Pollution and Performance: Do Investors Make Worse Trades on Hazy Days?*

Jiekun Huang† Nianhang Xu‡ Honghai Yu§

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†Department of Finance, University of Illinois at Urbana-Champaign; e-mail: huangjk@illinois.edu.

‡School of Business, Renmin University of China; e-mail: nhxu@ruc.edu.cn.

§School of Management and Engineering, Nanjing University; e-mail: hhyu@nju.edu.cn.

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Abstract

This paper explores the relation between air pollution and trading performance of stock investors. Using a sample of trades by over 100,000 investors from 28 cities in China, we find a negative relation between air pollution and trade performance. Our calendar-time portfolio tests show that the trades made by investors on days with poor air quality underperform those made on days with good air quality by 0.612 to 0.673 basis points per day at the average investment horizon of 40 trading days. This relation is more pronounced among females and elderly and is driven mainly by trades in stocks of firms that are more cognitively challenging to value, namely, small-cap firms, firms with low analyst coverage, and firms with high idiosyncratic volatility. Moreover, the negative relation between air pollution and trade performance persists after controlling for local weather conditions, city-fixed effects, and time-fixed effects. Overall, the results highlight a hitherto unexplored cost associated with ambient air pollution, namely underperformance of stock market investors.

JEL Classification: G11, G23, G14

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1 Introduction

Ambient air pollution is a major environmental health problem faced by countries worldwide. For example, European Environment Agency (2015) lists air pollution as the "single largest environmental health risk" in Europe. According to the *State of the Air 2016* report by the American Lung Association, more than half of the people in the U.S. live in counties that have unhealthful levels of either ozone or particle pollution. Medical studies have shown that ambient air pollution not only increases the incidence of respiratory and cardiovascular diseases and causes premature death, but also impairs cognitive functioning (see, e.g., Pope and Dockery, 2006; Block and Calderón-Garcidueñas, 2009). Such adverse cognitive effects suggest that air pollution can negatively impact activities and decisions that require mental acuity. While stock trading decisions are commonly viewed as cognitively demanding and can have large financial impact on households, the influence of air pollution on investor outcomes remains underexplored. In this paper, we provide the first examination of the relation between air quality and individual investors' stock trading behavior and performance.

Stock trading decisions are often complicated and involve an understanding of complex fundamental factors that influence stock prices and trade performance. Investors have to acquire and process information from a myriad of sources, consider various possibilities about the prospects of the firm, evaluate the risk-return tradeoff, decide on how to execute the trades to minimize transaction costs, and so on. A growing body of evidence suggests that cognitive ability matters for stock trading. For instance, Grinblatt, Keloharju, and Linnainma (2012) find evidence that trades by high-IQ investors outperform those by low-IQ investors due to their better stock-picking abilities and lower execution costs. Given that air pollution can negatively affect cognitive functioning and stock trading is cognitively demanding, we hypothesize that air pollution negatively affects trading performance.

We use a sample of account-level transaction data from a large Chinese brokerage house to examine the influence of air pollution on stock trading behavior and performance. China provides an ideal setting to test our hypothesis, because it is facing severe air pollution problems and there are large variations in air pollution across and within geographic areas in China (e.g., Chen, et al., 2013). For example, according to a World Bank (2016) report, China ranks second (to Mauritania) in the world for the level of concentration of fine particulate matter ($PM_{2.5}$). Our dataset covers $127,041$ households from 28 cities in China during the period from January 2007 through December 2013. We match our data to air quality data and construct a panel of city-dates. We find a negative relation between air pollution and the performance of stock trades. Our calendar-time portfolio tests show that the trades by investors made on days with the worst air quality underperform those made on days with the best air quality by about 1.696 percentage points in annualized terms at a holding horizon of two months. In dollar terms, investors in the average city suffer an annual performance penalty of about RMB43.74 million for their trades placed on days with the worst air quality relative to those on days with the best air quality at a horizon of two months, which amounts to 3.69% of the average portfolio value.

To shed light on the channel through which air quality affects trading performance, we conduct various subsample analyses. We find that the negative relation between air pollution and trade performance is more pronounced among females and elderly, which is consistent with the findings in medical studies that women and older people are more susceptible to air pollution. We also find that the results are driven mainly by trades in stocks of firms that are more cognitively challenging to value, namely, small-cap firms, firms with low analyst coverage, and firms with high idiosyncratic volatility. Since trading in such firms may require greater cognitive effort and attention, the results are consistent with air pollution negatively impacting cognitive functioning.

We conduct several additional tests to disentangle alternative explanations for our results. First, severe air pollution may cause local firms to underperform (e.g., because of public pressure to adopt stricter environmental policies or to shut down factories), thereby leading to underperformance of local stock investments by investors. We thus exclude local stocks from investors' trade portfolios and repeat our calendar-time portfolio tests. We find that the negative relation between air pollution and trade performance continues to hold, suggesting that our results are not driven by local firms.

Second, it is possible that residential sorting can lead to nonrandom assignment of air pollution. For example, since air quality is reflected in housing prices (Chay and Greenstone, 2005), more skilled investors may sort into cities with better air quality. We use panel regressions with city fixed effects to rule out the possibility that time-invariant city-specific effects drive the results. We find that the negative relation between air pollution and trading performance continues to hold in the panel setting, mitigating the concern that location-specific factors drive our results. A related possibility is that air pollution is correlated with other environmental factors such as weather, which drives the observed effect. We thus include weather conditions in our panel regression and find that our results on air quality are qualitatively unchanged, suggesting that the results are not driven by local weather conditions.

Third, poor air quality may negatively affect stock investors' mood, leading to reduced trading activities and more sell trades. We thus test whether air pollution is negatively related to trading volume and net purchases by individual investors. Our panel regressions suggest that there is little evidence that air pollution leads to less trading by investors. Moreover, there is no evidence that air pollution is significantly related to net purchases by investors.

Understanding the influence of air pollution on stock market trading carries important implications for public policies on environmental regulation. Public policies on air quality must weigh the benefits and costs of limiting the emissions of air pollutants. Our results suggest that a narrow focus on the health consequences and worker productivity may severely underestimate the actual benefits of limiting air pollution. Given the large economic costs of air pollution imposed on investors, public policies that aim at improving air quality may yield large economic gains.

