge funds citing a complete evaporation of liquidity.

This paper contributes by exploring the impact of weather on order imbalances. Although weather does not significantly effect market and limit order imbalances of both individual and institutional investors, order imbalances of individual and institutional investors are differently influenced by weather during financial crises. Furthermore, this study broadens the understanding of the effects of weather on order imbalances from different investor types when I control the influence of price movements. To the best of our knowledge, the study is the first to empirically examine such relationships.

The remainder of the paper is organized as follows. Section 1 presents the data from TAIFEX and introduces the methodology, section 2 presents the empirical findings regarding order imbalances, and the final section summarizes the results and concludes.

1. Data and methodology

1.1. Data. In the 10 years since its establishment in 1998, the Taiwan Futures Exchange (TAIFEX) has become a high-volume exchange in the derivatives market. As of the end of 2007, stock index contracts, interest contracts, and gold futures and options contracts are all traded on the TAIFEX. The number of trading accounts for individual (institutional) investors has grown from 303,438 (1,604) in 2000 to 1,143,031 (6,355) in 2007. Individual investors account for 99.45% of the total trading accounts. For 2007, the average daily trading volume has been 466,197 contracts, making the yearly volume 115,150,624 contracts, and making TAIFEX rank 21st among the derivatives exchange in the world, according to the Futures Industry Association (FIA). The trading hours for TAIFEX are 8:45 a.m. to 1:45 p.m.

Among several futures contracts traded on the TAIFEX, the Taiwan Stock Exchange Capitalization Weighted Stock Index Futures (TXF) are the most important. TXF is a stock index future whose underlying asset is the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX)[1] of the TWSE. The contract size of TXF is 200 New

[1] TAIEX is similar to the Standard & Poor's 500, weighted by the number of outstanding shares.

Taiwan Dollars[1] (NTD) per index point, and the tick size (minimum price fluctuation) is 1 index point. Across 2007, the trading volume of TXF was 11,813,150 contracts. Institutional investors are responsible for 28.67% of TXF trading volume. Therefore, both individual and institutional investors play important roles on TXF, and this offers us a good opportunity to explore the effects of weather on different types of investors.

In this study, I use a database from the TAIFEX that includes the unique orders and transactions for TXF. The period under study, which covers the durations of the dot-com bubble and the financial tsunami, is January 4th, 2000 through December 31st, 2007 (1,977 trading days). The order database includes contract code, order date, time, price, volume, code for new order/cancellation/emendation, and the identity of the investor. The transaction database includes contract code, transaction date, time, order type (i.e. market or limit order), price, buy and sell volumes and the identity of the investor. The database makes it possible to identify individual and institutional investors.

I obtain the daily weather data, which include cloudiness (in decile), precipitation (in millimeters), temperature (in degrees Celsius), and relative humidity (in percentage), from the Taipei Office of the Central Weather Bureau, Ministry of Transportation and Communications, Taiwan. Only the weather in Taipei City is investigated because the TWSE is located in Taipei City, and the weather on the location of the exchange is the most important (Goetzmann and Zhu, 2005). In addition, 78.42% of Futures Commission Merchants (FCMs) in Taiwan are located in Taipei City[2] at the end of 2007.

1.2. Methodology. This study aims to investigate the relationship between weather and order imbalances. Nevertheless, it is risky to make conjectures about the relationship by regressing order imbalances against *only* weather, because information is a major driver of order imbalances (e.g., Easley et al., 1998; Chordia and Subrahmanyam, 2004). Since prices adjust to the release of information, I define a control variable r as the natural logarithm of the TAIEX.

Furthermore, I define six order imbalances for the analysis:

$$OI_{ind}^{mkt} = ({}^{mkt}SV_{ind}^{buy} - {}^{mkt}SV_{ind}^{sell}) / ({}^{mkt}SV_{ind}^{buy} + {}^{mkt}SV_{ind}^{sell}),\ OI_{ind}^{\lim} = ({}^{\lim}SV_{ind}^{buy} - {}^{\lim}SV_{ind}^{sell}) / ({}^{\lim}SV_{ind}^{buy} + {}^{\lim}SV_{ind}^{sell})$$

$$OI_{inst}^{mkt} = ({}^{mkt}SV_{inst}^{buy} - {}^{mkt}SV_{inst}^{sell}) / ({}^{mkt}SV_{inst}^{buy} + {}^{mkt}SV_{inst}^{sell}),\ OI_{inst}^{\lim} = ({}^{\lim}SV_{inst}^{buy} - {}^{\lim}SV_{inst}^{sell}) / ({}^{\lim}SV_{inst}^{buy} + {}^{\lim}SV_{inst}^{sell}),$$

$$OI_{entire}^{mkt} = ({}^{mkt}SV_{ind}^{buy} + {}^{mkt}SV_{inst}^{buy} - {}^{mkt}SV_{ind}^{sell} - {}^{mkt}SV_{inst}^{sell}) / ({}^{mkt}SV_{ind}^{buy} + {}^{mkt}SV_{inst}^{buy} + {}^{mkt}SV_{ind}^{sell} + {}^{mkt}SV_{inst}^{sell}),$$

and $OI_{entire}^{\lim} = ({}^{\lim}SV_{ind}^{buy} + {}^{\lim}SV_{inst}^{buy} - {}^{\lim}SV_{ind}^{sell} - {}^{\lim}SV_{inst}^{sell}) / ({}^{\lim}SV_{ind}^{buy} + {}^{\lim}SV_{inst}^{buy} + {}^{\lim}SV_{ind}^{sell} + {}^{\lim}SV_{inst}^{sell}),$

