How Does Air Quality Affect Trading Performance?
A Study of the Role of Investor Sentiment and Limited Attention

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Abstract

Psychological evidence and casual intuition suggest that air quality is associated with investment decisions. In this paper, we use a city-trading day level analysis to examine the relationship between air quality in trading sessions and corresponding trading performance in subsequent days. The sample covers 679 branches of all security brokerage firms in 19 cities in Taiwan from 2016-2017. The results of our empirical analysis show that air quality is strongly correlated with trading turnover and one-day holding returns for retail investors. On days with good air quality, retail investors trade more but also suffer worse trading performance. Retail investors tend to be more optimistic on good air days, indicating that the relationship between air quality and trading behavior is driven by investor sentiment rather than limited attention, though past studies have identified both factors as possible channels. Meanwhile, our analysis indicates that air quality does not affect institutional investors whose job is to trade irrespective of air quality; this reinforces our argument that retail trading is more likely to be sentiment-driven.

Keywords: Air Quality; Retail Trader; Investor Sentiment; Limited Attention

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1. Introduction

Many studies have found that poor air quality negatively impacts investor performance. Stock market investors are not immune to air pollution's negative effects on human behavior. Taking previous findings into consideration, this study attempts to answer a simple but essential question: through what mechanism does air quality affect investors?

Most past studies have argued that the primary mechanism by which environmental conditions affect investment decisions is investor sentiment. There exists decades-old literature investigating how environmental conditions impact mood and subsequently affect decision-making. Schwarz and Clore (1983) and Cunningham (1979) make seminal contributions in this regard. Finance scholars have extended this line of research to examine the effects of weather on stock market prices and trading behavior, as mediated by the weather's impact on mood, with the weight of the evidence indicating that better weather leads to more optimism and higher prices. For example, Saunders (1993) and Hirshleifer and Shumway (2003) reveal the "sunshine effect" on stock prices; Kamstra, Kramer, and Levi (2003) document the relationship between daylight and stock prices; Goetzmann, Kim, Kumar, and Wang (2015) show the effect of cloud cover on institutional investors' pessimism. In recent years, studies have begun to link air quality to investor sentiment, indicating that air pollution affects stock market performance. For example, Vert et al. (2017) examine the association between air pollution and mood. Dong, Fisman, Wang, and Xu (2019) report a negative relationship between air pollution during investment analysts' corporate site visits and subsequent earnings forecasts; they argue that air pollution only affects predictions that are announced in the weeks immediately following the visits, indicating that mood likely plays a role.

Lu (2019) points out that the impact of air pollution on human behavior has multiple dimensions. In addition to its negative effect on emotions, its direct impact on cognitive ability—including on concentration, memory, mathematical abilities, and comprehension—is an alternative channel that could generate negative impacts. If air pollution does negatively impact human cognitive performance, it affects investor performance on the stock market as well. Interestingly, air pollution's effects on attention may also come from indirect sources. Qin and Zhu (2018) find that deteriorations in air quality (AQI increases by 100 points) produce significant 3%-5% increases in the frequency of internet searches regarding "immigration." Investors' focus on non-investment matters may also cause them to become less focused on investment decisions as air quality worsens.

Previous weather-related studies have provided evidence that events unrelated to investment easily affect investor attention. Hong and Yu (2009) find that stock trading volume is lower during the summer because market participants are on vacation and only pay limited attention to their portfolios. This finding echoes the work of Schmittmann, Pirschel, Meyer, and Hackethal (2015), who suggest that the opportunity cost for paying attention to the stock market on days with good weather is higher for retail investors since they more likely spend time planning their next vacations or off-work activities. In line with the limited attention argument, Bui, Lin, and Lin (2018) find that retail investors do allocate more attention to the stock market on rainy days. Larger retail trading volume and lower stock return co-movement on rainy days corroborate the rainy-day effect on investor attention.

In short, existing research suggests that the influence of air quality on investors could have multiple mechanisms. However, previous studies have not clarified which mechanism is more important and have often explained the correlation between air quality and investment behavior based on a single factor. Thus, the question remains: sentiment or attention allocation—which plays the major role? Our analysis attempts to answer to this question.

In this study, we use manually-collected stock trading data from 679 securities firms in 19 different cities in Taiwan to conduct a complete analysis. By combining this data with data regarding the different air quality measures in each city, we analyze the impact of air quality on investors' stock trading behaviors. The advantage of our dataset is that it fully covers both retail and institutional trades on the Taiwan stock exchange. The data's comprehensive coverage combined with the retail-dominated nature of the market allows us to observe and validate potential air quality-induced impacts like return co-movement and trading turnover. This important validation test of rational attention allocation and investor sentiment would not be feasible using data from a single brokerage firm.

Our main empirical findings are as follows. (1) on days with better air quality, the co-movement of individual stocks in the stock market is also lower, which indicates that retail investors are still able to pay attention to their own investment decisions. This finding is inconsistent with the hypothesis that air pollution negatively impacts investors' attention in trading. (2) On days with better air quality, the margin loan over stock loan ratio for the whole market is higher, indicating that retail investors are more optimistic when they trade. This finding supports the hypothesis that air pollution is related to investor sentiment since good air quality positively influences mood. (3) On days with better air quality, retail investors have relatively poorer trading performance and higher trading turnover rates, suggesting that good air quality leads investors to trade over-aggressively. (4) The effect of air quality can only be seen in retail investor-dominated security firm transactions. When we conduct the analysis for security firms dominated by institutional investors, the same effect does not manifest. (5) Given that the status of air quality may be correlated to rainfall levels, the effect of air quality cannot be explained by the rainfall variable documented in a prior study.

Our paper contributes to the literature in several ways. First, our findings supplement existing studies on the effects of investor sentiment and attention in financial markets with new insights. Second, our paper is also related to research regarding environmental impacts on trading behaviors, especially given that recent studies have focused more on air pollution or the risk-induced in the stock market. In contrast to these studies, our main contribution lies in our finding that air quality exerts a stronger influence on investor sentiment than attention allocation. More importantly, we examine the impact on the resulting trading profits—an area rarely addressed in existing studies.

