Weather, Stock Returns, and the Impact of Localized Trading Behavior

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Abstract: We document by several methods that trading in Nasdaq stocks is localized, but find little evidence that cloudy weather in the city in which a company is based affects its returns. The first evidence of localized trading is that the time zone of a company's headquarters affects intraday trading patterns in its stock. Second, firms in blizzard-struck cities see a dramatic trading volume drop compared to firms in other cities. Third, the Yom Kippur holiday dampens trading volume in companies located in cities with high Jewish populations. Despite the strong evidence of localized trading, cloudy conditions near the firm's headquarters do not provide profitable trading opportunities.

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I. Introduction

Psychologists have long known that sunlight, or rather a lack of sunlight, influences people's moods, thinking, and judgment. Researchers in finance have applied these findings in a search for behavioral influences on stock prices. For example, Hirshleifer and Shumway (2003) and Saunders (1993) find that stock returns are significantly lower on cloudy days than on sunny days. Their work appears to be the most direct evidence to date that stock prices are not rational reflections of value, but are instead influenced by investors' emotional states.[1]

One limitation of this research is that it measures the mood of stock market participants by cloudiness in New York City (or in the cities with stock exchanges). In fact, orders come into the New York Stock Exchange (NYSE) from all over the country and from all over the world. If it is order-submitting investors who set prices at the margin, and if moods of investors are affected by sunlight, cloudiness in New York is not a good proxy for the mood of the market.

Our study takes a different approach. We examine the relationship of weather and stock returns taking the cloud cover in the city of a Nasdaq company's listing as a proxy for the weather affecting investors submitting orders in the stock. This is a different and we believe better way to examine the effects of weather-induced moods on stock prices. By examining cloud cover at the exchanges and its effects on returns, Saunders (1993) and Hirshleifer and Shumway (2003) test whether investment professionals' moods are affected by cloudiness. We test to see if investors in general are affected by weather.

As such, our paper contributes to the growing literature on the bias toward local trading. Coval and Moskowitz (1999, 2001), Grinblatt and Keloharju (2001), Huberman (2001), and Zhu (2002) find that, all else equal, investors both hold and trade substantially more shares in local companies than in other firms. We expect this to be particularly true of Nasdaq firms, which

[1] Research into mood and weather includes the work of Avery, Bolte, Dager, Wilson, Weyer, Cox, and Dunner (1993), Bagby, Schuller, Levitt, Joffe, and Harkness (1996), Cohen, Gross, Nordahl, Semple, Oren, and Rosenthal (1992), Howarth and Hoffman (1984), Kamstra, Kramer, and Levi (2003), Sanders and Brizzolara (1982), and Williams and Schmidt (1993).

tend to be smaller and to have started trading publicly more recently than NYSE-listed companies.

We present three pieces of evidence that a disproportionate amount of trading for Nasdaq stocks in our sample originates in the city where the company is based. First, we show that intraday patterns in trading vary according to the time zone of the company headquarters. Trading in firms based in Alaska or Hawaii is far lower when it is morning in New York, and residents of those states are asleep, than later in the day. The dip in trading that corresponds to lunchtime on the East Coast is far more pronounced for firms with headquarters in the Eastern Time zone than on the West Coast.

Second, snowstorms in a city affect the trading volume of stocks based there. For most of the sample cities, blizzards are defined as at least eight inches of snow in a day. If snow is falling early in the day, investors may have to shovel snow, dig out cars, and take longer to get to and from work. These investors may simply not have time to trade stocks on that day. If snow falls at night, trading on the next day may also be affected. We find in cities experiencing blizzards that trading volume falls by more than 17% on the day of the storm and by almost 15 % the following day. Trading volume of stocks based in other cities is unaffected by the local blizzard conditions.

Third, holidays affect trading volume of stocks in various cities differently. We look at trading volume on Yom Kippur, an important Jewish holiday when the stock market remains open. While we find that trading volume drops on Yom Kippur for stocks based in most cities, the effect is significantly stronger for companies based in cities with higher percentages of Jewish residents.

We use portfolios of stocks of firms based in 25 large U.S. cities to test for a relationship between weather and stock returns. There are several reasons why our methodology provides a particularly powerful test of the effect of weather on stock returns. First, correlations of cloudiness across U.S. cities are low, so we can use much more information than would be available only in New York weather. This is in the spirit of Hirshleifer and Shumway (2003), but our use of U.S. stocks exclusively provides an important second advantage. We can examine the effects of cloud cover on returns after controlling for simultaneous market-wide moves. Market returns explain a considerable proportion of the stock returns for individual city portfolios. It is an easier task to find the effects of local weather on average excess returns than to explain the raw returns of market indexes with weather conditions.

Finally, our methodology is more likely to uncover the effects of weather on small investors. Tests using the weather in the city of the stock exchange, as in Hirshleifer and Shumway (2003) and Saunders (1993), examine instead whether cloud cover affects the behavior of the market professionals at or near the exchange. Cohen, Gompers, and Vuolteenho (2001) suggest that individual investors are more likely to deviate from rational valuation of securities than are institutional investors. Despite the power of our tests, we find almost no relation between local cloud cover and stock returns, even after adjusting for market returns.

This paper contributes to three important areas of the finance literature: investor behavior, local bias, and market efficiency. This study shows that inconvenience of trading (lunch hour during the trading session) or earthly transaction costs (such as digging cars out of snow), which are typically not considered in theoretical asset pricing framework, may in fact have a meaningful impact on the capital market. Using an event-study approach, we confirm the existing findings that investors are more likely to trade nearby stocks. More importantly, the nature of the events used in this study (adverse weather conditions and a religious holiday) implies that factors other than information advantage (Coval and Moskowitz, 1999), familiarity (Huberman, 2001), or over-reaction (Zhu, 2002), may be responsible for localized trading. Our finding that returns of local stocks are not related to local weather indicates that investor behavior may not be heavily influenced by local weather, as argued in Hirshleifer and Shumway (2003). Our finding of limited impact of weather on stock returns is consistent with the recent work of Goetzmann and Zhu (2003). Using data on trades of individual investors, Goetzmann and Zhu find no significant evidence that weather influences an individual's propensity to buy or sell stock.

The rest of the paper is organized as follows. In Section II we discuss previous studies of the weather, geographic holdings, and stock returns. Section III describes our data. Section IV reports our empirical results on localized firm trading volume. Section V reports the empirical results on weather and stock returns. The last section offers a summary and conclusions.

II. Background on Weather, Geographic Holdings, and Stock Returns

Numerous studies in psychology show that weather has a significant effect on human behavior and moods. Saunders (1993) was the first to study the effects of cloud cover on stock returns. He uses daily returns on the Dow Jones Industrial Average over 1927-1989, and daily returns on value and equal-weighted market indices over 1962-1989. As a proxy for weather conditions, Saunders uses the "percentage of cloud cover from sunrise to sunset" according to the New York weather station closest to Wall Street.

Saunders acknowledges that orders arrive on Wall Street from all over the country, and that the mood of those submitting orders may not be influenced by New York City weather. He observes, however, that "local trading agents" on the floor of the exchanges may affect prices, and thus New York City weather may be a proxy of sorts for the mood of market participants.

During both the 1927-1962 and 1962-1989 periods, Saunders finds that stock returns are lower on days of 100% cloud cover than on days when cloud cover is 20% or less. Similarly, positive index changes are more likely on days with cloud cover of 20% or less than on days with 100% cloud cover. Returns remain lower on cloudy days after adjusting for Monday and January effects. Interestingly, the relation between cloud cover and stock returns is only marginally significant before 1962, but is much more significant afterward.

Trombley (1997) suggests that the relation between weather and stock returns is not as obvious as Saunders (1993) suggests. Trombley replicates Saunders' result that returns are lower on days that are 100% cloudy than on days that are 0 to 20% cloudy. He shows, however, that returns on 100% cloudy days are not significantly different from returns on days with 0% cloud cover or 0 to 10% cloud cover. Trombley claims that Saunders' comparison of 100% cloudy days with 0 to 20% cloudy days "is the only comparison during this period that would produce a statistically significant test statistic…."

Hirshleifer and Shumway (2003) examine cloudiness and stock returns for 26 countries during 1982 to 1997. By examining the effects of weather in numerous locations rather than in a long time-series, they can see whether the influence of sunshine is pervasive, as the psychological literature predicts. Their multiple market focus also allows concentration on a more recent time period when markets are thought to be more efficient.