where ${}^{mkt}SV_{ind}^{buy}$ (${}^{mkt}SV_{ind}^{sell}$) and ${}^{\lim}SV_{ind}^{buy}$ (${}^{\lim}SV_{ind}^{sell}$) are market buy (sell) order submission in volume and limit order buy (sell) submission in volume from individual investors, respectively; ${}^{mkt}SV_{inst}^{buy}$ (${}^{mkt}SV_{inst}^{sell}$) and ${}^{\lim}SV_{inst}^{buy}$ (${}^{\lim}SV_{inst}^{sell}$) are market buy (sell) order submission in volume and limit order buy (sell) submission in volume from institutional investors, respectively. In addition, since investors face alternatives for submitting market orders and limit orders, market order imbalances and limit order imbalances may be correlated. Thus, I apply a multivariate multiple regression model, which takes into account the relationships between the multiple dependent variables when investigating the effect of weather on order imbalances. In particular, the models include cloud cover (*CD*, the daily cloud cover in decile), precipitation (*PP*, the daily precipitation in millimeters), temperature (*TX*, the daily temperature in degrees Celsius), and relative humidity (*RH*, the daily relative humidity in percentage) as independent variables to detect the weather effects on individual and institutional investors. In addition, to better understand whether weather differently effects individual and institutional investors during financial crises, two dummy variables, D_{dc} and D_{ft} are set, where D_{dc} = 1 for the year 2000 during which dot-com bubble burst, and D_{dc} = 0 otherwise; D_{ft} = 1 for the year 2007, during which financial tsunami initiated and D_{ft} = 0 otherwise. The winter dummy D_w = 1 for December, January, and February, and D_w = 0 otherwise. In addition, the summer dummy D_s is set because the weather of Taiwan in summer is also extreme (D_s = 1 for June, July, and September and D_s = 0 otherwise). Furthermore, the dummy variables, D_{Mon}, D_{Dec} and D_{Jan}, are set to verify the existence of Monday effect (e.g., Wang et al., 1997; Jaffe et al., 1989), December effect (e.g., Berges, 1984), and January effect (e.g., Seyhun, 1988). In order to detect whether the weather effects are different during winter, summer, and the financial crises, the intersection terms between weather variables and D_{dc}, D_{ft}, D_w, and D_s are set. Thus, for the entire market the models are:

[1] The currency rate is about 32.8 NTD per USD at the end of 2007.

[2] There are 139 FCMs and only 30 of them are located outside Taipei City in Taiwan at the end of 2007. These statistics are available from Chinese National Futures Association, website: www.futures.org.tw.

$$\begin{aligned}
OI_{entire}^{mkt} &= \alpha_1 + \beta_{1,1}D_{dc} + \beta_{1,2}D_{ft} + \beta_{1,3}D_w + \beta_{1,4}D_s + \beta_{1,5}D_{Mon} + \beta_{1,6}D_{Dec} + \beta_{1,7}D_{Jan} + \rho_1 r + \\
&+ \lambda_{1,1}CD + \lambda_{1,2}PP + \lambda_{1,3}TX + \lambda_{1,4}RH + \gamma_{1,1}D_{dc}CD + \gamma_{1,2}D_{dc}PP + \gamma_{1,3}D_{dc}TX + \gamma_{1,4}D_{dc}RH + \\
&+ \gamma_{1,5}D_{ft}CD + \gamma_{1,6}D_{ft}PP + \gamma_{1,7}D_{ft}TX + \gamma_{1,8}D_{ft}RH + \delta_{1,1}D_wCD + \delta_{1,2}D_wPP + \delta_{1,3}D_wTX + \\
&+ \delta_{1,4}D_wRH + \delta_{1,5}D_sCD + \delta_{1,6}D_sPP + \delta_{1,7}D_sTX + \delta_{1,8}D_sRH + \varepsilon_1 \\
OI_{entire}^{\lim} &= \alpha_2 + \beta_{2,1}D_{dc} + \beta_{2,2}D_{ft} + \beta_{2,3}D_w + \beta_{2,4}D_s + \beta_{2,5}D_{Mon} + \beta_{2,6}D_{Dec} + \beta_{2,7}D_{Jan} + \rho_2 r + \\
&+ \lambda_{2,1}CD + \lambda_{2,2}PP + \lambda_{2,3}TX + \lambda_{2,4}RH + \gamma_{2,1}D_{dc}CD + \gamma_{2,2}D_{dc}PP + \gamma_{2,3}D_{dc}TX + \gamma_{2,4}D_{dc}RH + \\
&+ \gamma_{2,5}D_{ft}CD + \gamma_{2,6}D_{ft}PP + \gamma_{2,7}D_{ft}TX + \gamma_{2,8}D_{ft}RH + \delta_{2,1}D_wCD + \delta_{2,2}D_wPP + \delta_{2,3}D_wTX + \\
&+ \delta_{2,4}D_wRH + \delta_{2,5}D_sCD + \delta_{2,6}D_sPP + \delta_{2,7}D_sTX + \delta_{2,8}D_sRH + \varepsilon_2,
\end{aligned} \tag{1}$$

and for individual and institutional investors, the models are:

