Gone with the Wind: Chicago's Weather and Futures Trading

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Abstract

We examine the relation between Chicago weather and the behavior of S&P 500 index futures floor traders. Trading for these traders' personal accounts suggests an association between weather and floor traders' behavior, especially when afternoon behavior is conditioned on morning weather. Specifically, we find evidence of an increase in the effective bid-ask spread on windy days. Sky cover and wind are also positively related to trader income and market timing ability. Thus, we provide direct evidence on the effect of local weather on investor behavior.

JEL Classification: G14; G10; G15
Keywords: Market efficiency; Weather effect; Futures market; Trading behavior

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I. Introduction

In the general area of behavioral finance, increasing attention is being paid to the relation between weather and stock market returns. The underlying premise of this line of investigation is that in the short run stock returns may be related to predictable changes in investors' psychological status, with prediction coming from observable exogenous variables such as the weather. This comes in addition to the growing evidence of unexplained retail investor irrationality (Odean 1998; Grinblatt and Keloharju 2000, 2001) and professional trader behavioral issues (Coval and Shumway 2005; Locke and Mann 2005).[1] Research has also investigated various exogenous factors which may drive investor behavior. For example, Dichev and Janes (2001) and Yuan, Zheng, and Zhu (2001) find that stock returns are affected by the lunar cycle. Kamstra, Kramer, and Levi (2002) show that the average return on daylight- saving weekends is significantly lower than that of other weekends of the year. Kamstra, Kramer, and Levi (2003) also find that the seasonal affective disorder (SAD) plays an important role on individuals' behavior and stock markets. Krivelyova and Robotti (2003) demonstrate that geomagnetic storms are negatively correlated with the stock returns. Altogether, the above suggests that investors' behavior may indeed be influenced by observable factors which alter trader psychology.

Saunders (1993), assuming weather conditions impact human moods and emotions, tests for long run effects of New York City weather on stock returns, and finds such evidence using data from 1927 to 1989. Hirshleifer and Shumway (2003) observe

[1] There may be definitions for the particular irrationalities, such as loss realization aversion, but this does not offer an explanation for such behavior.

that morning sunshine is strongly, and, depending on costs, possibly profitably, related to worldwide daily stock returns. Kliger and Levy (2003) also find that weather conditions affect trading decisions: "bad" weather-related moods lead to higher subjective probabilities of adverse events. Cao and Wei (2004) document a negative correlation between temperature and stock returns across a whole range of temperatures. All of these results, since they reveal predictable trading behavior, seem to be at odds with market efficiency.

Not all empirical results support a link from weather to returns, however. Loughran and Schultz (2004) look at the weather at companies' headquarters and their returns. Although they find a weak relation between New York City weather conditions and NYSE stock returns, they observe no such significant relation in other cities. Further, although Loughran and Schultz (2004) document localized trading effects, they find no relation between local cloudiness and company stock returns. Trombley (1997) also suggests that Saunders' findings may be sample specific. In an international setting, Pardo and Valor (2003) find that there is no influence of sunshine on prices of stocks traded on the Madrid Stock Exchange. Examining retail trading, Goetzmann and Zhu (2005) also find no significant relation between an individual's decision to buy or sell and daily weather. They hypothesize that the differing results might be explained by focusing on the weather in the city in which the market makers are present. In other words, they suggest that the trading of market makers or specialists, centrally located, not general market investors, who are distributed globally, may be more apparently influenced by weather effects. Local weather, such as the weather in New York, should have no effect in the long run on productivity and cash flows of companies based in Detroit or Silicone

Valley. As a result, Goetzmann and Zhu (2005) suggest that research ought to investigate weather effects on particular agents, such as market makers or specialists, who might exhibit trading behavior that varies with identifiable, localized weather conditions.

Our study extends the literature by testing the hypothesis that weather conditions in the Chicago metropolitan area systematically affect the trading behavior of a unique group of agents, namely floor traders of S&P500 index futures contracts at the Chicago Mercantile Exchange (CME). Most floor trading by members on commodity exchanges is day-trading or scalping, i.e., extremely short term investing, with this finding dating back to at least the work by Working (1967). If there is a relation between weather conditions and trading behavior, our results should reveal some discernible patterns between Chicago weather and futures floor trading.

From the generosity of the Commodity Futures Trading Commission we obtain personal transaction records of floor traders who traded S&P500 futures and E-mini S&P500 futures on the CME during 1997-2001. Our data allow a detailed examination of the relation between local weather and the behavior of this important group of traders. Following previous research, we test for weather conditions affecting these floor traders' behavior. We focus on variables derived from this data set: the bid-ask spread, order imbalance and trader income.

We also take advantage of Chicago's fame as the windy city"[2]. In this sense, CME floor traders form an interesting group to study since research has documented that variations in wind can lead to psychological and physical changes (Cooke, Rose and Becker 2000). In Canada and Europe, for example, researchers have documented that

[2] The tendency for long speeches by Chicago politicians is a secondary source of the term "windy city."

some particular types of strong wind can act as a trigger for physical conditions such as fatigue, headache, irritability and sleeplessness, on several types of people (Fletcher, 1988; Rose, Verhof and Ramcharan 1995). The specific mechanism of how wind induces mental changes is unknown. Strong winds may affect the air's electrical charge.[3] Increased positive ion concentration, which has been known to increase drastically when the wind velocity is high, may have adverse short term physiological effects. As a result, we expect that, given previously discovered weather, seasonal, and geomagnetic effects, variations in the strength of the Chicago wind may alter floor trader moods and some measures of their behavior.