This paper is related to three strands of literature, with the first being the nascent economics literature on the influence of air pollution. Several studies in labor economics find negative effects of air pollution on worker productivity (e.g., Graff Zivin and Neidell, 2012; Chang, Graff Zivin, Gross, and Neidell, 2016a). Three recent studies examine the influence of air pollution on activities that require cognitive processing. In particular, Lavy, Ebenstein, Roth (2014) find evidence that short-term exposure to air pollution negatively affects students' exam performance in Israeli high school exit exams. Chang, Graff Zivin, Gross, and Neidell (2016b) use a unique dataset on worker productivity in China and find that the productivity of call center workers whose primary tasks require cognitive effort is lower on days with poor air quality. Archsmith, Heyes, and Saberian (2016) find evidence that short-term exposure to air pollution is negatively associated with the work performance of a sample of professional baseball umpires whose jobs are brain-intensive and quality-focused. Our paper is the first in the literature to explore the influence of air pollution on investment decisions, which are cognitively demanding and have direct financial implications for the decision makers.

The second strand of literature is that on the influence of cognitive abilities on investment behavior and outcomes. Calvet, Campbell, and Sodini (2009a, 2009b) show that more sophisticated households are more likely to participate in risky financial markets and less prone to investment mistakes. Seru, Shumway, and Stoffman (2010) find evidence that investors learn from trading experience about their investing ability. Korniotis and Kumar (2011) show that older investors make worse trades, which is consistent with the notion that cognitive abilities decline with age. Grinblatt, Keloharju, and Linnainma (2012) find that trades by high-IQ investors outperform those by low-IQ investors and that high-IQ investors are less likely to exhibit behavioral biases. Our paper contributes to this literature by focusing on the influence of an environmental factor, namely air pollution. While the adverse effects of air pollution on cognitive functioning have been well established in the medical literature, our paper is the first to explore the implication of air pollution for investor outcomes.

Our paper also connects to a broader literature that investigates individual investors' trading behavior and performance. See, among others, Odean (1998), Barber and Odean (2000, 2001), Grinblatt and Keloharju (2001a, 2001b), Ivković and Weisbenner (2005), Ivković, Poterba, and Weisbenner (2005), Ivković, Sialm, and Weisbenner (2008), Barber and Odean (2008), Barber, Lee, Liu, and Odean (2009), Grinblatt and Keloharju (2009), and Seasholes and Zhu (2010). We contribute to this literature by identifying air pollution as a source of time-series variation in investment performance.

The remainder of this paper is organized as follows. Section 2 discusses the effect of air pollution on stock trading behavior and performance. Section 3 describes the data and summary statistics. Section 4 presents the empirical results, and Section 5 concludes.

2 Air Quality and Stock Market Trading

Medical studies provide substantial evidence that air pollution has adverse effects on cognitive functioning. In particular, air pollutants such as fine particulate matter (PM) can translocate from the upper respiratory tract to the brain, causing brain inflammation and cognitive deficits (e.g., Pope and Dockery, 2006; Block and Calderón-Garcidueñas, 2009). Exposure to air pollutants can also reduce the capacity of red blood cells' hemoglobin to transport oxygen, leading to reduced availability of oxygen to the brain and impaired concentration and confusion (Badman and Jaffe, 1996; Kampa and Castanas, 2008). Experimental studies using animals have shown that exposures to ambient air pollutants can produce neurotoxic effects and cognitive impairment (e.g., Rivas-Arancibia et al., 1998; Dorado-Martinez et al., 2001; Sorace et al., 2001; Campbell et al., 2005; Elder et al., 2006; Sirivelu et al., 2006). In a prospective cohort study of children, Suglia et al. (2008) show that high levels of black carbon (a marker for traffic particles) are associated with decreased cognitive function across assessments of verbal and nonverbal intelligence and memory constructs among children. Chen and Schwartz (2009) find evidence of adverse neurobehavioral effects of ambient air pollutants among adults. Calderón-Garcidueñas et al. (2008) show that children residing in a polluted urban environment exhibit significant deficits in a combination of fluid and crystallized cognition tasks and structural brain alterations as detected by MRI. In more extreme cases, short-term exposure to air pollution can increase the risk of cerebrovascular diseases. For example, using daily hospital admission data, Wellenius, Schwartz, and Mittleman (2005) find evidence that short-term exposure to an elevated level of ambient particles increases the risk of ischemic stroke (a type of stroke caused by shortage of oxygen/blood to the brain).

Consistent with the adverse effects of air pollution on the functioning of the brain, social scientists find evidence that short-term exposure to air pollution is negatively associated with cognitive performance in a number of activities that require mental acuity. In particular, Lavy, Ebenstein, Roth (2014) show that students' exam performance in Israeli high school exit exams is significantly negatively correlated with the level of air pollution on the exam day. Using a unique dataset on worker productivity in China, Chang, Graff Zivin, Gross, and Neidell (2016b) find that call center workers, whose primary tasks require cognitive effort, perform worse on days when the level of air pollution is high. These two studies are noteworthy particularly since they show direct evidence that outdoor air quality affects the cognitive performance of those indoors. Last but not least, Archsmith, Heyes, and Saberian (2016) find evidence that acute exposure to ambient air pollutants is negatively associated with the work performance of professional baseball umpires whose jobs are brain-intensive and quality-focused.

Stock investment decisions are cognitively demanding. Investors not only have to collect information from a myriad of sources, but also need to process information to determine what stocks to trade, how much to trade, in which direction, when to execute trades, etc. Since stock prices can fluctuate widely over time, investors often need to efficiently process large quantities of information related to the fundamentals of the stocks and take quick actions. Several recent studies show that cognitive abilities affect stock trading performance. For example, Grinblatt, Keloharju, and Linnainma (2012) find evidence that trades by high-IQ investors outperform those by low-IQ investors due to their better stock-picking abilities and lower execution costs. Given that air pollution can negatively affect cognitive functioning and stock trading decisions are cognitively demanding, we hypothesize that air pollution negatively affects stock investors' trade performance.

