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Weather and intraday patterns in stock returns and trading activity

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Abstract

We examine the relation between weather in New York City and intraday returns and trading patterns of NYSE stocks. While stock returns are found to be generally lower on cloudier days, cloud cover has a significant influence on stock returns only at the market open. There are significantly more seller-initiated trades when there is more cloud cover at the market open, which is consistent with the return results. Cloudy skies are associated with higher volatility and less market depth over the entire trading day. Finally, cloud cover is not significantly correlated with spread measures and turnover ratios. The findings overall suggest that weather has a significant influence on investors' intraday trading behavior.

JEL classification: G12; G14

Keywords: Intraday return; Intraday trading activity; Weather; Sentiment

1. Introduction

Traditional finance theory argues in the efficient markets hypothesis that securities markets are rational and appropriately reflect economic fundamentals. Yet we often read in the popular press that psychological factors have important influence on the trading decisions people make in financial markets.[1] An interesting line of research links psychological influences and financial markets. Saunders (1993) argues that weather influences stock returns because it affects the mood of investors. There is ample psychological evidence that people tend to have a more optimistic evaluation of future prospects when they are in a better mood (Arkes et al., 1988; Wright and Bower, 1992; Bagozzi et al., 1999; Hirshleifer, 2001). Saunders documents strong evidence that stock returns at the New York Stock Exchange (NYSE) are negatively correlated with cloudiness. Hirshleifer and Shumway (2003) in an extension of Saunders (1993) find supporting evidence of a negative relation between cloud cover and equity returns in 26 international stock markets.

Other research shows that the influence of biorhythms on mood affects share pricing. Kamstra et al. (2000) investigate the effect of sleep desynchronosis caused by daylight saving time changes on stock returns. They find that interruptions in sleep patterns have a negative influence on stock returns on the Mondays following daylight saving time changes. Kamstra et al. (2003) also document that seasonal affective disorder induced by fewer hours of daylight is predictive of a seasonal variation in equity returns.

Both Kamstra et al. (2000) and Hirshleifer and Shumway (2003) suggest that it is fruitful to investigate the potential effects of psychological factors on intraday returns, intraday volatility, and transactions volume. We thus extend the literature by examining the influence of

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[1] See *The Wall Street Journal* (October 26, 1992, p. C1) and *Business-Week* (February 13, 1995, p. 84, and May 29, 2000, p. 172).

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weather on intraday trading behavior. Our research makes at least three valuable contributions to the literature. First, previous examinations of the relation between weather and stock markets use aggregate data and base findings on the daily average of weather variables and daily stock returns. Yet it has been well documented in the market microstructure literature that there is a strong seasonality in intraday return patterns (Harris, 1986; Atkins and Dyl, 1990; Stoll and Whaley, 1990; Fabozzi et al., 1995). The intraday data we use allow us to measure the immediate impact of weather on stock returns, thus providing a finer picture that cannot be readily extracted from aggregating daily observations. The advantage of intraday information is particularly valuable if weather influences stock returns more significantly at certain trading hours, say, at market opening periods, and we cannot capture those effects by examining daily data.

Second, intraday data enable us to investigate the effects of weather on daily and intraday trading activities in the market. Most prior studies investigate the weather impact on stock returns only.[2] However, the literature suggests that investor sentiment may affect trading activities. Baker and Stein (2004) argue that in the presence of short-sales constraints, traders become more active in an overvalued market. As a result, investor sentiment is positively correlated with market liquidity. Mehra and Sah (2002) propose a model demonstrating that mood fluctuation induced by projection bias has an important influence on the volatility of equity prices. Brown (1999) provides strong evidence that both the number of trades and the return volatility of closed-end funds increase with unusual levels of investor sentiment. Lee et al. (2002) find that bullish shifts in sentiment are negatively correlated with market volatility and positively associated with future excess returns. Therefore, if weather affects the mood and sentiment of investors, it is likely that weather will have important effects on their trading behavior as well. The relation between weather and trading activities may be different for various intraday trading intervals, because trading patterns have been found to vary substantially among different trading intervals (Wood et al., 1985; Foster and Viswanathan, 1993).

Third, intraday data permit a more reliable and efficient estimation of the effect of psychological factors on share prices (Barclay and Litzenberger, 1988; Busse and Green, 2002). The short measurement period reduces the sources of variability that may be attributed to other unrelated extraneous factors. These advantages are important for the interpretation of the effect of psychological factors on stock markets, given that the correlation between mood-related variables and stock returns may be driven by outliers and subsamples (Pinegar, 2002).

We examine the relation between local New York City weather and intraday returns and trading patterns of NYSE stocks. That is, we explore the effects of cloud cover in New York City on intraday returns and a variety of trading variables for NYSE firms, including trading volume, bid-ask spread, quoted depth, return volatility, and order imbalance. We focus on cloud cover in light of the important findings in Saunders (1993) and Hirshleifer and Shumway (2003), as well as the psychological evidence that sunshine is among the most important weather variables affecting mood.[3] Our use of local New York City weather is based on the argument suggested by Saunders (1993) that traders physically present in New York City, such as brokers and floor traders, may sometimes affect prices in attempts to exploit their own interests. Because they assemble at the same location daily, a strictly local mood variable has the potential to affect this group to the exclusion of other market participants, who are geographically dispersed. In fact, our test results are biased against finding any effects of the New York City weather. The local traders in New York City are less likely to overlook exploitable opportunities induced by weather effects. Moreover, their number is small relative to the universe of market participants, and the existence of weather effect would show that weather in New York City does have impact on returns and trading activities, despite the dispersed locations of traders across the country.

We find that while stock returns are generally lower on cloudier days, cloud cover has a significant influence on stock returns only during the first 15-min interval of the trading day; its effect becomes insignificant for subsequent trading intervals. The effect is similar for order imbalance in that during only the first 15-min interval of the trading day, there are significantly more seller-initiated trades than buyer-initiated trades on cloudier days. For other trading hours, cloud cover does not affect order imbalance significantly. Our results on intraday returns and order imbalance suggest that when investors are gloomy because of cloudy weather around the market open, they tend to be pessimistic and be less inclined to buy than to sell, resulting in lower stock returns during the opening interval. Our evidence supports the argument suggested by Lo and Repin (2002) that investors experiencing significant psychological changes around opening hours reflect their mood in the opening trades, but these transient changes quickly become less important as more information comes to the market during the trading day.

Our findings on the very short-run impact of cloud cover on stock returns and sell-initiated trades suggest that psychological factors only have temporary influence on returns. Even though previous studies find that cloud cover seems to affect returns, they also point out that this phenomenon does not easily present a profitable opportunity.

[2] Loughran and Schultz (2004) study weather and trading volume, but do not investigate the effect of weather on intraday trading.

[3] The cloudier the weather is, the worse investor mood will be, and the more pessimistic investors become. The psychological evidence can be found in Persinger (1975), Cunningham (1979), and Howarth and Hoffman (1984).

Hirshleifer and Shumway (2003) argue that the weather effect may be profitable only for very low cost traders, but it is not going to be profitable for most investors. Our evidence of the very short-term weather effect suggests that trading on it is less likely to be profitable.