We find that Chicago weather is related to the behavior of CME floor traders. For example, the effective bid-ask widens on windy days in Chicago. Cloudiness and strong winds also are positively associated with the propensity for buying by floor traders. Further, the relation of wind to buying holds after controlling for market return, daily trading volume and temporal seasonality. Sky cover and wind strength also are related to trader income. Income is higher and timing is better on sunny days. Income is also higher on calm days. In fact, our most interesting findings are related to wind strength, especially when we perform intra-day analyses. Morning wind is significantly related to afternoon trade imbalance and income. Overall, the results provide further support to the

[3] Ions are charged particles, formed when enough energy acts on a molecule such as carbon dioxide, oxygen, water or nitrogen-to eject an electron. The displaced electron attaches itself to a nearby molecule, which then becomes a negative ion. The original molecule (minus an electron) is now a positive ion. These ions, in turn, react with dust and pollutants to form larger particles. Small negative ions (usually no more than 12 gaseous molecules clustered around a charged atom or molecule) are short-lived and highly mobile. According to medical experts, positive ions rob us of our good sense and disposition, while their counterpart, negative ions, enhances those positive senses, stimulating everything from plant growth to the human sex drive (Kellogg, 1984; Kreuger, 1976).

notion that weather conditions in a specific location can influence traders' behavior in that particular location.

The rest of the paper is organized as follows: In Section II we describe key characteristics of the data set. In Section III we present our tests and discuss the results. Finally, section IV we offer a few conclusions.

II. Data and Methodology

As stated, our data, generously supplied by the Commodity Futures Trading Commission, is personal account transaction records of futures floor traders who trade S&P500 futures and E-mini S&P500 futures on the CME during the period from January 1997 to December 2001. We have over 76 million records with detailed trade information, including masked floor trader identification, date and time of the trade, futures contract (month), quoted price, and the number of contracts bought or sold. There is also an indicator of whether the transaction was executed on the floor, or on GLOBEX. S&P 500 transactions are executed on the floor between 8:30 a.m. to 3:15 p.m., Chicago time (regular trading hours), and on GLOBEX outside the floor trading time. E-mini contracts (currently 1/5 the size of the standard S&P) are traded exclusively on GLOBEX for nearly 24 hours. The identification of proprietary trading is valid for both GLOBEX trading (using a terminal) and floor trading (shouting and waving) for standard S&P futures and E-mini trading. To focus on Chicago weather and the perceptions of floor traders, the analysis uses only the regular trading hours (when the traders are likely to be awake and aware of weather conditions).

During the 5-year period, there are 5,673 traders who trade for their personal account at least once, and, on average, they are present on the trading floor for 171.49 days. In fact, many traders execute only a few trades and then disappear from the sample, or execute only a few trades every once in a while. The first could be the result of a sharply unsuccessful trading experience, and the second the fact that some floor traders only execute personal trades in order to correct rare brokerage errors. In order to study the specific trading behavior of a relatively homogeneous group of floor traders, often labeled market makers, we restrict the sample to only those traders who satisfy the following rule: The trader must trade at least 4 times a day for at least 10 trading days within a month, for at least 50 months over the 5 year period. This filter results in the selection of 354 active traders from the initial set of 5,673. A similar filter rule was applied by Locke and Mann (2005), albeit they use a different rule for different markets and a much shorter data set. We present some statistics for these active traders in Table 1. For example, the active traders are present on average 58.71 trading months, 16.94 trading days per month, and make, on average, 55.8 transactions per day. From now on in the paper, referring to trader behavior refers to the trading of these 354 active traders.

Insert Table 1 about here

We obtain intraday weather conditions at Chicago O'Hare International Airport from the National Oceanic and Atmospheric Administration (NOAA), covering the period of January 1997-December 2001.[4] The NOAA data contain various weather conditions including wind speed and sky cover conditions. The raw measure of wind

[4] NOAA weather station data is used in Saunders (1993), Hirshleifer and Shumway (2003), Goetzmann and Zhu (2005), Trombley (1997), and Loughran and Schultz (2004), and is available on the internet.

strength is measured in miles per hour, while sky cover or cloudiness is reported as a categorical variable and an associated range of numerical values: “clear” 0, “few” 0-2, “scattered” 2-4, “broken” 5-7, and “over cast” 8. We redefine the sky cover ranges as 0, 2, 4, 6, and 8, for clear, few, scattered, broken, and over cast, respectively. Although we are most interested in wind, we include sky cover to control for effects documented in previous studies by Saunders (1993), Hirshleifer and Shumway (2003), and Loughran and Schultz (2004).