$$\begin{aligned}
OI_{ind}^{mkt} &= \alpha_1 + \beta_{1,1}D_{dc} + \beta_{1,2}D_{ft} + \beta_{1,3}D_w + \beta_{1,4}D_s + \beta_{1,5}D_{Mon} + \beta_{1,6}D_{Dec} + \beta_{1,7}D_{Jan} + \rho_1 r + \\
&+ \lambda_{1,1}CD + \lambda_{1,2}PP + \lambda_{1,3}TX + \lambda_{1,4}RH + \gamma_{1,1}D_{dc}CD + \gamma_{1,2}D_{dc}PP + \gamma_{1,3}D_{dc}TX + \gamma_{1,4}D_{dc}RH + \\
&+ \gamma_{1,5}D_{ft}CD + \gamma_{1,6}D_{ft}PP + \gamma_{1,7}D_{ft}TX + \gamma_{1,8}D_{ft}RH + \delta_{1,1}D_wCD + \delta_{1,2}D_wPP + \delta_{1,3}D_wTX + \\
&+ \delta_{1,4}D_wRH + \delta_{1,5}D_sCD + \delta_{1,6}D_sPP + \delta_{1,7}D_sTX + \delta_{1,8}D_sRH + \varepsilon_1 \\
OI_{ind}^{\lim} &= \alpha_2 + \beta_{2,1}D_{dc} + \beta_{2,2}D_{ft} + \beta_{2,3}D_w + \beta_{2,4}D_s + \beta_{2,5}D_{Mon} + \beta_{2,6}D_{Dec} + \beta_{2,7}D_{Jan} + \rho_2 r + \\
&+ \lambda_{2,1}CD + \lambda_{2,2}PP + \lambda_{2,3}TX + \lambda_{2,4}RH + \gamma_{2,1}D_{dc}CD + \gamma_{2,2}D_{dc}PP + \gamma_{2,3}D_{dc}TX + \gamma_{2,4}D_{dc}RH + \\
&+ \gamma_{2,5}D_{ft}CD + \gamma_{2,6}D_{ft}PP + \gamma_{2,7}D_{ft}TX + \gamma_{2,8}D_{ft}RH + \delta_{2,1}D_wCD + \delta_{2,2}D_wPP + \delta_{2,3}D_wTX + \\
&+ \delta_{2,4}D_wRH + \delta_{2,5}D_sCD + \delta_{2,6}D_sPP + \delta_{2,7}D_sTX + \delta_{2,8}D_sRH + \varepsilon_2 \\
OI_{inst}^{mkt} &= \alpha_3 + \beta_{3,1}D_{dc} + \beta_{3,2}D_{ft} + \beta_{3,3}D_w + \beta_{3,4}D_s + \beta_{3,5}D_{Mon} + \beta_{3,6}D_{Dec} + \beta_{3,7}D_{Jan} + \rho_3 r + \\
&+ \lambda_{3,1}CD + \lambda_{3,2}PP + \lambda_{3,3}TX + \lambda_{3,4}RH + \gamma_{3,1}D_{dc}CD + \gamma_{3,2}D_{dc}PP + \gamma_{3,3}D_{dc}TX + \gamma_{3,4}D_{dc}RH + \\
&+ \gamma_{3,5}D_{ft}CD + \gamma_{3,6}D_{ft}PP + \gamma_{3,7}D_{ft}TX + \gamma_{3,8}D_{ft}RH + \delta_{3,1}D_wCD + \delta_{3,2}D_wPP + \delta_{3,3}D_wTX + \\
&+ \delta_{3,4}D_wRH + \delta_{3,5}D_sCD + \delta_{3,6}D_sPP + \delta_{3,7}D_sTX + \delta_{3,8}D_sRH + \varepsilon_3 \\
OI_{inst}^{\lim} &= \alpha_4 + \beta_{4,1}D_{dc} + \beta_{4,2}D_{ft} + \beta_{4,3}D_w + \beta_{4,4}D_s + \beta_{4,5}D_{Mon} + \beta_{4,6}D_{Dec} + \beta_{4,7}D_{Jan} + \rho_4 r + \\
&+ \lambda_{4,1}CD + \lambda_{4,2}PP + \lambda_{4,3}TX + \lambda_{4,4}RH + \gamma_{4,1}D_{dc}CD + \gamma_{4,2}D_{dc}PP + \gamma_{4,3}D_{dc}TX + \gamma_{4,4}D_{dc}RH + \\
&+ \gamma_{4,5}D_{ft}CD + \gamma_{4,6}D_{ft}PP + \gamma_{4,7}D_{ft}TX + \gamma_{4,8}D_{ft}RH + \delta_{4,1}D_wCD + \delta_{4,2}D_wPP + \delta_{4,3}D_wTX + \\
&+ \delta_{4,4}D_wRH + \delta_{4,5}D_sCD + \delta_{4,6}D_sPP + \delta_{4,7}D_sTX + \delta_{4,8}D_sRH + \varepsilon_{4.}
\end{aligned} \tag{2}$$

In model (1), I assume that the random vector (ε_1, ε_2) follows a multivariate normal distribution with mean zero and variance Σ_2, where Σ_2 is a 2 × 2 positive definite matrix. In model (2), I assume that the random vector (ε_1, ε_2, ε_3, ε_4) follows a multivariate normal distribution with mean zero and variance Σ_1, where Σ_1 is a 4 × 4 positive definite matrix.

2. Empirical analysis

In this section, I begin the analysis by examining the summary statistics for the weather in Taipei City. Then I analyze the coefficients of correlation between returns, order imbalances and weather, respectively. Finally, I investigate the relationships between weather and order imbalances for the entire market and individual as well as institutional investors, respectively. In particular, the influence of information on order imbalances is controlled, and the dummy variables D_{dc} and D_{ft} for the periods of dot-com bubble financial tsunami and are set to explore whether the relationships are different during financial crises.

2.1. Summary statistics. Based on the weather database, I first calculate the basic statistics of daily weather in Taipei City during 2000 through 2007. Table 1 presents the summary statistics of daily weather in Taipei City during the sample period. Obviously, it is a cloudy city because Panel A of Table 1 shows that the mean of *CD* is 8.81 for the entire period. Interestingly, Panel B of Table 1 shows that the weather is apparently hotter in summer (June through September) and colder in winter (December through March). Also, it shows that the weather is more humid in winter than in summer. However, the seasonal pattern for precipitation is not clear during the sample period. In addition, Panel C of Table 2 presents the weather by year. In particular, I examine the differences of weather between years 2000 and 2007 because this paper aims to investigate whether weather differently effects order imbalances during financial crises, doc-com bubble in 2000 and financial tsunami in 2007. The results show that it is more cloudy and humid in 2000 because the means of *CD* and *RH* in 2000 are larger than those in 2007 at the 5% significance level. However, the precipitation and temperature are not significantly different.