We also show that cloudy skies are associated with higher volatility and less market depth. The positive relation between cloud cover and market volatility is consistent with the hypothesis that when moods are pessimistic, there is more disagreement in opinion among investors, so stock return is more volatile (Lee et al., 2002; Baker and Stein, 2004). Our finding of a negative relation between cloud cover and market depth is consistent with the argument that gloomy investors tend to be pessimistic and have less desire to participate in market activities (Loughran and Schultz, 2004; Goetzmann and Zhu, 2005).

We further show that the effects of cloud cover on return volatility and market depth are significant not merely for the opening hours, but also last for the entire trading day. It is well documented in the literature that shocks in volatility are highly persistent (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Bollerslev and Engle, 1993). Moreover, previous studies find that market depth is negatively related to volatility (Bessembinder and Seguin, 1993; Ahn et al., 2001; Goldstein and Kavajecz, 2004). Therefore, the effects of cloud cover on volatility and market depth tend to last longer.

We finally find that cloud cover is not significantly correlated with spread measures and turnover ratios, suggesting that weather is relatively unimportant in explaining these trading variables. Our results are similar for equally weighted or value-weighted stock indices and for individual stocks, and remain robust after controlling for other weather variables (Cooke et al., 2000; Hirshleifer and Shumway, 2003; Loughran and Schultz, 2004; Cao and Wei, 2005), day-of-the-week and month-of-the-year effects (Cross, 1973; Smirlock and Starks, 1986; Thaler, 1987a,b), daylight saving time changes (Kamstra et al., 2000), and intraday seasonality. Our findings overall suggest that weather has a significant influence on investors' intraday trading behavior – a phenomenon not yet documented in the literature.

The remainder of the paper proceeds as follows. Section 2 develops our hypotheses. Section 3 describes the sample and methodology. We present the empirical results in Section 4. The final section concludes the paper.

2. Hypothesis development

We develop a variety of hypotheses on the relation between investor sentiment and stock returns and trading activities throughout the entire day and among different intraday trading intervals. We first explore the impact of investor mood on returns. We then discuss the potential effects of investor sentiment on trading variables, such as return volatility, trading volume, bid-ask spread, quoted depth, and order imbalance.

Given the psychological evidence that people tend to be more optimistic as to future prospects when they are in a better mood (Wright and Bower, 1992; Bagozzi et al., 1999), we expect the relation between investor sentiment and stock returns to be positive. Saunders (1993) and Hirshleifer and Shumway (2003) using daily data show supporting evidence for the entire trading day that cloudy weather in New York City negatively influences stock returns at the NYSE by affecting the mood of investors. However, the literature documents that there are significant intraday return patterns (Harris, 1986; Atkins and Dyl, 1990; Stoll and Whaley, 1990; Fabozzi et al., 1995). It is thus likely that weather may affect stock returns more significantly at certain intraday trading intervals. For traders located physically in New York City, the good mood induced by sunshine may have a more profound influence on their decision-making process at the beginning of trading hours, as investors observing the weather and experiencing psychological changes right around the market open reflect their mood in their opening trades (Lo and Repin, 2002). Nevertheless, as more information arrives in the market during the trading day, the influence of weather on stock returns may diminish quickly. We thus predict a stronger weather effect on stock returns at the market open that may not last for the entire trading day.

There are two sets of competing, but not mutually exclusive, arguments predicting the relation between investor sentiment and return volatility. As suggested by Shiller (2003) and Nofsinger (2005), on the one hand, the poorer the social mood is, the more disagreement in opinion among investors. As a consequence of increased differences in valuation among investors, return volatility increases (Harris and Raviv, 1993; Shalen, 1993; Lee et al., 2002; Baker and Stein, 2004). Investor sentiment is thus expected to have a negative impact on return volatility, implying that cloudy weather is associated with higher return volatility. Brown (1999), Gervais and Odean (2001), and Statman et al. (2006), however, suggest that when the sentiments are bullish, investors may be overconfident and trade more, which causes return volatility to rise. These arguments would indicate a positive relation between investor sentiment and return volatility, implying that cloudy weather is associated with less return volatility.

Investor heterogeneity is likely to contribute to higher trading activity (Karpoff, 1986; Harris and Raviv, 1993). When sentiments are bullish, investors may become overconfident, overestimate the relative precision of their own private signals, and underestimate the information content embodied in either order flow or equity issues and others' trading decisions, as they consider others to be less well-informed than they are (Baker and Stein, 2004). Therefore, a market whose pricing is dominated by bullish sentiment levels is unusually liquid. A highly liquid market is usually characterized by high depth and trading volume as well as narrow bid-ask spreads. When investors are in a down mood, they may be pessimistic and have less of a desire to trade and tend to sell rather than buy (Loughran and

Schultz, 2004; Goetzmann and Zhu, 2005). These arguments suggest that investor sentiment is expected to be positively related to the turnover ratio, market depth, and number of buy orders, and negatively related to the bid-ask spread. Therefore, we hypothesize that on cloudier days, there will be lower turnover ratios, market depth, and numbers of buy orders, but higher bid-ask spreads.

Investor sentiment is likely to have differential effects on stock returns over different intraday trading intervals. Since stock price changes are caused by investors' trading activity, there may also be a different relation between weather and trading variables for various trading intervals. Furthermore, it is well documented that the trading pattern at the market open is substantially different from that for the rest of the day. Trading variables, including volume, spread, depth, and volatility, have all been found to vary substantially among different intraday trading intervals (Wood et al., 1985; Jain and Joh, 1988; McInish and Wood, 1992; Foster and Viswanathan, 1993; Chung et al., 1999). Therefore, it is possible that weather has different effects on trading variables in the opening trading interval and in the other trading intervals. As we examine the influence of weather on stock returns and trading variables both throughout the entire day and among different intraday trading intervals, we provide a finer picture of the effects of investor sentiment on intraday returns and trading patterns, not so far documented in any other study.

3. Data and methodology

Our sample includes firms listed on the NYSE, which are covered by the Trade and Quote (TAQ) database and the University of Chicago's Center for Research in Security Prices (CRSP) database in the period 1994–2004. We eliminate firms in the financial and utility industries (SIC codes 6000–6999 and 4900–4999). Intraday trading measures such as trade prices, bid-ask quotes, trading volume, and quote size are from TAQ. Shares outstanding and the market value of the sample firms are from CRSP.

To minimize data errors, we follow Chordia et al. (2002) and apply several filters to the data. First, a trade is excluded if it is out of sequence or has special settlement conditions, because it might then be subject to distinct liquidity considerations. Second, quotes recorded outside the regular trading hours (9:30–16:00) are excluded. Third, observations with negative bid-ask spreads are discarded. Finally, only BBO (best bid or offer)-eligible primary market (NYSE) quotes are retained.[4]

The weather data of New York City come from the *International Surface Weather Observations* (ISWO) dataset provided by the National Climatic Data Center.[5] Weather variables are recorded every hour throughout the entire day. We match the hourly weather variables and the return and trading data by splitting a trading day (9:30–16:00) into eight intervals. The period from 10:00 to 16:00 is divided into six 60-min intervals to coincide with the recorded weather variable. The first 30-min (9:30–10:00) of the trading period is split further into two 15-min intervals (9:30–9:45 and 9:45–10:00) in order to test the weather effect at the market open.