Similar to that of most cities in the Northern U.S., Chicago’s color keeps changing throughout the year, from a green spring and summer, to yellow and orange in the fall, and on to the dreary gray winter. Given these extreme seasonal patterns, we deseasonalize wind strength and sky cover as in Hirshleifer and Shumway (2003) and Goetzmann and Zhu (2005). We calculate the average wind strength and sky cover for each month of the year, using only weather observations from floor trading times for all 5 years of data. The daily seasonally-adjusted wind speed (hereafter WIND) and sky cover (hereafter SKY) are calculated as the differences between the observed daily value and the seasonal average. A day is considered a windy (cloudy) day if WIND (SKY) is greater than zero; i.e., the wind blows stronger (there are more clouds in the sky) than the monthly average that day. The deseasonalization results in variables SKY and WIND taking on values between -4 (clearest or calmest) and 4 (cloudiest and windiest).

In the next section we present results of the relation between wind and sky cover and various measures of trading behavior (liquidity provision, order imbalance, trade income and market timing ability).

III. Weather Conditions and Futures Traders' Behavior

3.1 Effective spread

We first examine liquidity provision. Since these floor traders are generally considered market makers, liquidity provision in this competitive setting is the result of these floor traders competing at the bid for incoming sell orders or competing at the ask for incoming buy orders. There are many models of market maker behavior, most of them involve some degree of risk aversion, and some perception of inventory risk, related to price volatility, and we imagine that theory could allow weather to play some role in these models.

We use two measures of liquidity provision, the effective spread, and the percentage effective spread. The effective spread measured each day is the difference between the quantity weighted average sell price (trading at the ask) and the quantity weighted average buy price (trading at the bid) for floor traders. The percentage effective spread normalizes the effective spread by dividing by the quantity weighted average trade price for the day and then multiplying by 100. We test for the effect of weather on the distribution of the effective and percentage effective spread using the nonparametric Wilcoxon test, and then control for other effects using multivariate regression.

Insert Table 2 and 3 about here

In Table 2 we report the results for the relation between weather and the effective spread. In Table 3 we report similar analysis using the percentage effective spread. The tables report various binary comparisons between weather extremes. For example, the first row of Panel A of Table 2 splits the sample into more cloudy (SKY >0) and more sunny (SKY <0) days. Moving down the rows, looking at columns 1 and 2, the comparisons are between more extreme weather days, i.e., more and more sunny (SKY < -1, -2, -3, -4) vs. more and more cloudy (SKY > 1, 2, 3, 4). The same set of increasingly extreme comparisons are performed using wind speed in Panel B of Table 2. Columns 3 and 4 give the number of days in each weather category. Column 5 and 6 present median spreads for each set of weather conditions; column 7 presents the differences between these medians; and in column 8 we report the p-value from the Wilcoxon non parametric test comparing the distributions. We use this same layout in all four panels of Table 2 and 3 as well as Tables 5 through 7, and Tables 9 through 11.

From Panel A of Table 2, examining the median differences and associated Wilcoxon p-values, there appears to be no significant impact of sky cover on the effective spread. However, there is some evidence that wind strength influences floor trader behavior. Specifically, the effective spread tends to be lower on relatively calm days. The results show that wind strength effects are apparent even when days are classified by relatively weak wind conditions (0 and +/-1). The findings are similar for both effective spread in Table 2, and percentage effective spread in Table 3.

In Table 4 we present the results of our regression analysis, testing for weather effects on the effective spread while conditioning on other market variables. The regression results indicate that, after controlling for returns, volume and temporal seasonality (Monday and January effect), there is no statistically significant relation between weather and the effective spread. Thus, the apparent effects of wind strength on the effective spread may be explained by other factors.

Insert Table 4 about here

3.2 Trade imbalance

We next test for asymmetry in S&P 500 futures trading. We calculate two measures of trading asymmetry, or floor trader trading imbalance. The first is in terms of the number of transactions. For each trader, each day, we calculate a transaction imbalance the difference between the number of buy transactions and the number of sell transactions, as a ratio of the total number of transactions. A positive value for the transaction imbalance indicates the trader is buying more times than selling on a day. We calculate a similar measure using the quantity of contracts traded. The quantity imbalance is the number of contracts purchased minus the number of contracts sold, as a ratio of the total number of contracts traded, with a positive value indicating more contracts purchased than sold for a trader on a day. Analogous to our analysis of effective spreads, we first use a univariate nonparametric analysis.

Insert Table 5 and 6 Here

In Table 5 and Table 6 we present the univariate analysis for transaction and quantity imbalance and weather conditions, with the column and row layout identical to that of Table 2 described above. The unit of analysis is now a trader day, rather than a day as in Table 2 and Table 3. From Table 5 Panel A, the results for sky cover show weak evidence that floor traders tend to execute buying trades more frequently on sunny days than they do on cloudy days. The effect of wind strength is clearer: the Wilcoxon test statistics are highly significant for all wind strength classifications. The positive signs indicate that futures traders execute buying-trades more frequently on relatively calm days compared to relatively windy days. Although futures traders seem to be net buyers regardless of weather conditions (Table 5), interesting results in Table 6 show that these futures traders seem to be net sellers unconditionally in terms of the quantity traded. The Wilcoxon tests on quantity traded, however, are consistent with the results on the number of transactions, in that calmer days lead to more buying by floor traders. One interpretation of this result is that the floor traders' quotes reveal a bias depending on the weather, disproportionately attracting customer sell orders, originating from around the world (with various weather conditions), on calm days.

