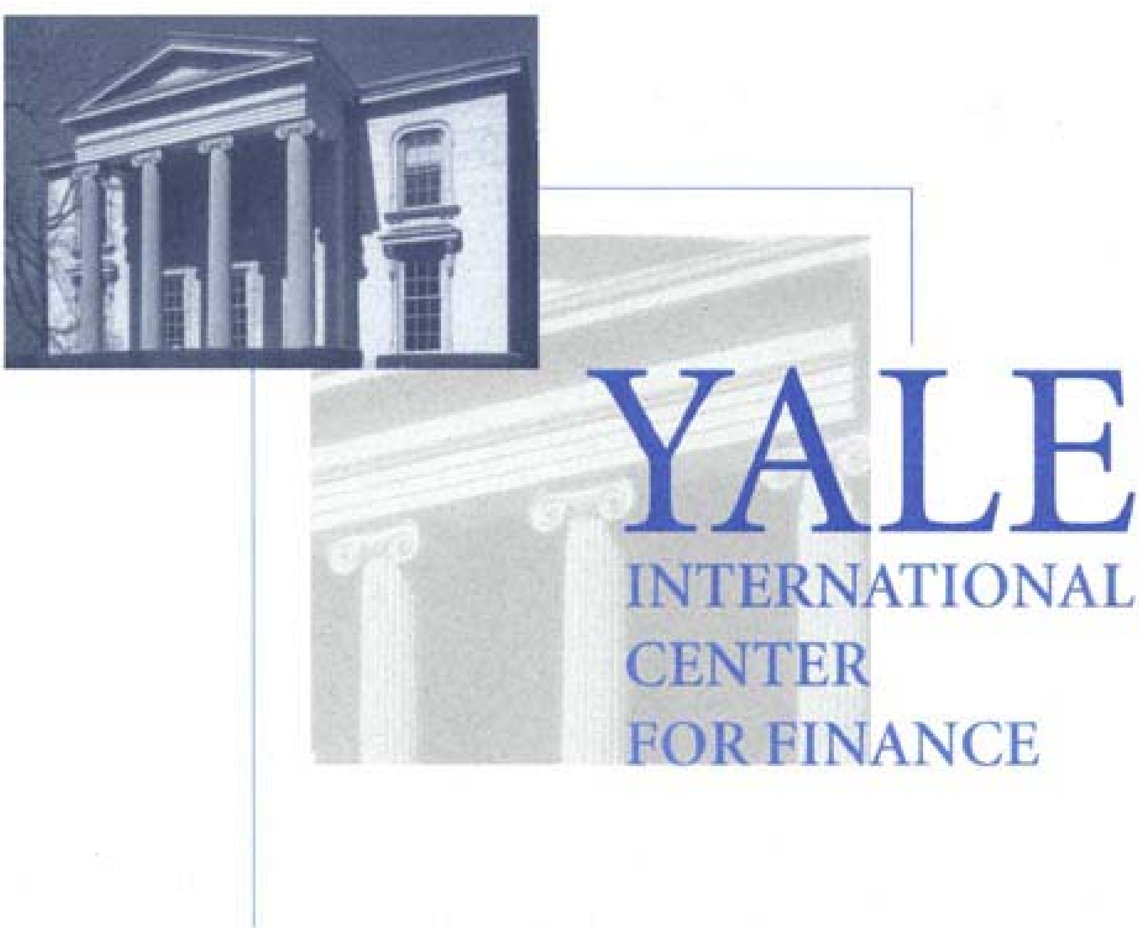

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Rain or Shine: Where is the Weather Effect?*

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Abstract

Saunders (1993) and Hirshleifer and Shumway (2001) document the effect of weather on stock returns. The proposed explanation in both papers is that investor mood affects cognitive processes and trading decisions. In this paper, we use a database of individual investor accounts to examine the weather effects on traders. Our analysis of the trading activity in five major U.S. cities over a six-year period finds virtually no difference in individuals' propensity to buy or sell equities on cloudy days as opposed to sunny days. If the association between cloud cover and stock returns documented for New York and other world cities is indeed caused by investor mood swings, our findings suggest that researchers should focus on the attitudes of market-makers, news providers or other agents physically located in the city hosting the exchange. NYSE spreads widen on cloudy days. When we control for this, the significance of the weather effect is dramatically reduced. We interpret this as evidence that the behavior of market-makers, rather that individual investors, may be responsible for the relation between returns and weather.

Keywords: Weather Effect, Market Efficiency, Order Flow, Volatility, Individual Behavior

JEL Classification: G12 G14

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Some of the most interesting empirical evidence in behavioral finance is the recent documentation of astronomical and weather effects on stock market returns. Saunders (1993) shows that the NYSE rises more on sunny days in New York City. Hirshleifer and Shumway (2001) replicate Saunders' study out of sample and extend it to the major stock markets around the world. Dichev and James (2001) and Yuan, et al. (2001) both find that investors are affected by lunar cycles. While these effects might at first seem implausible, researchers cite convincing evidence from the psychology literature that the weather and the moon can affect human emotions. If stock prices are driven by investor actions based upon mood rather than upon reason, it suggests two things about the price formation process. First, that mood affects individual investment decisions, and second, and more importantly, mood affects actions of the marginal investor, i.e. the investor setting prices. While it is not difficult to believe that emotion plays a role in the individual decision-making process, it is striking, in light of the efficient market theory, that valuation by rational investors does not compensate for the irrationality of others. If the marginal investor is one whose outlook for the stock market depends on the weather or the phases of the moon, then the market is plainly not efficient – or else frictions and other factors prevent the profitable exploitation of irrational behavior.