To observe the univariate relationships, I calculate the coefficients of correlation among returns, order imbalances, and weather variables. Table 2 shows that the relationships between returns and market order imbalances of both individual and institutional investors are highly positive (0.726269 for individual and 0.718463 for institutional). However, the relationships are slightly negative for limit orders of both of them (-0.071260 for individual investors and -0.047552 for institutional investors). Furthermore, the coefficients between returns and weather variables are all negative, indicating that cloudy, rainy, hot and humid weather are associated with negative returns. In particular, the coefficients among order imbalances are high (*e.g.*, 0.975266 for OI_{ind}^{mkt} and OI_{inst}^{mkt}, and 0.683203 for $OI_{ind}^{\lim}$ and $OI_{inst}^{\lim}$), consistent the conjecture that market order imbalances and limit order imbalances may be correlated. On the other hand, the weather variables are also correlated, e.g., cloudy, rainy, and cool days are more humid (coefficient of correlation = 0.609521, 0.358913, and -0.433920 for *RH* and *CD*, *RH* and *PP*, and *RH* and *TX*, respectively).

2.2. Analysis of daily order imbalances for the entire market. To assess whether weather drives market/limit order imbalances, I perform multivariate multiple regression using models (1) and (2). Investors may submit market and limit orders that cause imbalances, and multivariate multiple regression takes into account not only the relationships between independent variables and dependent variables, but also the relationships between the dependent variables. The results in Table 3 show that information is the key driving force for market order imbalances for the entire market as evidenced by ρ_1 being highly significantly positive (*t* value = 46.053). Moreover, it is consistent with Lee et al. (2004) that limit orders provide liquidity as evidenced by ρ_2 being negative at the 1% significance level. Interestingly, the results show that January effect (e.g., Seyhun, 1988) exists through limit order imbalances as evidenced by $\beta_{2,7}$ being positive at the 1% significance level and $\beta_{2,6}$ being insignificantly negative, i.e. investors sell in December and buy in January. Again, it shows investors are likely to submit market orders on information, because the corresponding coefficients in the regression for market order imbalances, $\beta_{1,7}$ and $\beta_{1,6}$, are not significantly different from zero. On the other hand, weather does not significantly effect market order imbalances of the entire market since $\lambda_{1,1}$, $\lambda_{1,2}$, $\lambda_{1,3}$, and $\lambda_{1,4}$ are not different from zero at the 10% significance level. However, the relationship between temperature and limit order imbalances of the entire market is positive as evidenced by $\lambda_{2,3}$ being positive at the 1% level. Interestingly, it shows that limit order imbalances lean against the wind during the dot-com bubble period as evidenced by $\beta_{2,1}$ being positive at the 1% significance level. However, it is less evident during the financial tsunami period because the *t*-value of $\beta_{2,2}$ is only 1.612. Furthermore, the coefficients on the intersection terms show that the limit order imbalances of the entire market react differently to weather during financial crises. That is, the coefficients $\lambda_{2,3}$ for the dot-com bubble period and $\lambda_{2,7}$ for the financial tsunami period are respectively negative at the 10% and 1% significance level, contrasting to $\lambda_{2,3}$ being positive at the 1% level. In addition, the coefficients $\lambda_{2,1}$ and $\lambda_{2,2}$ for the dot-com bubble period are respectively negative at the 10% and 5% significance level, contrasting to $\lambda_{2,1}$ and $\lambda_{2,2}$ being insignificantly positive.

2.3. Analysis of daily order imbalances for individual and institutional investors. In this section, I further analyze market and limit order imbalances by dividing the entire market into individual and institutional investors, because individual and institutional investors are like play different roles in financial markets (e.g., Boehmer and Wu, 2008). As Table 4 shows, information is the key driver for market order imbalances both for individual and institutional investors as evidenced by ρ_1 and ρ_3 being both positive at the 1% significance level. In addition, limit orders of both individual and institutional investors provide liquidity as evidenced by both ρ_2 and ρ_4 being negative at the 1% significance level. With respect to January effects, it is more significant for individual investors than institutional investors that sell more through limit orders in December as evidenced by only $\beta_{2,6}$ being negative at the 10% significance level, whereas both individual and institutional investors buy more through limit orders in January as evidenced by both $\beta_{2,7}$ and $\beta_{2,7}$ being significantly positive at the 1% level. Weather does not significantly effect market order imbalances of individual and institutional investors as evidenced by $\lambda_{1,1}$, $\lambda_{1,2}$, $\lambda_{1,3}$, $\lambda_{1,4}$, $\lambda_{3,1}$, $\lambda_{3,2}$, $\lambda_{3,3}$, and $\lambda_{3,4}$ being insignificantly different from zero. Weather neither effects limit order imbalances of institutional investors as evidenced by $\lambda_{4,1}$, $\lambda_{4,2}$, $\lambda_{4,3}$, and $\lambda_{4,4}$ being insignificant at the 10% level. Furthermore, it shows that individual investors submit more limit buy orders during hot days as evidenced by $\lambda_{2,3}$ being positive at the 1% level.