Finally, our study is comparable to past research considering causal effects of exogenous shocks to investor attention on the financial market. For example, Huang, Huang, and Lin (2017) examine large jackpot lotteries as exogenous shocks that distract investors' attention from the stock market, finding evidence that stock returns co-move more with the market on these days. Similarly, Peress and Schmidt (2018) consider sensational news stories as exogenous shocks that distract traders' attention from the stock market, showing that trading activity, liquidity, and volatility drop on days when such stories are published. Although medical and psychological research has suggested that air quality is related to people's abilities to allocate attention our findings show that the causal effect of air quality on paying attention to trading is less apparent among retail traders on the Taiwan stock market.

The remainder of this study is organized as follows. Section 2 briefly discusses previous research regarding the relationship between air pollution and decision making. Section 3 describes our data, methodology, and sample construction in detail. Section 4 presents our main empirical findings. Section 5 explains the robustness tests we employ and Section 6 concludes the study.

2. Recent Research in the Literature

An increasing number of studies have shown that air pollution not only harms human health but also affects people's psychological status. Lu, Lee, Gino, and Galinsky (2018) examine American and Indian subjects in their study. They ask these two groups of subjects to look at pictures of a polluted or non-polluted place, respectively, then test subjects' moral behavior in a dice game. The results of experiment show that people looking at the picture of air pollution tend to be more anxious, leading them to engage in immoral behaviors when playing the dice game. Meanwhile, Szyszkowicz, Rowe, and Colman (2009) find that, in Canada, when the CO concentration is 0.8 PPM, the number of visits to the emergency room increases by 15.5% and when the NO2 concentration is 20.1 PPB, the number of visits increases by 20%. They also find that when the concentration of PM10 is 19.4 mug/m^3 and is combined with exposure to the cold climate, the daily number of emergency room visits increases by 7.2%. They conclude that exposure to higher air pollution in the environment increases the number of emergency room visits due to mental depression, suggesting that air pollution causes psychiatric symptoms including anxiety, cognitive decline, and behavioral biases.

In addition to its psychological effects, air pollution has been shown to affect the labor force. Chang, Zivin, Gross, and Neidell (2016) conduct a comparative analysis of air pollution data and the number of daily calls made by customer service centers. They show that on days with high air pollution, employee rest times increase so that the number of calls completed decrease as well, leading to an overall reduction in workplace productivity. Meyer and Pagel (2017) use the trading behavior of retail investors to measure the working efficiency of white-collar workers and assess the impact of air quality on their willingness to participate in cognitive tasks. They find that when air quality is poor, investors are significantly less likely to log into their investment accounts and trade.

Many studies have also linked air pollution to the financial markets. For example, Zhang, Jiang, and Guo (2017) find that haze has a significant negative impact on stock returns in China, while Wu, Chen, Guo, and Gao (2018) show that when AQI reaches 300, air pollution has a significant negative impact on the stock returns of listed companies on the Chinese stock market. Moreover, Wu, Hao, and Lu (2018) point out that severe air pollution reduces stock returns, liquidity and volatility. For stocks that are hard to evaluate and arbitrage, the effects of air pollution are even more pronounced.

All of these studies suggest that air pollution negatively affects individuals and, in turn, negatively impacts their trading performance in the financial markets.

3. Data and Descriptive Statistics

In this section, we introduce the institutional details of our data, construct the variables of interest, and present descriptive statistics.

3.1 Sample

We manually collect daily trading data for all security brokerage firms in Taiwan from the Stock Exchange (TWSE)'s website to construct comprehensive firm-day trading observations at the brokerage branch level. In particular, for every branch of every security firm, we observe the total number of shares bought and sold, the total value of shares bought and sold, and the average buy and sell prices within a trading day for each stock.[1] Our primary sample only incorporates the branches of security firms out of Taipei city—the capital city of Taiwan—since the trading of non-Taipei security firm branches is dominated by retail investors. Because all brokerage firm headquarter branches exclusively serve their institutional clients in Taiwan and almost all headquarters are in Taipei city, we are able to separate retail traders and institutional traders based on branch locations.[2] In total, our dataset contains daily trading data for 679 branches, covering 76 brokers for individual investors, from January 2016 to December 2017.

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[1] We obtain other trading-related variables from the Taiwan Economic Journal (TEJ)—a leading financial data vendor in Taiwan.

[2] In one of our robustness tests, we perform the analysis exclusively using trading data affiliated with security firms in Taipei to compare the results with the main sample results.

3.2 Air quality measures

We obtain hourly air quality index (AQI) observations from the Environmental Protection Administration, Executive Yuan, Taiwan. The calculation formula of the air quality index is as follows:

$$\text{AQI} = \text{Max}(\text{O}_{3,8\text{hr}}, \text{O}_3, \text{PM}_{2.5}, \text{PM}_{10}, \text{CO}_{8\text{hr}}, \text{SO}_2, \text{SO}_{2,24\text{hr}}, \text{NO}_2)$$

For an hour in a day, $\text{O}_{3,8\text{hr}}$ and $\text{CO}_{8\text{hr}}$ is measured based on the most recent 8-hour moving average, O_3, SO_2, and NO_2 are hourly values, $\text{PM}_{2.5}$ and PM_{10} equals 0.5 $\times$ (the average of recent 12 hours + the average of recent 4 hours). $\text{SO}_{2,24\text{hr}}$ is the most recent 24-hour moving average. In addition to AQI, we also test the effect of PM2.5 and PM10 separately.

Since the TWSE operates from 9:00 AM to 1:30 PM, we synchronize the trading variables and air quality measures by calculating the air quality indicator as the hourly-average of each air quality measure from 8:00 AM to 2:00 PM for each day in each city and associate the air quality indicator with the transactions of all security firms in the same city.