3.3 Trader income

Floor traders execute proprietary trades with the expectation to earn positive income, and most likely expect to earn this income over a rather short period of time, perhaps a matter of minutes. If weather impacts trader moods, and this is transmitted to their strategies, then trader income might also be influenced by the weather as well. The trader daily income is calculated by marking each trade each day to market at the daily settlement price, and multiplying by the contract multiplier, the method employed by Fishman and Longstaff (1992). We perform the univariate nonparametric analysis first, parallel to the analysis for execution spreads and trade imbalance, using a trader day as the unit of analysis.

We present the results for income and weather in Table 7. In all sky cover classifications, futures traders are able to generate more income on clearer days (Panel A, Table 7). All differences are statistically significant at conventional levels. These results on income are consistent with the conjecture of Saunders (1993) and Hirschleifer and Shumway (2003) that good weather affects investors' mood which, in turn, leads to positive income. This mood could be reflected in floor traders' ability to concentrate on their market making strategies, earning a higher income from customers. However, the results offer no consistent evidence regarding the effect of wind strength on income.

Insert Table 7 about here

3.4 Multivariate analysis for trade imbalance and income

We next report regression results for the previous set of variables, using the same methodology as for the effective spread analysis, except that the unit of analysis is the trader day. Table 8 reports results from regression analyses examining the relation between weather conditions and floor trader behavior, with the same controls as for the effective spread. The results are quite striking as, even after controlling for market factors, there appears to be a negative relation between wind strength and both trade imbalance measures. The negative coefficients indicate that floor traders execute buying-trades more frequently on relatively calm days compared to relatively windy days, again perhaps indicative of a bias in market maker quotes. Although the findings for the effect of wind strength on trade imbalance measures confirm the univariate results (Table 5 and 6), the finding for income is not consistent with the univariate analyses (Table 7). Specifically, there is no statistically significant relation between weather condition variables and the floor trader income when controlling for other market effects.

Insert Table 8 about here

3.5 Intra-day analyses

Everyday, people in colored jackets are observed outside the CME building, especially around noon. They might be running errands, grabbing a bite to eat, out for a cigarette, or simply want to have some fresh air. An alternative method of determining whether the trading behavior of futures floor traders is influenced by weather conditions is to examine whether their trading behavior in the afternoon session is affected by weather conditions in the morning. This analysis allows a time for traders to absorb the weather, and build some reaction, which we examine through their trading in the afternoon. In Tables 9 and 10 and 11 we present univariate analysis of afternoon trader behavior as it relates to morning weather. The structure of Table 9 through Table 11 is similar to Table 2, except that Column 1 and Column 2 now show the classifications of average weather conditions in the morning, rather than daily averages. The medians for trade imbalance and income are then calculated for the afternoon only. We use a time of 11:59:59AM to split the day into morning and afternoon.

Insert Table 9-11 about here

We find that afternoon behavior is related to morning weather. Although the results in Table 9 for transactions are not clear (median transaction imbalance=0, high p values), the Wilcoxon statistics in Table 10 show that futures traders tend to sell relatively more contracts on windy days. Furthermore, results from Table 11 indicate that futures floor traders are able to generate more income on sunny days than on cloudy days. Compared to the daily univariate analysis (Panel B, Table 7), morning wind strength has a more significant impact on the afternoon income (Panel B, Table 11).

We next repeat the regression analysis using morning weather conditions and afternoon trader behavior variables. Table 12 presents the regression results. Although the morning sky cover shows no significant relationship to floor trader behavior once we control for seasonality and macro conditions, morning wind strength is clearly related to the trading behavior of the floor traders, living up to the reputation of "the windy city". Perhaps when these traders step out to get a bite to eat or a smoke, a very windy day drives them back inside with a relatively sour disposition, they lose their concentration, and as a result, have a poor day trading.

IV. Conclusions

There is somewhat of an ongoing debate on whether financial markets exhibit any irrationality. We provide in this study a direct test for a particular anomaly, the relation between local weather conditions and trader behavior. If trader behavior is predictable by looking at the weather, and this behavior results in price effects which are not related to fundamentals, then such behavior is irrational. Chicago, with its highly variable weather, provides a wonderful setting for testing the association between sky cover, wind strength and investor behavior. We employ detailed transaction records, allowing an in-depth analysis of the relation between weather and individual trading.

Our findings support the existence of particular market irrationalities alluded to in the literature, but they also suggest that a new exogenous weather variable, wind, belongs in the behavioral mix. Specifically, floor traders exhibit trading behavior that appears related to local weather. For example, we find that these traders are more likely to buy on relatively calm days, suggesting a weather induced bias in quoting behavior. In addition, the effective spread is smaller on calmer days, suggesting improved attention on calm days. More importantly, we find that weather may also influence the bottom line for futures floor traders. Our results show that daily floor trader income varies with both cloud cover and wind strength. These results are strongest when we relate morning weather to predict afternoon behavior. Specifically, we find a significant relation between morning wind conditions and trading behavior, as measured by order imbalance and trading income, in the afternoon sessions on the same day. A possible explanation is that morning wind affects the moods of these futures traders, perhaps through the ion imbalance, which, in turn, make them exhibit a quoting bias on relatively windy days. In addition, morning wind strength tends to reduce trading ability as afternoon income is lower on average on windy days.