As previously mentioned, Table 3 shows that limit order imbalances of the entire market lean against the wind during financial crises. The results of Table 4 further demonstrate that individual investors misjudge the market rather than institutional investors as evidenced by $\beta_{2,1}$ and $\beta_{2,2}$ being positive at the 10% and 1% significance level, respectively, whereas $\beta_{4,1}$ and $\beta_{4,2}$ are insignificant at the 10% level. In addition, limit order imbalances of the entire market react differently to temperature during financial crises. Interestingly, the results of Table 4 indicate that individual investors are responsible for the different response on temperature rather than institutional investors. That is, $\gamma_{2,3}$ and $\gamma_{2,7}$ are negative at the 5% and 1% significance level, respectively. However, both $\gamma_{4,3}$ and $\gamma_{4,7}$ are insignificantly negative at the 10% level.

On the other hand, both individual and institutional investors are partly responsible for the different responses upon cloud and precipitation during the dot-com bubble period as evidenced by $\gamma_{2,1}$ and $\gamma_{2,2}$ being negative at the 10% significance level and $\gamma_{4,1}$ and $\gamma_{4,2}$ being negative at the 5% and 1% significance level, respectively. However, the results show that no significant responses upon cloud and precipitation happen to market order imbalances of both individual and institutional investors during the financial tsunami period. I conjecture the possibilities that lead the differences. First, temperature influences individual investors more than institutional investors. During relatively calm periods, high temperature stimulates individual investors to act aggressively to buy. In contrast, during panic periods, high temperature pushes individual to act aggressively to sell. However, the effects of temperature on order imbalances of institutional investors are not significant. Second, the sample period may make the difference. It is recognized that the dot-com bubble ended in 2000, but 2007 may be the beginning of the financial tsunami.

In sum, the above findings reveal that weather does not significantly effect market and limit order imbalances of both individual and institutional investors. However, order imbalances of individual and institutional investors are differently influenced by weather during financial crises.

Summary and conclusions

Order imbalances are associated with asset price movements in financial markets. This implies that order submissions are informative because order submissions directly determine both order imbalances and asset price movements when new information is released. Our dataset provides a good opportunity to study the order submissions from individual and institutional investors in order to understand the influence of weather on each investor type.

This study applies the unique order database on the TAIEX futures (TXF) to document that weather does not significantly effect market order imbalances of the entire market, but the relationship between temperature and limit order imbalances of the entire market is positive. Interestingly, it shows that limit order imbalances of the entire market lean against the wind during the dot-com bubble period. Although weather does not significantly effect market order imbalances of individual and institutional investors, it shows that individual investors submit more limit buy orders during hot days. Moreover, individual investors misjudge the market rather than institutional investors. In addition, limit order imbalances of the entire market react differently to temperature during financial crises, and individual investors are responsible for the different response on temperature rather than institutional investors. On the other hand, both individual and institutional investors are partly responsible for the different responses upon cloud and precipitation during the dot-com bubble period. During relatively calm periods, high temperature stimulates individual investors to act aggressively to buy. In contrast, during panic periods, high temperature pushes individual to act aggressively to sell.

In sum, although weather does not significantly effect market and limit order imbalances of both individual and institutional investors, order imbalances of individual and institutional investors are differently influenced by weather during financial crises. The findings of this study indicates the necessity for future study on individual investors' abnormal behaviors during financial crises.

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Appendix

Table 1. Summary statistics of daily weather in Taipei City, 2000-2007

	Cloud (*CD*, in decile)					Precipitation (*PP*, in mm)					Temperature (*TX*, in ℃)					Humidity (*RH*, in %)				
	Mean	Median	Max	Min	S.D.	Mean	Median	Max	Min	S.D.	Mean	Median	Max	Min	S.D.	Mean	Median	Max	Min	S.D.
Panel A. Entire period																				
	8.81	9.00	10.00	0.00	2.07	1.243	0.000	142.50	0.00	5.603	25.00	25.37	35.50	9.23	5.81	71.40	69.50	99.67	41.83	11.36
Panel B. By month																				
January	8.54	9.50	10.00	0.67	1.98	0.856	0.000	27.50	0.00	3.209	17.49	17.72	24.67	10.32	3.17	75.25	76.33	99.67	50.83	11.92
February	8.17	9.50	10.00	1.17	2.38	0.941	0.000	18.30	0.00	2.676	18.67	18.47	25.55	10.72	3.81	73.86	73.50	96.33	48.83	13.01
March	8.55	9.50	10.00	1.67	1.96	1.341	0.000	27.80	0.00	3.860	20.05	20.00	28.67	11.37	4.02	73.40	73.17	96.83	42.67	13.27
April	8.51	8.67	10.00	0.00	2.16	1.937	0.000	35.40	0.00	6.229	23.77	23.52	31.85	14.73	4.07	73.19	73.33	98.00	41.83	12.10
May	8.44	9.33	10.00	0.00	1.95	1.442	0.000	37.00	0.00	5.024	27.50	27.58	34.02	18.93	3.08	71.18	70.25	96.33	47.33	11.37
June	8.37	9.00	10.00	3.33	1.67	1.488	0.000	58.00	0.00	6.943	30.05	30.52	34.52	18.42	2.71	70.19	67.67	95.50	51.33	10.05
July	7.46	7.83	10.00	1.00	1.89	1.162	0.000	56.50	0.00	5.798	32.08	32.40	35.50	26.62	1.76	65.34	64.00	98.50	48.50	8.61
August	7.50	7.83	10.00	1.00	2.13	1.043	0.000	27.00	0.00	3.900	31.58	31.87	35.22	27.02	1.61	67.09	65.50	90.17	50.83	7.81
September	7.82	8.33	10.00	0.67	2.19	1.885	0.000	37.50	0.00	5.882	29.18	29.54	32.98	22.68	2.36	70.44	67.50	98.17	51.50	10.74
October	7.95	8.50	10.00	1.00	2.14	0.391	0.000	20.00	0.00	1.757	26.13	25.77	31.92	19.38	2.73	70.21	68.33	95.33	51.67	10.59
November	8.32	9.33	10.00	1.17	2.03	1.780	0.000	142.50	0.00	11.410	22.85	22.37	29.87	15.58	3.05	72.91	73.50	96.33	47.00	11.90
December	8.49	9.33	10.00	0.00	2.02	0.570	0.000	23.50	0.00	2.519	19.53	19.85	26.35	9.23	3.35	74.03	74.17	96.17	47.17	10.09
Panel C. By year																				
2000	8.90	9.50	10.00	5.00	1.36	1.784	0.000	142.50	0.00	9.993	24.74	25.13	34.32	10.32	5.92	73.22	72.00	98.00	47.83	11.89
2001	8.66	9.33	10.00	3.50	1.57	1.243	0.000	37.50	0.00	4.616	24.28	23.93	34.33	12.20	5.56	71.25	69.50	98.17	46.00	11.87
2002	8.50	9.00	10.00	5.00	4.53	0.796	0.000	38.00	0.00	3.340	25.53	26.66	34.52	11.58	5.67	70.34	68.17	98.50	42.67	11.70
2003	8.49	8.83	10.00	3.33	1.48	0.840	0.000	34.50	0.00	3.696	25.17	25.67	35.50	12.02	6.02	71.80	70.00	95.67	52.50	10.57
2004	8.25	8.67	10.00	4.00	1.62	1.006	0.000	28.00	0.00	3.860	24.82	24.85	33.97	9.23	5.71	69.27	66.92	96.17	41.83	11.73
2005	7.51	8.33	10.00	0.00	2.71	1.106	0.000	37.00	0.00	4.177	25.01	26.42	34.03	10.93	6.29	71.60	69.00	96.33	47.17	10.87
2006	7.66	8.67	10.00	1.00	2.58	1.476	0.000	31.30	0.00	4.524	25.24	25.70	34.47	11.37	5.60	72.71	71.67	93.17	49.50	10.58
2007	7.48	8.33	10.00	0.00	2.62	1.574	0.000	58.00	0.00	6.685	25.19	25.40	34.75	11.90	5.61	70.84	69.00	99.67	47.17	11.20
Difference between 2000 and 2007	1.42					0.210					-0.45					2.38				
t-value	7.876***					0.284					-0.888					2.350**				