Furthermore, we consider the following standard to identify whether the air quality in a city is good or bad: if the value of air quality indicator in a city on a specific day is lower than the third quartile of all its values over the preceding 12 months, we define the trading sessions on that day as having relatively good air quality.[3] In the robustness test, we alternatively consider the fourth quantile as the cutoff point. The thresholds for identifying good air quality for different cities are therefore different. This process

[3] Shortening the period to 9 months or 6 months does not cause any significant changes to the empirical results reported in subsequent sections.

enables us to more effectively gauge the impacts of air quality since people living in different cities may have become adjusted to different air quality index levels and perceive the status of air quality based on relative rather than absolute standards.

3.3 Trading activity measures

Since our air quality measure is at the city level, we need to construct city-day level portfolios to test the influence of air quality on trading volume and investment performance in a two-step procedure. In the first step, we aggregate firms' relevant variables (e.g., volume, value, and price) from the branch-level to the city-level. Specifically, for each day *t* and each stock *i*, we sum the trading volume and trading value that take place at branch b within the same city c as follows:

$$Volume_{i,c,t} = \sum_{b=1}^{B} Volume_{i,b,t} \tag{1}$$

$$Value_{i,c,t} = \sum_{b=1}^{B} Value_{i,b,t} \tag{2}$$

Where *t* is the trading day, *b* is the branch, *i* is the stock, *c* is the city, and *B* is the total number of branches.

We obtain the daily number of shares outstanding from TEJ to calculate trading turnover rates. The calculation formula is as follows:

$$Turnover_{i,c,t} = \sum_{b=1}^{B} Volume_{i,b,t} / Outstanding\ Shares_{i,t} \tag{3}$$

We also calculate the returns of the cities to the *i* shares for the next one to five days after trading day *t*. First, we calculate each branch's buying and selling stock return rate with the following formula:

$$Buy\ return_{i,b,t}^{k} = \frac{Close\ Price_{i,b,t+k} - Average\ Price_{i,b,t}}{Average\ Price_{i,b,t}} \times 100 \tag{4}$$

$$Sell\ return^k_{i,b,t} = \frac{Average\ Price_{i,b,t} - Close\ Price_{i,b,t+k}}{Average\ Price_{i,b,t}} \times 100 \quad (5)$$

Where k is the k-th day after the trading date t.

Next, following Barber, Lee, Liu, and Odean (2009), we divide the trades of each branch on individual stocks into buy and sell positions according to net buys or net sells. For example, when the weighted average price of A shares today is 40 NTD, 3,000 shares are bought, 2,500 shares are sold, and the excess is 500 shares, meaning the value of the bought position is 20,000 NTD (500×40) and the value of the sold position is 0 NTD. We then multiply the value of the position by the daily excess return rate to calculate the returns.

$$Profit^k_{i,c,t} = \sum_{b=1}^{B} Portfolio\ Value_{i,b,t} \times (Return^k_{i,b,t} - Return_{m,t}) \quad (6)$$

Where $Profit^k_{i,b,t}$ can be obtained from Equations (4) and (5) and $Return_{m,t}$ is the market return on trading day t.

Next, we aggregate the variables of interest from firm-level to city-level. For each city c and each day t, we aggregate trading volume, trading value, turnover, and profit for all stocks (N) that are traded within city c as follows:

$$Volume_{c,t} = \sum_{i=1}^{N} Volume_{i,z,t} \quad (7)$$

$$Value_{c,t} = \sum_{i=1}^{N} Value_{i,z,t} \quad (8)$$

$$Turnover = \sum_{i=1}^{N} Turnover_{i,z,t} \quad (9)$$

$$Profit_{c,t} = \sum_{i=1}^{N} Profit_{i,z,t} \quad (10)$$

3.4 Descriptive statistics

Table 1 shows the descriptive statistics for the main variables. Our study consists of 490 trading days, with a total of 9,310 city-trading days. Panel A shows the descriptive statistics of air quality measures (AQI, PM2.5, and PM10) for each city. The results show that the mean and median values of air quality measures for each city are various, implying that people living in different cities may get used to very different air quality conditions. Also, the standard deviation of each air quality measure for each city is large enough, indicating that air quality conditions change sufficiently on each day for us to detect the influence of air quality on investors' trading behaviors.

[Insert Table 1 here]

Panel B shows the descriptive statistics of air pollution rate by AQI, PM2.5, and PM10, respectively, which is the ratio (%) of cities with relatively good air quality in 19 cities for each day. For each city, the daily indicator of "relatively good air quality" equals to one if the air quality measure on that day is less than its third quartile in the same year and zero otherwise. On average, for each day, about 75% of cities (nearly 15 cities) in our sample period do not suffer severe air pollution problem. Also, given the standard deviation, P25, and P75, we can expect that 60% to nearly 100% of cities have relatively good air quality for most days in the sample period.

Panel C shows the descriptive statistics of all trading variables, including trading volume, turnover, and profits. As for trading activities, the average daily buying and selling turnover rate for retail investors is 12.8% and 12.9%, respectively, the average daily buying and selling value is 1.067 billion and 1.097 billion, respectively, and the average daily buying and selling volume is 29.58 million and 30.279 million, respectively. As for trading performance, the average trading losses from holding stocks for one to five days are nearly 37 million, 37 million, 36 million, 35 million and 34 million, respectively. This finding suggests that retail investors, on average, lose money in trading, which is consistent with phenomena documented in previous studies (see, e.g., Barber et al., 2009)

4. Empirical Results

In this section, we conduct four tests. First, we seek to determine whether the days with good air quality affect investor attention or sentiment. Therefore, in the first and second tests, we examine whether the attention of retail investors increases and whether investment sentiment becomes more positive on days with good air quality. Next, we further examine whether the trading performance of retail investors is different on the days with good air quality. In addition, we add a rainy-day variable to the model to compare the impacts of air quality and rainfall on the performance of retail investors. Finally, we examine retail investors' trading turnover to see if they tend to trade more frequently when the air quality is better.