The findings are consistent with the literature showing that people are affected in a very real way by weather. The search should continue for additional external factors, such as weather, that may cause irrational shifts in investors' mood and hence on securities price movements. If some effects (lunar, solar, geomagnetic) are global, these may affect the global price of risk. However, if some effects are local, and only affect some traders, then any temporary, localized effects, need not be troubling. Nonetheless, traders may wish to be informed as to their potential for weather-induced biases. As Eugene Fama said "the fact that some individuals might be irrational doesn't mean the market is inefficient."[5]

[5] "As two economists debate markets, the tide shifts", Wall Street Journal, October 18, 2004; page A1.

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Table 1

Descriptive statistics of active S&P 500 futures floor traders

The table presents summary statistics for transactions records of active S&P500 futures floor traders from 1997-2001 included in this study. The sample is limited to the 345 active traders who meet the filter requirements of trading at least 4 times in a day, for at least 10 trading days per months, and for at least 50 months during the 5-year sample period. In the table, “Months” indicates the number of months during the 5 year period that the trader was present on the trading floor. Days/month is the number of days per month that the trader was present on the trading floor. Average daily transactions, purchases, and sales represent the average numbers of total transactions executed, purchases and sales made by the active traders, respectively.

	Months	Days/month	Average daily transactions	Average daily purchases	Average daily Sales
Maximum	60.00	20.27	411.00	213.03	191.51
Minimum	50.00	10.00	2.00	1.00	1.00
Mean	58.71	16.94	55.80	28.49	26.35
S.D.	2.69	2.45	80.46	41.12	39.75

Table 2
The effective bid-ask spread and the weather

The table reports the median daily effiective bid-ask spreads of the S&P500 futures contract and the results of a Wilcoxon test for the relation between the distribution of the effective spread and various categories of sky cover (Panel A) and between various categories of wind strength (Panel B) from January 1997 to December 2001. A day is classified according to sky cover using the average NOAA O'Hare SKC value classifications, and into a calm or a windy day using the average NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. The effective bid-ask spread is the difference between the quantity weighted average sell price and the quantity weighted average buy price, for 345 active floor traders. The one-tailed p-values of the Wilcoxon test for the difference in the distribution of effective bid-ask spreads by weather category are reported in the last column.

Panel A

Classifications		N		Median Spread			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny days	Cloudy Days	Sunny Day	Cloudy day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	429	405	0.158760	0.145212	0.013549	0.3502
-1	1	233	217	0.164813	0.134454	0.030358	0.1970
-2	2	89	116	0.137354	0.130964	0.006391	0.4075
-3	3	38	54	0.148057	0.131932	0.016125	0.2616
-4	4	9	6	0.108204	0.166990	-0.058786	0.2979

Panel B

Classifications		N		Median Spread			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy day	Calm - Windy	p-value
0	0	444	390	0.138464	0.163526	-0.02506	0.0519
-1	1	333	294	0.134743	0.159042	-0.02429	0.0154
-2	2	255	206	0.134743	0.157326	-0.02258	0.0863
-3	3	173	144	0.131331	0.126809	0.00452	0.4121
-4	4	98	99	0.131576	0.126417	0.00516	0.3912
-5	5	51	66	0.119699	0.128095	-0.00839	0.4486

Table 3
The percentage effective bid-ask spread and the weather

The table reports median daily percentage bid-ask spread of S&P500 futures contracts and the results of Wilcoxon tests for the relation between the distribution of daily percentage effective bid-ask spreads and various weather categories from January 1997 to December 2001. A day is classified according to sky cover using the average NOAA O'Hare SKC value classifications, and into a calm or a windy day using the average NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Percentage spread is calculated by dividing the difference between the quantity weighted floor trader sell price and buy price by the the quantity weighted average prices (i.e., the average notional value on the same day), then multiplying by 100, for 345 active floor traders. The one-tailed p-values of the Wilcoxon test for the difference in the distribution of percentage bid-ask spreads by category are reported in the last column.

Panel A

Classifications		N		Median Percentage Spread			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny Days	Cloudy Days	Sunny Day	Cloudy Day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	429	405	0.0131	0.0127	0.0004	0.4067
-1	1	233	217	0.0138	0.0120	0.0018	0.4298
-2	2	89	116	0.0136	0.0119	0.0017	0.4523
-3	3	38	54	0.0138	0.0116	0.0022	0.2908
-4	4	9	6	0.0136	0.0163	-0.0027	0.3841

Panel B

Classifications		N		Median Percentage Spread			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy day	Calm - Windy	p-value
0	0	444	390	0.0122	0.0138	-0.0015	0.0690
-1	1	333	294	0.0115	0.0137	-0.0022	0.0204
-2	2	255	206	0.0115	0.0136	-0.0021	0.1110
-3	3	173	144	0.0119	0.0111	0.0009	0.4347
-4	4	98	99	0.0120	0.0109	0.0011	0.3960
-5	5	51	66	0.0109	0.0109	0.0000	0.4486

Table 4

Regression results for effective bid-ask spreads and weather conditions

The table reports the regression results of the bid-ask spread measures on the weather variables. A day is classified according to sky cover using the average NOAA O'Hare SKC value classifications, and into a calm or a windy day using the average NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Spread is the difference in the quantity weighted average floor trader sell price and the floor trader buy price, for 345 active traders. PSpread is calculated by dividing Spread by the quantity weighted average of all prices, i.e., the average notional value on the same day, and then multiplying by 100. FSPRET is the daily return of the S&P500 futures contract. FSPVOL is the S&P500 futures contract trading volume. MON and JAN are dummy variables indicating Monday and the month of January, respectively. We present t-statistics in parentheses, and let *, **, and *** denote statistical significance at 10, 5 and 1 percent levels, respectively.