In each trading interval, we find the nearest hourly weather observations right before the beginning of that interval. Stock returns and trading variables are calculated for each firm during each trading interval, and then averaged across all firms either equally weighted or value weighted by a firm's market capitalization as of the end of the prior month. We calculate the interval return (*RET*) to check whether intraday returns are correlated with weather.

Trading measures include volatility, market depth, spread, turnover ratio, and order imbalance variables. Two volatility variables are calculated, including price range (*RANGE*), which is calculated as the interval's high price minus low price, and standard deviation (*RETSTD*), which is calculated as the percentage standard deviation of the bid-ask mid-point returns. Market depth (*DEPTH*) is measured by the average quote size at the best bid and ask prices. Spreads are highly serially correlated and exhibit strong intraday patterns. To control for intraday spread autocorrelation and seasonality, we follow Chordia et al. (2002) and Goetzmann and Zhu (2005) by examining the difference between the spread of the interval and the spread of the same interval on the prior trading day. We calculate two first difference spread measures, the percentage effective (*DIF_ES*) and percentage quoted (*DIF_QS*) first difference spreads.[6] For variables related to trading volume, we calculate two turnover ratios, average trading volume per trade (*TURNPER*) and cumulative trading volume (*TURN*) in the interval, both scaled by number of firm shares outstanding at the end of the previous month. We calculate two order imbalance ratios. The first is based on trading volume (*OISVOL*), and is calculated as the trading volume of seller-initiated trades divided by the total trading volume in the interval. The other is based on number of trades (*OISNUM*), and is calculated as the number of seller-initiated trades divided by the total number of trades.[7] Finally, to make variables in 15-min and 60-min intervals comparable, we multiply the interval return, price range, and cumulative trading volume in the first two 15-min intervals by 4, and multiply the standard deviations in the first two 15-min intervals by the square root of 4.

Our specific focus is on whether intraday return and trading activity are related to cloud cover, a factor found

[4] Chordia et al. (2001) provide a justification for using only NYSE quotes.

[5] The same data source is used in Hirshleifer and Shumway (2003) and Loughran and Schultz (2004).

[6] The percentage effective spread is defined as twice the absolute value of the difference between the trading price and the mid-point of the ask and the bid prices, scaled by the mid-point of the ask and the bid prices. The percentage quoted spread is the difference between the ask price and the bid price scaled by the mid-point of the ask and bid prices.

[7] We use the Lee and Ready (1991) algorithm for signing trades.

Table 1
Number of sample firms in each month from 1994 through 2004

Year	January	February	March	April	May	June	July	August	September	October	November	December
1994	1252	1253	1253	1251	1256	1267	1273	1282	1287	1291	1291	1303
1995	1286	1284	1337	1344	1343	1347	1357	1358	1367	1359	1374	1407
1996	1401	1417	1417	1431	1436	1444	1456	1439	1457	1470	1499	1531
1997	1537	1547	1545	1539	1554	1564	1590	1589	1592	1600	1609	1633
1998	1621	1626	1634	1641	1638	1641	1650	1647	1641	1639	1639	1643
1999	1643	1622	1626	1629	1609	1599	1600	1580	1577	1573	1590	1592
2000	1583	1577	1564	1543	1519	1524	1504	1493	1477	1474	1467	1448
2001	1436	1468	1459	1463	1473	1465	1465	1455	1465	1451	1461	1466
2002	1458	1457	1461	1457	1456	1464	1465	1459	1455	1451	1460	1461
2003	1458	1456	1449	1451	1446	1450	1445	1442	1446	1446	1449	1452
2004	1456	1454	1452	1451	1439	1434	1433	1435	1438	1435	1444	1451

Our sample includes firms listed on the NYSE, which are covered by the Trade and Quote (TAQ) database and the University of Chicago's Center for Research in Stock Prices (CRSP) database. We delete firms in the financial industry (SIC codes 6000–6999) and utility industry (SIC codes 4900–4999).

to have a significant influence on returns (Saunders, 1993; Hirshleifer and Shumway, 2003). We index cloud cover (*CC*) from 1 to 4, where 1 indicates a clear sky, 2 indicates scattered clouds, 3 indicates broken clouds, and 4 indicates overcast.[8] Because all the weather variables are highly seasonal, it is important to control for seasonality. To make sure that the results are not driven by seasonal effects, we follow Hirshleifer and Shumway (2003) and deseasonalize each weather variable by subtracting its average value of each calendar week during the sample period from the weather observations at New York City.

We regress stock returns and each trading variable on cloud cover. As the effect of cloud cover may be driven by other adverse weather conditions, we control for other weather variables examined in prior research, including snowiness (Loughran and Schultz, 2004), raininess (Hirshleifer and Shumway, 2003), temperature (Cao and Wei, 2005), and wind speed (Cooke et al., 2000). A dummy variable for snowiness (D_{snow}) is defined as 1 if the data from ISWO show that it is snowing or has snowed within the last observation period. Raininess (D_{rain}) is defined similarly. Temperature ($TEMP$) is measured in Fahrenheit, and wind speed ($WIND$) is measured by miles per hour. All these weather variables are deseasonalized in a similar way as cloud cover. We also control for day-of-the-week and month-of-the-year effects (Cross, 1973; Smirlock and Starks, 1986; Thaler, 1987a,b), effect of daylight saving time changes in the fall and spring (Kamstra et al., 2000), and the intraday trading session effect. Dummy variables for Monday (D_{Mon}), Friday (D_{Fri}), January (D_{Jan}), December (D_{Dec}), and two days of the daylight saving time changes (one for the first Sunday in April, DDL_{Apr}, and another for the last Sunday in October, DDL_{Oct}) and dummy variables for trading intervals are included in the regressions.[9]

Table 1 shows the number of sample firms in each month for 1994–2004. The number of NYSE listed firms in our sample increases initially, then drops slightly afterwards, and finally stabilizes at around 1400. Table 2 shows the summary statistics of weather variables, stock returns, and trading measures. Panel A indicates average cloud cover of 1.78 and average temperature of 56.97 degrees Fahrenheit in New York City. Panels B and C show the equally weighted and value-weighted stock returns and trading variables, respectively. The average interval return (*RET*) is close to zero. The averages of the equally weighted return standard deviations (*RETSTD*) and turnover ratios (*TURNPER* and *TURN*) are higher than those of the value-weighted variables, indicating that small firms are more volatile and traded more actively. The lag-one differences in quoted and effect spreads (*DIF_ES* and *DIF_QS*) are on average close to zero. There are generally more buyer-initiated trades on the market, as the average order imbalance ratio (*OISVOL* and *OISNUM*) is less than 0.5.

4. Empirical results

4.1. The impact of cloud cover on intraday returns

Table 3 presents results of stock returns regressed against cloud cover and control variables. Panel A shows the equally weighted regression results. While the results for the entire trading day indicate that stock returns are generally lower on cloudier days, cloud cover has a significantly negative impact on interval returns only during the opening interval. For other intraday trading intervals, cloud cover does not significantly influence stock returns. Our findings indicate that while cloud cover affects stock returns, its influence is only short-term. The evidence is consistent with the hypothesis that investors observing the weather and experiencing psychological changes right

[8] The data description indicates that a clear sky represents cloud cover of less than 1/8, scattered clouds is cloud cover between 1/8 and 4/8, broken clouds is cloud cover between 5/8 and 7/8, and overcast is cloud cover of more than 7/8. To test the robustness of our results, we also use an alternative measure for each group: 0 for clear sky, 5/16 (the average of 1/8 and 4/8) for scattered clouds, 3/4 (the average of 5/8–7/8) for broken clouds, and 1 for overcast sky. The results are similar.