4.1 Retail investors' attention

Bui, Lin, and Lin (2018) find that the co-movement between individual stocks and market returns is low on rainy days, indicating that retail investors pay more attention to their own investment decisions on those days.[4] Following a similar approach, we test whether air quality impacts investors' attention by examining whether the co-movement between stock and market returns is different on days with different air quality statuses. If air pollution negatively impacts investors' attention, we expect

[4] If investors pay less attention to their investment portfolios and make their own decisions, they are more likely to follow public news and trade or chase recent market trends. The co-movement of individual stocks, therefore, should be high rather than low.

stocks to be more closely correlated with the market on days with poor air quality.

To classify good air days and bad air days, as Panel A of Table 1, we define the air pollution rate based on the proportion of the 19 cities that have good air quality. We then divide each trading day in the sample into two groups: the top 20% air pollution rate days (relatively good air quality) and the bottom 80% air pollution rate days (relatively poor air quality). Next, we estimate the co-movement between individual stock returns and market returns on both low air pollution rate days and high air pollution rate days. Applying the method of Huang, Huang, and Lin (2017), we use two indicators to calculate the return co-movement. The first indicator is the Pearson correlation coefficient between individual returns and market returns, and the second is the adjusted R^2.

We obtain the adjusted R^2 from the following regression equation (the market model):

$$Excess\ return_{i,t} = \alpha_i + \beta_i \times Market\ excess\ return_t + \varepsilon_{i,t} \qquad (11)$$

Where $Excess\ return_{i,t}$ indicates the return of individual stock i at day t. $\mathrm{Market\ excess\ return_t}$ is the difference between the market return and the risk-free interest rate at day t.[5] We compute the value-weighted average of each co-movement indicator for all stocks in the good air quality and bad air quality groups and present the results in Table 2.

As Table 2 shows, regardless of AQI, PM2.5, or PM10, the correlation coefficient and adjusted R^2 for low air pollution rate days are higher than those for high air

[5] We adopt the one-year deposit rate of First Commercial Bank—one of three major state-owned commercial banks in Taiwan—as the risk-free interest rate. The selection of a risk-free rate does not affect the reported results given that other Taiwanese studies use the interest rates from the other two banks.

pollution rate days. As for the correlation coefficient of AQI (PM2.5, PM10), for example, the average number in days with low air pollution rates is 13.57% (15.79%, 10.82%) higher than that the average number of days with high air pollution rates. Similarly, the average R^2 of AQI (PM2.5, PM10) on days with low air pollution rates is 16.79% (17.93%, 10.07%) higher than on days with high air pollution rates. These findings do not align with our expectations, indicating that air quality likely does not explain differences in retail investors' attention.

[Insert Table 2 here]

4.2 Retail investor sentiment

The results reported in the previous section indicate that a correlation between the attention of retail investors and air quality is unlikely. In this section, we further examine whether air quality affects the moods of retail investors. Since margin trading is mostly carried out by retail investors, we use the margin loan over stock loan ratio (M/S ratio) as the indicator of retail investors' sentiment.[6] We postulate that good air quality will put investors in good moods and make them optimistic about the future of the stock market, which will increase their willingness to hold more risky assets, leading to increased margin loan balances and therefore increased M/S ratios. Again, we calculate correlation coefficients and adjusted R^2 using Equation (11) for good air days and bad air days, respectively. Table 3 reports the results.

As the results in Table 3 show, regardless of AQI, PM2.5 or PM10, the average

[6] The margin loan or stock loan balance is reported in either quantity volume or dollar volume. We try different versions of this ratio in the subsequent analysis.

M/S ratio value by quantity volume on low air pollution rate days is nearly 23—higher than on high air pollution rate days. The median values follow the same pattern. Likewise, the average and median M/S ratio values by dollar volume on low air pollution rate days are both nearly 9, while the average and median M/S ratio values on high air pollution rate days are both nearly 8. All differences are statistically significant. Overall, the results in Table 3 support the sentiment explanation and show that the sentiment of retail investors is related to air quality. If the air quality is better, retail investors are more likely to be in positive moods and vice versa.

[Insert Table 3 here]

4.3 Air quality and trading performance

Since we find that investor sentiment is related to air quality, we further examine the causal impact of air quality on trading performance. In this subsection, we use the following regression to test the effect of air quality on the trading performance of individual investors who hold stocks for one to five days:

$$Profit_{c,t} = \beta \times GAir_{c,t} + c_c + y_t + m_t + w_t + \varepsilon_{c,t} \qquad (12)$$

Where $Profit_{c,t}$ is defined as in Equation (10) measuring trading performance for retail investors in city c at trading day t, $GAir_{c,t}$ is a good air quality dummy variable that equals 1 if the air quality index in city c is below its third quartile and equals 0 otherwise. c_c, y_t, m_t, and w_t control for the fixed effects of city, month, year, and week, respectively. Also, we examine the trading performance of individual investors for one- to five-day holding periods.

Table 4 shows the regression results. As the results in Panel A indicate, when AQI is relatively low, the profits for holding stocks from one to four days tend to be negative and the coefficient of the first-day return is statistically significant. Similarly, as Panel B shows, for the effect of PM2.5, the coefficients of one-, two-, and three-day returns are negative and the coefficient for one-day returns is statistically significant. As for PM10, Panel C shows that there is a negative relationship between PM10 and the stock-holding profits for one to five days and the coefficients of one-, two-, and three-day returns reach statistical significance. Overall, three air quality measurements show that retail investors suffer higher losses when the air quality is good, but the losses gradually decrease as the holding period increases. These findings are consistent with our supposition that retail investors trade in overly optimistic manners on days with good air quality. Such overly optimistic trading results in worse trading performance.

[Insert Table 4 here]

Biu, et al. (2018) show that retail investors have higher returns on rainy days. Thus, given the possibility of a correlation between air quality and rainfall, is our current finding driven by or influenced by rainfall? To further clarify the causal effects, we construct a rainfall variable based on the definition of Biu, et al. (2018), and add it to Equation (12) to analyze whether the influence of air quality on performance remains. The regression equation is as follows:

$$Profit_{c,t} = \beta_1 \times GAir_{c,t} + \beta_2 \times Rain_{c,t} + c_c + y_t + m_t + w_t + \varepsilon_{c,t} \qquad (13)$$

Where $Rain_{c,t}$ is a dummy variable that equals 1 if the rainfall in city c is more than 3 mm at day t and equals 0 otherwise. The definitions of the other variables are the same as in Equation (12). Table 5 reports the regression results.