The negative effects of air pollution on trade performance may vary across investors and across stocks. Medical studies suggest that women and elderly are more susceptible to air pollution (Gouveia and Fletcher 2000; Katsouyanni et al. 2001; Hong et al., 2002; Kan et al., 2008). We thus hypothesize that the negative effect of air pollution on trade performance should be particularly pronounced among women and older people. Also, the effect may vary across stocks, because some stocks may require greater cognitive effort and attention to trade than others. For instance, stocks such as small-cap stocks, stocks with low analyst coverage, and stocks with high idiosyncratic volatility are often associated with poor information quality, a greater influence of firm-specific information relative to industry- or market-wide information, and high costs of information processing (e.g., Hirshleifer and Teoh, 2003), which could offer more room for cognitive mistakes. We thus hypothesize that the performance of trades in more cognitively challenging stocks should be particularly affected by air pollution.

The null hypothesis of our study is that air pollution does not influence investors' trading performance. This may arise because outdoor air pollution may not affect trading decisions that are made primarily in an indoor environment. In particular, investors may purchase air cleaners to reduce their exposure to air pollutants, which may result in no correlation between air pollution and trade performance. Also, a high level of air pollution may induce investors to refrain from making trading decisions, which again implies that air pollution should have little effects on trade performance. Therefore, the relation between air pollution and trade performance is an empirical question.

3 Data and Summary Statistics

3.1 Account-level transaction data from a large Chinese brokerage firm

We obtain account-level trading data from a large brokerage firm in China. After matching with data on air quality (as will be discussed below), the trading data cover equity trades of $127,041$ households from 28 cities in China for the period from January 2007 through December 2013. The cities included in our data are shown in Figure 1. Cities represented in our sample include major cities such as Beijing, Shanghai, Chongqing, Nanjing, Changsha, and Nanchang. We focus on investors' trading of common stocks on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. As of December 2013, there are $2,515$ stocks traded on the two exchanges with a combined market capitalization of RMB28.40 trillion (US$4.52 trillion based on an exchange rate of 6.29), making the Chinese stock market one of the largest in the world. For each transaction, the data include the date of the transaction, the stock traded (identified by stock code), the number of shares traded, the dollar principal traded, and whether it is a buy or sell. For each investor, the data include an identifier for the investor (customer ID), the branch (city) where the investor's account is located, the gender of the investor, the year and month the account was open, and the birth year and month of the investor. Since our daily air quality data are at the city level, we aggregate trades by all investors residing in a given city at the daily frequency. Panel A of Table 1 reports summary statistics of our trading data at the city-date level. The average number of unique trading accounts on a given city-day is 803.6. The average total number of trades is $1,538.2$, the average total principal traded is RMB48.84 million, and the average total portfolio value is RMB$1,184.05$ million for a city-day.

[Insert Figure 1 about here]

Following Barber and Odean (2000; 2001), we calculate the monthly turnover rate for each city in each month as the average of the monthly buy turnover and the monthly sell turnover. Sell turnover for city i in month t is calculated as the total dollar value of stocks sold by invetors in that city-month scaled by the total value of their stock holdings at the beginning of month t. Buy turnover is calculated as the total dollar value of stocks bought during month t scaled by the total value of their stock holdings at the end of month t. The average monthly turnover rate at the city level is 52.54%, indicating an average holding period of two months. In untabulated analysis, we find that the average monthly share turnover rate in the two exchanges in China during our sample period is 41.99%, which is comparable to the turnover rate for our sample of individual investors at the city level.

[Insert Table 1 about here]

3.2 Air quality and weather variables

We use the Air Quality Index (AQI) as a measure for air quality. AQI ranges from 0 to 500, with a larger value indicating worse air quality. The AQI level is based on the level of five air pollutants, namely sulfur dioxide (SO_2), nitrogen dioxide (NO_2), fine particulate matter smaller than 10 micrometers (PM_{10}), carbon monoxide (CO), and ozone (O_3) measured throughout each day. We obtain daily observations of AQI from the air quality report published by the Ministry of Environmental Protection of China.[1] We merge the daily AQI data with the trading data. Panel B of Table 1 reports summary statistics of AQI in our merged sample. The average AQI in our sample is 69.46 and the standard deviation is 40.22. There are large variations in AQI across cities and within cities. The standard deviation of mean AQI across cities is 44.14, and the average within-city standard deviation is 50.48.

A number of studies contend that environmental factors, such as cloudiness (Saunders, 1993; Hirshleifer and Shumway, 2003), can negatively affect investor moods, which in turn influence stock returns. We thus collect data on weather conditions at the city level from China Meteorological Administration for our sample of city-dates. We consider various weather variables, including the number of sunny hours, temperature, humidity, precipitation, and wind speed. Panel B of Table 1 shows that the average city-day has 5.26 sunny hours, a temperature of 16.96 °C (62.53 °F), a humidity of 69.82%, a precipitation of 3.22 millimeters (0.127 inches), and a wind speed of 2.63 meters/second (5.88 miles/hour).

4 Empirical Results

4.1 Calendar-time portfolio tests

We use a calendar-time portfolio approach to examine the performance of stock trades. On each day from January 1, 2007 through December 31, 2013, we sort our sample of city-dates into quartiles based on AQI. The bottom quartile (least polluted city-days) has an average AQI of 49.82, whereas the top quartile (most polluted city-dates) has an average AQI of

[1] Since the data are reported by local municipalities, they may be subject to manipulation by local government officials. It should be noted that manipulation of air quality data is likely to introduce noise to our tests (because of misclassification of polluted-air days and clean-air days) and bias against finding significant results.