	Dependent Variable	
	Spread	Pspread
Intercept	0.68842***	0.00056***
	(15.63)	(15.16)
SKY	-0.01480	-0.00001
	(-1.44)	(-1.22)
WIND	0.00310	0.00001
	(0.59)	(0.43)
FSPRET	-0.05035***	-0.00004***
	(-3.85)	(-4.23)
FSPVOL	-0.00001***	-0.00001***
	(-9.88)	(-9.40)
MON	0.03775	-0.00004
	(-0.83)	(-0.79)
JAN	-0.02472	-0.00003
	(-0.38)	(-0.50)
R-square	0.121	0.114
Adj. R-square	0.115	0.108
F-Statistic	18.98***	17.75***

Table 5
Floor trader transaction imbalance and the weather

The table reports the median transaction imbalance and the Wilcoxon test for the relation of daily transaction imbalance to sky cover (Panel A) and wind strength (Panel B). A day is classified according to sky cover using the average NOAA O'Hare SKC value classifications, and into a calm or a windy day using the average NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Transaction imbalance, for the 345 active floor traders, is defined as the difference between the number of buy transactions and the number of sale transactions divided by the total number of all transactions during the day. The one-tailed p-values of the Wilcoxon test for the difference in the distribution of daily transaction imbalances by category are reported in the last column.

Panel A

Classifications		N		Median Trade Imbalance			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny Days	Cloudy days	Sunny day	Cloudy Day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	178952	173431	0.0513	0.0526	-0.0013	0.1634
-1	1	97678	92599	0.0556	0.0526	0.0029	0.0609
-2	2	38365	50433	0.0538	0.0566	-0.0028	0.3371
-3	3	16424	23760	0.0588	0.0529	0.0059	0.2243
-4	4	4410	2799	0.0706	0.0270	0.0436	0.0008

Panel B

Classifications		N		Median Trade Imbalance			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy day	Calm - Windy	p-value
0	0	180382	172001	0.0526	0.0492	0.0035	0.0012
-1	1	136589	131282	0.0541	0.0476	0.0064	0.0001
-2	2	100923	92853	0.0526	0.0468	0.0058	0.0008
-3	3	68699	64723	0.0541	0.0448	0.0093	0.0001
-4	4	39718	46217	0.0549	0.0435	0.0114	0.0001
-5	5	21383	30720	0.0559	0.0435	0.0124	0.0001

Table 6
Floor trader quantity imbalance and the weather

Table 10 reports the median daily quantity imbalance and the Wilcoxon test for the relation of daily quantity imbalance to the weather. A day is classified according to sky cover using the average NOAA O'Hare SKC value classifications, and into a calm or a windy day using the average NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Quantity imbalance is calculated as the difference between the number of contracts bought and the number of contracts sold for active floor traders divided by the total number of contracts traded during the day by the active floor trader. The one-tailed p-values of the Wilcoxon test for the difference in the distribution of daily floor trader quantity imbalances by weather category are reported in the last column.

Panel A

Classifications		N		Median Quantity Imbalance			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny days	Cloudy days	Sunny day	Cloudy Day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	178952	173431	-0.0667	-0.0667	0.0000	0.3566
-1	1	97678	92599	-0.0628	-0.0667	0.0039	0.0208
-2	2	38365	50433	-0.0602	-0.0588	-0.0014	0.4507
-3	3	16424	23760	-0.0566	-0.0625	0.0059	0.0336
-4	4	4410	2799	-0.0286	-0.1000	0.0714	0.0001

Panel B

Classifications		N		Median Quantity Imbalance			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy day	Calm - Windy	p-value
0	0	180382	172001	-0.06452	-0.07143	0.00691	0.0001
-1	1	136589	131282	-0.06280	-0.07255	0.00975	0.0001
-2	2	100923	92853	-0.06667	-0.07251	0.00584	0.0078
-3	3	68699	64723	-0.06522	-0.07438	0.00916	0.0001
-4	4	39718	46217	-0.06692	-0.07674	0.00982	0.0020
-5	5	21383	30720	-0.06494	-0.07615	0.01122	0.0017

Table 7
Floor trader income and the weather

The table reports the median daily trader income from trading of the S&S500 futures contracts and the Wilcoxon test for the difference in daily overall income for the 345 active floor traders on sunny vs. cloudy days (Panel A) and on calm vs. windy days (Panel B). A day is classified according to sky cover using the average NOAA O'Hare SKC value classifications, and into a calm or a windy day using the average NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Trader income represents the daily income earned by an active trader, with each trade's income calculated by offsetting it at the daily settlement price. The one-tailed p-values of the Wilcoxon test for the difference in the distribution of trader income by weather category are reported in the last column.