[9] The baseline trading interval is the first trading interval of each regression.

Table 2
Summary statistics

Variable	Mean	Standard deviation	Q1	Median	Q3	N
Panel A: weather variables						
CC	1.7842	0.9809	1	2	3	21,629
WIND	12.1122	5.8568	8	11	15	21,629
D_{snow}	0.0172	0.1302	0	0	0	21,629
D_{rain}	0.0676	0.2511	0	0	0	21,629
TEMP	56.9720	17.4419	44	57	72	21,629
Panel B: equally weighted stock return and trading variables						
RET	−0.0039	0.3591	−0.1239	0.0119	0.1286	21,629
RANGE	0.1835	0.2038	0.0212	0.1388	0.2494	21,629
RETSTD	0.7677	0.2344	0.5887	0.7208	0.8998	21,629
DEPTH	95.8697	55.4325	38.8903	90.7375	146.0107	21,629
DIF_ES	−0.0001	0.0390	−0.0148	−0.0002	0.0145	21,629
DIF_QS	−0.0002	0.0342	−0.0177	−0.0009	0.0166	21,629
TURNPER	0.1143	0.2374	0.0450	0.0741	0.0990	21,629
TURN	1.5148	4.0009	0.6227	0.8544	1.2373	21,629
OISVOL	0.4719	0.0400	0.4453	0.4695	0.4960	21,629
OISNUM	0.4733	0.0375	0.4492	0.4730	0.4967	21,629
Panel C: value-weighted stock return and trading variables						
RET	−0.0024	0.4608	−0.1781	0.0082	0.1806	21,629
RANGE	0.4026	0.4622	0.0706	0.2571	0.5193	21,629
RETSTD	0.6117	0.2165	0.4546	0.5660	0.7193	21,629
DEPTH	148.2820	95.3379	63.0399	120.2533	220.6747	21,629
DIF_ES	−0.0001	0.0257	−0.0047	−0.0002	0.0046	21,629
DIF_QS	−0.0001	0.0162	−0.0068	−0.0003	0.0062	21,629
TURNPER	0.0096	0.0063	0.0040	0.0074	0.0149	21,629
TURN	0.4852	0.1755	0.3545	0.4503	0.5864	21,629
OISVOL	0.4630	0.0515	0.4292	0.4593	0.4925	21,629
OISNUM	0.4705	0.0420	0.4437	0.4690	0.4947	21,629

The sample period is from January 1, 1994, through December 31, 2004. We split the trading day (9:30–16:00) into eight intervals. The period from 10:00 to 16:00 is divided into six 60-min intervals to coincide with the recorded weather variable. The first 30-min (9:30–10:00) of the trading period is further split into two 15-min intervals (9:30–9:45 and 9:45–10:00). For each interval, we find the nearest hourly weather variables in New York City before the beginning of that interval. The weather variables include (i) *CC*: cloud cover which ranges from 1 (clear) to 4 (overcast); (ii) *WIND*: wind speed in miles per hour; (iii) D_{snow}: dummy variable for snowiness; (iv) D_{rain}: dummy variable for raininess; (v) *TEMP*: temperature in Fahrenheit. In Panels B and C, we calculate stock returns and trading variables for each firm during each trading interval, and then calculate the equally weighted (Panel B) and value-weighted (Panel C) averages across the firms. The variables include (i) *RET*: percentage return; (ii) *RANGE*: price range; (iii) *RETSTD*: percentage standard deviation of the bid-ask mid-point return; (iv) *DEPTH*: average quote size, defined as the sum of the bid size and ask size, in 100 shares; (v) *DIF_ES*: difference between the percentage effective spread and that of the last trading day, where effective spread is defined as twice the absolute value of the difference between the trading price and the bid-ask mid-point, scaled by the mid-point; (vi) *DIF_QS*: difference between the percentage quoted spread and that of the last trading day, where quoted spread is defined as the difference between the ask and the bid prices scaled by the bid-ask mid-point; (vii) *TURNPER*: average trading volume per trade scaled by shares outstanding at the end of the last month; (viii) *TURN*: total trading volume scaled by the outstanding shares at the end of the last month; (ix)*OISVOL*: order imbalance ratio by trading volume calculated as the trading volume of the seller-initiated trades divided by the total trading volume; and (x) *OISNUM*: order imbalance ratio by number of trades calculated as the number of the seller-initiated trades divided by the total number of trades.

around the market open reflect their mood in the opening trades, and the impact of these changes on returns is transient, vanishing quickly as more information arrives in the market during the trading day (Lo and Repin, 2002). Our results also suggest that the relation between cloud cover and daily returns found by Saunders (1993) and Hirshleifer and Shumway (2003) is likely to be driven by the influence of weather in the opening period. Our evidence on the short-term effect of cloud cover offers one potential explanation for the inconsistent evidence in previous research that uses daily average data.[10]

In Panel A, we also take a closer look at the period of after lunch hours, assuming that most of the traders go out for lunch and observe the weather again. The period of after lunch hours is defined from 13:00 to 13:30. We obtain similar results if it is defined from 12:00 to 12:30 or from 12:30 to 13:00, so we do not report them here.[11] Panel A shows that stock returns during the after lunch hours are not significantly related to cloud cover. There are two possible explanations for our findings. First, unlike the market open, where all traders on the NYSE reflect their mood on trading at the same time, traders

[10] For example, Loughran and Schultz (2004) study the weather in the city of a firm's headquarters and its stock returns. They find no evidence that cloud cover is related to equity returns.

[11] We also use a 15-min interval to define the period of after lunch hours. That is, we define the after lunch hours as 12:00–12:15, 12:30–12:45, or 13:00–13:15. The conclusions in this study remain unchanged.