90.60. We construct a trade (i.e., buy-minus-sell) portfolio for each of the four groups of city-dates and calculate daily abnormal returns on these portfolios. We consider four holding horizons around the average holding period of two months (as indicated by Table 1), namely 20, 40, 60, and 120 days. Consider, for example, the portfolio that mimics the trades of investors in the top quartile of AQI (i.e., Q4). We aggregate all buy (sell) trades by these investors on each day and hold (short) them for the specified holding period. We rebalance the portfolio daily by adding new trades placed by Q4 investors and remove positions that have reached their holding periods. All positions are marked to market at the end of each trading day. We calculate the daily return on this portfolio as the return on the buys minus the return on the sells. This effectively replicates the performance of trades placed by investors on days with the worst air quality. We conduct statistical tests using the daily time series of the portfolio return and abnormal returns from the Fama-French three-factor model. Since our sample spans 7 years, there are around $1,750$ observations in each time series of portfolio returns. We compute a three-factor alpha by regressing daily portfolio excess returns on the daily returns from the risk factors.

Panel A of Table 2 reports the raw returns of the calendar-time portfolios. Trades placed on days with the worst air quality deliver significantly negative returns ranging from -0.650 to -0.259 basis points per day depending on the holding period considered. On the other hand, trades placed on days with the best air quality have returns statistically indistinguishable from zero. A spread portfolio that goes long the trade portfolio on days with the worst air quality and sells short the trade portfolio on days with the best air quality earns a return of around -0.695 to -0.322 basis points per day.[2] Panel B of Table 2 shows the Fama-French three-factor alphas from the daily calendar-time portfolio regressions. We find similar patterns: the spread portfolio yields a three-factor alpha between -0.714 and -0.335 basis points per day. For example, the three-factor alpha is

[2] To put these numbers in perspective, Barber, Lee, Liu, and Odean (2009) find that individual investors on the Taiwan Stock Exchange incur trading losses of 0.37 basis points per day.

-0.673 basis points per day (or -1.696 percentage points in annualized terms) at a horizon of 40 days (i.e., the average holding horizon in our sample). These results are consistent with a negative effect of air pollution on trade performance.

[Insert Table 2 about here]

To shed light on the sources of underperformance of trades placed on days with poor air quality, we conduct various subsample analyses by investor characteristics as well as by stock characteristics. Motivated by medical evidence that women and elderly are more susceptible to air pollution (Gouveia and Fletcher 2000; Katsouyanni et al. 2001; Hong et al., 2002; Kan et al., 2008), we partition investors by gender and by age. We construct trade portfolios for each investor group sepearately. Panel A of Table 3 reports the Fama-French three-factor alphas of the two spread portfolios partitioned by gender. The spread portfolio that goes long females' trades on the worst air quality days and goes short females' trades on the best air quality days earns a negative and significant three-factor alpha over all horizons considered. For example, the alpha on women's spead portfolio is -1.127 basis points per day at a horizon of 40 trading days. In contrast, the spread portfolio for males delivers an insignificant alpha over all four horizons. The difference in the alpha between the two groups of investors is negative and significant at horizons of 40 and 60 days.

Panel B of Table 3 reports the Fama-French three-factor alphas of the two spread portfolios partitioned by age. We use the 75th percentile of age for our sample of investors (53 years) as a cutoff for age and define old investors as those aged 53 and older and young investors as those aged below 53. The spread portfolio that goes long old investors' trades on the most polluted days and goes short old investors' trades on the least polluted days earn a negative and significant three-factor alpha over all horizons considered. The magnitudes of the alphas are quite large. For example, the alpha on old investors' trade portfolio is -2.530 (-1.044) basis points per day at a horizon of 20 (120) trading days. In contrast, the alphas on the spread portfolios for young investors are smaller in absolute magnitudes. The difference in the alpha between the two groups of investors is negative and significant at horizons of 20 and 120 days. These results are generally consistent with the hypothesis that the performance of trades by women and elderly are particularly affected by poor air quality.

[Insert Table 3 about here]

As for stock characteristics, we use analyst coverage, market capitalization, and idiosyncratic volatility to classify stocks into those likely more cognitively challenging to value and those likely less cognitively challenging to value. We partition the sample of stocks into two groups based on the median values of each of these variables in each month. We define cognitively challenging stocks as those with the number of analysts fewer than the median, market cap less than the median, and idiosyncratic volatility higher than the median. The stock price of these firms is likely influenced to a large extent by firm-specific information, which may require greater cognitive effort. We compute idiosyncratic volatility for a stock-month as the standard deviation of the residuals estimated from the Fama and French (1993) three-factor model on daily data during the prior 90 days. We construct calendar-time spread portfolios for each of the two groups of stocks separately. Panel A of Table 4 reports the Fama-French three-factor alphas of the two spread portfolios partitioned by analyst coverage. The three-factor alphas of the spread portfolios consisting of stocks with low analyst coverage are around -1.311 to -1.017 basis points per day and are statistical significant at the 1% level in three out of four holding horizons, whereas those for high-coverage stocks are statistically insignificant. The difference in the abnormal returns between the two spread portfolios is around -1.208 to -0.756 basis points and is significant at conventional levels.

Panels B and C of Table 4 show that the results are similar when market capitalization and idiosyncratic volatility are used as proxies for cognitively challenging stocks. In particular, the underperformance of trades placed on days with the worst air quality appears concentrated among small-cap stocks and stocks with high idiosyncratic volatility. To the extent that trading in cognitively challenging stocks requires greater mental acuity (e.g., to acquire and process firm-specific information), these findings are consistent with the idea that cognitive functioning is a channel through which air pollution affects trade performance.

[Insert Table 4 about here]

We also calculate dollar trading profits earned by investors conditional on air quality. We follow Barber, Lee, Liu, and Odean (2009) to calculate daily dollar profits. Specifically, we construct the trade portfolio for each of the four groups of city-dates. We again assume a holding period of 20, 40, 60, or 120 days. The daily dollar profits for the trade portfolio are calculated as the dollar profits on the buy trades minus those on the sell trades. We calculate the market-adjusted dollar profits for the buy trades on day t as the total value of the buy positions at the close of trading on day $t-1$ multiplied by the spread between the return on the portfolio of buy positions and the market on day t. Similarly, the market-adjusted dollar profits for the sell trades on day t are calculated as the total value of the sell positions at the close of trading on day $t-1$ multiplied by the negative of the spread between the return on the portfolio of sell positions and the market on day t. Table 5 reports the results on dollar profits from the trade portfolios by AQI. Trades by investors on days with the worst air quality incur daily losses between RMB105.6 thousand to RMB197.4 thousand depending on the horizon considered.[3] On the other hand, trades by investors on days with the best air quality in general deliver positive dollar gains, although statistically insignificant. The spread portfolio that goes long the trade portfolio on days with the worst air quality and sells short the trade portfolio on days with the best air

