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Air pollution, behavioral bias, and the disposition effect in China ☆

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ABSTRACT

Inspired by the recent health science findings that air pollution affects mental health and cognition, we examine whether air pollution can intensify the cognitive bias observed in the financial markets. Based on a proprietary data set obtained from a large Chinese mutual fund family consisting of complete trading information for more than 773,198 accounts in 247 cities, we find that air pollution significantly increases investors' disposition effects. Analysis based on two plausible exogenous variations in air quality (the vast dissipation of air pollution caused by strong winds and the Huai River policy) supports a causal interpretation. Mood regulation provides a potential mechanism.

"That yellow haze of smog hovering over the skyline isn't just a stain on the view. It may also leave a mark on your mind."

– Weir (2012) in a cover story of Monitor on Psychology of the American Psychological Association

1. Introduction

Environmental issues are intriguing in a modern economy. On the one hand, industrial development and economic activities are often associated with severe pollution in developing countries. Zheng and Kahn (2013), for instance, survey the recent literature on China's urban pollution and conclude that economic growth has caused major environmental problems. On the other hand, pollution is known to affect human health, which should hypothetically reduce the well-being and effectiveness of individuals

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participating in economic activities and thus the pace of economic development (e.g., Graff Zivin and Neidell, 2013). The relation between the environment and economic activity is therefore quite subtle, if not paradoxical, making it crucial for policy makers and academic researchers to fully understand the mutual influence between the two. This task is challenging, however, because it is considerably more difficult to establish the causal impact of pollution on economic activities above and beyond certain health issues than the other way around—say, to understand how a steel mill pollutes the air. As a result, our knowledge of how widely and seriously pollution can affect our economy (other than health issues) remains limited.[1]

This paper aims to contribute to the literature a new intuition, a new data set, and new evidence regarding the causal influence of pollution by linking air pollution to behavioral finance. The new intuition is built on health science literature's recent heuristic finding that air pollution, "the biggest environmental risk to health" according to the World Health Organization (2016), can affect humans' moods, cognition, and mental well-being—e.g., by increasing the risk of anxiety, depression, and cognitive decline (e.g., Block and Calderón-Garcidueñas, 2009; Fonken et al., 2011; Mohai et al., 2011; Weuve et al., 2012; Weir, 2012 summarizes recent findings)—in addition to its better-known impacts on respiration, vascular health, and mortality (e.g., Pope, 1989; Pope et al., 2002, 2011). Given that investors' trading behavior is influenced by their mental condition (e.g., Kamstra et al., 2003) and brain functioning (e.g., Frydman et al., 2014) and that limited cognitive resources are known to give rise to biases (e.g., Kahneman et al., 1982; Hirshleifer, 2015), we expect air pollution to induce investors to exhibit more behavioral biases in their trading.

To subject this intuition to falsification tests using the best data available, we obtain a new and unique proprietary data set that contains complete account-level information for all investors in one of China's largest mutual fund families. It consists of 773,198 valid investment accounts trading seven equity funds from 2007–2015. Its investors come from all 31 provinces and 247 cities in mainland China. The data set is ideal for an examination of the effects of air pollution for two reasons. First, air pollution is among the most challenging environmental problems facing developing countries, such as China and India. Thus, a proper assessment of this issue could have both academic value and important normative implications. Second, our data set covers most of China's major cities. As we will see shortly, this extensive coverage (the largest in the literature) is crucial to our ability to design tests that can identify the influence of air pollution.

We then collect data from the air quality index (AQI; higher values, especially those above 100, indicate pollution), which we link to one of the most important and robust trading anomalies reported in the finance literature—the disposition effect, or the tendency to sell winning assets while holding onto losing assets (Shefrin and Statman, 1985). Although the causes and consequences of the disposition effect are still under debate (e.g., Barberis and Xiong, 2009, 2012; Ben-David and Hirshleifer, 2012; Henderson, 2012; Li and Yang, 2013; Frydman et al., 2014; An, 2015), the effect is typically viewed as among the most prominent trading mistakes of investors originating from cognitive bias (see Hirshleifer, 2015 for a recent survey).

To better link the disposition effect to air pollution, for which data are available at the city level, we aggregate investor accounts at the same level. More explicitly, for each trading date, we first identify for each investor whether a position in a fund implies a capital gain or a capital loss based on that investor's entire trading history. As a result of differing trading histories, the same price and fund may imply capital gains for some investors but losses for others. We then aggregate these accounts at the city level as follows. In the spirit of Ben-David and Hirshleifer (2012), we compute the probability of selling winners (PSW) as the fraction of investors in a given city, among those who have unrealized capital gains from their fund investments, to realize gains by selling funds. Analogously, the probability of selling losers (PSL) is the fraction of investors selling at capital losses. The city-level disposition effect is then defined as the difference between the PSW and the PSL.[2]

We then empirically explore the potential influence of air pollution on the disposition effect in three steps. In the first step, we examine the general relation between the disposition effect and air pollution (the logarithm of AQI). When we double-sort city-level observations independently into nine portfolios, according to their AQIs and disposition effects on each trading date, and we find a positive correlation between the two variables. When a city has a high AQI, for instance, the probability that its investors exhibit a high disposition effect is three to four times higher than the probability that they exhibit a medium or low-disposition effect. Multivariate regressions confirm this positive relation. Moreover, investors located in low-AQI/low-disposition cities outperform those in high-AQI/high-disposition cities. The trading difference between the two groups can be as high as 8.97%, 4.2%, and 3.4% per year for benchmark-adjusted, market-adjusted, and three-factor-adjusted returns, respectively, suggesting that the AQI-associated disposition effect can indeed be interpreted as a trading mistake or behavioral bias with sizable financial costs.