Table 3
Regressions of intraday return

Variable	Trading interval					
	9:30–16:00	9:30–9:45	9:45–10:00	9:45–16:00	13:00–13:30	15:00–16:00
Panel A: equally weighted index						
Intercept	0.0361***	0.0352**	−0.0581***	−0.0420***	0.0022	0.0470***
CC	−0.0034	−0.0316***	0.0070	0.0007	0.0019	−0.0001
WIND	−0.0002	0.0007	−0.0006	−0.0003	−0.0001	−0.0003
D_{snow}	0.0265	0.1351	−0.0108	0.0133	0.0041	0.0190
D_{rain}	0.0143	0.0720	0.0002	0.0057	−0.0048	0.0339*
TEMP	0.0001	0.0023	0.0007	−0.0001	0.0000	−0.0005
D_{Mon}	−0.0078	−0.0149	0.0345	−0.0068	0.0005	−0.0348***
D_{Fri}	0.0111*	0.0105	0.0084	0.0110**	0.0088**	0.0073
D_{Jan}	−0.0035	−0.0572	0.0139	0.0038	0.0064	0.0074
D_{Dec}	0.0304***	0.1032**	0.0800**	0.0203***	−0.0020	0.0160
DDL_{Apr}	0.0369	0.0636	0.2934*	0.0329	−0.0023	0.0855
DDL_{Oct}	−0.0344	−0.0877	0.2328	−0.0276	−0.0093	−0.2047***
Interval dummies	Yes	N/A	N/A	Yes	N/A	N/A
Adj. R^2 (%)	0.66	0.38	0.01	0.67	0.10	0.59
N	21,629	2649	2649	18,980	2708	2708
Panel B: value-weighted index						
Intercept	0.0080	0.0030	−0.0547***	−0.0314***	0.0048	0.0235**
CC	−0.0024	−0.0379***	0.0178	0.0030	0.0075	−0.0016
WIND	−0.0001	−0.0011	0.0012	0.0000	0.0003	−0.0010
D_{snow}	0.0179	0.0798	−0.0419	0.0103	−0.0012	0.0328
D_{rain}	0.0209*	0.1122**	0.0021	0.0080	0.0021	0.0362
TEMP	0.0001	0.0003	0.0013	0.0001	0.0000	−0.0011
D_{Mon}	0.0089	0.0116	0.0829**	0.0086	0.0005	−0.0153
D_{Fri}	−0.0010	−0.0040	−0.0158	−0.0007	0.0038	0.0100
D_{Jan}	−0.0077	−0.0896*	0.0387	0.0036	0.0107	0.0242
D_{Dec}	0.0335***	0.1879***	0.0811	0.0120	−0.0124	−0.0273
DDL_{Apr}	0.0615	0.1884	0.3602	0.0428	−0.0114	0.1512
DDL_{Oct}	−0.0858*	−0.1751	0.1969	−0.0743	−0.0129	−0.3221***
Interval dummies	Yes	N/A	N/A	Yes	N/A	N/A
Adj. R^2 (%)	0.10	0.81	0.10	0.07	0.16	0.32
N	21,629	2649	2649	18,980	2708	2708
Panel C: individual stock						
Intercept	0.0677***	0.0517***	−0.0545***	−0.0483***	0.0049*	0.0473***
CC	−0.0065	−0.0873***	0.0026	0.0004	0.0042	−0.0011
WIND	0.0000	−0.0004	−0.0008	0.0000	0.0004	−0.0003
D_{snow}	−0.0229	0.0023	0.0347	0.0076	0.0562	0.0636
D_{rain}	−0.0069	0.0256	−0.0279	−0.0032	0.0117	0.0019
TEMP	0.0000	−0.0117	0.0001	−0.0001	0.0003	−0.0005
D_{Mon}	−0.0125***	−0.0127	0.0343***	−0.0108***	−0.0025	−0.0068
D_{Fri}	0.0135***	0.0429***	0.0216***	0.0149***	0.0070***	0.0100***
D_{Jan}	−0.0007	−0.0577***	0.0099	0.0061***	0.0075***	0.0039
D_{Dec}	0.0214***	0.0586***	0.0618***	0.0145***	−0.0029	0.0140***
DDL_{Apr}	0.0287**	−0.1710	0.2305***	0.0097	−0.0068	0.0835***
DDL_{Oct}	−0.0453***	−0.0676	0.1651***	−0.0487***	−0.0766***	−0.2142***
Interval dummies	Yes	N/A	N/A	Yes	N/A	N/A

The dependent variable is the intraday return. The independent variables include: (i) cloud cover (*CC*) and weather control variables, including wind speed (*WIND*), snowiness (D_{snow}), raininess (D_{rain}), and temperature (*TEMP*); (ii) dummy variables of Monday (D_{Mon}), Friday (D_{Fri}), January (D_{Jan}), December (D_{Dec}), and two days of the daylight saving time changes (one for the first Sunday in April, DDL_{Apr}, and another for the last Sunday in October, DDL_{Oct}); and (iii) dummy variables indicating trading intervals (baseline comparison is to the first trading interval of each regression). A trading day is divided into two 15-min intervals after the market open, and six 60-min intervals for the following trading hours. Each weather variable is deseasonalized by subtracting its average value of each calendar week during the sample period from the weather observations at New York City. Panels A and B show the ordinary least squares regression results for the equally weighted and value-weighted indices, respectively. In Panel C, we perform time-series regressions on each stock and then calculate the cross-sectional averages of regression coefficients. The coefficients on the dummy variables indicating trading intervals are suppressed to save space. "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.

may go for lunch during different time intervals. While they may reflect their mood on trading due to weather observed during the lunch hours, the diverse lunch schedules are likely to cause the impact of weather to be insignificant. Second, as we argue above, the arrivals of other economically important information during the period of after lunch hours may also reduce the impact of weather on returns.