[3] It is useful to note that while daily portfolio returns generally decrease in absolute magnitude with the holding horizon, the daily dollar profits generally *increase* in absolute magnitude with the holding horizon. This arises because the size of the portfolio increases with the holding horizon (i.e., positions stay longer in the portfolios), resulting in larger magnitudes of dollar profits and losses.

quality incur daily losses of around RMB104.2 thousand to RMB209.2 thousand. In terms of annual dollar losses at a horizon of 40 trading days (i.e., the average holding horizon), investors in the average city lose RMB43.74 million (RMB$173,583 \times 252$) from their trades placed on the most polluted days relative to those placed on the least polluted days. Since the average total portfolio value for a city in our sample is RMB1.18 billion (as Table 1 shows), these losses amount to 3.69% of the portfolio value.

[Insert Table 5 about here]

4.2 Alternative explanations

Our results so far show that air pollution is negatively related to stock investors' trade performance. While reduced mental acuity seems a plausible channel through which poor air quality affects trade performance, it is possible that alternative channels may be at work as well. In this subsection, we conduct additional tests to evaluate three alternative explanations for our results.

First, severe air pollution may cause local firms to underperform (e.g., because of public pressure to adopt stricter environmental policies or to shut down factories), thereby leading to underperformance of local stock investments by investors. Since investors exhibit a local bias (e.g., Ivković and Weisbenner, 2005; Seasholes and Zhu, 2010), the underperformance of stock trades on days with poor air quality may be driven by the underperformance of their trades in local stocks. To rule out this possibility, we exclude local stocks from investors' trade portfolio and repeat the calendar-time portfolio test. We define local stocks as those of firms with headquarters in the same city as the investor. Table 6 reports the three-factor alphas on the calendar-time portfolios as well as those on the spread portfolio. The results show that the negative relation between air pollution and trade performance continues to hold, suggesting that the results are not driven by local firms.

[Insert Table 6 about here]

Second, it is possible that residential sorting can lead to nonrandom assignment of air pollution. For example, since air quality is reflected in housing prices (Chay and Greenstone, 2005), more skilled investors may sort into cities with better air quality. We use panel regressions with city fixed effects to rule out the possibility that time-invariant city-specific effects drive the results. Specifically, we regress the market-adjusted return of the trade portfolio for a given city-date on AQI and weather of that city-date, city fixed effects, and date fixed effects. We include date fixed effects to rule out the possibility that seasonal or day of the week patterns drive our main results. Since air quality may be correlated with other city-level environmental variables such as weather conditions, we include weather variables as additional controls in our panel regressions. Table 7 presents the results. We find that the negative relation between air pollution and trading performance continues to hold in the panel setting, mitigating the concern that location-specific factors drive our results. The economic magnitude is meaningful as well. For example, Model (2) suggests that as the AQI quartile rank increases by one, the abnormal buy-and-hold return at a 40-day holding horizon decreases by 5.7 basis points. Notably, the weather variables are generally insignificant in predicting trade performance.

[Insert Table 7 about here]

Third, poor air quality may negatively affect stock investors' mood, which in turn affects stock trading decisions. Psychological studies, however, suggest that the effect of mood on trade performance is ambiguous. On the one hand, an unpleasant mood may lead to worse trading decisions, because it gives rise to less cognitive flexibility in the processing of information (e.g., Isen, Means, Patrick, and Nowicki, 1982; Murray, Sujan, Hirt, and Sujan, 1990; Isen, Rosenzweig, and Young, 1991). On the other hand, an unpleasant mood may improve trading performance, because people with an unpleasant mood may be less likely to exhibit heuristic behaviors (Schwartz and Clore, 1983; Wyer et al., 1999). Therefore, the direction of the effect of investor moods on trading performance is theoretically unclear. Nevertheless, a direct prediction of the investor mood hypothesis is that unpleasant moods due to poor air quality should be associated with a lower level of trading activities and more sell trades. We use our panel regressions to test whether air pollution is negatively related to trading volume and net purchases by individual investors. Specifically, we regress the logarithm of total principal traded as well as net purchases for a given city-date on AQI and weather of that city-date, city fixed effects, and date fixed effects. We define net purchases as the total principal bought as a fraction of total principal traded. The results, reported in Table 8, show that there is little evidence that air pollution leads to reduced trading activities by investors.[4] Moreover, there is no evidence that air pollution is significantly related to net purchases by investors. While these results do not definitively rule out the possibility that air pollution affects trading performance through its effects on investor moods, they provide suggestive evidence that investor moods do not represent the main channel through which air pollution affects trading decisions.

[Insert Table 8 about here]

Taken together, these results suggest that the above channels are not the main drivers of the negative relation between air pollution and trade performance. While cognitive functioning is a plausible channel through which air pollution affects trade performance, we note that there remain other possibilities. For example, poor air quality may make people distracted (e.g., because they may be concerned about their own health or their families' health) and restrict physical activities that can potentially improve trade performance (e.g., word-of-mouth communication with other market participants). Unfortunately, our data do not allow us to distinguish among these different possibilities directly. We thus em-

[4]If investors fully understand the negative impacts of air pollution on trade performance, they should refrain from trading when air quality is poor. The non-results here suggest that investors do not fully recognize the negative cognitive impacts.

phasize that our analysis uncovers an unexplored cost associated with air pollution, namely poor trade performance, and provides a necessary first step towards an understanding of the impact of air pollution on investor outcomes. Future research should discriminate among these other channels using more detailed data.

4.3 Robustness tests

We conduct several tests to evaluate the robustness of our calendar-time portfolio results. First, we use the cut-off points for pollution levels to construct calendar-time portfolios. China defines AQI values between 0 and 50 as "excellent", values between 51 and 100 as "good", and values above 101 as "unhealthy". We thus construct three portfolios corresponding to the three levels of air pollution. About 11.79% of the city-dates in our sample have "unhealthy" air, and the rest have "good" or "excellent" air. Panel A of Table 9 reports the three-factor alphas on the spread portfolio of going long the trade portfolio placed on days with "unhealthy" air and going short the trade portfolio on days with the "excellent" air. The alpha ranges from -0.327 to -0.862 basis points per day depending on the holding horizons.