Contrary to the findings of Bui et al. (2018), our analysis indicates that the coefficients of $Rain_{c,t}$ are statistically insignificant in all models, while the impact of air quality is similar to the impact reported in Table 4. As the results in Panel A show, when holding the stock for one day, the trading profits of all security firms drop by nearly 2 billion for every one-unit rise of AQI. Similarly, as the results in Panel B indicate, when holding the stock for one day, the trading profits drop by nearly 1.2 billion for every one-unit rise of PM2.5. Finally, as shown in Panel C, a one-unit rise of PM10 causes a drop of 4 to 3 billion for one- to three-day stock-holding performance. These findings suggest that the effect of air quality on trading performance is not driven or affected by the contemporaneous status of rainfall.

[Insert Table 5 here]

4.4 Air quality and trading turnover

Our results to this point show that investors tend to experience worse trading performance on days with relatively good air quality. This relationship is driven by the rationale that retail traders tend to be overly optimistic on good air days, which leads them to trade too much. Over-trading deteriorates trading performance since trading aggressiveness is negatively related to transaction profits (Chuang, Lin, and Weng, 2019). Thus, given our current findings, we examine whether air quality affects trading frequency. Similar to the analysis in Section 4.3, we run the following regression equation:

$$Turnover_{c,t} = \beta \times GAir_{c,t} + c_c + y_t + m_t + w_t + \varepsilon_{c,t} \quad (14)$$

Where $Turnover_{c,t}$ is defined as in Equation (9) and represents the total buy or sell turnover rate for all stocks in city c at day t. The other variables are defined as in previous regression equations. We expect the coefficient of β to be positive since good air quality should trigger better moods and encourage retail investors to trade more. Table 6 shows the regression results.

As the results in Panel A indicate, every unit increase of AQI leads to a buying turnover rate increase of 0.7% and a selling turnover rate increase of 0.73%. Similarly, as Panel B shows, when PM2.5 increases by one unit, the buying turnover rate increases by 0.27% and the selling turnover rate increases by 0.32%. Finally, as the findings in Panel C show, when PM10 increases by one unit, the buying turnover rate increases by 1.12% and the selling turnover rate increases by 1.16%. In sum, the three air quality indicators are positively correlated with turnover rate and almost all of the relationships are statistically significant; these findings align with our expectations.

[Insert Table 6 here]

Furthermore, as in Section 4.3, we inserted the air quality and the rainy-day variables into the regression model together to verify that the effect of rainfall does not compound the effect of air quality. Table 7 shows the regression results.

As Panel A shows, although both AQI and rainfall have a positive relationship with trading turnover, only the effect of AQI is statistically significant. Similar results can be found in Panels B and C, given that only PM2.5 has a significant effect on selling turnover. Overall these findings show that, regardless of the air quality measures, on any given day, better air quality leads retail investors to trade, more frequently.

[Insert Table 7 here]

5. Robustness Checks

In this section, we redefine air quality and conduct additional tests to verify our previous conclusions. As in the preceding analysis, we put both the air quality variable and the rainy-day variable into the model, thereby testing whether their impacts on retail trading returns and turnover rates are consistent with our initial findings.

5.1 Air quality measures

First, we use the alternative air quality definition in the regression analysis. When $Air_{c,t}$ is 1, it means that AQI (or PM2.5, PM10) is lower than the fourth quintuple in city *c* at day *t*; otherwise, it is 0. Next, we repeat the previous analysis and compare the effects of air quality and rainfall on the performance of retail stocks held for one to five days. Table 8 shows the results.

As the results in Panel A indicate, for every unit rise of AQI, the one-day profits from holding stocks fall by 2,106.3 million, while the effect of rainfall at the same time is not significant. This corresponds to the findings previously reported in Table 5. Similar results appear in Panels B and C. After controlling for the effect of rainfall, the air quality measured by PM2.5 is also significantly correlated with the performance of holding stocks for one day, while the air quality measured by PM10 is significantly correlated with the performance of holding stocks for one to three days. Overall, the results in Table 8 show that the use of a different definition for the air quality dummy does not affect our original finding that investors tend to trade poorly on good air days.

[Insert Table 8 here]

We apply the same replacement of $Air_{c,t}$ to the analysis of turnover rate. We re-run the regression of Equation (14), report the results in Table 9, and compare them with Table 7.

Consistent with the results in Table 7, the results in Table 9 show that all air quality measures are related to trading turnover rate, while rainfall has no significant relationship with trading turnover rate. Again, the use of a different definition for the air quality dummy does not affect our existing findings.

[Insert Table 9 here]

5.2 Institutional trading activities and air quality

Our focus is on retail investors as they tend to be sentiment-driven and easily-affected by air quality, meaning their moods are worse on bad air days. In this subsection, we test whether the effect of air quality also manifests among institutional investors. Given that institutional investors are subjected to fewer mental constraints, and it is their job to trade in the trading room, this analysis serves as a placebo test. We anticipate that institutional trading is not influenced by air quality.

Since institutional trades are exclusively handled by the headquarter branches of brokers that are located in Taipei City, we perform a time-series regression with trading turnover and trading profits as dependent variables and the Taipei City air quality dummy as the main independent variable. The regression model is the same as Equation (13) with $GAir_{Taipei,t}$ and $Rain_{Taipei,t}$ replacing $GAir_{c,t}$ and $Rain_{c,t}$, respectively. Tables 10 and 11 show the results of $Profits_{Taipei,t}$ and $Turnover_{Taipei,t}$ as dependent variables, respectively.