Table 4
Regressions of 1-min return for the first 30-min after the market open

Trading interval	CC	$WIND$	D_{snow}	D_{rain}	$TEMP$	Adj. R^2 (%)
Panel A: equally weighted index						
9:30–9:31	−0.0078*	−0.0003	0.0236*	−0.0003	0.0000	0.13
9:31–9:32	−0.0042	−0.0001	0.0108	−0.0030	0.0001	0.22
9:32–9:33	−0.0038*	−0.0001	0.0024	−0.0016	0.0004***	0.31
9:33–9:34	−0.0031*	−0.0001	−0.0041	−0.0009	0.0002**	0.04
9:34–9:35	−0.0034*	−0.0001	0.0011	0.0013	0.0001	0.07
9:35–9:36	−0.0058***	0.0000	0.0089	0.0042	0.0001	0.18
9:36–9:37	−0.0051***	0.0000	0.0032	0.0023	0.0000	0.28
9:37–9:38	−0.0026*	0.0001	−0.0018	0.0013	0.0000	0.12
9:38–9:39	−0.0028*	0.0001	−0.0061	0.0006	0.0000	0.18
9:39–9:40	−0.0018	0.0000	0.0013	0.0022	0.0001	0.02
9:40–9:41	−0.0040***	0.0001	0.0049	0.0048**	0.0001*	0.45
9:41–9:42	−0.0036***	0.0001	0.0088**	0.0016	0.0002***	0.47
9:42–9:43	−0.0019	0.0000	0.0078**	0.0002	0.0000	0.03
9:43–9:44	−0.0020	0.0000	0.0078**	0.0022	0.0000	0.13
9:44–9:45	−0.0008	−0.0001	0.0006	−0.0016	0.0000	0.16
9:45–9:46	0.0013	−0.0001	0.0036	−0.0010	0.0000	0.05
9:46–9:47	−0.0009	0.0000	0.0065*	0.0007	0.0000	0.04
9:47–9:48	−0.0017	−0.0001	0.0029	0.0009	0.0000	0.01
9:48–9:49	−0.0001	0.0000	−0.0021	−0.0005	0.0000	0.02
9:49–9:50	0.0011	−0.0001	−0.0015	0.0007	0.0000	0.05
9:50–9:51	0.0009	−0.0001	−0.0036	0.0002	−0.0001	0.09
9:51–9:52	−0.0008	0.0000	−0.0007	−0.0010	0.0000	0.27
9:52–9:53	0.0001	0.0001	−0.0031	0.0021	0.0000	0.02
9:53–9:54	−0.0006	0.0000	−0.0010	0.0033**	0.0001**	0.22
9:54–9:55	0.0009	0.0000	0.0008	0.0005	0.0000	0.29
9:55–9:56	0.0019*	0.0000	−0.0002	−0.0028*	0.0000	0.15
9:56–9:57	0.0010	0.0000	−0.0023	−0.0016	0.0000	0.10
9:57–9:58	0.0008	0.0000	0.0019	−0.0026*	0.0001	0.10
9:58–9:59	−0.0005	0.0000	0.0029	−0.0010	0.0000	0.12
9:59–10:00	0.0006	0.0000	−0.0019	−0.0003	0.0000	0.10
Panel B: value-weighted index						
9:30–9:31	−0.0069*	−0.0005	0.0251*	0.0028	−0.0003	0.28
9:31–9:32	−0.0113***	−0.0002	0.0080	−0.0050	0.0001	0.04
9:32–9:33	−0.0027	0.0000	0.0015	−0.0021	0.0004**	0.05
9:33–9:34	−0.0038*	−0.0004**	−0.0108	0.0003	0.0003**	0.44
9:34–9:35	−0.0031*	0.0001	−0.0047	0.0054	0.0000	0.33
9:35–9:36	−0.0128***	0.0000	−0.0009	0.0076**	0.0000	0.06
9:36–9:37	−0.0035	−0.0001	−0.0025	0.0060	−0.0003**	0.15
9:37–9:38	0.0080**	0.0001	−0.0073	0.0046	−0.0001	0.12
9:38–9:39	−0.0003	0.0000	−0.0057	0.0011	−0.0001	0.12
9:39–9:40	−0.0043*	−0.0001	0.0089	−0.0004	0.0001	0.21
9:40–9:41	−0.0060**	0.0000	0.0056	0.0073**	0.0000	0.21
9:41–9:42	−0.0047**	0.0001	0.0121*	0.0025	0.0001	0.11
9:42–9:43	−0.0016	0.0001	0.0084	−0.0020	0.0000	0.21
9:43–9:44	0.0016	0.0001	0.0042	0.0030	−0.0001	0.08
9:44–9:45	0.0002	−0.0002	−0.0039	−0.0035	0.0000	0.02
9:45–9:46	0.0036	0.0000	−0.0010	−0.0040	0.0000	0.01
9:46–9:47	0.0012	−0.0002	0.0081	0.0026	0.0000	0.09
9:47–9:48	−0.0007	0.0001	0.0031	0.0009	0.0002*	0.05
9:48–9:49	0.0034	0.0001	−0.0124*	−0.0008	0.0000	0.19
9:49–9:50	0.0030	−0.0003**	−0.0031	0.0040	−0.0001	0.18
9:50–9:51	0.0019	0.0000	−0.0119*	0.0017	−0.0001	0.10
9:51–9:52	−0.0029	0.0000	0.0044	−0.0026	−0.0001	0.09
9:52–9:53	0.0005	0.0002*	0.0004	0.0013	0.0001	0.08
9:53–9:54	0.0000	0.0001	0.0047	0.0032	0.0002*	0.04
9:54–9:55	0.0016	0.0000	0.0088	0.0013	0.0001	0.12
9:55–9:56	0.0024	−0.0001	−0.0089	−0.0123***	0.0000	0.25
9:56–9:57	0.0009	−0.0001	0.0021	−0.0025	0.0001	0.03
9:57–9:58	−0.0008	0.0002	−0.0005	−0.0061**	0.0001	0.09
9:58–9:59	−0.0031	0.0000	−0.0026	0.0002	0.0000	0.11
9:59–10:00	−0.0016	0.0000	−0.0042	0.0018	0.0000	0.13

(*continued on next page*)

Table 4 (*continued*)

Trading interval	CC	$WIND$	D_{snow}	D_{rain}	$TEMP$	$Adj.\ R^2$ (%)
Panel C: individual stock						
9:30–9:31	−0.0127**	0.0002	0.0622	−0.0270**	0.0000	
9:31–9:32	−0.0055*	0.0009	0.4140**	0.0328	0.0000	
9:32–9:33	−0.0015	−0.0003	−0.0571	0.0166	0.0001	
9:33–9:34	−0.0037***	−0.0002**	0.0024	0.0012	0.0002*	
9:34–9:35	−0.0027***	−0.0001	−0.0024	0.0009	0.0000	
9:35–9:36	−0.0026**	−0.0001	−0.0116	0.0021	0.0001	
9:36–9:37	−0.0043***	0.0000	0.0419***	−0.0015	0.0001*	
9:37–9:38	−0.0017***	0.0000	−0.0023	0.0007	0.0000	
9:38–9:39	−0.0027***	0.0000	−0.0003	0.0009	0.0000	
9:39–9:40	0.0002	0.0000	0.0089	0.0156***	0.0001	
9:40–9:41	−0.0020***	0.0001	0.0099	0.0039	0.0002*	
9:41–9:42	−0.0035***	0.0000	0.0029	0.0029	0.0002*	
9:42–9:43	−0.0008	0.0000	0.0019	0.0003	0.0000	
9:43–9:44	−0.0014	0.0000	0.0043	0.0040***	0.0000	
9:44–9:45	−0.0001	0.0000	0.0051*	−0.0013**	0.0000	
9:45–9:46	0.0005	−0.0001	0.0050	−0.0007	0.0000	
9:46–9:47	−0.0009	0.0000	0.0004	0.0004	0.0000	
9:47–9:48	−0.0018*	0.0000	0.0088*	0.0003	0.0000	
9:48–9:49	−0.0006	0.0000	−0.0122*	−0.0006	0.0000	
9:49–9:50	0.0004	−0.0001*	0.0061	0.0002	0.0000	
9:50–9:51	0.0002	−0.0001	−0.0023	0.0007	0.0000	
9:51–9:52	−0.0004	0.0000	−0.0013	0.0001	0.0000	
9:52–9:53	0.0006	0.0000	0.0048	0.0012	0.0000	
9:53–9:54	−0.0006	0.0000	−0.0001	0.0027*	0.0001*	
9:54–9:55	−0.0003	0.0000	0.0017	0.0022	0.0000	
9:55–9:56	0.0010	0.0000	−0.0007	−0.0008	0.0000	
9:56–9:57	0.0006	0.0001	−0.0004	−0.0006	0.0000	
9:57–9:58	−0.0005	0.0001	0.0008	−0.0009	0.0000	
9:58–9:59	0.0005	0.0000	0.0026*	−0.0005	0.0000	
9:59–10:00	0.0002	−0.0001*	−0.0034*	−0.0006	0.0000	

The dependent variable is the 1-min return during the first 30-min after the market open. The independent variables include: (i) cloud cover (CC) and weather control variables, including wind speed ($WIND$), snowiness (D_{snow}), raininess (D_{rain}), and temperature ($TEMP$); and (ii) dummy variables for Monday, Friday, January, December, and two days of the daylight saving time changes (one for the first Sunday in April and another for the last Sunday in October). Each weather variable is deseasonalized by subtracting its average value of each calendar week during the sample period from the weather observations at New York City. Panels A and B show the ordinary least squares regression results for the equally weighted and value-weighted indices, respectively. In Panel C, we perform time-series regressions on each stock and then calculate the cross-sectional averages of regression coefficients. Only the coefficients on the weather variables are reported to save space. "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A also shows detailed regression results of returns on weather control variables, day of the week, calendar month, and daylight saving time changes. In general, weather control variables (i.e., $WIND$, D_{snow}, D_{rain}, and $TEMP$) are not significantly related to returns throughout the entire day or among various intraday trading intervals, except for D_{rain} in the closing trading period (15:00–16:00) (marginally significant at the 10% level). In the regression for entire day returns (9:30–16:00), Friday has significantly higher returns, consistent with findings in Cross (1973), Keim and Stambaugh (1984), and Smirlock and Starks (1986). The Monday effect is concentrated in the period of closing trading. The January effect is weak during our sample period, similar to findings in Maberly and Maris (1991) and Szakmary and Kiefer (2004). Contrary to Kamstra et al. (2000), we find that the effects of daylight saving time changes in April and October are not significant for the entire day, but are significant in some trading intervals.