Notes: This table presents the basic statistics of daily weather in Taipei City. The period covers from January 4th, 2000 through December 31st, 2007 (1977 trading days). The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2. Coefficients of correlation between returns, order imbalances and weather

	r	OI_{ind}^{mkt}	$OI_{ind}^{\lim}$	OI_{inst}^{mkt}	$OI_{inst}^{\lim}$	CD	PP	TX	RH
r	1.000000	0.726269	-0.071260	0.718463	-0.047552	-0.018950	-0.048614	-0.034413	-0.021442
OI_{ind}^{mkt}		1.000000	0.148504	0.975266	0.230704	-0.006586	-0.027911	-0.042279	-0.004123
$OI_{ind}^{\lim}$			1.000000	0.152276	0.683203	-0.097045	0.000161	0.103304	-0.045881
OI_{inst}^{mkt}				1.000000	0.237613	-0.011597	-0.035433	-0.039403	-0.006806
$OI_{inst}^{\lim}$					1.000000	-0.026854	0.003660	0.057159	-0.051895
CD						1.000000	0.167037	-0.377201	0.609521
PP							1.000000	-0.106244	0.358913
TX								1.000000	-0.433920
RH									1.000000

Notes: This table presents the relationships between returns, order imbalances and weather, respectively. r, OI_{ind}^{mkt}, $OI_{ind}^{\lim}$, OI_{inst}^{mkt}, $OI_{inst}^{\lim}$, CD, PP, TX and RH stands for returns of TAIEX (in %), market order imbalances of individual investors (in %), limit order imbalances of individual investors (in %), market order imbalances of institutional investors (in %), limit order imbalances of institutional investors (in %), cloud (in decile), precipitation (in mm), temperature (in ℃), and relative humidity (in %), respectively.

Table 3. Analysis of weather and order imbalances for the entire market model (1)