Using hourly data from the International Surface Weather Observations dataset, Hirshleifer and Shumway calculate average cloud cover each day for the city of each stock exchange. They deseasonalize the cloudiness data by subtracting average cloudiness for that city during that week of the year. A simple OLS regression of daily stock returns on the cloudiness index for each of the 26 cities produces negative coefficients on cloudiness in 18 cases. In addition, logit model results suggest that cloudiness is associated with a lower probability of positive returns for 25 of the 26 cities. These findings are consistent with the casual intuition that overcast weather is associated with downbeat moods and that moods affect stock prices.

Coefficients from the Hirshleifer and Shumway (2003) pooled regressions suggest that the difference in returns between completely overcast and completely sunny days is about nine basis points, which they claim to be sufficient to allow profitable trading assuming trading costs of less than five basis points per transaction. The authors' analysis of trading strategies, however, is based on some strong assumptions. They assume that traders execute index futures trades at previous closing prices. They also assume that trading costs under five basis points are obtainable for futures contracts on the stock exchange indices of Rio de Janeiro, Taipei, Istanbul, Buenos Aires, and others used to generate the pooled estimate of nine basis points.

Goetzmann and Zhu (2003) find that while cloud cover does not affect the propensity of investors to buy or sell, it does seem to be associated with wider bid-ask spreads. They conjecture that mood swings by individual specialists may account for this observation. They find that when changes in spreads are incorporated in regressions of returns on weather, the weather effect is greatly reduced.

We contribute to the literature by testing whether local weather conditions affect returns of locally headquartered Nasdaq stocks. To document the importance of localized trading, we examine intraday trading patterns for stocks based in different time zones, the effects of blizzards on trading volume for companies based in the blizzard city, and how Yom Kippur affects trading volume for stocks from cities with differing Jewish populations. Our evidence is consistent with other findings that company shares are held disproportionately by investors who live nearby. For example, Huberman (2001) looks at holdings of the seven regional Bell operating companies (RBOCs). The RBOC that provides service in a state is held by more investors in the state than any of the other six RBOCs everywhere except Montana. On average, twice as many accounts hold the local RBOC as hold the next most popular RBOC.

Grinblatt and Keloharju (2001) examine the stockholdings of Finnish investors. They find that investors who live in the same city as a company's headquarters are far more likely to own the stock or buy the stock than investors living elsewhere. This is true for both households and institutions, and holds after adjustment for culture and language.

Coval and Moskowitz (1999) report that holdings of U.S. investment managers during 1995 consist of stocks that are 160 to 184 kilometers closer than the average company that a manager could hold. When investing in small and highly levered stocks, managers display an even stronger bias toward local companies. Using data from a large discount brokerage firm, Zhu (2002) finds that individual U.S. investors also have a strong local bias. Portfolios of investors in his sample are about 13% closer to their homes than the market portfolio.

Coval and Moskowitz (2001) examine holdings of mutual funds over 1975 through 1994. A typical fund displays a modest but significant bias toward holding local companies. Some funds, however, strongly bias their holdings toward local securities. The authors show that mutual funds earn about 118 basis points more annually on their positions in local stocks than on more distant stocks. Conversely, local stocks shunned by local mutual funds underperform benchmarks by over 1% per year.

Our study differs from these previous papers in that we look at trading, not holdings. Our evidence, while consistent with earlier results on holdings, does not preclude the possibility that holdings are evenly distributed geographically but investors turn over holdings in local companies more rapidly than other holdings.

III. Data

We confine our attention to Nasdaq stocks because we believe their returns are particularly likely to be affected by local weather conditions. Nasdaq-listed companies tend to be smaller than NYSE companies. Coval and Moskowitz (1999) show that the local bias of fund managers is more severe for small capitalization stocks than large ones. Zhu (2002) finds the same result for individual investors. In addition to being smaller, Nasdaq companies are typically newer public companies than New York Stock Exchange listed stocks. If share ownership becomes more dispersed over time, a Nasdaq firm's shareholders will be more likely to be close to the company headquarters than shareholders of a more seasoned NYSE firm. Finally, even if

NYSE and Nasdaq shareholders are equally concentrated geographically, most trading in NYSE-listed stocks takes place at the NYSE, a location distant from the company itself. Many Nasdaq market makers who trade a company's stock, however, also are located near the company (Schultz, 2003).

Nasdaq provides us with the locations of headquarters of Nasdaq-listed companies for each year from 1984 through 1997. The data from 1984 through 1987 include only the state. Data from 1988 on also include city and zip code. We use the zip codes from 1988 to assign cities to Nasdaq companies in earlier years. We include companies located in the city's metropolitan area and not just the city itself. Hence Microsoft, which is headquartered in suburban Redmond, is included in Seattle's stock portfolio. We then form portfolios of Nasdaq stocks for each of the 25 cities with the largest number of Nasdaq firms.

The University of Chicago's Center for Research in Security Prices (CRSP) provides the returns, trading volume, and price information for the sample. To minimize the impact of low-priced stocks, we require the firm to have a stock price of at least $3 two days before entering the sample on any particular trading day. Firms remain in the sample for the entire period the company trades on Nasdaq. If a firm transfers from Nasdaq to another exchange, we calculate returns up until the last trading day before the firm begins trading on the new venue. For tests related to intraday trading volume, we also collect transaction data from the New York Stock Exchange's TAQ data set.

Our source for weather data is the International Surface Weather Observations dataset provided by the National Oceanic and Atmospheric Administration. This is the same source Hirshleifer and Shumway (2003) use. This information includes hourly observations of cloud cover for weather reporting stations. Sky conditions are defined as clear, scattered clouds, broken clouds, or overcast.[2] We calculate the average amount of time each day each condition is in effect using observations from 8 am through 4 pm New York time. Cloud cover is examined for these hours because we are concerned with cloud cover while the market is open for trading.

[2] Our weather data is taken from reporting stations at U.S. airports. The data format description for the International Surface Weather Observations Data lists seven possible values for the airway and U.S. METAR sky cover variable: 0 is clear, 2 is scattered clouds, 7 is broken, 8 is overcast, 9 is obscured (not observable), 10 is partially obscured, and 99 is missing. Hirshleifer and Shumway (2003) use weather data primarily from foreign reporting stations. The total sky cover variable for these stations ranges from 0 (clear) to 8 (overcast).

In most cases, there is more than one reporting station near a city. To be consistent for all locations, we use cloud cover observations taken at the city=s major airport.

Table 1 reports correlations between the percentage of time overcast for Chicago, Los Angeles, New York, and Seattle with the other major U.S. cities included in our sample. To reduce table clutter, not all city correlations are reported. Two important results are evident in Table 1. First, cloud cover in New York is a poor proxy for the cloud cover experienced in the rest of the U.S. Except for nearby cities on the East Coast, New York generally has near-zero overcast correlations with the rest of the U.S. Second, the low correlations of cloudiness across cities suggests that using information on the weather in different cities should allow for much more powerful tests of the relation between cloud cover and stock returns than using New York weather only.

IV. Localized Trading

To illustrate the influence of localized trading, we present three separate inquiries. The first test of localized trading examines the impact of different time zones on intraday trading patterns. The second examines the effect of blizzards on the trading volume of local firms. Finally, the last test examines the influence of a religious celebration (Yom Kippur) on trading volume of local firms in cities with varying proportions of Jewish populations. Each of our findings suggest that investors located in the same city as a Nasdaq firm's headquarters do a disproportionate amount of the trading in that stock.

A. Evidence from Intraday Patterns that Stocks are Traded Locally

If stocks are held and traded disproportionately by investors who live near the company, we might expect to see different intraday trading patterns in stocks based in different parts of the country. For example, it is well known that trading volume is low during the lunchtime in New York. The obvious explanation for this pattern is that people on the East Coast are not submitting orders because they are at lunch. If West Coast investors disproportionately trade companies based on the West Coast, the volume of these stocks may not decline as much over the East Coast lunch hour.