The possibility that the weather is salient in the price formation process actually affords the opportunity to explore whether investors in any specific part of the country are the price-setters. The implicit assumption in both Saunders (1993) and Hirshleifer and Shumway (2001) is that the marginal investors are in New York City, or the city in which the exchange is located. While this may be plausible for some countries with few large cities, or one financial center, the individual and institutional ownership of stocks in the United States is geographically dispersed. In this paper, we use a panel database of individual investor accounts that is coded geographically to investigate the basis for the weather effect. We confirm the findings of Saunders (1993) and Hirshleifer and Shumway (2001) for New York weather. On the other hand, our analysis of the trading activity in five major cities (New York, Los Angeles, San Francisco, Chicago and Philadelphia) over a six-year period finds virtually no difference in the propensity to buy or sell equities on cloudy days as opposed to sunny days. We also show that in our sample investors' net fund flow into individual equities is only weakly related to the S&P 500 index, which indicates that investor trading in individual securities does not significantly impact asset prices in our sample. If the association between cloud cover and stock returns documented for New York and other world cities is indeed caused by mood swings, our findings suggest that researchers should focus on the attitudes and risk-aversion of market-makers, news providers or other agents physically located in the city hosting the exchange.

Our dataset contains trades of individuals not institutions. Thus there is the possibility that institutional traders are emotionally affected by the weather, while individuals are not. If this were true, it would contradict most assumptions about the relative sophistication of these two groups. Ruling out individual traders and institutional traders are the source of the weather effect leaves us with one other set of candidates for a behavioral explanation for the association between weather and returns: market-makers. NYSE market making is not a fully competitive mechanism. Thus, when spreads widen, no short-term competitive mechanism exists to tighten them up. Thus, we might expect to see persistent, behavioral-based anomalies in this setting.

To investigate whether market-maker behavior might be the source of the weather effect, we examine the relationship between liquidity and weather. We find that the change in the average daily bid-ask spread for the NYSE stocks in the S&P 100 over the period of our study widens on cloudy days and narrows on sunny days. The weather effect on returns becomes insignificant after we control for weather-related liquidity changes. One potential explanation is that on cloudy days, market makers become less active or more risk-averse, and that this, in turn, affects market prices.

The paper is structured as follows: Section 2 describes the data and outlines the methodology; Section 3 shows that individual propensity to buy stocks is not influenced by local weather; Section 4 establishes the correlation between individual fund flow into different asset classes and the NYSE index returns; Section 5 documents how market liquidity changes are influenced by local weather, and can in part explain the weather effect; and Section 6 concludes.

2. Data and methodology

Our investor trading record extends from January, 1991 to November, 1996 and is obtained from a large U.S. discount brokerage firm. Our data contains information on anonymous investor characteristics, trade date, securities identification, trade quantity, and price. Investor location is determined by the home zip code provided in a file on key investor characteristics from the same source. We present a summary of trade and investor characteristic data in Table 1. We focus in this study on investors living in five large U.S. metropolitan areas. These five metropolitans are New York, Los Angeles, San

Francisco, Chicago and Philadelphia. These five cities have a total population of more than 20 million, which offers a good representation of U.S. urban residents. Our sample also constitutes about 40 percent of all our individual trade records in the entire database, making it a fair sample of national individual investors. Another advantage of our sample is that it includes cities from the eastern and western U.S, which have quite different weather patterns.

The weather data is obtained from the National Oceanic and Atmospheric Administration, U.S. Department of Commerce (www.noaa.gov) and contains hourly weather condition of 221 stations throughout the U.S. between 1990 and 1995. The data contains hourly readings of the Total Sky Cover (SKC), which is defined as the total amount of sky dome (in tenths) covered by clouds. SKC ranges from 0 (none of the sky is covered by clouds) to 10 (all of the sky is covered by clouds).

We calculate the daily sky cover in a manner similar to Hirshleifer and Shumway (2002). We first compute the daily Total Sky Cover (SKC) of each city by taking the average SKC of each day's trading hours.[1] Since there are seasonal weather patterns, we compute the SKC of each month as the average of SKC of all days during the month. We then compute the average SKC for each month of the year (January through December) as averages of the 6 observations on SKC for that particular month of the year during our 6-year sample. We present the seasonal pattern of SKC for these cities in Figure 1. Finally, we compute the daily seasonally-adjusted SKC (SASKC) as the SKC of a particular day minus the SKC of the month to which it belongs (All SKC hereafter is season-adjusted SKC (SASKC)). This generates a measurement of a particular day's

[1] We also compute the daily SKC as average of SKC of all 24 hours of every day. The correlation coefficient between these two measures is greater than 0.9. We do not report the results for this daily SKC measure in our study.

weather relative to the average seasonal weather, which captures the “unexpected” component of that day’s weather change.

We measure the individual tendency to buy relative to sell in both shares and volume. The net buy in shares (NBS) of a particular day is defined as the total number of shares of stocks bought minus the total number of shares of stocks sold by our sample individuals on that day. Positive/negative NBS means that local individuals are net buyers/sellers during a particular day. We compute a city’s NBS as above for all trades made by investors from that city.