As both tables show, no $GAir_{Taipei,t}$ measures are significantly related to $Profits_{Taipei,t}$ or $Turnover_{Taipei,t}$, indicating that air quality has no effect on institutional trading activities. Compared to retail traders, institutional investors tend to be less driven by air quality-induced sentiment when they trade. Also, showing that the coefficients of $Rain_{Taipei,t}$ are insignificant in almost all models, our analysis indicates that there are no distinct differences in institutional investors' trading turnover and trading profits on rainy days. These results are inconsistent with Goetzmann, et al. (2015) who apply a weather-induced model and find that cloud cover can affect institutional investors' perceptions of mispricing and trading decisions in Germany.

[Insert Table 10 and Table 11 here]

6. Conclusion

Existing studies have pointed out that the influence of air quality on investors could have multiple mechanisms. However, these studies have not clarified which mechanisms are most important and have often explained the correlation between air quality and investment behavior based on a single factor. Does the influence of air quality—if it has an influence—impact investor sentiment or the ability to allocate attention? Which factor serves as the primary channel explaining the relationship between air quality and trading activities? In this study, we try to answer this infrequently-explored question.

We take advantage of a brokerage branch-level dataset that contains records of the trading activity of all individual and institutional investors in Taiwan to study the relationship between air quality and trading activities on the stock market. Our findings show that retail traders tend to be more optimistic regarding the stock market on days with good air quality, meaning that individual investors are subject to more trading losses on those days. This finding supports the notion that investor sentiment harms trading performance and reinforces the results of existing studies. We also find that the air quality effect is not triggered by an influence on investor attention—our results indicate the co-movement of individual stocks on days with poor air quality remains low; this is inconsistent with the predictions of prior studies. Furthermore, we find that the air quality effect is not mainly driven by the influence of rainfall as we show that the variable of rainfall does not explain trading performance or trading turnover when included with the air quality indicator in the regression model. Interestingly, the air quality effect does not impact institutional investors who are professionally charged with trading irrespective of air quality—a finding that reinforces our contention that retail trading tends to be more sentiment-driven. Finally, our results prove robust under alternative good air quality indicator definitions.

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Table 1: Descriptive Statistics

This table presents descriptive statistics. Panel A shows the descriptive statistics of air quality measures (AQI, PM2.5, and PM10) for each city. Panel B shows the descriptive statistics of air pollution rate, which is the ratio (%) of cities with relatively good air quality in 19 cities for each day. For each city, the daily indicator of "relatively good air quality" equals one if the air quality measure on that day is less than its third quartile over the preceding 12 months and zero otherwise. Panel C shows the descriptive statistics of all trading variables. The sample period is from January 2016 to December 2017.

Panel A: Air Quality Measures in Each City

	AQI			PM2.5			PM10		
County	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.
Keelung	43.00	41.55	14.01	15.27	13.29	9.89	26.61	24.43	13.75
Taipei	46.37	44.25	14.78	17.49	15.40	10.16	35.97	34.21	16.11
New Taipei	48.49	46.62	15.68	18.52	16.25	10.19	39.27	36.45	17.02
Yilan	42.09	39.79	12.74	12.32	11.08	7.21	35.66	33.29	14.77
Taoyuan	50.06	46.64	16.10	19.23	15.86	11.11	45.07	41.26	17.53
Hsinchu County	46.49	43.44	14.68	20.21	17.43	10.05	36.89	33.29	16.86
Hsinchu City	47.95	45.00	16.89	17.26	14.71	11.07	40.92	37.43	19.41
Miaoli	48.99	45.57	15.77	19.67	17.76	10.58	41.01	37.10	17.81
Taichung	51.75	48.86	17.79	22.36	19.69	12.58	43.02	39.11	20.12
Changhua	54.71	50.90	20.47	24.58	20.86	13.64	49.49	46.24	22.97
Nantou	51.46	50.95	16.12	24.83	23.25	11.82	43.38	41.55	17.44
Yunlin	63.57	60.40	29.07	27.83	24.96	14.74	58.49	54.07	30.91
Chiayi County	65.19	60.79	29.52	26.46	23.17	15.62	62.26	56.43	31.14
Chiayi City	59.45	56.86	22.68	28.76	25.57	17.23	54.35	50.14	25.12
Tainan	58.72	55.36	24.01	27.81	23.82	16.86	54.03	49.03	25.79
Kaohsiung	65.12	62.14	26.74	28.91	27.40	16.54	58.39	54.98	25.57
Pingtung	55.05	55.15	18.79	22.76	21.38	12.02	46.17	43.52	18.19
Hualien	36.77	35.73	12.77	11.35	10.00	5.80	27.59	24.86	12.65
Taitung	33.29	30.79	17.12	8.92	7.86	4.68	26.21	22.29	18.32

Panel B: Air Pollution Rate (%)

	Mean	Std.	Min.	P25	P50	P75	Max.
AQI	75.10	26.81	0.00	57.89	84.21	98.68	100.00
PM2.5	75.04	27.93	0.00	57.89	84.21	100.00	100.00
PM10	75.02	27.71	0.00	57.89	84.21	100.00	100.00

Panel C: Trading Variables

	Mean	Std.	Min.	P25	P50	P75	Max.
Turnover and Volume							
Buy Turnover	0.128	0.219	0.001	0.016	0.041	0.137	1.996

Sell Turnover	0.129	0.220	0.001	0.016	0.042	0.138	1.983
Buy Value (billion NTD)	1.067	2.023	0.006	0.120	0.314	1.077	22.678
Sell Value (billion NTD)	1.097	2.077	0.005	0.124	0.322	1.098	22.767
Buy Volume (million shares)	29.580	52.333	0.144	3.784	9.569	31.168	524.619
Sell Volume (million shares)	30.279	53.795	0.164	3.863	9.738	31.520	545.222
Trading Profit (billion NTD)							
One day	-0.037	0.070	-0.765	-0.036	-0.011	-0.004	0.016
Two days	-0.037	0.074	-1.072	-0.036	-0.010	-0.004	0.036
Three days	-0.036	0.077	-1.464	-0.033	-0.010	-0.003	0.066
Four days	-0.035	0.081	-1.653	-0.031	-0.009	-0.003	0.143
Five days	-0.034	0.084	-1.627	-0.030	-0.008	-0.002	0.218

Table 2: Return Co-Movement in Different Days

This table presents the estimation of return co-movement by either of correlation coefficients or adjusted R^2 of market model for high air pollution days and low air pollution days, respectively. High air pollution days are days where the air pollution rate ranks in the top 20% of the sample period, whereas low air pollution days are days otherwise. Air pollution rate is calculated by AQI, PM2.5, and PM10, respectively. The definition of air pollution rate can be seen in Table 1. ***, **, and * indicate significance at the 1%, 5%, and10% level, respectively.