To test whether company location affects intraday trading patterns, we count all trades of all stocks that occur in each five-minute interval of the trading day over the entire year of 1993 for companies based on the East Coast, the West Coast, and in Alaska and Hawaii. We then calculate the proportion of all trades that occur in each five-minute period. It is possible that different intraday trading patterns may arise from different patterns of information arrival. To insure that differences in the timing of news releases are not behind a divergence in intraday trading patterns, we include a stock's trades for a day only if the stock's inside bid and ask quotes never change during the trading day. Even with this restriction, sample sizes are quite large. We have 943,568 trades of stocks from Eastern time zone companies, 414,552 trades of stocks from Pacific time zone companies, and 8,601 trades of stocks of companies based in Alaska and Hawaii.[3]

Figure 1 compares intraday trading patterns for Alaska/Hawaii and East Coast firms (on New York time). Alaska is four hours behind New York while Hawaii is five hours behind. With relatively few companies headquartered in Alaska or Hawaii, there is considerable variability in the proportion of trades minute by minute. Nevertheless, a clear pattern exists. A much smaller proportion of Alaska or Hawaii trades occur soon after the market opens than stocks on the East Coast. When it is 10 am in New York, it is 5 am in Honolulu, and many investors are still in bed. Alaska or Hawaii stocks experience a much greater proportion of their trades when it is the afternoon on the East Coast than do East Coast companies.

Figure 2 compares intraday trading in East and West Coast stocks. The patterns are clearly different. A smaller proportion of West Coast daily stock trades occur between 10 am and 11 am Eastern time than stocks of companies on the East Coast. This corresponds to 7 am to 8 am on the West Coast, when investors there are likely to be preparing for work or commuting. In addition, West Coast companies experience a greater proportion of their trades between 12:30 pm and 1:30 pm Eastern time than East Coast companies. This is lunchtime in New York, when investors on the East Coast are less likely to be at their desks, but is between 9:30 and 10:30 am on the West Coast.

[3] We also tried including trades for every stock every day but only if they were for less than 500 shares. Barclay and Warner (1993), Hasbrouck (1991), and Huang and Stoll (1996) all show that small trades provide little information. The results are unchanged.

We apply a chi-square test to determine whether the allocation of trades across five-minute intervals differs between East and West Coast stocks and between Alaska/Hawaii stocks and East Coast stocks. The differences are highly significant, an unsurprising result, given the large number of trades and the clear differences in patterns in the graphs.[4] All in all, differences in intraday trading patterns across the East Coast, West Coast, and Alaska/Hawaii suggest that Nasdaq stocks are disproportionately traded by local investors.

B. Impact of Blizzards on Local Trading Volume

As a second test, we examine firm trading volume around blizzards. The impact of a blizzard should be area-specific. That is, large snowfalls in St. Louis should affect the trading behavior of St. Louis residents, not traders located in Los Angeles. One might believe that large snowfalls will influence trading volume by making it harder for people to reach work or encouraging them to leave their jobs early, both of which will remove investors from their desks. Similarly, if trading is motivated by calls from stockbrokers, and stockbrokers are having trouble reaching work, we would expect volume to decline. Thus, if stock ownership and trading are concentrated near a company's headquarters, we would expect to see a decline in trading volume for firms in cities experiencing a blizzard, while firms in non-blizzard cities should not see a trading volume decline on the same trading day.

Table 2 reports average firm trading volumes for blizzard and non-blizzard cities during the 1984-1997 time period. During that period, there were 48 trading days when a blizzard occurred in at least one of our 25 cities. For most cities, we define a blizzard as at least eight inches of snowfall within a day. Snow is likely to be an even greater disruption for cities that seldom experience snowfall, so we use a lower threshold for cities that never have eight inches of snow. Hence, a blizzard is defined as five inches for Atlanta, Portland, and Seattle. Not

[4] When the entire trading day is used, the chi-square statistic is 2,237 for East Coast versus West Coast stocks and 444 for East Coast versus Alaska/Hawaii stocks. In each case there are 77 degrees of freedom. When the time from 10 am on is used, as in the graphs, the chi-square statistic is 1,854 for East Coast versus West Coast stocks and 363 for East Coast versus Alaska/Hawaii stocks. A chi-square statistic of 124.8 rejects a null hypothesis that trades from the different regions are allocated equally across time intervals at the 0.1% confidence level when there are 80 degrees of freedom.

surprisingly, the following warm weather cities never reported even five inches of snow: Dallas, Los Angeles, Miami, Phoenix, San Diego, San Francisco, and Tampa.[5]

Panel A of Table 2 reports average trading volume for firms in the days around one of the 48 blizzards. Nasdaq-listed firms are classified as being in blizzard cities if the company's headquarters are located in a metropolitan area that experienced a blizzard on that particular trading day. For example, firms located in Cleveland, Ohio, are in the blizzard category only on the five particular trading days that their city had at least eight inches of snowfall within a day. For comparison, the table also lists average trading volume for each Nasdaq-listed sample firm during days t-11 to day t-2 prior to the blizzard date (day t).

On the blizzard dates, trading volume for stocks located in snowbound cities averages 65,933 shares, a 17% decline in volume from the previous trading volume. Firms in non-blizzard cities experience no real change in average trading volume (108,973 shares versus 108,921 shares).

Our data only provides snowfall over a 24-hour period. In many cases, snowfall occurs late in a day. It is not surprising then, that the last column of Panel A reports that trading patterns continue to be impacted the day after the blizzard. While firms in non-blizzard locations see a slight increase in trading volume following a blizzard date, firms in the blizzard cities see an average trading volume decline of approximately 15%. In unreported results, the average trading volume for companies located in blizzard cities reverts to normal levels on day t+2.

Panel B of Table 2 reports results from a regression of daily trading volume as the dependent variable. The two independent variables are the firm-specific trading volume in the period prior to the blizzard date and a blizzard dummy variable. The blizzard dummy variable takes a value of 1 on a trading day if the firm is in a city experiencing a blizzard; otherwise it takes a value of 0. The reported t-statistics are calculated using White's (1980) heteroskedasticity-consistent method.

The coefficient of 1.05 on the mean trading volume during the prior period implies that volume is 5% higher for non-blizzard firms on the blizzard date. The blizzard dummy variable has a statistically significant value of –12,356 on the day of the event (row 1). This implies that,

[5] Hirshleifer and Shumway (2003) estimate the effects of snowfall on stock returns (not volume) for such warm weather cities as Bangkok, Kuala Lumpur, Manila, Rio De Janeiro, and Singapore by using a continuous snowfall variable.

all else equal, firms in cities experiencing a blizzard would be expected to see trading volume drop by an average of more than 12,000 shares. Not surprisingly, trading volume is negatively affected in blizzard locations even the day after the event (row 2). Yet, the coefficient on average prior volume implies that firms in non-blizzard cities report only a 3% decline in trading volume on the subsequent day.[6]

C. Trading Volume Impact of Yom Kippur

In a third test of the impact of localized trading behavior, we examine whether trading volume is affected by the celebration of religious holidays. For historical or self-selection reasons, ethnic or religious groups tend to cluster in particular cities in the United States. The Jewish holiday of Yom Kippur offers a date to gauge the impact of localized trading behavior. Yom Kippur is a single day, generally in mid-September to mid-October, and widely regarded as the most important Jewish holiday of the year. Sometimes Yom Kippur falls on a non-trading day. For example, in 1984, the holiday fell on Saturday, October 6th. We have identified nine times Yom Kippur occurs on a trading day during our time period. Our hypothesis is that firms in cities with a higher concentration of Jewish population would see greater drops in firm trading volume on the Yom Kippur holiday than firms in cities with lower Jewish concentrations.

Panel A of Table 3 shows average firm trading volume in the 25 U.S. cities around Yom Kippur. Column 3 reports that the average firm trading volume is 103,913 shares the day before Yom Kippur compared to 99,518 shares in the prior period (days t-11 to t-2). Column 4 lists the average firm trading volume on Yom Kippur as 82,984 shares, a decline of almost 17% compared to the typical prior-period firm trading volume. This trading volume difference is highly significant (t-statistic less than –8.00).

Panel B of Table 3 provides a more direct test of the impact of localized trading around Yom Kippur. In the regression, firm trading volume on Yom Kippur is the dependent variable. The first independent variable, firm trading volume in the prior period (days t-11 to t-2), controls

[6] We cannot for sure say why volume falls during blizzards. We hypothesize that it is the drain on investor's time from a longer commute, shoveling snow, etc. Of course, it is possible that blizzards could lead to decreased trading if they affected the mood of investors in such a way as to reduce their desire to trade.

for the normal level of trading for each company. The second independent variable takes a value of 1 if the city is among the top five in percentage of residents who are Jewish.

Information on Jewish populations of metropolitan areas of U.S. cities for 1990 is obtained from the 1991 American Jewish Yearbook. Total populations for the metropolitan areas are obtained from 1990 U.S. census figures. Of the 25 cities in our sample, Boston, Los Angeles, Miami, New York City, and Philadelphia are the only cities in which at least 5% of the metropolitan area's population is Jewish.