Similar to Hong and Kumar (2002) and Zhu (2002), we define the buy-sell imbalance (BSI) in dollar value as the dollar value of the buying trades minus the selling trades, relative to the daily average of total value of stocks traded by sample investors. Positive/negative BSI means individuals are net buyers/sellers during a particular day. In particular, buy-sell imbalance (BSI) is defined as:

$$BSI_i^t = \frac{VB_i^t - VS_i^t}{ADTV_i} \qquad (1)$$

where

VB_i^t = Dollar value of all stocks purchased during day *t* by investors from city *i*;

VS_i^t = Dollar value of all stocks sold during day *t* by investors from city *i*;

$ADTV_{i,}$ = Daily average dollar value of buying and selling trades made by investors from city *i*.

3. Weather and individual investment

Regression of NYSE index return on SKC of New York City

We first explore whether the weather effect documented in previous studies obtains for our 1991 to 1995 sample period. Saunders (1993) shows that the relationship between stock market return and Wall Street weather weakened in the second half of his study period. We also have a shorter period than previous studies, which may also bias against our finding the weather effect. Similar to Saunders (1993), we also regress NYSE index daily return on New York City's sky cover (SKC). In addition, we also include the one-day lag NYSE index return, a Monday dummy and a January dummy to control for price movement persistence, the Monday effect, and the January effect.

In Table 2, the coefficient for total sky cover (SKC) is negative and significant at the 1 percent level. We thus confirm previous findings that the stock return is indeed higher in sunny days and that these results are robust to the period of study. Consistent with previous studies, the NYSE index return is weakly higher on Monday. The coefficients for all other variables are insignificant and the regression R-square is only 1 percent. Having shown that the weather effect is significant during our sample period, we next investigate whether individual investor behavior is responsible for the phenomenon.

Weather and individuals' propensity to buy

We first present the descriptive statistics for NBS on cloudy and sunny days for the five cities in Table 3. We define cloudy days as those on which SKC is positive (when more sky dome is covered by clouds than the monthly average) and sunny days as those on which SKC is negative (when less sky dome is covered by clouds than the monthly average). For the 5 studied cities, there are a total of 4,274 sunny days and 4,726 cloudy days.

The null hypothesis, that the net buy in shares (NBS) on sunny and cloudy days is equal, cannot be rejected for any of the five cities or for the pooled data. We also report the results of the univariate regression of NBS on SKC in Table 4. No SKC coefficient is significant and the explanatory power of all regressions is close to zero. Weather does not have a significant impact on our sample of investors' decision to buy or sell stocks.

The results are similar for the buy-sell imbalance (BSI) in dollar value. In Table 5, the BSI on sunny days is no different than on cloudy days for four out of the five cities -- the BSI during sunny days is weakly larger for Philadelphia.

We next perform a univariate regression of BSI on SKC and report the results in Table 6. The coefficients for SKC are insignificant for all 5 cities, which offers additional evidence that total sky cover does not influence individual investors' decisions to buy or sell stocks. How about differences between sunny and cloudy cities in general? We take Philadelphia, Miami, and Portland as proxies for moderate, mostly sunny and mostly cloudy weather, respectively. We present the seasonal weather patterns for these three cities in Figure 2. The results in Table 7 show that investors from cities with mostly sunny days, do not tend to make more purchases relative to sales in general, or on sunny days in particular. Again, we find little association between weather and individual investment decisions.

Weather and local trading volume

Another way that weather could potentially influence the stock market is through trading volume. Lee and Swaminathan (1998) find a relationship between trading volume and the momentum effect. Chordia et al. (2001) use trading volume as a proxy for market liquidity and find changes in trading volume are negatively correlated with market returns. If the behavioral assumptions suggested in Hirshleifer and Shumway (2002) indeed hold, the trading volume by individual investors could be significantly different on sunny days vs. cloudy days.

Our empirical results, however, do not support this hypothesis. We compare the total dollar value of trades made by our sample individuals during sunny and cloudy days for the five cities and report the result in Table 8. The trading volume during sunny days is not significantly greater than during cloudy days for all five cities. For Chicago the trading volume in sunny days is actually significantly smaller than that during cloudy days, which offers direct counter evidence that individuals trade more on sunny days.

We further perform a univariate regression analysis of total trading volume in dollars (TTV) on SKC in Table 9. The results are consistent with Table 8: with the exception of Los Angeles, the coefficient for SKC is insignificant. The R-squares of these regressions are extremely low, indicating that weather has little explanatory power for variations in the total dollar value of trades.

4. Individual investor investment flow and market performance

Another assumption implicit in Saunders (1993) and Hirshleifer and Shumway (2002) is that it is the marginal investors, the investors setting the prices, who are likely to be influenced by exchange weather. To examine this assumption, we next consider the evidence in our sample on the question of whether the aggregate fund flow of individual investors can move aggregate stock prices (c.f. Goetzmann and Massa, 2001). In particular, we divide our data into fund flow into individual securities, equity mutual funds and bond mutual funds (no individual security fixed income flow is available). Our sample contains a total of 1,851,131 trades on common stocks, 223,282 on equity funds and 40,565 on bond funds. For each asset class, we implement the buy-sell imbalance measure described in Equation (1).