Panel A

Classifications		N		Median Trader Income			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny Days	Cloudy days	Sunny day	Cloudy Day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	178952	173431	208.07	97.75	110.31	0.0020
-1	1	97678	92599	250.00	0.00	250.00	0.0001
-2	2	38365	50433	496.15	9.64	486.51	0.0001
-3	3	16424	23760	731.87	-115.24	847.11	0.0001
-4	4	4410	2799	1351.40	25.27	1326.13	0.0012

Panel B

Classifications		N		Median Trader Income			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy day	Calm - Windy	p-value
0	0	180382	172001	165.15	130.09	35.06	0.1029
-1	1	136589	131282	97.56	125.00	-27.44	0.4487
-2	2	100923	92853	83.69	150.00	-66.31	0.0906
-3	3	68699	64723	69.05	150.00	-80.95	0.1329
-4	4	39718	46217	150.00	57.14	92.86	0.3335
-5	5	21383	30720	200.00	75.00	125.00	0.3473

Table 8

Regression results for transaction and quantity imbalance, trader income, and the weather

The table reports the regression results of floor traders' imbalance and income and the weather. A day is classified according to sky cover using the average NOAA O'Hare SKC value classifications, and into a calm or a windy day using the average NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Transaction imbalance is defined as the difference between the number of buy transactions and the number of sale transactions divided by the total number of all transactions during the day, for an active floor trader. Quantity imbalance is calculated as the difference between the number of contracts bought and the number of contracts sold divided by the total number of contracts traded during the day, for 345 active floor traders. Trader income represents the daily income earned by an active floor trader. The income is calculated for each trade by offsetting it at the daily settlement price. FSPRET is the daily return of the S&P500 futures contract. FSPVOL is the daily trading volume of the S&P500 futures contracts. MON and JAN are dummy variables indicating Monday and the month of January, respectively. We present t-statistics in parentheses, and let *, **, and *** denote statistical significance at 10, 5 and 1 percent levels, respectively.

	Dependent Variable		
	Trade imbalance	Quantity imbalance	Trader income
Intercept	0.07355***	-0.02503***	-2105.86*
	(41.63)	(-12.16)	(-1.80)
SKY	-0.00034	-0.00091*	-68.33
	(-0.83)	(-1.91)	(-0.25)
WIND	-0.00097***	-0.00101***	-69.56
	(-4.66)	(-4.18)	(-0.51)
FSPRET	0.00782***	0.00636***	-7432.76***
	(15.28)	(10.68)	(-21.95)
FSPVOL	-0.00001	-0.00001***	0.11***
	(-0.01)	(-12.64)	(4.59)
MON	0.00770***	-0.00558***	4292.55***
	(-4.15)	(-2.58)	(3.50)
JAN	0.01345	0.01931***	491.49
	(5.13)	(6.32)	(0.28)
R-square	0.0008	0.0009	0.0015
Adj. R-square	0.0008	0.0009	0.0015
F-statistics	49.83***	55.42***	86.75***

Table 9
Afternoon transaction imbalance and the morning weather

The table reports the median afternoon transaction imbalance and the results of Wilcoxon tests for the relation of the afternoon transaction imbalance to morning weather. Panel A compares the distribution of trade imbalance by the cloudiness conditions while Panel B compares the distribution of trade imbalance by the wind strength. A morning is classified according to sky cover using the average morning NOAA O'Hare SKC value classifications, and into a calm or a windy morning using the average morning NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Floor trader transaction imbalance is defined as the difference between the number of buy transactions and the number of sale transactions divided by the total number of all transactions during the day, for an active floor trader. The one-tailed p-values of the Wilcoxon test for the difference in the distribution of daily trade imbalance by weather category are reported in the last column.

Panel A

Classifications of AM Weather Condition		N		Median PM Trade Imbalance			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny days	Cloudy days	Sunny day	Cloudy Day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	157939	145145	0	0	0	0.2725
-1	1	93143	89599	0	0	0	0.4345
-2	2	40887	50235	0	0	0	0.3283
-3	3	19880	28815	0	0	0	0.1789
-4	4	7165	3316	0	0	0	0.0573

Panel B

Classifications of AM Weather Condition		N		Median PM Trade Imbalance			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy Day	Calm - Windy	p-value
0	0	155446	147638	0	0	0	0.0019
-1	1	119075	112868	0	0	0	0.0036
-2	2	86945	82091	0	0	0	0.0008
-3	3	59865	60514	0	0	0	0.0296
-4	4	39588	41284	0	0	0	0.0258
-5	5	21861	28546	0	0	0	0.0157

Table 10
Afternoon quantity imbalance and the morning weather

The table reports the median quantity imbalance and the results of Wilcoxon tests for the relation between afternoon quantity imbalance of active traders to the morning weather. Panel A compares the quantity imbalance by sky cover while Panel B shows the median quantity imbalance by the wind strength. A morning is classified according to sky cover using the average morning NOAA O'Hare SKC value classifications, and into a calm or a windy morning using the average morning NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Quantity imbalance is calculated as the difference between the number of contracts bought and the number of contracts sold divided by the total number of contracts traded during the day for an active floor trader. The one-tailed p-values of the Wilcoxon test for the difference in the distribution of daily floor trader quantity imbalance by weather category are reported in the last column.