In regressions with trading volume on the day before the holiday as the dependent variable, the coefficient on both the top five Jewish city dummy variable (row 1) and the Jewish population percentage (row 2) are statistically insignificant. The coefficient of 1.01 on the mean volume during the prior 10-day period implies that firm trading volume is 1% higher than would otherwise be expected.

When the dependent variable is the firm trading volume on Yom Kippur (row 3), the 0.74 coefficient on the mean prior volume indicates a sharp decline in trading volume for all firms. In the row 3 regression, the coefficient on the dummy variable is a statistically significant –10,733 (t-statistic of –3.21). In row 4, the coefficient on the Jewish population percentage is also statistically significant (t-statistic of –3.15). Hence, firms located in cities with high Jewish population concentrations experience significantly greater volume declines than cities with smaller Jewish populations on the most important Jewish holiday of the year.[7]

In three separate empirical tests, we have shown that a large proportion of a stock's trades come from investors located near the company headquarters. These results give us confidence that the weather in the city where a company is located is a good proxy for the weather facing the investors who trade the stock.

[7] Eight days prior to Yom Kippur, many people of the Jewish faith celebrate the two-day holiday of Rosh Hashana. As a robustness check, we also examined firm trading volume surrounding this important Jewish holiday. If the dependent variable of the Table 3, Panel B, regression includes firm trading volume on both Yom Kippur and Rosh Hashana, the Jewish concentration city dummy variable coefficient is –7,812 (t-statistic of –3.94). Consistent with our findings, Frieder and Subrahmanyam (2002) also find that trading volume is down significantly on Rosh Hashana and Yom Kippur. Market returns are down sharply as well for Yom Kippur, yet are positive for Rosh Hashana.

V. Weather and Stock Returns

If investor pessimism brought on by overcast weather affects stock returns, we would expect to find a negative relation between local cloud cover and stock returns of local firms. Table 4 reports weather and stock return summary statistics during the 1984-1997 period for our 25 U.S. cities. During the time period, there were 3,540 trading days. Across cities in our sample, the sky is clear an average of 18.7% compared to overcast 36.0% of the time. The rest of the time the cities have scattered or broken clouds. There is a wide range of weather conditions in the continental U.S. For example, Phoenix reports clear weather 48.6% of the time, while skies over Miami are clear only 6.9% of the time.

The sixth column of Table 4 reports the mean daily return on a stock portfolio of locally headquartered Nasdaq firms. A total of 4,949 Nasdaq firms are in the sample universe for at least one trading day. The stock return portfolios are equally weighted. The average daily return on the 25-city stock portfolios is 0.071%. The last column of Table 4 reports the stock portfolio standard deviation.

A. Impact of New York Weather on Market Index Returns

Using a logit model that relates the probability of a positive daily stock return to cloudiness, Hirshleifer and Shumway (2003) find a statistically significant link between returns and cloudiness in New York City. We replicate part of their findings in Table 5. In the logit regressions, the dependent variable is set to 1 if the stock market index return is greater than 0, and to 0 for all non-positive values. Here, and in the remainder of the paper, the variable "cloudy" or "cloudiness" is the percentage of time from 8 am to 4 pm that the sky is overcast. The variable clear, is the percentage of time the sky is clear. Two different stock market indexes are used to gauge the linkage: a value-weighted (VW) and an equally weighted (EW) NYSE/Amex/Nasdaq CRSP Index.

The result of the logit regression in row 1 is consistent with the evidence provided by Hirshleifer and Shumway (2003) and Saunders (1993). The regression reports a significant negative relationship between cloudiness in New York and the probability of a positive return for the VW index. When the dependent variable is the EW CRSP Index (row 2), however, no significant weather-return relationship is found. In row 3, we also report that clear (i.e., sunny) weather days are associated with positive value-weighted market stock returns. That is, clear New York City weather has a positive influence on stock index returns.

B. Impact of Local Weather on Locally Headquartered Company Stock Returns

To examine whether local weather conditions affect returns on locally headquartered stocks, we create an equally weighted daily stock portfolio for each city in our sample using only Nasdaq-listed firms. As noted previously, we require the firms to have a stock price of at least $3 two days prior to entering the daily index on a particular trading day. This requirement should help reduce the influence of bid-ask spreads on the daily portfolio return series. Some firms drift in and out of our sample due to stock price fluctuations surrounding the $3 screen.

To be consistent with Hirshleifer and Shumway (2003), we report both OLS and logit model regressions. Columns 2-4 of Table 6 relate weather and city portfolio returns using an OLS regression framework, while columns 5-7 use a logit regression model. Overall, the results do not support the hypothesis that cloudy weather impacts stock returns. In the OLS regressions, 12 of the 25 slope coefficients on percentage of time overcast have a negative sign (column 3), but none are statistically significant at conventional levels.

In the logit regression results, the local cloudiness variable is the sole explanatory variable. The logit model relates the probability of a positive daily portfolio return on cloudiness for each U.S. city. The dependent variable takes the value of 1 if the portfolio return is positive; otherwise the variable is set to 0. Consistent with the OLS results, the logit model yields a negative coefficient on the cloudiness variable for 13 of the 25 cities, but none of the coefficients are significant. To summarize, we find no evidence that weather conditions in the city where a company is located affect its stock return, despite strong evidence that a disproportionate amount of the trading comes from investors who live in the same city.

So far, our analysis has slightly diverged from the Hirshleifer and Shumway methodology by not deseasonalizing the weather pattern. Hirshleifer and Shumway deseasonalize their data set by calculating the average cloudiness for each week by city and subtracting that week's mean cloudiness from each day's weather. The reasonable premise of this procedure is to adjust for any seasonal patterns in cloud cover.

There are two potential problems with this procedure, however. First, it is not clear that investors "seasonalize" weather observations in their heads. That is, it may not be true that investors say, "today is a sunny day in January if I account for yearly overcast trends." The weather today is either sunny or not sunny. Second, the weather deseasonalization procedure possibly introduces a look-ahead bias into the analysis. As of the first week in January of 1984, no person could perfectly forecast early January weather patterns for the future 13 years.

Not withstanding these caveats, we deseasonalized the weather data following the Hirshleifer and Shumway (2003) methodology. As in Hirshleifer and Shumway, the results remain the same, whether or not we do this. Since deseasonalizing the weather series does not affect the interpretations of the results, we do not report the deseasonalized patterns henceforth.

To show the combined impact of local and New York City weather patterns on stock returns, we report in Table 7 the OLS regression results using the daily city portfolio returns as the dependent variable and local and NYC cloudiness as the right-hand side variables. For the New York location, the regression is not reported since the two independent variables are the same. None of the 24 city regressions result in a statistically significant negative coefficient.

The fifth and sixth columns of Table 7 report the NYC cloudiness variable and its significance level. Consistent with Hirshleifer and Shumway (2003) and Saunders (1993), the NYC cloudiness variables are overwhelmingly negative. In 21 of the 24 regressions, NYC cloudiness is negatively related to the city portfolio returns. Only two of the negative NYC cloudiness coefficient values, however, are statistically significant at conventional levels. The last column of Table 7 reports the adjusted R^2 values for each of the regressions. Although the dependent variable is a stock portfolio and not individual firm returns, the very low R^2 numbers imply that little of the variation in returns is explained by the weather variables. All of the R^2 values are approximately zero.[8]

[8] It is possible that cloud cover in the cities in which they live does affect investor's propensity to buy or sell stocks, but that rational traders in New York arbitrage away any effects. In this case, we might expect local effects to emerge when local skies are cloudy and cloudiness in New York prevents traders there from dampening the effects of local moods. To test this, we replicate Table 7 but replace the New York weather variable with an interaction between cloudiness in New York and local cloudiness. In these regressions, the coefficient on the interaction term is negative and significant in one of the 24 regressions. The term on local cloudiness is never significant. We also replicate Table 7 using both a New York cloudiness variable and an interaction. Results are similarly weak.

C. Local Weather and Local Excess Returns

Our tests of the effects of cloud cover on stock returns have so far been similar to those of Hirshleifer and Shumway (2003) and Saunders (1993). Use of portfolios of stocks that trade on the same market but have different weather patterns, however, permits more powerful tests. We exploit our sample characteristics by regressing returns of portfolios of stocks headquartered in a city on the cloud cover in that city and the equal-weighted CRSP index return for the same day. In these regressions, we are testing whether a city's cloud cover is related to the average excess returns of stocks in the city.

Results are reported in Table 8. The last column of the table reports that average adjusted R^2 values range from 0.31 to 0.78. When we regressed portfolio returns on weather alone adjusted R^2 values were close to zero. Thus virtually all of this explanatory power comes from inclusion of the index return.