For each asset class, we regress the daily NYSE index return on fund flow, one-day lagged fund flow, and the lagged NYSE index. We report the results in Table 10. For flow into common stocks, the order imbalance coefficient is negative and significant at the 1 percent level. The coefficient on one-day lagged fund flow is positive and significant at the 10 percent level, suggesting that some impact of individual order flow is temporary and reversed the next day. Although previous studies using similar data (Hong and Kumar, 2002; Zhu, 2002) find that individuals tend to be contrarians around events such as analyst recommendation changes and earnings announcements, it is still somewhat surprising that individual fund flow into the equity market is strongly negatively related to equity market return.

One trading mechanism could potentially explain this contrarian finding. Since individuals make infrequent trades in our sample, it is possible that the negative relation we observe is due to "stale" limit orders, that is limit orders that individuals have made but are not careful enough to cancel.[2] When there are sharp increases in stock prices, limit orders to sell are triggered and vice versa, which could conceivably lead to the

[2] We thank Terry Odean for this suggestion.

observed contrarian pattern. We perform a simple test to control for potential limit orders. We argue that limit orders are more likely to take place at round dollars or half dollars. The rationale is that, compared to market orders, investors are more likely to use rounding when setting limit orders, which is easier for them to conceptualize. Presumably, it is difficult to be extraordinarily precise about absolute security valuation. We therefore exclude all equity trades made at round dollar prices or half dollar prices and re-run the analysis. The coefficients for order imbalance and lagged order imbalance are still negative but much smaller in magnitude and insignificant, confirming our conjecture. Therefore, we conclude that the link between individuals' flow into common stocks and overall stock market return for non-limit orders is weak.

For equity mutual funds, the pattern is quite the opposite. The coefficient for the equity fund order imbalance is positive and significant at the 1 percent level. This provides some support for the Brown et al. (2002) argument that daily mutual fund flows may proxy for investor sentiment. The contrast between individuals flow into equities vs. equity funds suggest that individual trading based on beliefs about the market *per se* can have a market impact. For particular stocks, however, individual trades based on security-specific information have no apparent net effect, and on balance, orders based on security valuation are effectively contrarian on days when the market moves significantly.

Is the mutual fund flow influenced by weather? Again, we compare the buy-sell imbalance in equity funds for investors from the five cities. The results in Table 11 and 12 show that the net flow into equity funds is not influenced by local weather, either. The NBS and BSI of equity funds are not significantly greater on sunny than cloudy days in all of the five cities, which re-confirms our finding that individual trading is not influenced by local weather. Weather and flow are unrelated, and this is not due to the confounding effects of stale limit orders. The coefficient for bond fund flow is positive but insignificant, indicating that individual investors' bond flow has little impact on the stock market or vice versa. The R-square for all 4 specifications is low.

5 Weather and market maker behavior

Thus far, we have established that individuals do not have stronger tendency to buy on sunny days. We have also shown that trading in individual equities do not have a significant impact on aggregate asset prices. Even New York City investors are not influenced by New York weather. Therefore, we turn to other market participants for an explanation of the weather effect.

As we argue above, institutions are unlikely candidates for two reasons. First, they are typically assumed to be more sophisticated and less susceptible to behavioral biases than individuals. The findings of Grinblatt and Keloharju (2000) and Shapira and Venezia (2001) suggest that fund manager trading decisions are less irrational than the decisions of individuals. Also, like individual investors, institutional investors are located across the entire country, so that they should also be less influenced by the local weather of New York City.

Market makers located at the New York Stock Exchange might, on the other hand, be influenced by the weather there. There is little doubt that market makers can have a potentially critical impact on stock market prices. Also, since market markers do not work in a fully competitive environment, there is the possibility that they can deviate from rational behavior. One important way that market makers can influence the stock market is through the bid-ask spread, which is the most widely-used measure of market liquidity. Recent research also suggests that liquidity, as measured by the bid-ask spread, is priced. For example, Chordia et al, (2001) show with comprehensive trade and quote (TAQ) data that returns are negatively related to changes in liquidity.

If market-maker behavior is the mechanism by which weather changes influence stock returns, we presumably should detect this in changes in liquidity. Our test is straightforward: we examine the daily relation between the average bid-ask spread change and the New York City weather for the period of our sample. Since spreads are highly serially correlated, we follow Chordia (2002) and examine the change in the spread rather than the spread itself. We first ask whether the overall market spread change is associated with total sky cover (SKC). Since no finance theory has suggested that market liquidity should respond to exchange weather, our null hypothesis is that the total sky cover (SKC) has no significant influence on market liquidity.

We use Trade and Quote (TAQ) data to compute the daily spread change. We first compute the daily spread of each of the S&P 100 stocks listed in NYSE. The daily spread for each stock is computed as the average of all bid-ask spreads within a trading day. We then compute the market spread as equal-weighted average of the spread of the S&P 100 stocks. We use the equal-weighted instead of value-weighted average, because the equal-weighted average of the spread better reflects the average market marker's behavior. Since the TAQ data goes back only to 1993, we focus on observations between 1993 and 1995, the last year that we have weather data. Two reasons motivate us to focus on aggregate market spread. First, since we are interested in exploring the weather effect of the market index, it serves our purpose perfectly to study the overall market spread. In addition, previous studies (c.f. Easley et al., 2002) have shown that asymmetric information can play an important role in an individual stock's liquidity and expected return. The market makers of particular stocks are concerned about information-based trades. Asymmetric information should be largely alleviated at the aggregate market level, which enables us to isolate the relation between spread change and local weather.