	OI_{entire}^{mkt}				$OI_{entire}^{\lim}$		
	Estimate	Std. error	*t*-value		Estimate	Std. error	*t*-value
α_1	-0.00682	0.04307	-0.158	α_2	-0.05707	0.03859	-1.479
$\beta_{1,1}$	0.02601	0.09330	0.279	$\beta_{2,1}$	0.16220	0.08358	1.941*
$\beta_{1,2}$	-0.03123	0.07930	-0.394	$\beta_{2,2}$	0.11450	0.07104	1.612
$\beta_{1,3}$	-0.01014	0.06665	-0.152	$\beta_{2,3}$	0.18690	0.05971	3.130***
$\beta_{1,4}$	-0.22983	0.18810	-1.222	$\beta_{2,4}$	0.12820	0.16850	0.761
$\beta_{1,5}$	0.00268	0.00613	0.438	$\beta_{2,5}$	0.00307	0.00550	0.558
$\beta_{1,6}$	-0.00527	0.00939	-0.561	$\beta_{2,6}$	-0.01268	0.00842	-1.507
$\beta_{1,7}$	0.00289	0.01110	0.260	$\beta_{2,6}$	0.02869	0.00994	2.886***
ρ_1	7.28601	0.15821	46.053***	ρ_2	-0.45430	0.14170	-3.205***
$\lambda_{1,1}$	0.00225	0.00228	0.987	$\lambda_{2,1}$	0.00046	0.00205	0.224
$\lambda_{1,2}$	0.00105	0.00089	1.184	$\lambda_{2,2}$	0.00117	0.00080	1.470
$\lambda_{1,3}$	-0.00037	0.00098	-0.374	$\lambda_{2,3}$	0.00280	0.00088	3.183***
$\lambda_{1,4}$	-0.00042	0.00044	-0.961	$\lambda_{2,4}$	0.00017	0.00039	0.436
$\gamma_{1,1}$	-0.00165	0.00676	-0.245	$\gamma_{2,1}$	-0.01140	0.00606	-1.883*
$\gamma_{1,2}$	-0.00151	0.00106	-1.417	$\gamma_{2,2}$	-0.00212	0.00095	-2.225**
$\gamma_{1,3}$	-0.00075	0.00157	-0.482	$\gamma_{2,3}$	-0.00261	0.00140	-1.862*
$\gamma_{1,4}$	-0.00021	0.00092	-0.224	$\gamma_{2,4}$	-0.00009	0.00083	-0.113
$\gamma_{1,5}$	-0.00222	0.00228	-0.973	$\gamma_{2,5}$	-0.00041	0.00205	-0.202
$\gamma_{1,6}$	0.00015	0.00147	0.104	$\gamma_{2,6}$	-0.00102	0.00132	-0.774
$\gamma_{1,7}$	0.00030	0.00147	0.203	$\gamma_{2,7}$	-0.00581	0.00131	-4.427***
$\gamma_{1,8}$	0.00063	0.00086	0.734	$\gamma_{2,8}$	0.00006	0.00077	0.084
$\delta_{1,1}$	-0.00309	0.00369	-0.837	$\delta_{2,1}$	-0.00652	0.00330	-1.973**
$\delta_{1,2}$	-0.00412	0.00214	-1.922*	$\delta_{2,2}$	0.00001	0.00192	0.007
$\delta_{1,3}$	-0.00155	0.00188	-0.823	$\delta_{2,3}$	-0.00431	0.00168	-2.564***
$\delta_{1,4}$	0.00101	0.00068	1.476	$\delta_{2,4}$	-0.00055	0.00061	-0.901
$\delta_{1,5}$	-0.00559	0.00361	-1.550	$\delta_{2,5}$	-0.00782	0.00323	-2.422***
$\delta_{1,6}$	-0.00041	0.00131	-0.313	$\delta_{2,6}$	0.00073	0.00117	0.621
$\delta_{1,7}$	0.00461	0.00421	1.096	$\delta_{2,7}$	-0.00289	0.00377	-0.766
$\delta_{1,8}$	0.00199	0.00112	1.776*	$\delta_{2,8}$	0.00063	0.00101	0.623
	Adjusted R-squared: 0.5296				Adjusted R-squared: 0.06034		

Notes: This table presents results of multivariate regressions of order imbalance against weather for the entire market on a daily basis. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. Analysis of weather and order imbalances for individual and institutional investors, model (2)