AQI		High air pollution days	Low air pollution days	Difference	Percentage change
Correlation	Mean	0.2923	0.3381	-0.0459***	-0.1357***
	Median	0.2019	0.2547	-0.0529***	-0.2075***
Adjusted R^2	Mean	0.1541	0.1851	-0.0311***	-0.1679***
	Median	0.0379	0.0537	-0.0159***	-0.2951***
PM2.5					
Correlation	Mean	0.2907	0.3452	-0.0545***	-0.1579***
	Median	0.2066	0.2584	-0.0518***	-0.2003***
Adjusted R^2	Mean	0.1535	0.1870	-0.0335***	-0.1793***
	Median	0.0395	0.0557	-0.0162***	-0.2908***
PM10					
Correlation	Mean	0.2954	0.3313	-0.0359***	-0.1082***
	Median	0.2076	0.2524	-0.0448***	-0.1775***
Adjusted R^2	Mean	0.1578	0.1755	-0.0177***	-0.1007***
	Median	0.0401	0.0531	-0.0131***	-0.2460***

Table 3: Investor Sentiment and Air Quality

This table presents the investor sentiment index for high air pollution days and low air pollution days, respectively. The investor sentiment index is measured by the ratio of margin loan over stock loan (M/S ratio) for the whole market. M/S ratio is calculated by quantity volume or dollar volume. High air pollution days are days where the air pollution rate ranks in the top 20% of the sample period, whereas low air pollution days are days otherwise. Air pollution rate is calculated by AQI, PM2.5, and PM10, respectively. The definition of air pollution rate can be seen in Table 1. ***, **, and * indicate significance at the 1%, 5%, and10% level, respectively.

	M/S Ratio (quantity volume)		M/S Ratio (dollar volume)	
AQI	Mean	Median	Mean	Mean
High air pollution days	21.46	19.87	8.26	7.57
Low air pollution days	23.18	22.94	9.03	8.58
Difference	-1.72***	-3.07***	-0.77	-1.01**
PM2.5				
High pollution days	21.62	19.87	8.36	7.65
Low pollution days	22.52	22.30	8.60	8.39
Difference	-0.90*	-2.34***	-0.24	-0.74*
PM10				
High pollution days	21.60	19.68	8.34	7.56
Low pollution days	22.59	22.46	8.69	8.51
Difference	-0.99**	-2.78***	-0.35	-0.96**

Table 4: Air Quality and Trading Profits

	Profit				
	One day	Two day	Three day	Four day	Five day
Panel A：AQI					
GAir	-1.9071**	-1.6583	-1.5584	-0.1888	0.7066
	(-2.058)	(-1.462)	(-1.198)	(-0.128)	(0.441)
Control for:					
County fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7132	0.6213	0.54	0.4617	0.4124
Panel B：PM2.5					
GAir	-1.0627**	-0.7708	-0.6523	0.6338	1.3205
	(-2.084)	(-1.192)	(-0.876)	(0.743)	(1.421)
Control for:					
County fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7106	0.6037	0.5124	0.4325	0.3824
Panel C：PM10					
GAir	-4.2083***	-3.5924***	-2.8237**	-2.01	-1.2176
	(-4.443)	(-3.098)	(-2.123)	(-1.328)	(-0.742)
Control for:					
County fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7137	0.6216	0.5401	0.4618	0.4125

Table 5: Air Quality and Trading Profits – Control Rainy Day Effect

	Profit				
	One day	Two day	Three day	Four day	Five day
Panel A：AQI					
GAir	-1.9963**	-1.6987	-1.4101	-0.0464	0.8106
	(-2.117)	(-1.472)	(-1.065)	(-0.031)	(0.497)
Rain	0.5007	0.2267	-0.8325	-0.7999	-0.584
	(0.508)	(0.188)	(-0.602)	(-0.508)	(-0.342)
Control for:					
County fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7132	0.6212	0.5399	0.4616	0.4124
Panel B：PM2.5					
GAir	-1.1683**	-0.8521	-0.64047	0.5797	1.2486
	(-2.259)	(-1.299)	(-0.848)	(0.670)	(1.325)
Rain	0.6426	0.4948	-0.0718	0.3288	0.4372
	(1.212)	(0.736)	(-0.093)	(0.371)	(0.453)
Control for:					
County fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7106	0.6036	0.5123	0.4325	0.3823
Panel C：PM10					
GAir	-4.3519***	-3.681***	-2.7182**	-1.9312	-1.1807
	(-4.528)	(-3.129)	(-2.014)	(-1.258)	(-0.709)
Rain	0.8659	0.5336	-0.6362	-0.4746	-0.222
	(0.882)	(0.444)	(-0.461)	(-0.303)	(-0.131)
Control for:					
County fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7136	0.6216	0.5401	0.4617	0.4124

Table 6: Air Quality and Trading Turnover

	Turnover rate	
	Buy turnover	Sell turnover
Panel A：AQI		
GAir	0.0070**	0.0073***
	(2.442)	(2.573)
Control for:		
County fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7267	0.7296
Panel B：PM2.5		
GAir	0.0027	0.0032*
	(1.516)	(1.796)
Control for:		
County fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7393	0.738
Panel C：PM10		
GAir	0.0112***	0.0116***
	(3.8390)	(3.987)
Control for:		
County fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7269	0.7298