We first regress the daily spread change on the sky cover. The results are shown in specification (1) of Table 13. Surprisingly, the coefficient for SKC is positive and significant at the 5 percent level, which implies that the spread increases on cloudy days and decreases on sunny ones. In Specification (2), we include the current index return. Since the market return is known to be negatively correlated with liquidity changes (c.f. Chordia et. al., 2001), we must control for it in our analysis of SKC's impact on spread change. The coefficient for SKC remains largely unchanged and is still significant at the 5 percent level. Consistent with Chordia et al. (2001), the spread change and the market return are significantly negatively correlated. We next include the one-day lag of the NYSE index return and the spread change in specification (3) and the main results become even stronger. The four independent variables can explain 16 percent of the variation in the spread change. We also include an interaction term, the product of SKC and NYSE index return, to control for the fact that market returns are higher on sunny days. Our main findings still hold. Finally, we include Monday and January dummy variables to examine whether spread change varies during a particular day of week or month of year. Both coefficients are negative and insignificant, indicating limited Monday and January effect on spread change during our sample.

We next examine whether systematic shifts in the spread change on sunny vs. cloudy days can explain the weather effect. We first regress the market return on the total sky cover (SKC) of New York between 1993 and 1995 in (1) of Table 14. The coefficient for SKC is negative and significant at the 5 percent level. This confirms all previous findings of the weather effect with our data. We then include the lagged return in specification (2) and the coefficient for SKC is negative and still significant. Consistent with short-term price momentum, the coefficient for lagged return is positive and significant at the 1 percent level.

In specifications (3) and (4), we add market liquidity changes and the product of market liquidity changes and total sky cover (SKC). Since we have found that the spread widens on cloudy days, we suspect that it is partly responsible for lower market returns on cloudy days. In both specifications, the coefficients of SKC become much smaller and less significant than they were in specification (1) and (2). For specification (4), the coefficient of SKC becomes insignificant. This confirms our hypothesis that spread change, which itself may be affected by exchange local weather, in part drives the weather effect on returns documented in the literature. The coefficient for DQSP is negative and significant at the 1 percent level, indicating that the spread change, at least in part, explains the weather effect.

Conclusion

In this paper we take a deeper look at the weather effect documented in Saunders (1993) and Hirshleifer and Shumway (2001). Contrary to expectations, it does not seem to be driven by weather-induced mood swings of individual investors. However the effect is plainly there in the data. We consider another potentially interesting behavioral mechanism for the result: weather-induced changes in the risk-aversion of the NYSE specialist. We document a significant relation between liquidity as measured by bid-ask spread, and the cloud cover in New York City. When included as an explanatory variable in a regression of returns on weather, the previously documented weather effect is greatly reduced. Following previous researchers, we conjecture that the association between weather and liquidity may be due to weather-induced mood swings. However, rational explanations for such behavior are also possible. It is plainly not a “vacation” effect in which market makers take off early on sunny days, because that would lead to a relationship of opposite sign. Perhaps, instead market-makers are more apt to depart the city early to beat the rush out of town on rainy days. In any case, whether the relationship we identify is due to market-maker irrationality or is simply a rational response to the information-generating process – or even New York City traffic – is a matter for further conjecture.

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Footnotes

[1] We also compute the daily SKC as average of SKC of all 24 hours of every day. The correlation coefficient between these two measures is greater than 0.9. We do not report the results for this daily SKC measure in our study.

[2] We thank Terry Odean for this suggestion.

Table 1 Descriptive of individual trade data

The data is between January, 1991 and November, 1996. Panel A presents the number of households in the data. Panel B describes household characteristics and Panel C outlines individual trades.

Time Period:	January, 1991–November, 1996
Panel A: Households	
Number of households	79,995
Number of households with position in equities	62,387
Panel B: Household Characteristics	
Average investor portfolio size	$35,629 (Median=$13,869)
Average number of stocks in the portfolio	4 (Median-3)
Average number of trades per year	3 (Median=2)
Average age of the household	50 (Median=48)
Panel C: Individual Trades	
Total number of trades	2,886,912
Total number of trades in equities	1,854,776
Total number of trades in equity funds	223,282
Total number of trades in bond funds	40,565
Average holding period for equities	187 trading days (Median=95)

Table 2 Regression of S&P Index Return and New York City Total Sky Cover

The dependent variable is the daily New York Stock Exchange index return between January, 1991 and December, 1995. SKC is the season-adjusted sky coverage of New York City; $Return_{(t-1)}$ is one day lag of New York Stock Exchange index return; Monday is a dummy variable equaling to 1 if the observation is on Monday and 0 otherwise; and January is a dummy variable equaling to 1 if the observation is in January and 0 otherwise. There are a total of 1,247 observations. T-statistics are provided in parentheses.

	NYSE Index Return	
	Coefficients	Significance
Intercept	0.000263	
	(1.216)	0.224
SKC	-0.00038	
	(-2.582)**	0.00993
$Return_{(t-1)}$	0.0547	
	(1.382)	0.167
Monday	0.000777	
	(1.654)*	0.0984
January	0.000214	
	(0.321)	0.748
R-square	0.01	

**, and * indicate significant at 5, and 10 percent.

Table 3 Mean of Net Buy in Share (NBS) for Sunny and Cloudy Days

The net buy in shares (NBS) of a particular day is defined as the total number of shares of stocks bought minus the total number of shares of stocks sold by sample individuals in that day. In column 2 and 3, the numbers of observations are provided in brackets. In column 4, the t-statistics of 2-sample t-test are provided in parentheses.