Second, we use abnormal levels of AQI to construct calendar-time portfolios. We calculate the abnormal AQI as the difference between the AQI on a day and the average daily AQI in the prior 12 months. We again construct four calendar-time portfolios based on the abnormal AQI. Panel B of Table 9 shows that the spread portfolio yields a three-factor alpha of -0.355 to -0.906 basis points per day, suggesting that the results are robust to alternative specifications of our AQI variable.

Third, since about a third of the cities in our sample are from Jiangsu province, we repeat the analysis after excluding cities from Jiangsu. Panel C of Table 9 shows that the three-factor alphas on the spread portfolio remain negative, suggesting that our results are not driven by these cities. If anything, the magnitudes of the alphas appear larger when we exclude cities in Jiangsu.

Last, we repeat our tests using the Fama-French-Carhart four-factor model to adjust returns. Panel D of Table 9 shows that the the results are quantitatively similar to those obtained in our baseline tests.

[Insert Table 9 about here]

5 Conclusions

In this paper, we examine the relation between air pollution and trading performance of stock investors. Using a sample of trades by $127,041$ investors from 28 cities in China, we find a negative relation between air pollution and trade performance. Our calendar-time portfolio tests show that the trades made by investors on days with poor air quality underperform those made on days with good air quality by 0.612 to 0.673 basis points per day at the average investment horizon of 40 trading days. This relation persists after controlling for local weather conditions, city-fixed effects, and time-fixed effects. We also find evidence that the negative relation is more pronounced among women and elderly and is driven mainly by stocks that may require greater cognitive effort, namely stock with low analyst coverage, small-cap stocks, and stocks with high idiosyncratic volatility. We conduct several additional tests to evaluate alternative explanations for our results such as the performance of local stocks, residential sorting, and investor moods. Overall, the results seem most consistent with the hypothesis that impaired cognitive functioning is a channel through which air pollution negatively impacts investment performance.

Our findings highlight a hitherto unexplored cost associated with ambient air pollution. The evidence contributes to our understanding of the impacts of air pollution on stock trading decisions, which are cognitively demanding and have large financial implications. Given the large economic costs imposed by air pollution on investor outcomes, regulatory policies that aim at improving air quality may yield much larger benefits than previously recognized.

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Figure 1: Cities included in our sample

This figure shows the 28 cities that are included in our sample. Each city is represented by a red dot.

Table 1: Summary statistics

This table reports the summary statistics for the account-level transaction data from a large Chinese brokerage firm for the period from January 2007 through December 2013 as well as those for air quality and weather variables. The unit of observation is a city-day. Panel A reports the summary statistics for the trade-related variables, including the number of trading accounts, the total number of trades, total principal traded (in millions of RMB), total portfolio value (in millions of RMB), and monthly portfolio turnover rate for a city-date. Panel B reports the summary statistics for environmental variables including Air Quality Index (AQI), the number of sunny hours, temperature, humidity, precipitation, and wind speed. For each variable, we report the mean, median, standard deviation, 25th percentile, and 75th percentile.

	Mean	Median	Std Dev	P25	P75
Panel A: Trading-related variables					
Total # of trading accounts	803.63	467.00	860.68	125.00	1,271.00
Total # of trades	1,538.23	921.00	1,663.07	249.00	2,377.00
Total principal traded (RMB mil)	56.78	34.12	62.14	11.70	83.18
Total portfolio value (RMB mil)	1,184.05	126.26	3,526.02	95.85	773.54
Monthly turnover (%)	52.54	48.94	26.79	30.07	73.31
Panel B: Environmental variables					
AQI	69.36	62.00	40.13	46.00	83.00
Sunny hours	5.26	5.80	23.64	0.00	8.60
Temperature (Celsius)	16.96	17.90	9.56	8.60	25.30
Humidity (%)	69.84	71.00	14.28	61.00	80.00
Precipitation (mm)	3.22	0.00	10.91	0.00	0.70
Wind speed (m/s)	2.63	2.40	1.18	1.80	3.30

Table 2: Calendar-time portfolio returns

This table reports calendar-time portfolio returns. On each day from January 1, 2007 through December 31, 2013, we sort our sample of city-dates into quartiles based on AQI. We construct a trade (i.e., buy-minus-sell) portfolio for each of the four groups of city-dates and calculate daily abnormal returns on these portfolios. We consider four holding horizons, namely 1, 20, 40, and 60 days. Consider, for example, the portfolio that mimics the trades of investors in the top quartile of AQI (i.e., Q4). We aggregate all buy (sell) trades by these investors on each day and hold (short) them for the specified holding period. We rebalance the portfolio daily by adding new trades placed by Q4 investors and remove positions that have reached their holding periods. All positions are marked to market at the end of each trading day. We calculate the daily returns on this portfolio. Panel A reports the raw returns on the trade portfolios, and Panel B reports the abnormal returns obtained using the Fama-French three-factor model. Long/short is a spread portfolio that goes long the trade portfolio in the top quartile of AQI (i.e., Q4) and goes short the trade portfolio in the bottom quartile of AQI (i.e., Q1). Numbers in parentheses are *t*-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	20-day	40-day	60-day	120-day
Panel A: Raw returns				
Q1 (low AQI)	0.045	0.104	0.058	0.062
	(0.16)	(0.53)	(0.36)	(0.55)
Q2	-0.458	-0.243	-0.288	-0.304
	(1.81)*	(1.35)	(1.94)*	(2.74)***
Q3	-0.320	-0.093	-0.037	0.017
	(1.47)	(0.58)	(0.28)	(0.17)
Q4 (high AQI)	-0.650	-0.509	-0.359	-0.259
	(2.76)***	(3.04)***	(2.68)***	(2.59)***
Long/Short (Q4 – Q1)	-0.695	-0.612	-0.417	-0.322
	(1.89)*	(2.37)**	(2.00)**	(2.13)**
Panel B: Fama-French three-factor adjusted returns				
Q1 (low AQI)	0.005	0.109	0.068	0.074
	(0.02)	(0.51)	(0.38)	(0.52)
Q2	-0.429	-0.233	-0.275	-0.306
	(1.27)	(0.84)	(1.07)	(1.31)
Q3	-0.270	-0.085	0.009	0.050
	(1.16)	(0.48)	(0.06)	(0.42)
Q4 (high AQI)	-0.656	-0.562	-0.362	-0.277
	(2.75)***	(3.19)***	(2.62)***	(2.58)***
Long/Short (Q4 – Q1)	-0.714	-0.673	-0.450	-0.335
	(2.05)**	(2.78)***	(2.30)**	(2.41)**