Even after eliminating the noise in the returns from market-wide economic factors, we have trouble detecting an effect of cloud cover on stock returns. Coefficients on cloudiness, measured as the percentage of the day the sky was overcast, are negative for 15 of the 25 sample cities and positive for the other ten. This is hardly convincing evidence of a relationship between cloud cover and weather. If the coefficients are independent across the 25 regressions, and positive and negative coefficients are equally likely, there is a 21.2% chance of observing 15 or more negative coefficients. Also, only three of the 15 negative coefficients are significantly different from zero at the five percent level. The average of the coefficients on cloudiness is -0.006, indicating that the difference in returns between days when the sky is never completely overcast and days when the sky is completely overcast all the time is less than one basis point, or one cent on a $100 stock.

The last table creates four weather-stock portfolios on the basis of both local and New York City weather conditions for our sample of 4,949 Nasdaq-listed firms. In Panel A of Table 9, all firms in locations with clear skies for the entire trading day are pooled into the second column. Thus, Nasdaq-listed firms in Chicago, Hartford, Phoenix, and Tampa would be pooled into a single stock portfolio if those cities all experienced totally clear weather on the same trading day (column 2). Firms in locations with scattered clouds the entire day are pooled into the third column, and so on. In columns 6-9, stock portfolios are created on the basis of New York City weather conditions. There are numerous trading days when none of the 25 cities experienced a particular weather pattern. But, out of 3,540 possible trading days during the time period, on 2,777 trading days at least one city in the U.S. had clear skies for the entire day.

For both the local and New York City weather categorizations, no strong patterns emerge. Surprisingly, the weather portfolio with the highest average stock return is perfectly overcast (0.073%), compared to an average return of 0.063% when local skies are clear all day. Scattered and broken clouds had average returns of 0.046% and 0.054%, respectively. When New York City is overcast the entire day, stock returns averaged of 0.028%, as compared to 0.015% for days when New York was totally clear.

We can again take advantage of using stocks that trade in the same market to design a more powerful test of the relation between weather and returns. Panel B of Table 9 reports average stock returns for cities that are overcast all day and cities that are clear all day on the same day.[9] For the 2,530 trading days with firms in each category, the returns are 0.061% and 0.070% for the totally clear and cloudy weather conditions. The last column of Panel B reports that the return difference of less than one basis point (0.009%) between the two portfolios is not significant.

VI. Conclusions

Numerous studies in psychology have established that people's moods and judgments are affected by exposure to sunlight. Research in finance has exploited this finding to test whether exogenous determinants of individuals' moods can affect stock prices. Saunders (1993) finds that cloudiness in New York City is associated with lower returns on U.S. stocks. Hirshleifer and Shumway (2003) use cloud cover in cities with stock exchanges around the world to predict returns on the exchanges. They also find evidence that stock returns are lower on cloudy days.

A limitation of both of these studies is that the weather at the stock exchange is often not the same as the weather experienced by investors who are submitting orders to the exchanges. Orders arrive at the New York Stock Exchange from all over the U.S. and all over the world.

[9] A criticism of the results in Panel A is that the month of January, which has historically had high average stock returns, might also be more likely to have overcast skies. This criticism does not apply to Panel B, where we compare same-day returns of stocks from clear and cloudy cities.

New York City weather is therefore a poor proxy for the cloud cover and mood of investors submitting orders. Similarly, cloud cover in cities with stock exchanges is unlikely to be the same as the cloudiness facing investors submitting orders to those exchanges. In some cases, like Brussels or Copenhagen, the weather in the stock exchange city is likely to reflect the weather facing all investors in the country. In other cases, like Rio de Janeiro or Sydney, the cloud cover in the stock exchange city is unlikely to reflect the cloud cover over the entire country. In all cases, orders arrive at the exchanges from the U.S. and elsewhere.

To get an alternative measure of the weather investors are experiencing, we use the findings of Coval and Moskowitz (1999, 2001), Grinblatt and Keloharju (2001), Huberman (2001), and Zhu (2002) that investors invest disproportionately in local companies. We assemble portfolios of 4,949 Nasdaq stocks based in 25 U.S. cities and demonstrate that trading has a strong local component. Our evidence that trading in our sample stocks is concentrated among investors living near the company headquarters includes different intraday patterns for stocks from different time zones, diminished volume for stocks from cities that are experiencing blizzards, and lower volume on Yom Kippur for stocks from cities with large Jewish populations.

The strong local component in trading of Nasdaq provides a compelling case for using weather near a company's headquarters to test for effects of cloudiness on returns. There are several advantages to these tests. First, using weather near a company's headquarters allows many more observations of weather conditions and stock returns than if we had restricted our attention to weather in New York. Second, while a justification for using New York weather is that many institutions trade from there, it seems implausible to us that the trading of these sophisticated investors is particularly likely to be affected by cloudiness. Our focus on cloudiness near company headquarters allows us to see if moods of the less sophisticated individual investors who trade a stock affect returns. Finally, and most important, by using stocks that trade in the same market but face different weather conditions, we can look for influences of weather on stock returns after eliminating the noise from the economic factors that affect returns market-wide.

Despite these advantages, we are unable to find any evidence of a relation between cloud cover near a company headquarters and its stock's return. Like Hirshleifer and Shumway (2003) and Saunders (1993), however, we do find weak evidence that returns of our stocks are lower on days it is cloudy in New York City. Is this because of trading by institutions that are based in New York? We find this hard to believe. We are examining equal-weighted portfolios of Nasdaq stocks, and many of these securities are too small to attract institutional interest. It is also doubtful that professional investors are more prone to biases in judgment brought on by cloudiness than the small investors located near a company. It is also possible, as Goetzmann and Zhu (2003) suggest, that specialist's moods are affected by weather, leading to wider spreads and larger returns. We would, however, not dismiss the possibility that the relationship between cloud cover in New York and stock returns is spurious.

An unambiguous result of our analysis is that U.S. weather effects are too slight to provide opportunities for profitable trading of Nasdaq stocks. The average coefficient on New York City cloudiness in Table 7 is -0.038. This means that a $100 Nasdaq stock can be expected to rise in price by 3.8 cents more on totally sunny days than on days that are completely overcast. The effects of local cloudiness are even smaller. Trading costs would swamp any profits to be found in implementing a weather-based trading strategy.

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Table 1
Correlations of Percentage of the Time Overcast for Various U.S. Cities, 1984-1997

U.S. City (1)	Chicago, IL (2)	Los Angeles, CA (3)	New York, NY (4)	Seattle, WA (5)
Atlanta, GA	0.13	-0.05	0.20	0.03
Boston, MA	0.04	-0.05	0.66	0.02
Chicago, IL	1.00	-0.02	0.10	0.03
Cincinnati, OH	0.38	-0.06	0.29	0.05
Cleveland, OH	0.38	-0.04	0.32	0.06
Columbus, OH	0.39	-0.03	0.33	0.04
Dallas, TX	0.07	-0.04	-0.01	0.03
Denver, CO	0.11	-0.02	0.00	-0.09
Detroit, MI	0.55	-0.05	0.25	0.01
Hartford, CT	0.06	-0.03	0.79	0.00
Houston, TX	0.07	-0.08	0.02	0.04
Los Angeles, CA	-0.02	1.00	-0.02	-0.07
Miami, FL	-0.04	-0.00	-0.04	0.01
Minneapolis, MN	0.38	-0.05	-0.02	0.02
New York, NY	0.10	-0.02	1.00	0.00
Philadelphia, PA	0.10	-0.02	0.78	0.00
Phoenix, AZ	0.03	0.12	-0.01	-0.00
Portland, OR	0.06	-0.08	0.02	0.65
St. Louis, MO	0.50	-0.04	0.09	0.04
Salt Lake City, UT	0.08	0.03	0.04	0.11
San Diego, CA	-0.06	0.69	-0.05	-0.09
San Francisco, CA	0.00	0.23	0.02	0.07
Seattle, WA	0.03	-0.07	0.00	1.00
Tampa, FL	-0.02	-0.02	0.04	0.02
Washington, DC	0.15	-0.02	0.56	0.02

Weather data are from the International Surface Weather Observations (ISWO). Each hour, ISWO characterizes the sky as clear, scattered clouds, broken clouds, or overcast. We calculate the percentage of time the sky is overcast between 8 am and 4 pm New York time for each trading day over the 1984-1997 time period.