	NBS		
	Sunny	Cloudy	Sunny-Cloudy
New York	4128.6	4442.5	313.9
	[665]	[582]	(0.367)
San Francisco	2560.3	2894.9	-334.6
	[602]	[646]	(-0.296)
Chicago	1906.6	1432.4	474.2
	[538]	[709]	(0.961)
Philadelphia	1245.3	721.81	523.49
	[571]	[676]	(1.12)
Los Angeles	2462.4	2622.0	-159.6
	[934]	[313]	(-0.176)
Total	2536.7	2335.1	201.6
	[3,310]	[2,926	(0.554)

Table 4 Regression of Net Buy in Shares (NBS) on Total Sky Cover (SKC)

The net buy in shares (NBS) of a particular day is defined as the total number of shares of stocks bought minus the total number of shares of stocks sold by sample individuals in that day. SKC is the total sky dome covered by cloudy of one day (in tenth) relative to average seasonal SKC. There are a total of 1,247 observations for each city. T-statistics are provided in parentheses.

	Coefficients		
	Intercept	SKC	R-square
New York	4273.896	-67.41	0.00
	(10.014)	(-0.543)	
San Francisco	2733.498	4.698	0.00
	(4.842)	(0.027)	
Chicago	1637.08	-71.62	0.01
	(6.70)	(-1.10)	
Philadelphia	958.858	-41.098	0.00
	(4.103)	(-0.578)	
Los Angeles	2535.831	-79.19	0.00
	(5.603)	(-0.575)	
Total	2428.21	-51.642	0.00
	(13.373)	(-0.968)	

Table 5 Mean of Buy-Sell Imbalance (BSI) for Sunny and Cloudy Days

Buy-sell imbalance (BSI) in dollar value is defined as the dollar value of the buying trades minus the selling trades, relative to the daily average of total value of stocks traded by sample investors. In column 2 and 3, the numbers of observations are provided in brackets. In column 4, the t-statistics of 2-sample t-test are provided in parentheses.

	BSI		
	Sunny	Cloudy	Sunny-Cloudy
New York	0.0281	0.0233	0.0048
	[665]	[582]	(0.311)
San Francisco	-0.0137	-0.0059	-0.0077
	[602]	[646]	(-0.502)
Chicago	0.0399	0.0328	0.0071
	[538]	[709]	(0.303)
Philadelphia	0.0378	-0.0108	0.0486
	[571]	[676]	(1.853)*
Los Angeles	0.0145	0.00648	0.00802
	[934]	[313]	(-0.38)
Total	0.0203	0.0095	0.0108
	[3,310]	[2,926]	(0.394)

* indicates significant at 10 percent

Table 6 Regression of Buy-Sell Imbalance (BSI) on Total Sky Cover (SKC)

Buy-sell imbalance (BSI) in dollar value is defined as the dollar value of the buying trades minus the selling trades, relative to the daily average of total value of stocks traded by sample investors. SKC is the total sky dome covered by cloudy of one day (in tenth) relative to average seasonal SKC. There are a total of 1,247 observations for each city. T-statistics are provided in parentheses.

	Coefficients		
	Intercept	Beta	R-square
New York	0.02552	-0.00136	0.00
	(3.359)	(-0.613)	
San Francisco	-0.00971	0.00133	0.00
	(-1.264)	(0.559)	
Chicago	0.03588	-0.0008266	0.001
	(3.12)	(-0.268)	
Philadelphia	0.0316	-0.00185	0.001
	(0.883)	(-0.464)	
Los Angeles	0.0104	-0.0025	0.00
	(0.985)	(-0.774)	
Total	0.01473	-0.000351	0.00
	(3.192)	(-0.259)	

Table 7 Mean of Buy-Sell Imbalance (BSI) for Cities with Different Weather Patterns.

Buy-sell imbalance (BSI) in dollar value is defined as the dollar value of the buying trades minus the selling trades, relative to the daily average of total value of stocks traded by sample investors. In column 2 and 3, the numbers of observations are provided in brackets. In column 4, the t-statistics of 2-sample t-test are provided in parentheses.

	BSI		
	Sunny	Cloudy	Sunny-Cloudy
Miami	0.0248	0.0385	-0.0137
(Mostly sunny)	[632]	[591]	(0.306)
Philadelphia	0.0378	-0.0108	-0.0486
(Average)	[571]	[676]	(1.853)*
Portland, Oregon	-0.0095	-0.1022	0.0927
(Mostly cloudy)	[605]	[385]	(0.8837)

* indicates significant at 10 percent

Table 8 Mean of Total Trading Volume (TTV) during Sunny and Cloudy Days

Total trading volume (TTV) is the dollar value of trades made by investors from a particular city. In column 2 and 3, the numbers of observations are provided in brackets. In column 4, the t-statistics of 2-sample t-test are provided in parentheses.