Table 3: Calendar-time portfolio returns: Subsamples partitioned by investor characteristics

This table reports the Fama-French three-factor alphas on a calendar-time spread portfolio that goes long the trade portfolio in the top AQI quartile and goes short the trade portfolio in the bottom AQI quartile for various subsamples by gender and age. For example, the spread portfolio for females goes long the trades placed by women in the top AQI quartile and goes short the trades by women in the bottom AQI quartile. Investors that are 53 years (the 75th percentile of age for our sample of investors) and above are classified as old investors. The last row in each panel reports the difference in alpha between the two spread portfolios in the panel. Numbers in parentheses are *t*-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	20-day	40-day	60-day	120-day
Panel A: By gender				
Female	-1.003	-1.127	-0.931	-0.551
	(1.90)*	(2.97)***	(3.04)***	(2.52)**
Male	-0.490	-0.314	-0.165	-0.251
	(1.29)	(1.15)	(0.75)	(1.60)
Diff (Female – Male)	-0.514	-0.813	-0.767	-0.300
	(0.79)	(1.74)*	(2.03)*	(1.11)
Panel B: By age				
Old (age ≥ 53)	-2.530	-1.385	-1.001	-1.044
	(2.63)***	(2.05)**	(1.87)*	(2.87)***
Young (age < 53)	-0.279	-0.519	-0.378	-0.237
	(0.79)	(2.10)**	(1.91)*	(1.63)
Diff (Old – Young)	-2.251	-0.866	-0.623	-0.807
	(2.20)**	(1.20)	(1.09)	(2.06)**

Table 4: Calendar-time portfolio returns: Subsamples partitioned by stock characteristics

This table reports the Fama-French three-factor alphas on a calendar-time spread portfolio that goes long the trade portfolio in the top AQI quartile and goes short the trade portfolio in the bottom AQI quartile for various subsamples partitioned by stock characteristics. *Low analyst coverage firms* are firms with the number of analysts below median, and *High analyst coverage firms* are those with a higher-than-the-median number of analysts. *Small-cap firms* are firms with a below median market cap, and *Large-cap firms* are those with a market cap above the median. *Low idiosyncratic volatility firms* are firms with idiosyncratic volatility below median, and *High idiosyncratic volatility firms* are those with a higher-than-the-median idiosyncratic volatility. The last row in each panel reports the difference in alpha between the two spread portfolios in the panel. Numbers in parentheses are *t*-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	20-day	40-day	60-day	120-day
Panel A: by analyst coverage				
Low analyst coverage	-1.159	-1.311	-1.107	-1.017
	(2.08)**	(3.23)***	(3.35)***	(3.02)***
High analyst coverage	0.049	-0.280	-0.149	-0.261
	(0.12)	(0.95)	(0.64)	(1.64)
Diff (Low – High)	-1.208	-1.030	-0.958	-0.756
	(1.73)*	(2.05)**	(2.38)**	(2.03)**
Panel B: by market cap				
Small-cap	-1.675	-1.283	-1.283	-0.660
	(2.66)***	(2.86)***	(3.47)***	(2.54)**
Large-cap	-0.368	-0.526	-0.235	-0.277
	(0.92)	(1.87)*	(1.04)	(1.74)*
Diff (Large – Small)	-1.307	-0.757	-1.048	-0.383
	(1.75)*	(1.43)	(2.42)**	(1.25)
Panel C: by idiosyncratic vol				
High idiosyncratic vol	-1.614	-0.874	-0.573	-0.489
	(3.26)***	(2.51)**	(1.98)**	(2.43)**
Low idiosyncratic vol	0.081	0.064	-0.070	-0.240
	(0.18)	(0.20)	(0.27)	(1.00)
Diff (High – Low)	-1.695	-0.938	-0.503	-0.248
	(2.51)**	(1.98)**	(1.29)	(0.79)

Table 5: Dollar trading profits

This table reports dollar profits on calendar-time portfolios. On each day from January 1, 2007 through December 31, 2013, we sort our sample of city-dates into quartiles based on AQI. We construct a trade (i.e., buy-minus-sell) portfolio for each of the four groups of city-dates and calculate daily dollar profits on these portfolios. We consider four holding horizons, namely 1, 20, 40, and 60 days. Consider, for example, the portfolio that mimics the trades of investors in the top quartile of AQI (i.e., Q4). We aggregate all buy (sell) trades by these investors on each day and hold (short) them for the specified holding period. We rebalance the portfolio daily by adding new trades placed by Q4 investors and remove positions that have reached their holding periods. All positions are marked to market at the end of each trading day. We calculate the daily dollar profits on this portfolio as the dollar profits on the buy trades minus the dollar profits on the sell trades. Long/short is a spread portfolio that goes long the trade portfolio in the top quartile of AQI (i.e., Q4) and goes short the trade portfolio in the bottom quartile of AQI (i.e., Q1). Numbers in parentheses are *t*-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	20-day	40-day	60-day	120-day
Q1 (low AQI)	-1.010	37.061	23.282	11.790
	(0.03)	(0.92)	(0.49)	(0.19)
Q2	-54.899	-35.917	-85.820	-165.969
	(1.67)*	(0.83)	(1.66)*	(2.39)**
Q3	-60.176	-55.120	-69.362	-35.173
	(1.85)*	(1.23)	(1.32)	(0.48)
Q4 (high AQI)	-105.631	-136.522	-147.833	-197.381
	(3.13)***	(3.06)***	(2.80)***	(2.81)***
Long/Short (Q4 – Q1)	-104.219	-173.583	-171.115	-209.172
	(2.30)**	(2.89)***	(2.41)**	(2.23)**