Table 7: Air Quality and Trading Turnover – Control Rainy Day Effect

	Turnover rate	
	Buy turnover	Sell turnover
Panel A：AQI		
GAir	0.0067**	0.0071**
	(2.326)	(2.463)
Rain	0.0012	0.0011
	(0.392)	(0.353)
Control for:		
City fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7266	0.7295
Panel B：PM2.5		
GAir	0.0027	0.0033*
	(1.517)	(1.790)
Rain	-0.0002	-0.0002
	(-0.133)	(-0.118)
Control for:		
City fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7393	0.738
Panel C：PM10		
GAir	0.0111***	0.0115***
	(3.751)	(3.904)
Rain	0.0006	0.0005
	(0.192)	(0.152)
Control for:		
City fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7269	0.7298

Table 8: Air Quality and Trading Profits – Alternative Definition of GAir

	Trading Profit				
	One day	Two day	Three day	Four day	Five day
Panel A：AQI					
GAir	-2.1063**	-1.8248	-1.4902	-0.0220	0.8384
	(-2.095)	(-1.482)	(-1.055)	(-0.014)	(0.482)
Rain	0.4707	0.2021	-0.8518	-0.8035	-0.5489
	(0.483)	(0.169)	(-0.623)	(-0.516)	(-0.325)
Control for:					
City fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7137	0.6215	0.5401	0.4618	0.4124
Panel B：PM2.5					
GAir	-1.897*	-1.3471	-1.0378	0.6201	1.4481
	(-1.869)	(-1.084)	(-0.728)	(0.382)	(0.824)
Rain	0.3907	0.0918	-0.9504	-0.8926	-0.6126
	(0.403)	(0.077)	(-0.697)	(-0.576)	(-0.365)
Control for:					
City fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7137	0.6215	0.5401	0.4618	0.4124
Panel C：PM10					
GAir	-4.0415***	-3.1982***	-2.6814*	-0.9653	-0.6197
	(-3.953)	(-2.554)	(-1.866)	(-0.591)	(-0.350)
Rain	0.7309	0.3824	-0.6942	-0.6633	-0.3206
	(0.753)	(0.321)	(-0.509)	(-0.427)	(-0.190)
Control for:					
City fixed effect	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	9310	9310	9310	9310	9310
Adjusted R^2	0.7141	0.6217	0.5402	0.4618	0.4124

Table 9: Air Quality and Trading Turnover – Alternative Definition of GAir

	Turnover rate	
	Buy turnover	Sell turnover
Panel A：AQI		
GAir	0.0071**	0.0073**
	(2.272)	(2.354)
Rain	0.0013	0.0013
	(0.447)	(0.419)
Control for:		
City fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7266	0.7295
Panel B：PM2.5		
GAir	0.0056*	0.0062**
	(1.771)	(1.960)
Rain	0.0017	0.0016
	(0.574)	(0.534)
Control for:		
City fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7266	0.7295
Panel C：PM10		
GAir	0.0112***	0.0116***
	(3.539)	(3.679)
Rain	0.0008	0.0007
	(0.274)	(0.239)
Control for:		
City fixed effect	yes	yes
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	9310	9310
Adjusted R^2	0.7269	0.7298

Editor

Table 10: The Air Quality Effect on Institutional Trading Profits

	Trading Profit				
	One day	Two day	Three day	Four day	Five day
	(1)	(2)	(3)	(4)	(5)
Panel A：AQI					
GAir	12.7300	22.1886	35.8741	36.4584	38.1567
	(0.402)	(0.561)	(0.718)	(0.602)	(0.577)
Rain	-5.9165	3.9898	-7.3370	-23.1075	-26.9406
	(-0.197)	(0.106(	(-0.155)	(-0.402)	(-0.429)
<u>Control for:</u>					
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	490	490	490	490	490
Adjusted R^2	0.727	0.6192	0.5	0.4015	0.3599
Panel B：PM2.5					
GAir	-10.0671	-1.7810	15.1710	26.0889	37.3069
	(-0.314)	(-0.044)	(0.299)	(0.425)	(0.556)
Rain	-1.4197	8.9971	-2.4821	-20.0894	-25.5778
	(-0.048)	(0.241)	(-0.053)	(-0.352)	(-0.410)
<u>Control for:</u>					
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	490	490	490	490	490
Adjusted R^2	0.727	0.619	0.4995	0.4013	0.3598
Panel C：PM10					
GAir	-35.5221	-28.5332	-11.9333	-19.4988	-28.5292
	(-1.106)	(-0.710)	(-0.235)	(-0.317)	(-0.424)
Rain	2.2799	13.1009	2.0917	-12.3825	-14.4568
	(0.077)	(0.353)	(0.045)	(-0.218)	(-0.233)
<u>Control for:</u>					
Year fixed effect	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes
Day-of-week fixed effect	yes	yes	yes	yes	yes
Observations	490	490	490	490	490
Adjusted R^2	0.7277	0.6194	0.4995	0.4012	0.3596

Table 11: The Air Quality Effect on Institutional Trading Turnover

	Turnover rate	
	Buy turnover	Sell turnover
	(1)	(2)
Panel A：AQI		
GAir	-0.0337	-0.0512
	(-0.576)	(-0.861)
Rain	0.0926*	0.0987
	(1.666)	(1.447)
Control for:		
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	490	490
Adjusted R^2	0.7207	0.719
Panel B：PM2.5		
GAir	0.0228	0.0079
	(0.383)	(0.131)
Rain	0.0814	0.0864
	(1.473)	(1.539)
Control for:		
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	490	490
Adjusted R^2	0.7206	0.7185
Panel C：PM10		
GAir	-0.0066	-0.0313
	(-0.112)	(-0.518)
Rain	0.0865	0.0927*
	(1.573)	(1.659)
Control for:		
Year fixed effect	yes	yes
Month fixed effect	yes	yes
Day-of-week fixed effect	yes	yes
Observations	490	490
Adjusted R^2	0.7205	0.7187