Panel B of Table 3 presents the value-weighted regression results of returns. As in Panel A, interval returns are significantly negatively related to cloud cover only during the opening interval, and the relation is weak beyond the first 15-min trading interval. These findings again show that cloud cover affects stock returns negatively, but its influence lasts for only a short period.

We also examine individual stocks traded on the NYSE. We perform time-series regressions on each stock and then calculate the cross-sectional averages of regression coefficients. As shown in Panel C of Table 3, the impact of cloud cover on returns is again significantly negative at the market open only and its effect diminishes quickly.

We further closely examine finer intervals during the first 30-min after the market open. Table 4 reports the minute-by-minute results for the equally weighted index, the value-weighted index, and individual stocks, where only the coefficients of weather variables are presented in order

Table 5
Regressions of intraday trading variables

Variable	Trading interval					
	9:30–16:00	9:30–9:45	9:45–10:00	9:45–16:00	13:00–13:30	15:00–16:00
Panel A: order imbalance						
A.1. OISVOL						
CC	1.0308	9.8264***	−2.5062	−0.2643	0.3697	−2.6384
WIND	−0.0867	0.0582	−0.2135	−0.1085	−0.2790	−0.0581
D_{snow}	−0.5817	−27.9887*	−1.9126	2.4247	7.3977	−7.8677
D_{rain}	0.6149	−9.5004	4.0033	1.9421	0.5873	0.3759
TEMP	0.0873	0.0295	−0.0664	0.0934	0.0664	0.0900
Adj. R^2 (%)	0.84	0.61	0.40	0.04	0.37	0.55
N	21,629	2649	2649	18,980	2708	2708
A.2. OISNUM						
CC	1.5213	5.6041***	2.8808	0.9530	0.0042	0.8497
WIND	−0.2523	−0.1925	−0.2372	−0.2624	−0.3580*	−0.3651*
D_{snow}	−27.7189	−9.2940	−47.1395	−30.3050	5.9344	−4.1798
D_{rain}	−0.5894	−10.8757*	−5.9128	0.6577	−0.9503	−0.2275
TEMP	−0.0461	−0.2154	−0.1391	−0.0231	−0.0577	0.0067
Adj. R^2 (%)	0.86	0.25	0.10	0.82	0.89	0.51
N	21,629	2649	2649	18,980	2708	2708
Panel B: volatility						
B.1. RANGE						
CC	41.5129***	101.8320***	102.7749***	31.0077***	4.0105	17.1529*
WIND	4.7245*	6.4450*	7.9596**	3.9237*	0.7373	4.0634*
D_{snow}	1.3105	63.2427	47.4596	−6.1053	3.6136	−17.3783
D_{rain}	−0.2284	41.4344	41.5998	−5.4820	−17.6588**	−12.6192
TEMP	1.7883*	3.6724*	4.1818*	1.2527*	−0.1550	1.1310
Adj. R^2 (%)	61.46	2.50	3.87	56.98	0.44	1.36
N	21,629	2649	2649	18,980	2708	2708
B.2. RETSTD						
CC	20.7130***	41.1196***	37.1572***	17.5029***	3.9088	8.5619
WIND	3.5749*	4.4862*	4.6719*	3.4459*	1.6966	3.7978*
D_{snow}	9.3146	61.3954	24.5280	3.6640	16.2277	−2.3708
D_{rain}	−6.3615	1.9146	−11.0022	−7.3212	−4.6876	−1.6365
TEMP	1.3901*	1.7319*	2.7816*	1.3381*	0.7297	0.8965
Adj. R^2 (%)	35.21	1.55	3.06	31.93	1.68	1.61
N	21,629	2649	2649	18,980	2708	2708
Panel C: market depth						
CC	−16.9306***	−9.3644***	−14.3265***	−17.9674***	−18.8466***	−24.5570***
WIND	−0.7610*	−0.3603	−0.5970**	−0.8161*	−0.8898*	−1.0608**
D_{snow}	1.8575	−18.6680*	−22.0430*	4.1905	15.5020	6.4137
D_{rain}	13.8222*	−0.9981	1.3128	15.7483*	32.2327**	23.5949**
TEMP	0.0478	−0.3551	−0.4730*	0.0944	0.3863	−0.1578
Adj. R^2 (%)	4.27	1.14	1.17	2.39	0.81	1.07
N	21,629	2649	2649	18,980	2708	2708
Panel D: spread						
D.1. DIF_ES						
CC	−0.2035	0.0841	0.1430	−0.2418	−0.129	−0.1661
WIND	0.0131	0.0520	0.0686	0.0076	−0.0591	0.0271
D_{snow}	−1.1326	−1.8003	−3.1079	−1.0465	0.8878	−0.4743
D_{rain}	0.3244	0.3203	1.5118	0.3301	−0.7661	−1.0230
TEMP	0.0155	0.0145	0.0066	0.0157	0.0180	0.0194
Adj. R^2 (%)	0.17	0.17	0.26	0.25	0.25	0.48
N	21,629	2649	2649	18,980	2708	2708
D.2. DIF_QS						
CC	−0.1809	−0.1870	−0.0607	−0.1624	0.1438	0.3636
WIND	0.0308	0.0551	0.0983*	0.0274	−0.0797	0.0601
D_{snow}	−1.4142	−5.9790*	−3.9497	−0.8949	0.6690	−0.8103
D_{rain}	0.7388	0.7445	1.3934	0.7395	0.9306	−1.6900*
TEMP	0.0158	−0.0020	0.0111	0.0188	0.0108	0.0183
Adj. R^2 (%)	0.81	0.12	0.50	1.12	1.12	2.04
N	21,629	2649	2649	18,980	2708	2708

(*continued on next page*)

Table 5 (*continued*)