	Total Trading Volume		
	Sunny	Cloudy	Sunny-Cloudy
New York	770,429.2	778,086.5	-7657.3
	[665]	[582]	(-0.3915)
San Francisco	1,333,120	1,333,482	-362
	[602]	[646]	(0.0095)
Chicago	289,005.2	304,997.8	-15992.6
	[538]	[709]	(-1.737)*
Philadelphia	280,655.0	275,204.0	5451
	[571]	[676]	(0.56)
Los Angeles	572,522.6	554,410.2	18112.4
	[934]	[313]	(1.05)
Total	659,361.5	640,879.9	18,481.6
	[3,310]	[2,926]	(1.34)

* indicates significant at 10 percent

Table 9 Regression of total trading value (TTV) on Total Sky Cover (SKC)

Total trading volume (TTV) is the total dollar value of trades executed by investors from a particular city. SKC is the total sky dome covered by cloudy of one day (in tenth) relative to average seasonal SKC. There are a total of 1,247 observations for each city. T-statistics are provided in parentheses.

	Coefficients		
	Intercept	SKC	R-square
New York	774,537.8	1438.58	0.00
	(73.37)	(0.507)	
San Francisco	1,333,297	-513.39	0.00
	(69.89)	(-0.087)	
Chicago	298,095.9	1632.41	0.001
	(65.33)	(1.34)	
Philadelphia	277,634.5	-1886.15	0.001
	(1.274)	(-1.274)	
Los Angeles	563,266.1	-5210.3	0.003
	(65.42)	(-1.99)**	
Total	649,542.8	-399.57	0.00
	(94.50)	(-0.198)	

** indicates significant at 5 percent

Table 10 Market Return and Fund Flow between 1991 and 1996

There are 1,851,131 trades on common stocks, 1,186,577 trades on common stocks in "Equities Sub-sample" made on prices other than round dollar or half dollar prices; 223,282 trades on equity mutual funds; 40,565 trades on bond funds. For each asset class, there are 1,497 observations between January, 1991 and November, 1996. T-statistics are provided in parentheses.

	NYSE Index			
	Equities	Equities Sub-sample	Equity Funds	Bond Funds
Intercept	0.0006130	0.0006480	0.0006226	0.0004666
	(3.67)	(4.107)	(4.058)	(2.943)
Fund flow	-0.00367	-0.000929	0.0003217	0.0001270
	(-4.262)***	(-0.812)	(5.427)***	(0.402)
Fund flow -1	0.001633	-0.00125	-0.0000544	0.0003433
	(1.919)*	(-1.107)	(-0.944)	(1.091)
Ret-1	0.07022	0.09443	0.06261	0.102
	(2.447)**	(3.623)***	(2.343)**	(3.610)***
F-statistics	9.743	5.832	14.892	5.078
R-square	0.02	0.01	0.03	0.01

***, **, and * indicate significant at 1,5, and 10 percent

Table 11 Mean of Equity Mutual Funds' Net Buy in Shares (NBS) in sunny and cloudy days

The net buy in shares (NBS) of a particular day is defined as the total number of shares of equity mutual funds bought minus the total number of shares of equity mutual funds sold by sample individuals in that day. There are 2,838 trades in New York, 5,106 trades in San Francisco, 1,270 trades in Chicago, 1,288 trades in Philadelphia, and 5,785 traded in Los Angeles, on equity mutual funds. In column 2 and 3, the numbers of observations are provided in brackets. In column 4, the t-statistics of 2-sample t-test are provided in parentheses.

	NBS of Equity Funds		
	Sunny	Cloudy	Sunny-Cloudy
New York	651.28	1506.2	-854.92
	[437]	[489]	(0.8427)
San Francisco	1340.4	2424.1	1083.7
	[525]	[576]	(-0.7809)
Chicago	-222.08	1938.9	-2161.0
	[248]	[344]	(1.2455)
Philadelphia	4647.9	-2860.8	7,508.7
	[283]	[314]	(1.1825)
Los Angeles	2338.3	918.21	1420.1
	[581]	[552]	(0.768)
Total	1741.3	1060.2	681.1
	[2,074]	[2,275]	(0.616)

Table 12 Mean of Equity Mutual Funds' Buy-Sell Imbalance (BSI) in sunny and cloudy days

Buy-sell imbalance (BSI) in dollar value is defined as the dollar value of the buying trades minus the selling trades on equity mutual funds, relative to the daily average of total value of equity mutual funds traded by sample investors. There are 2,838 trades in New York, 5,106 trades in San Francisco, 1,270 trades in Chicago, 1,288 trades in Philadelphia, and 5,785 traded in Los Angeles, on equity mutual funds. . In column 2 and 3, the numbers of observations are provided in brackets. In column 4, the t-statistics of 2-sample t-test are provided in parentheses.

	BSI of Equity Mutual Funds		
	Sunny	Cloudy	Sunny-Cloudy
New York	0.143	0.149	-.006
	[437]	[489]	(-.086)
San Francisco	0.137	0.282	-0.145
	[525]	[576]	(-1.78)*
Chicago	0.210	0.115	-0.095
	[248]	[344]	(1.13)
Philadelphia	0.182	-0.001	0.183
	[283]	[314]	(1.34)
Los Angeles	0.0496	0.0062	0.0434
	[581]	[552]	(-1.02)
Entire sample	0.151	0.161	-0.01
	[2,074]	[2,275]	(-0.187)

* indicates significant at 10 percent

Table 13 Changes in NYSE Liquidity and New York Weather in 1993-1995

The dependent variable (DQSP) is the percentage change in the quoted bid-ask spread. DQSP is a equal weighted average of spread change for all S&P 100 stocks that are listed in NYSE. Explanatory variables include the total sky cover (SKC), the contemporary and lagged NYSE index return, lagged DQSP, and the interaction between SKC and NYSE return. Monday and January are two dummy variables taking the value of 1 if a day is Monday or in January. The data are for 1993-1995 period with 739 observations. T-statistics are provided in parentheses.