Table 6: Calendar-time portfolio returns: Excluding trades in local stocks

This table reports calendar-time portfolio returns after excluding trades in local stocks. We define local stocks as those of firms with headquarters in the same city as the investor. On each day from January 1, 2007 through December 31, 2013, we sort our sample of city-dates into quartiles based on AQI. We construct a trade (i.e., buy-minus-sell) portfolio excluding local stocks for each of the four groups of city-dates and calculate daily abnormal returns on these portfolios. We consider four holding horizons, namely 1, 20, 40, and 60 days. Long/short is a spread portfolio that goes long the trade portfolio in the top quartile of AQI (i.e., Q4) and goes short the trade portfolio in the bottom quartile of AQI (i.e., Q1). Numbers in parentheses are *t*-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	20-day	40-day	60-day	120-day
Q1 (low AQI)	0.001	0.085	0.015	0.040
	(0.01)	(0.48)	(0.10)	(0.40)
Q2	-0.454	-0.153	-0.175	-0.188
	(2.00)**	(0.96)	(1.33)	(2.04)**
Q3	-0.392	-0.122	-0.099	-0.008
	(1.90)*	(0.83)	(0.84)	(0.10)
Q4 (high AQI)	-0.696	-0.453	-0.327	-0.251
	(3.15)***	(2.93)***	(2.66)***	(2.86)***
Long/Short (Q4 – Q1)	-0.737	-0.643	-0.406	-0.350
	(2.17)**	(2.71)***	(2.15)**	(2.61)***

Table 7: Fixed-effects panel regression analysis of trade performance

This table reports fixed-effect panel regressions of abnormal holding-period returns of trade portfolios. The unit of observation is a city-date. The dependent variable is the abnormal holding-period returns, in percentage, obtained using the Fama-French three-factor model. All regressions include city fixed effects and date fixed effects. Numbers in parentheses are t-statistics based on standard errors clustered by city. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

Dependent =	Abnormal holding-period returns							
	20-day		40-day		60-day		120-day	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AQI quartile rank	-0.041	-0.042	-0.057	-0.057	-0.036	-0.037	-0.094	-0.072
	(3.57)***	(3.42)***	(2.64)**	(2.55)**	(2.28)**	(2.58)**	(1.72)*	(1.61)
Sunny Hours		-0.004		0.016		0.037		0.122
		(0.26)		(1.06)		(2.13)**		(0.92)
Temperature		0.011		-0.006		-0.001		-0.448
		(0.56)		(0.19)		(0.03)		(1.75)*
Precipitation		-0.006		0.002		-0.005		-0.097
		(1.60)		(0.29)		(0.74)		(1.55)
Humidity		-0.011		-0.005		-0.018		-0.027
		(1.99)*		(0.70)		(1.54)		(0.45)
Wind speed		-0.022		-0.050		-0.131		-0.020
		(0.79)		(0.78)		(1.56)		(0.04)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	17,742	17,742	17,742	17,742	17,742	17,742	17,742	17,742
Adjusted R-squared	0.08	0.08	0.09	0.09	0.11	0.11	0.12	0.12

Table 8: Fixed-effects panel regression analysis of trading volume and net purchases

This table reports fixed-effect panel regressions of total trading volume and net purchases. The dependent variable in the first two columns is the logarithm of total principal traded, and that in the last two columns is total principal bought as a fraction of total principal traded (in percentage). The unit of observation is a city-day. All regressions include city fixed effects and date fixed effects. Numbers in parentheses are *t*-statistics based on standard errors clustered by city and by date. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

Dependent =	Log(Total trading volume)		Net purchases	
	(1)	(2)	(3)	(4)
AQI quartile rank	-0.010	-0.008	-0.084	-0.083
	(1.22)	(0.93)	(1.55)	(1.48)
Sunny Hours		0.012		0.059
		(1.70)		(1.71)*
Temperature		-0.007		0.118
		(1.26)		(3.09)***
Precipitation		0.004		0.010
		(1.21)		(0.66)
Humidity		0.001		-0.001
		(0.44)		(0.03)
Wind speed		0.013		0.166
		(1.02)		(1.83)*
Time fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Number of observations	17,742	17,742	17,742	17,742
Adjusted R-squared	0.91	0.91	0.02	0.02

Table 9: Calendar-time portfolio returns: Robustness checks

This table reports robustness checks of our calendar-time portfolio results. Panel A uses the cut-off points for pollution levels to construct calendar-time portfolios. AQI values between 0 and 50 are defined as "excellent", and values above 101 are defined as "unhealthy". Panel B uses abnormal levels of AQI to construct calendar-time portfolios. We calculate the abnormal AQI as the difference between the AQI on a day and the average daily AQI in the prior 12 months. Panel C excludes cities in Jiangsu province. Panel D uses the Fama-French-Carhart four-factor model to adjust returns. Numbers in parentheses are *t*-statistics. Significance at the 10% (*), 5% (**), or 1% level (***) is indicated.

	20-day	40-day	60-day	120-day
Panel A: $0 < AQI \leq 50$ (Excellent) vs. $AQI > 100$ (Unhealthy)				
Long/Short (Unhealthy – Excellent)	-0.862	-0.509	-0.430	-0.327
	(2.74)***	(2.34)**	(2.44)**	(2.50)**
Panel B: Using abnormal AQI				
Long/Short (Q4 – Q1)	-0.906	-0.515	-0.459	-0.355
	(2.71)***	(2.21)**	(2.39)**	(2.53)**
Panel C: Excluding cities in Jiangsu province				
Long/Short (Q4 – Q1)	-1.366	-1.486	-1.727	-1.249
	(1.42)	(2.31)**	(3.45)***	(3.66)***
Panel D: Fama-French-Carhart four-factor alphas				
Long/Short (Q4 – Q1)	-0.627	-0.679	-0.413	-0.332
	(1.77)*	(2.76)***	(2.08)**	(2.35)**