Variable	Trading interval					
	9:30–16:00	9:30–9:45	9:45–10:00	9:45–16:00	13:00–13:30	15:00–16:00
Panel E: turnover						
E.1. TURNPER						
CC	−0.3980	−0.3704	−0.4328	−0.4213	−0.6030	−0.5962
WIND	−0.0560*	−0.0338	−0.0510	−0.0592*	−0.0404	−0.0847*
D_{snow}	−0.4928	0.0372	0.4525	−0.5529	0.9886	0.7818
D_{rain}	0.6421*	0.1500	0.2213	0.7658*	0.8592*	0.9205
TEMP	0.0269*	−0.0027	−0.0044	0.0325*	0.0188	0.0314*
Adj. R^2 (%)	4.00	1.58	1.30	2.04	1.54	1.41
N	21,629	2649	2649	18,980	2708	2708
E.2. TURN						
CC	5.7850	−11.4418	−14.2848	4.9393	0.7377	17.8101
WIND	1.4368	1.8492	2.6181*	1.3808	0.2326	1.9011*
D_{snow}	−2.5802	17.7259	40.6775	−7.2683	−1.5141	−34.3965
D_{rain}	−2.7337	−14.6084	−19.4639	−3.5338	−2.1745	−10.7800
TEMP	−0.0680	0.1842	0.5182	−0.1025	−0.0312	−1.0211*
Adj. R^2 (%)	49.94	4.21	8.44	53.48	5.66	3.22
N	21,629	2649	2649	18,980	2708	2708

The dependent variables are the value-weighted average trading variables. Two order imbalance ratios, one by trading volume (*OISVOL*) and one by number of trades (*OISNUM*), are defined. Order imbalance by trading volume is calculated as the trading volume of seller-initiated trades divided by the total trading volume. Order imbalance by number of trades is calculated as the number of seller-initiated trades divided by the total number of trades. Two volatility variables, price range (*RANGE*) and returns standard deviation (*RETSTD*), are examined. Price range is the interval high price minus the interval low price during the indicated interval. Return standard deviation is the square root of the sum of the squared tick return of the bid-ask midpoint. Market depth (*DEPTH*) is defined as sum of the bid size and ask size, in 100 shares. The first differences in effective spreads (*DIF_ES*) and quoted spreads (*DIF_QS*) are defined as the differences between the spread of the interval and that of the same interval of the previous trading day, to control for the well-known intraday seasonality and correlation in spreads. The percentage effective spread is defined as twice the absolute value of the difference between the trading price and the mid-point of the ask and the bid prices, scaled by the mid-point of the ask and the bid prices. The percentage quoted spread is the difference between the ask price and the bid price scaled by the mid-point of the ask and bid prices. Turnover per trade (*TURNPER*) is defined as the average trading volume per trade scaled by the outstanding shares at the end of last month. Cumulative turnover (*TURN*) is the total trading volume in the interval scaled by the outstanding shares at the end of the last month. The independent variables include: (i) cloud cover (*CC*) and weather control variables, including wind speed (*WIND*), snowiness (D_{snow}), raininess (D_{rain}), and temperature (*TEMP*); (ii) dummy variables for Monday, Friday, January, December, and two days of the daylight saving time changes (one for the first Sunday in April and another for the last Sunday in October); and (iii) dummy variables indicating trading intervals (baseline comparison is to the first trading interval of each regression). A trading day is divided into two 15-min intervals after the market open, and six 60-min intervals for the following trading hours. Each weather variable is deseasonalized by subtracting its average value of each calendar week during the sample period from the weather observations at New York City. The coefficients on dummy variables indicating month, day of the week, daylight saving time changes, and trading intervals are suppressed to save space. All the regression coefficients other than those for *DEPTH* are multiplied by 1000. "***", "**", and "*"denote significance at the 1%, 5%, and 10% levels, respectively.

to save space.[12] We find that during the first 12-min after the market open, the impact of cloud cover on stock returns is, in general, significantly negative. This impact then diminishes quickly. The effects of other weather variables on returns are generally insignificant. The results in Table 4 provide further support for our evidence in Table 3. Cloud cover has a significant influence on stock returns only during the first few minutes after the market open, and its impact diminishes gradually as more information comes to the market throughout the day.

4.2. The impact of cloud cover on trading variables

Table 5 shows the effects of cloud cover and other weather variables on trading activities, where again only the coefficients of weather variables are presented in order to save space. These are value-weighted regression results. The results for the equally weighted index and individual stocks are qualitatively similar, so we do not report them here.

Panel A shows the impact of weather on order imbalance. In the first 15-min interval, there are generally significantly more seller-initiated trades than buyer-initiated trades when the sky is cloudier. In other trading periods (including the period of after lunch hours), however, order imbalance is not found to be significantly correlated with cloud cover. This evidence is consistent with that presented in Table 3. As investors are in a worse mood around the market open, they tend to be pessimistic and less inclined to buy rather than to sell, resulting in lower stock returns during the opening interval.

The influences of cloud cover on return volatility and market depth are shown in Panels B and C, respectively. Panel B indicates that price range and return standard deviation both increase significantly with cloud cover. Our results suggest that investor sentiment is negatively associated with market volatility, consistent with the hypothesis that when investors are in a poor mood, there is more

[12] Our results are qualitatively similar if we use the two-, three-, or 5-min intervals for the first 30-min.

disagreement in opinion among them, and hence return volatility increases (Lee et al., 2002; Baker and Stein, 2004). Panel C shows that market depth drops significantly as cloud cover increases. This evidence supports the hypothesis that cloudy weather makes investors pessimistic and reduces their inclination to trade in the market (Loughran and Schultz, 2004; Goetzmann and Zhu, 2005).

Panels B and C also show that cloud cover influences return volatility and market depth not just in the first two 15-min periods, but also over the entire trading day. Previous studies document that shocks in volatility are highly persistent (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Bollerslev and Engle, 1993). Moreover, market depth is found to be negatively related to volatility in the literature (Bessembinder and Seguin, 1993; Ahn et al., 2001; Goldstein and Kavajecz, 2004). Therefore, the effects of cloud cover on volatility and market depth last longer.

Panels D and E of Table 5 show the impact of cloud cover on spreads and turnover ratios, respectively. Neither variable is significantly related to cloud cover. When we combine these observations with the findings in Panels A, B, and C, clearly cloud cover has a more profound influence on order imbalance, return volatility, and market depth, than on spreads and turnover ratios.

4.3. Robustness checks

To check the robustness of our results, we examine results for different partitions of intraday trading intervals. We split a trading day into seven intervals, a 30-min first interval followed by 6-h-long intervals. We also try thirteen equal-length intervals of 30-min each. Results for these alternative definitions of intraday intervals are similar, and our conclusions remain the same. We also use a 6-h average for weather observations before the beginning of an interval to define the weather variables, and the results are again very similar to those reported. Finally, to acknowledge the non-synchronous trading problem for illiquid stocks, we repeat all tests excluding 10% of the least liquid firms, and obtain similar findings.

5. Concluding remarks

Our examination of the impact of weather contributes to the literature by its focus on intraday return and trading activity for NYSE firms. We find that greater cloud cover induces a significantly negative intraday return only in the first 15-min period of the trading day. We also find more seller-initiated trades during the opening period when the skies are cloudier. Weather affects stock returns and order imbalance only around the market open, and it diminishes in importance quickly as more information arrives in the market throughout the day.

We further show that spreads and turnover ratios are not significantly related to cloud cover, but it has a significantly positive effect on return volatility and a significantly negative effect on market depth. These effects occur not only in the opening hours, but also over the entire trading day. Our findings overall suggest that weather influences intraday trading behavior because it affects investor mood.

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