	DQSP				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.000572	0.0007956	0.001	0.0009178	0.001044
	(0.746)	(1.034)	(1.406)	(1.278)	(1.267)
SKC	0.0004882	0.0004475	0.0005051	0.0005172	0.0005135
	(2.155) **	(1.977) **	(2.406) **	(2.466) **	(2.452) **
NYSE		-0.387	-0.409	-0.397	-0.396
		(-2.549)**	(-2.885)***	(-2.803) ***	(-2.786) ***
NYSE $_{(t-1)}$			0.107	0.110	0.111
			(0.753)	(0.776)	(0.779)
DQSP$_{(t-1)}$			-0.372	-0.370	-0.371
			(-10.899) ***	(-10.879) ***	(10.868) ***
SKC*NYSE				-0.0728	(-0.0727)
				(-1.907)*	(-1.900) *
Monday					-0.000409
					(-0.228)
January					-0.000592
					(-0.227)
R-square	0.01	0.02	0.16	0.16	0.16

***, **, and * indicate significant at 1,5, and 10 percent

Table 14 Market Return, Liquidity and Local Weather in 1993-1995

The dependent variable is the NYSE index return. Explanatory variable include total sky cover (SKC), one-day lagged NYSE return current and one-day lagged change in quoted spread, and the interaction between total sky cover and change in quoted spread. DQSP is a equal weighted average of spread change for all S&P 100 stocks that are listed in NYSE. The value weights are proportional to market capitalization at the end of the previous calendar year. The data are for 1993-1995 period with 739 observations. T-statistics are provided in parentheses.

	NYSE Daily Return				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0005774	0.0005181	0.0005296	0.0005817	0.0005849
	(3.117)	(2.793)	(2.867)	(3.155)	(3.168)
SKC	-0.000105	-0.000104	-0.0000916	-0.0000865	-0.0000852
	(-1.971)**	(-1.921)*	(-1.684)*	(-1.599)	(-1.573)
$NYSE_{(t-1)}$		0.114	0.119	0.115	0.114
		(3.118)***	(3.268)***	(3.169)***	(3.121)***
DQSP			-0.0242	-0.0325	-0.0339
			(-2.744)***	(-3.544)***	(-3.492)***
SKC*DQSP				-0.00785	-0.00768
				(-3.113)***	(-3.007)***
$DQSP_{(t-1)}$					-0.00418
					(-0.437)
R-square	0.01	0.02	0.03	0.04	0.04

***, ** and * indicate significant at 1,5, and 10 percent

Figure 1 Seasonal Pattern of Metropolitan Weather

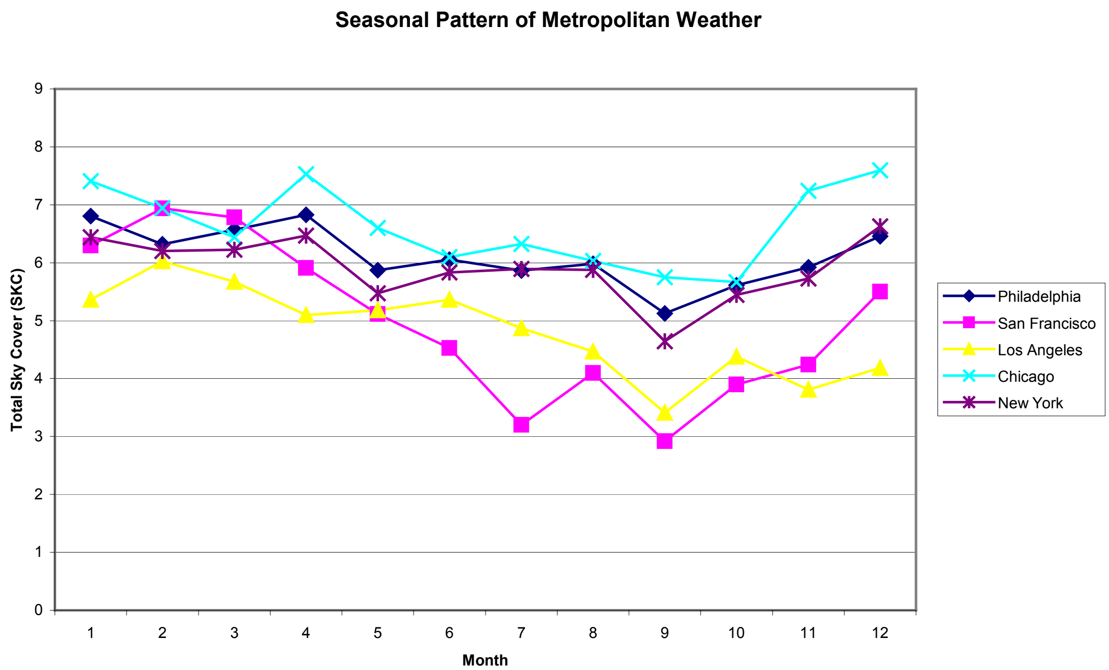

Figure 2 Different Seasonal Weather Patterns