Table 2
Trading Volume on Nasdaq-Listed Stocks During Local Blizzards, 1984-1997

Panel A: Summary Firm Trading Volume Statistics for Blizzard and Non-Blizzard Days

Item (1)	Average Firm Volume During Days t-11 to t-2 (2)	Average Firm Volume on Day t (Blizzard Date) (3)	Average Firm Volume on Day t+1 (4)
Non-Blizzard Cities	108,921	108,973	112,480
Blizzard Cities	79,625	65,933	67,834

Panel B: Regressions with Firm Trading Volume on Blizzard Days (t and t+1) as Dependent Variable

Row	Dependent Variable	Intercept	Mean Firm Trading Volume during Days t-11 to t-2	Blizzard Dummy Variable	Adjusted R^2
1	Day t Firm Trading Volume	-5,108.62 (-0.54)	1.05 (10.39)	-12,356.02 (-2.72)	0.465
2	Day t+1 Firm Trading Volume	6,894.75 (1.81)	0.97 (24.04)	-16,247.49 (-4.45)	0.603

The time period is limited to the 48 days in which a blizzard occurred on a trading day for the 25 U.S. cities examined during 1984-1997. A blizzard is defined as eight or more inches of snow within a 24-hour period for most of the sample. Atlanta, Portland, and Seattle use a five inch screen for the definition of a blizzard. Trading volume is obtained from CRSP. The sample is composed of Nasdaq-listed firms headquartered in the metropolitan areas of the 25 U.S. cities. The t-statistics (in parentheses) are calculated using White's (1980) heteroskedasticity-consistent method.

Table 3
Trading Volume Around Jewish Holiday of Yom Kippur, 1984-1997

Panel A: Firm Trading Volume on Day Before and Day of Yom Kippur

U.S. City (1)	Mean Volume During Days t-11 to t-2 (2)	Mean Trading Volume on Day Before (3)	Mean Trading Volume on Yom Kippur (4)	Trading Volume Difference (4) –(2)
Atlanta, GA	85,855	100,068	78,409	-7,446
Boston, MA	79,745	78,722	63,663	-16,082
Chicago, IL	60,661	62,722	52,557	-8,104
Cincinnati, OH	44,378	49,015	98,492	54,114
Cleveland, OH	49,897	50,299	34,766	-15,131
Columbus, OH	65,015	60,311	38,748	-26,267
Dallas, TX	81,548	82,120	59,921	-21,627
Denver, CO	94,964	88,741	71,396	-23,568
Detroit, MI	38,184	38,276	31,649	-6,535
Hartford, CT	25,981	38,747	32,771	6,790
Houston, TX	57,665	58,296	46,102	-11,563
Los Angeles, CA	74,698	80,305	59,766	-14,932
Miami, FL	71,013	67,022	43,655	-27,358
Minneapolis, MN	52,203	56,419	47,674	-4,529
New York, NY	55,201	60,036	42,100	-13,101
Philadelphia, PA	91,741	93,717	68,594	-23,147
Phoenix, AZ	129,216	123,549	84,366	-44,850
Portland, OR	93,933	135,678	92,071	-1,862
St. Louis, MO	47,364	51,627	37,501	-9,863
Salt Lake City, UT	73,970	163,056	73,268	-702
San Diego, CA	166,815	81,024	78,117	-88,698
San Francisco, CA	239,980	253,888	212,452	-27,528
Seattle, WA	136,465	133,651	110,356	-26,109
Tampa, FL	65,869	67,265	61,949	-3,920
Washington, DC	100,845	97,289	74,215	-26,630
Average	99,518	103,913	82,984	-16,534

Panel B: OLS Regressions with Firm Trading Volume as Dependent Variable

Row	Dependent Variable	Intercept	Mean Volume During Days t-11 to t-2	Top 5 Jewish City Dummy Variable	Jewish Population Percentage of Metropolitan Area	Adjusted R^2
1	Firm Trading Volume for Day Prior to Yom Kippur	4,731 (0.81)	1.01 (14.54)	-3,226 (-0.88)		0.672
2	Firm Trading Volume for Day Prior to Yom Kippur	6,813 (1.42)	1.01 (14.57)		-813 (-1.60)	0.672
3	Firm Trading Volume for Day of Yom Kippur	12,656 (3.75)	0.74 (21.46)	-10,733 (-3.21)		0.607
4	Firm Trading Volume for Day of Yom Kippur	14,519 (3.94)	0.74 (21.49)		-1,425 (-3.15)	0.607

The time period is limited to the nine times Yom Kippur occurs on a trading day during 1984-1997. Trading volume is obtained from CRSP. The sample is Nasdaq-listed firms headquartered in the 25 U.S. metropolitan areas with the largest number of Nasdaq firms. The five U.S. cities with the highest Jewish population percentage in the metropolitan area are Boston, Los Angeles, Miami, New York City, and Philadelphia. In Panel B, the dependent variable is firm trading volume on the day prior to and the day of Yom Kippur. The t-statistics (in parentheses) are calculated using White's (1980) heteroskedasticity-consistent method.

Table 4
Weather and Return Summary Statistics by 25 U.S. Cities, 1984-1997

U.S. City (1)	Percentage of Time Clear (2)	Percentage of Time Scattered Clouds (3)	Percentage of Time Broken Clouds (4)	Percentage of Time Overcast (5)	Mean Daily Return (6)	STD Return (7)
Atlanta, GA	21.7	23.2	21.0	34.1	0.076%	0.92
Boston, MA	16.1	20.5	20.4	43.0	0.071%	0.84
Chicago, IL	16.9	19.9	19.5	43.7	0.082%	0.73
Cincinnati, OH	14.9	17.5	23.8	43.8	0.095%	0.77
Cleveland, OH	13.1	16.8	19.1	51.0	0.083%	0.76
Columbus, OH	15.3	18.1	19.0	47.6	0.077%	0.91
Dallas, TX	24.8	22.4	21.1	31.7	0.061%	0.81
Denver, CO	17.6	36.0	31.5	14.9	0.053%	0.93
Detroit, MI	12.8	20.0	22.1	45.1	0.082%	0.82
Hartford, CT	17.0	27.1	21.8	34.0	0.079%	0.98
Houston, TX	14.4	20.4	33.8	31.3	0.047%	0.88
Los Angeles, CA	28.3	21.5	17.9	32.3	0.064%	0.81
Miami, FL	6.9	37.8	40.8	14.6	0.046%	0.96
Minneapolis, MN	17.9	20.3	17.5	44.2	0.087%	0.84
New York, NY	17.9	23.6	22.7	35.8	0.050%	0.69
Philadelphia, PA	14.6	26.3	25.2	33.8	0.071%	0.76
Phoenix, AZ	48.6	23.8	17.2	10.2	0.051%	1.18
Portland, OR	16.2	12.7	19.0	52.1	0.077%	1.08
St. Louis, MO	17.4	20.6	21.5	40.5	0.090%	0.78
Salt Lake City, UT	24.3	21.2	20.2	34.3	0.071%	1.11
San Diego, CA	25.0	18.7	18.0	38.3	0.060%	1.14
San Francisco, CA	25.1	22.6	21.8	30.4	0.073%	1.12
Seattle, WA	13.1	13.7	20.7	52.5	0.087%	0.99
Tampa, FL	12.9	37.7	29.6	19.8	0.072%	1.07
Washington, DC	13.6	23.9	19.7	42.8	0.080%	0.87
Average	18.7	22.7	22.6	36.0	0.071%	0.91

The sample is operating firms listed on Nasdaq and headquartered within the metropolitan areas of 25 U.S. cities. Portfolio stock returns are created from CRSP and are equally weighted. Weather data are from the International Surface Weather Observations.

Table 5
Logit Regressions of Market Index Returns and New York City Weather, 1984-1997

Row	Dependent Variable = 1 if Return > 0	Intercept	Cloudy	Clear	Pseudo R^2
1	Value-Weighted CRSP Index	0.28 (6.06)	-0.18 (-2.16)		0.001
2	Equally Weighted CRSP Index	0.56 (12.00)	-0.02 (-0.28)		0.000
3	Value-Weighted CRSP Index	0.16 (4.15)		0.26 (2.33)	0.019
4	Equally Weighted CRSP Index	0.52 (12.80)		0.19 (1.62)	0.001

Weather data are from the International Surface Weather Observations. The logit model relates the probability of a positive daily index return on clearness and cloudiness of New York City weather. The dependent variable takes the value of 1 if the index return is greater than 0; otherwise the variable is set to 0. Market indexes are obtained from CRSP. Due to missing New York City weather conditions, 35 trading days are excluded. All of the regressions have 3,505 observations. The z-statistics are in parentheses.