Panel A

Classifications of AM Weather Condition		N		Median PM Quantity Imbalance			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny days	Cloudy days	Sunny day	Cloudy day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	157939	145145	-0.1500	-0.1538	0.0038	0.4719
-1	1	93143	89599	-0.1500	-0.1529	0.0029	0.4263
-2	2	40887	50235	-0.1429	-0.1429	0.0000	0.4351
-3	3	19880	28815	-0.1361	-0.1429	0.0068	0.0383
-4	4	7165	3316	-0.1187	-0.1694	0.0507	0.0040

Panel B

Classifications of AM Weather Condition		N		Median PM Quantity Imbalance			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy day	Calm - Windy	p-value
0	0	155446	147638	-0.1475	-0.1563	0.0087	0.0032
-1	1	119075	112868	-0.1518	-0.1579	0.0061	0.0046
-2	2	86945	82091	-0.1525	-0.1624	0.0099	0.0023
-3	3	59865	60514	-0.1481	-0.1556	0.0074	0.0611
-4	4	39588	41284	-0.1478	-0.1579	0.0101	0.0379
-5	5	21861	28546	-0.1429	-0.1574	0.0145	0.0056

Table 11
Afternoon trader income and the morning weather

The table reports the median overall income and the results of Wilcoxon tests for the relation of afternoon trader income to the morning weather. Panel A compares median trader income from trading by sky cover while Panel B shows the median trader income by the wind strength. A morning is classified according to sky cover using the average morning NOAA O'Hare SKC value classifications, and into a calm or a windy morning using the average morning NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Trader income represents the daily income earned by active floor traders, with each trade's income calculated by offsetting it at the daily settlement price. The one-tailed p-values of the Wilcoxon test for the difference in daily overall trading income by weather category are reported in the last column.

Panel A

Classifications of AM Weather Condition		N		Median PM Overall Income			
Sunny day SKY less than	Cloudy day SKY greater than	Sunny days	Cloudy days	Sunny day	Cloudy day	Sunny - Cloudy	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0	157939	145145	61.36	-21.41	82.78	0.0001
-1	1	93143	89599	44.81	-13.45	58.26	0.0001
-2	2	40887	50235	100.00	-26.63	126.63	0.0001
-3	3	19880	28815	75.00	-75.00	150.00	0.0001
-4	4	7165	3316	50.00	-31.25	81.25	0.0109

Panel B

Classifications of AM Weather Condition		N		Median PM Overall Income			
Calm day WIND less than	Windy day WIND greater than	Calm days	Windy days	Calm day	Windy day	Calm - Windy	p-value
0	0	155446	147638	45.63	-0.09	45.71	0.0061
-1	1	119075	112868	27.00	0.00	27.00	0.0377
-2	2	86945	82091	78.61	0.00	78.61	0.0017
-3	3	59865	60514	75.00	0.00	75.00	0.0035
-4	4	39588	41284	100.00	68.63	31.37	0.0450
-5	5	21861	28546	73.65	105.54	-31.90	0.2900

Table 12
Regression results for afternoon imbalance, income, and morning weather conditions

This table reports the regression results on the relation between morning weather conditions and trading (transaction and quantity) imbalance and trader income in the afternoon trading sessions. A morning is classified according to sky cover using the average morning NOAA O'Hare SKC value classifications, and into a calm or a windy morning using the average morning NOAA O'Hare wind speed, both calculated as deviations from sample monthly averages. Transaction imbalance is defined as the difference between the number of buy transactions and the number of sale transactions divided by the total number of all transactions during the day for an active trader. Quantity imbalance is calculated as the difference between the number of contracts bought and the number of contracts sold divided by the total number of contracts traded during the day for an active trader. Trader income represents the daily income earned by an active trader, with each trade's income calculated by offsetting it at the daily settlement price. FSPRET is the return of the S&P500 futures contract. FSPVOL is the trading volume of the S&P500 futures contracts. MON and JAN are dummy variables indicating Monday and the month of January, respectively. We present t-statistics in parentheses, and let *, **, and *** denote statistical significance at 10, 5 and 1 percent levels, respectively.

	Dependent Variable		
	Trade imbalance	Quantity imbalance	Overall Income
Intercept	-0.0761***	-0.1443***	-351.91
	(-30.44)	(-54.35)	(-0.61)
SKY	-0.0003	-0.0007	-223.06
	(-0.64)	(-1.29)	(-1.27)
WIND	-0.0008***	-0.0009***	-145.98*
	(-2.67)	(-3.06)	(-1.84)
FSPRET	-0.0012	-0.0004	-1256.39***
	(-1.16)	(-0.38)	(-5.15)
FSPVOL	0.00005***	-0.00002*	0.08***
	(5.37)	(-1.77)	(3.82)
MON	-0.0143***	-0.0120***	2219.68***
	(-5.30)	(-4.19)	(3.58)
JAN	0.0389***	0.0378***	-1671.24*
	(10.37)	(9.48)	(-1.78)
R-square	0.0007	0.0004	0.0003
Adj. R-square	0.0006	0.0004	0.0002
F-statistics	32.57***	20.01***	10.35***