Panel A. Individual investors							
	OI_{ind}^{mkt}				$OI_{ind}^{\lim}$		
	Estimate	Std. error	*t*-value		Estimate	Std. error	*t*-value
α_1	0.00120	0.04337	0.028	α_2	-0.09034	0.04337	-2.083**
$\beta_{1,1}$	0.02118	0.09394	0.225	$\beta_{2,1}$	0.18140	0.09394	1.932*
$\beta_{1,2}$	-0.03543	0.07984	-0.444	$\beta_{2,2}$	0.18590	0.07985	2.328***
$\beta_{1,3}$	-0.02588	0.06710	-0.386	$\beta_{2,3}$	0.23410	0.06711	3.488***
$\beta_{1,4}$	-0.25190	0.18939	-1.330	$\beta_{2,4}$	0.11010	0.18940	0.581
$\beta_{1,5}$	0.00296	0.00618	0.479	$\beta_{2,5}$	0.00289	0.00618	0.467
$\beta_{1,6}$	-0.00620	0.00946	-0.656	$\beta_{2,6}$	-0.01735	0.00946	-1.834*
$\beta_{1,7}$	0.00317	0.01118	0.283	$\beta_{2,7}$	0.03046	0.01118	2.726***
ρ_1	7.31878	0.15930	45.945***	ρ_2	-0.53060	0.15930	-3.331***
$\lambda_{1,1}$	0.00230	0.00230	0.998	$\lambda_{2,1}$	0.00017	0.00230	0.075
$\lambda_{1,2}$	0.00106	0.00090	1.182	$\lambda_{2,2}$	0.00119	0.00090	1.332
$\lambda_{1,3}$	-0.00052	0.00099	-0.530	$\lambda_{2,3}$	0.00356	0.00099	3.607***
$\lambda_{1,4}$	-0.00047	0.00044	-1.077	$\lambda_{2,4}$	0.00041	0.00044	0.939
$\gamma_{1,1}$	-0.00118	0.00681	-0.173	$\gamma_{2,1}$	-0.01135	0.00681	-1.668*
$\gamma_{1,2}$	-0.00139	0.00107	-1.294	$\gamma_{2,2}$	-0.00205	0.00107	-1.918*
$\gamma_{1,3}$	-0.00070	0.00158	-0.445	$\gamma_{2,3}$	-0.00326	0.00158	-2.068**
$\gamma_{1,4}$	-0.00022	0.00093	-0.239	$\gamma_{2,4}$	-0.00016	0.00093	-0.172
$\gamma_{1,5}$	-0.00227	0.00230	-0.985	$\gamma_{2,5}$	-0.00009	0.00230	-0.041
$\gamma_{1,6}$	0.00016	0.00148	0.105	$\gamma_{2,6}$	-0.00147	0.00148	-0.991
$\gamma_{1,7}$	0.00034	0.00148	0.229	$\gamma_{2,7}$	-0.00880	0.00148	-5.963***
$\gamma_{1,8}$	0.00068	0.00086	0.793	$\gamma_{2,8}$	-0.00011	0.00086	-0.132
$\delta_{1,1}$	-0.00279	0.00371	-0.752	$\delta_{2,1}$	-0.00949	0.00371	-2.558***
$\delta_{1,2}$	-0.00402	0.00216	-1.864*	$\delta_{2,2}$	0.00007	0.00216	0.035
$\delta_{1,3}$	-0.00110	0.00189	-0.583	$\delta_{2,3}$	-0.00538	0.00189	-2.842***
$\delta_{1,4}$	0.00106	0.00069	1.550	$\delta_{2,4}$	-0.00054	0.00069	-0.780
$\delta_{1,5}$	-0.00555	0.00363	-1.529	$\delta_{2,5}$	-0.01166	0.00363	-3.212***
$\delta_{1,6}$	-0.00031	0.00132	-0.237	$\delta_{2,6}$	0.00038	0.00132	0.289
$\delta_{1,7}$	0.00501	0.00424	1.181	$\delta_{2,7}$	-0.00223	0.00424	-0.526
$\delta_{1,8}$	0.00214	0.00113	1.896*	$\delta_{2,8}$	0.00111	0.00113	0.978
	Adjusted *R*-squared: 0.5282				Adjusted *R*-squared: 0.0816		
Panel B. Institutional investors							
	OI_{inst}^{mkt}				$OI_{inst}^{\lim}$		
	Estimate	Std. error	*t*-value		Estimate	Std. error	*t*-value
α_3	-0.01986	0.04391	-0.452	α_4	0.01724	0.03651	0.472
$\beta_{3,1}$	0.03128	0.09512	0.329	$\beta_{4,1}$	0.11981	0.07908	1.515
$\beta_{3,2}$	-0.02481	0.08085	-0.307	$\beta_{4,2}$	-0.01326	0.06721	-0.197
$\beta_{3,3}$	0.01726	0.06795	0.254	$\beta_{4,3}$	0.08242	0.05649	1.459
$\beta_{3,4}$	-0.19502	0.19176	-1.017	$\beta_{4,4}$	0.16191	0.15943	1.016
$\beta_{3,5}$	0.00235	0.00625	0.376	$\beta_{4,5}$	0.00382	0.00520	0.734
$\beta_{3,6}$	-0.00388	0.00958	-0.405	$\beta_{4,6}$	-0.00328	0.00796	-0.411
$\beta_{3,7}$	0.00250	0.01132	0.221	$\beta_{4,7}$	0.02519	0.00941	2.678***
ρ_3	7.23489	0.16130	44.855***	ρ_4	-0.31612	0.13410	-2.357***
$\lambda_{3,1}$	0.00213	0.00233	0.917	$\lambda_{4,1}$	0.00173	0.00194	0.892
$\lambda_{3,2}$	0.00106	0.00091	1.163	$\lambda_{4,2}$	0.00109	0.00075	1.446
$\lambda_{3,3}$	-0.00010	0.00100	-0.104	$\lambda_{4,3}$	0.00101	0.00083	1.213
$\lambda_{3,4}$	-0.00033	0.00045	-0.741	$\lambda_{4,4}$	-0.00040	0.00037	-1.088
$\gamma_{3,1}$	-0.00220	0.00689	-0.319	$\gamma_{4,1}$	-0.01230	0.00573	-2.147**
$\gamma_{3,2}$	-0.00172	0.00108	-1.583	$\gamma_{4,2}$	-0.00220	0.00090	-2.436***
$\gamma_{3,3}$	-0.00081	0.00160	-0.507	$\gamma_{4,3}$	-0.00123	0.00133	-0.926
$\gamma_{3,4}$	-0.00018	0.00094	-0.195	$\gamma_{4,4}$	0.00015	0.00078	0.195
$\gamma_{3,5}$	-0.00210	0.00233	-0.901	$\gamma_{4,5}$	-0.00174	0.00194	-0.898

Table 4 (cont.). Analysis of weather and order imbalances for individual and institutional investors, model (2)

Panel B. Institutional investors							
	OI_{inst}^{mkt}				$OI_{inst}^{\lim}$		
	Estimate	Std. error	*t*-value		Estimate	Std. error	*t*-value
$\gamma_{3,6}$	0.00015	0.00150	0.100	$\gamma_{4,6}$	-0.00029	0.00125	-0.229
$\gamma_{3,7}$	0.00025	0.00149	0.167	$\gamma_{4,7}$	-0.00037	0.00124	-0.302
$\gamma_{3,8}$	0.00053	0.00087	0.612	$\gamma_{4,8}$	0.00047	0.00073	0.647
$\delta_{3,1}$	-0.00357	0.00376	-0.950	$\delta_{4,1}$	-0.00100	0.00313	-0.320
$\delta_{3,2}$	-0.00427	0.00218	-1.955*	$\delta_{4,2}$	-0.00013	0.00181	-0.073
$\delta_{3,3}$	-0.00230	0.00191	-1.201	$\delta_{4,3}$	-0.00195	0.00159	-1.225
$\delta_{3,4}$	0.00090	0.00070	1.292	$\delta_{4,4}$	-0.00048	0.00058	-0.828
$\delta_{3,5}$	-0.00570	0.00368	-1.551	$\delta_{4,5}$	-0.00087	0.00306	-0.286
$\delta_{3,6}$	-0.00056	0.00134	-0.418	$\delta_{4,6}$	0.00144	0.00111	1.294
$\delta_{3,7}$	0.00396	0.00429	0.921	$\delta_{4,7}$	-0.00398	0.00357	-1.114
$\delta_{3,8}$	0.00178	0.00114	1.555	$\delta_{4,8}$	-0.00030	0.00095	-0.315
	Adjusted R-squared: 0.5166				Adjusted R-squared: 0.01656		

Notes: This table presents results of multivariate regressions of order imbalance against weather for the individual and institutional investors on a daily basis. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.