Table 6
Ordinary Least Squares and Logit Regressions of Daily City Portfolio Returns on Cloudiness for U.S. Cities, 1984-1997

$$\text{Daily City Portfolio Returns}_i = a_0 + a_1\text{Cloudiness}_i + e_i$$

	OLS Model			Logit Model		
U.S. City (1)	Intercept (2)	Cloudiness (3)	Cloudiness t-statistic (4)	Intercept (5)	Cloudiness (6)	Cloudiness z-statistic (7)
Atlanta, GA	0.07	0.01	0.38	0.18	0.05	0.61
Boston, MA	0.09	-0.04	-1.19	0.35	-0.06	-0.78
Chicago, IL	0.08	0.00	0.02	0.35	-0.04	-0.49
Cincinnati, OH	0.08	0.04	1.43	0.24	-0.01	-0.14
Cleveland, OH	0.07	0.02	0.54	0.19	0.10	1.20
Columbus, OH	0.07	0.02	0.67	0.17	-0.05	-0.61
Dallas, TX	0.05	0.02	0.70	0.25	-0.00	-0.00
Denver, CO	0.06	-0.01	-0.25	0.16	0.03	0.27
Detroit, MI	0.08	-0.00	-0.09	0.24	-0.03	-0.32
Hartford, CT	0.08	-0.01	-0.33	0.19	-0.05	-0.64
Houston, TX	0.03	0.06	1.66	0.11	0.17	1.90
Los Angeles, CA	0.08	-0.05	-1.49	0.34	-0.15	-1.69
Miami, FL	0.05	-0.03	-0.48	0.17	-0.16	-1.31
Minneapolis, MN	0.09	-0.00	-0.14	0.32	0.03	0.39
New York, NY	0.05	-0.00	-0.13	0.29	-0.04	-0.43
Philadelphia, PA	0.08	-0.02	-0.70	0.31	-0.08	-0.98
Phoenix, AZ	0.04	0.12	1.40	0.09	0.09	0.61
Portland, OR	-0.00	0.15	3.30	0.11	0.08	0.94
St. Louis, MO	0.08	0.03	1.07	0.23	0.07	0.86
Salt Lake City, UT	0.04	0.09	1.93	0.10	0.14	1.61
San Diego, CA	0.04	0.03	0.66	0.23	-0.10	-1.10
San Francisco, CA	0.08	-0.01	-0.22	0.25	0.05	0.54
Seattle, WA	0.05	0.06	1.45	0.21	0.10	1.14
Tampa, FL	0.09	-0.08	-1.33	0.12	0.00	0.04
Washington, DC	0.10	-0.05	-1.33	0.24	-0.09	-1.10

The sample is Nasdaq-listed firms headquartered in the 25 U.S. metropolitan areas with the largest number of Nasdaq firms. Weather data are from the International Surface Weather Observations. Columns 2-4 report OLS regression results; columns 5-7 use a logit regression model. The OLS t-statistics are calculated using White's (1980) heteroskedasticity-consistent method. The logit model relates the probability of a positive daily portfolio return to the cloudiness of the weather of each U.S. city. The dependent variable takes the value of 1 if the portfolio return is positive, and 0 otherwise. Cloudiness is defined as the percentage of the trading day with overcast skies. The number of observations in each regression varies between 3,448 and 3,529 due to missing city weather data.

Table 7
Ordinary Least Squares Regressions of Daily City Portfolio Returns on Local and New York City Cloudiness Levels, 1984-1997

$$\text{Daily City Portfolio Returns}_i = a_0 + a_1\text{Cloudiness}_i + a_2\text{NYC Cloudiness}_i + e_i$$

U.S. City (1)	Intercept (2)	Cloudiness (3)	Cloudiness t-statistic (4)	NYC Cloudiness (5)	NYC Cloudiness t-statistic (6)	Adjusted R^2 (7)
Atlanta, GA	0.06	0.01	0.38	0.01	0.22	0.000
Boston, MA	0.09	-0.04	-0.96	0.00	0.10	0.000
Chicago, IL	0.10	0.00	0.04	-0.04	-1.30	0.001
Cincinnati, OH	0.08	0.06	1.77	-0.04	-1.05	0.001
Cleveland, OH	0.08	0.03	1.09	-0.05	-1.50	0.001
Columbus, OH	0.08	0.04	1.03	-0.05	-1.31	0.001
Dallas, TX	0.06	0.02	0.72	-0.04	-1.06	0.001
Denver, CO	0.08	-0.02	-0.34	-0.07	-1.89	0.001
Detroit, MI	0.10	0.02	0.57	-0.08	-2.28	0.002
Hartford, CT	0.08	-0.00	-0.07	-0.01	-0.19	0.000
Houston, TX	0.03	0.07	1.79	0.01	0.35	0.001
Los Angeles, CA	0.11	-0.05	-1.45	-0.07	-2.20	0.002
Miami, FL	0.07	-0.02	-0.42	-0.07	-1.73	0.001
Minneapolis, MN	0.09	-0.01	-0.24	-0.02	-0.51	0.000
New York, NY	NA	NA	NA	NA	NA	NA
Philadelphia, PA	0.08	0.01	0.16	-0.04	-0.79	0.000
Phoenix, AZ	0.07	0.11	1.31	-0.09	-1.80	0.002
Portland, OR	0.00	0.15	3.32	-0.02	-0.38	0.003
St. Louis, MO	0.08	0.04	1.16	-0.02	-0.46	0.000
Salt Lake City, UT	0.05	0.09	1.95	-0.03	-0.74	0.001
San Diego, CA	0.05	0.03	0.64	-0.03	-0.54	0.000
San Francisco, CA	0.10	-0.01	-0.14	-0.06	-1.40	0.001
Seattle, WA	0.08	0.06	1.30	-0.06	-1.45	0.001
Tampa, FL	0.10	-0.07	-1.23	-0.05	-1.15	0.001
Washington, DC	0.10	-0.04	-0.92	-0.00	-0.11	0.000

The sample is Nasdaq-listed firms headquartered in the 25 U.S. metropolitan areas with the largest number of Nasdaq firms. Weather data are from the International Surface Weather Observations. Cloudiness is defined as the percentage of the trading day with overcast skies. The t-statistics are calculated using White's (1980) heteroskedasticity-consistent method. The number of observations in each regression varies between 3,448 and 3,529 due to missing city weather data.

Table 8
Ordinary Least Squares Regressions of Daily City Portfolio Returns on City Cloudiness and CRSP EW Index, 1984-1997

$$\text{Daily City Portfolio Returns}_i = a_0 + a_1\text{Cloudiness}_i + a_2\text{CRSP EW Index}_i + e_i$$

U.S. City (1)	Intercept (2)	Cloudiness (3)	Cloudiness t-statistic (4)	CRSP EW Index (5)	CRSP EW Index t-statistic (6)	Adjusted R^2 (7)
Atlanta, GA	-0.03	-0.00	-0.02	1.07	37.01	0.492
Boston, MA	-0.05	-0.00	-0.19	1.22	44.40	0.777
Chicago, IL	-0.00	-0.01	-0.50	0.94	46.14	0.606
Cincinnati, OH	0.01	0.03	1.13	0.76	26.00	0.357
Cleveland, OH	0.00	-0.00	-0.04	0.86	32.48	0.458
Columbus, OH	-0.01	0.01	0.34	0.88	20.22	0.339
Dallas, TX	-0.03	-0.04	-1.76	1.09	44.29	0.660
Denver, CO	-0.05	-0.03	-0.79	1.14	29.93	0.558
Detroit, MI	-0.00	-0.00	-0.12	0.92	27.39	0.453
Hartford, CT	-0.01	0.01	0.33	0.93	33.74	0.321
Houston, TX	-0.04	-0.03	-0.96	1.01	39.04	0.473
Los Angeles, CA	-0.04	-0.04	-2.00	1.17	37.33	0.753
Miami, FL	-0.05	-0.09	-2.10	1.10	41.02	0.479
Minneapolis, MN	-0.04	0.02	1.19	1.17	65.34	0.713
New York, NY	-0.05	0.01	0.08	0.97	41.36	0.714
Philadelphia, PA	-0.02	-0.01	-0.66	1.04	55.07	0.688
Phoenix, AZ	-0.06	0.02	0.27	1.13	33.90	0.336
Portland, OR	-0.08	0.08	2.39	1.14	26.36	0.403
St. Louis, MO	0.01	0.01	0.37	0.82	28.50	0.404
Salt Lake City, UT	-0.03	-0.01	-0.18	1.06	23.76	0.332
San Diego, CA	-0.09	0.04	1.22	1.41	46.30	0.564
San Francisco, CA	-0.08	-0.00	-0.02	1.63	39.28	0.776
Seattle, WA	-0.04	0.00	0.04	1.33	45.97	0.664
Tampa, FL	-0.00	-0.09	-1.97	0.99	26.99	0.314
Washington, DC	-0.00	-0.03	-1.39	1.02	34.48	0.495

The sample is Nasdaq-listed firms headquartered in the 25 U.S. metropolitan areas with the largest number of Nasdaq firms. Weather data are from the International Surface Weather Observations. The CRSP equally weighted index (EW) includes firms listed on the NYSE, Amex, and Nasdaq. Cloudiness is defined as the percentage of the trading day with overcast skies. The t-statistics are calculated using White's (1980) heteroskedasticity-consistent method. The number of observations in each regression varies between 3,448 and 3,529 due to missing city weather data.

Table 9
Aggregate Daily Return Portfolios Categorized by Local and New York City Weather Conditions, 1984-1997

Panel A: Percentage Returns for all Possible Trading Days (N = 3,540)

Item (1)	Clear Local Weather All Day (2)	Scattered Local Weather All Day (3)	Broken Local Weather All Day (4)	Overcast Local Weather All Day (5)	Clear NYC Weather All Day (6)	Scattered NYC Weather All Day (7)	Broken NYC Weather All Day (8)	Overcast NYC Weather All Day (9)
Percentage Returns	0.063%	0.046%	0.054%	0.073%	0.015%	-0.059%	0.070%	0.028%
Standard Deviation	0.87	0.87	0.90	0.78	0.90	1.12	0.72	0.64
Number of Observations	2,777	1,824	1,478	3,237	197	104	84	671

Panel B: Returns when both Clear All Day and Overcast All day have Observations

Item (1)	Clear Local Weather All Day (2)	Overcast Local Weather All Day (3)	Difference in Returns (4)	T-test on Difference (5)
Percentage Returns	0.061%	0.070%	-0.009%	-0.68
Standard Deviation	0.87	0.79	0.65	
Number of Observations	2,530	2,530	2,530	

The sample is Nasdaq-listed firms headquartered in the 25 U.S. metropolitan areas with the largest number of Nasdaq firms. Weather data are from the International Surface Weather Observations. Four weather portfolios across the 25 cities are created on the basis of local and New York City weather. In column 2, the totally clear local weather portfolio is created by equally weighting all firms in the Nasdaq sample in cities with clear skies all day on a given trading day. In columns 6 to 9 of Panel A, stock portfolios for the Nasdaq sample are created on the basis of New York City weather. Panel B restricts the sample to only trading days when some cities were clear all day and others were overcast all day.

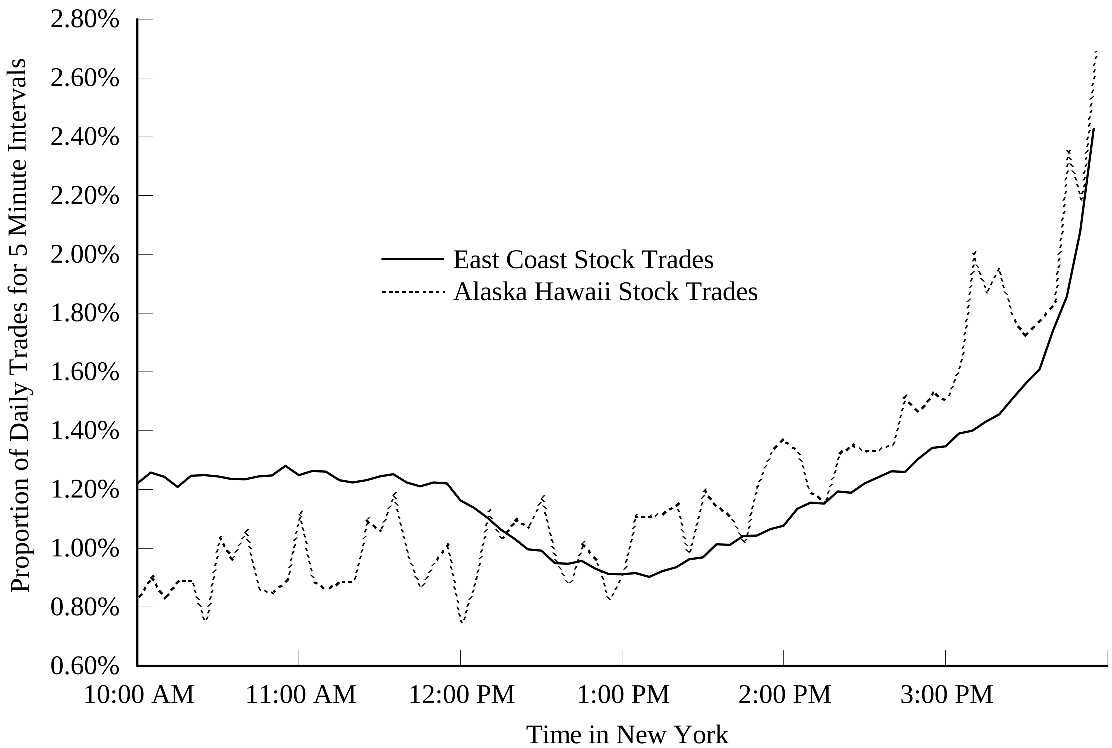

Figure 1. Intraday trading behavior of Nasdaq firms headquartered on the East Coast or Alaska/Hawaii, January 1993 to December 1993.

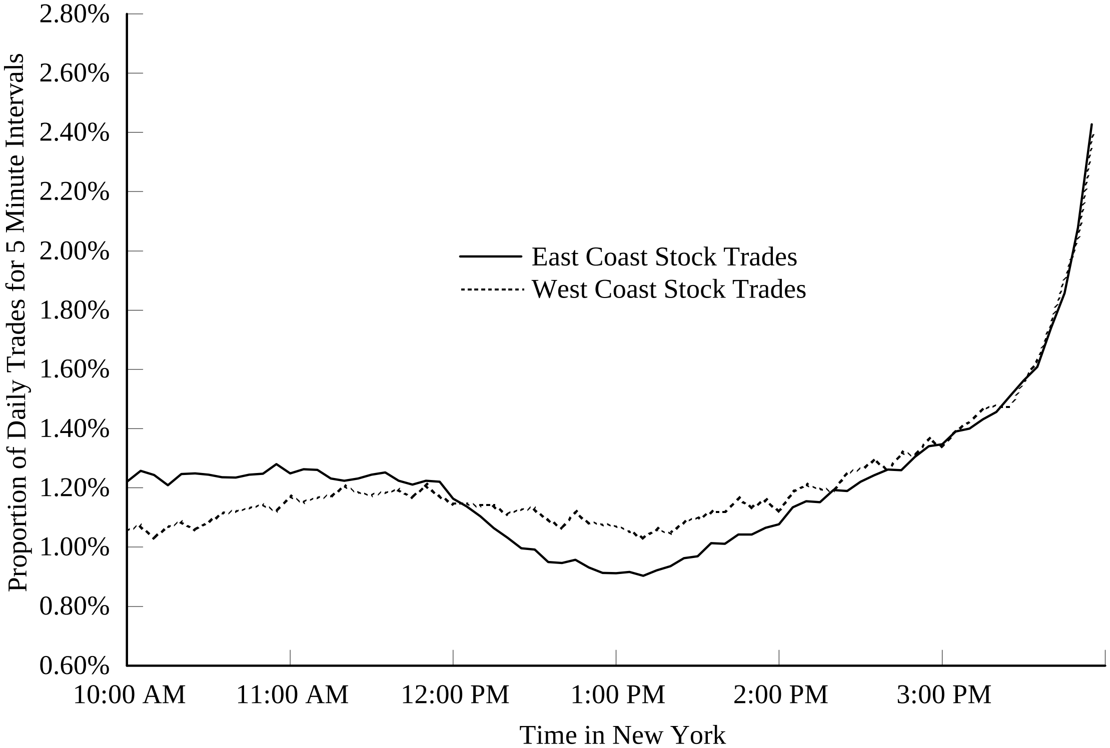

Figure 2. Intraday trading behavior for East and West Coast firms listed on Nasdaq, January 1993 to December 1993.