To further explore whether the above relation implies a causal impact of air pollution on trading behavior, our sec-

[1] Recent progress mostly focuses on human capital measures related to education (e.g., Currie et al., 2009; Mohai et al., 2011), labor supply (e.g., Hanna and Oliva, 2015), productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016a,b; Isen, Rossin-Slater, Walker, 2017), and crime (Herrnstadt et al., 2016).

[2] In contrast to the reverse disposition effect observed among US mutual fund investors (e.g., Ivković and Weisbenner, 2009; Chang et al. 2016), the Chinese mutual fund investors in our sample exhibit a positive disposition effect, with an economic magnitude very close to that of US stock investors. The difference between the Chinese and US mutual fund investors is consistent with the notion that tax-motivated trading could be important to generating the reverse disposition effect (e.g., Ivković and Weisbenner, 2009) because Chinese investors do not pay taxes on capital gains or dividend payouts. Indeed, in Ivković and Weisbenner (2009), the reverse disposition effect was observed only among taxable accounts of US mutual fund investors, whereas tax-deferred accounts exhibited a positive, although insignificant, disposition effect.

ond step of analysis involves two identification tests based on plausible exogenous variations in AQI. The first test exploits exogenous variations in AQI caused by meteorological conditions, such as wind. It is well known in the atmospheric environment literature that the formation and dissipation of air pollution are heavily influenced by meteorological conditions in general and wind conditions in particular (e.g., Seaman, 2000; Arain et al., 2007). China is no exception (Su et al., 2015): drastic improvements in air quality are often caused by strong winds, whereas drastic deteriorations in air quality often occur under opposite meteorological conditions that favor accumulations of air pollutants. Drastic drops in AQI are particularly exogenous to financial markets, allowing us to use difference-in-difference (DID) tests to identify the influence of air pollution.

The spirit of our test is as follows. We start with two cities—call them A and B. Investors in both cities trade the same financial asset. Assume that both cities are exposed to similarly severe air pollution early in the week. Further assume that a strong wind blows away air pollution in city A on Wednesday (i.e., its AQI drops sharply on Wednesday and remains low for the rest of the week), while the AQI of city B remains unchanged. In this case, we can use the trading behavior of investors located in these two cities before and after the drastic drop of AQI in city A to identify the potential influence of air pollution: if pollution has a short-term influence, the disposition effect of the treatment group (city A's investors) should decrease in the post-wind period (Wednesday through Friday in this example) compared with that of the control group (city B's investors) and the treatment-group bias in the pre-wind period (Monday through Tuesday).

We investigate two versions of the DID test to capture the effect of a drastic dissipation of air pollution in general and that caused by strong winds in particular. In the first version, we identify all city-level observations with high AQIs in the early part of the week and sharp AQI drops of more than two standard deviations (which is 88 in AQI values) on Wednesday/Thursday in our data (using Wednesday alone will not change the results), and we then create a control group similar to that of city B. Empirically, we first verify that the disposition effect does not differ between the two cities in the pre-wind part of the week—thus, our specification satisfies the parallel trend assumption. We then conduct the DID test and find that the disposition effect is significantly attenuated for the treatment group after the drastic reduction in AQI.

In the second version, we identify the treatment group as cities that have high AQIs on Monday/Tuesday and experience strong wind on Wednesday/Thursday (i.e., with wind speeds greater than five meters per second, which typically suffices to blow away air pollutants). The sample coverage decreases in this case because not all large AQI drops are caused by strong wind, but the conclusion that investors in the treatment group start to exhibit lower disposition effect when air pollution is blown away remains unchanged. To further differentiate the effect of air pollution from that of the wind itself, we conduct a placebo test in which both treatment and control cities have no air pollution at the beginning of the week. In this case, a strong wind blowing mid-week does not affect the disposition effect, suggesting that it is changes in AQI introduced by the strong wind—not the wind itself—that causes the disposition effect observed in our sample. Moreover, when we adopt alternative identification approaches, i.e., use strong winds as an instrument, and alternative specifications of the DID test, i.e., use different thresholds to define large AQI decreases and strong winds, our results remain highly robust.

We next exploit a quasi-experiment in which government policies generate exogenous variations in air pollution in the (geographical) cross-section, i.e., the Huai River policy (Almond et al., 2009; Chen et al., 2013). More explicitly, the Huai River, together with the Quinling Mountains, splits China into two geographic (i.e., northern and southern) parts. The central government of China has turned this geographic concept into an interesting policy: it provides free winter heating to homes and offices as a basic right for and only for the urban regions north of the Huai River. Because winter heating operates via the provision and burning of free coal for boilers, which release air pollutants, this policy has unintentionally worsened the air quality of cities north of the river (Almond et al., 2009). In other words, the Huai River policy creates a "discontinuity" in terms of AQI along the river, which researchers have used to identify the plausible causal influence of air pollution on life expectancy (e.g., Chen et al., 2013; Ebenstein et al., 2017).

Our second identification test adopts a regression discontinuity (RD) methodology similar to that of Chen et al. (2013). We find that across different empirical specifications, the disposition effect changes drastically across the discontinuity point. More explicitly, cities located to the north of the Huai River exhibit a significantly higher disposition effect. Because the trading preferences of urban investors are unlikely to differ drastically on the two sides of a river, except through the influence of air pollution changes, we can use a two-stage specification, treating the location to the north of the river as an instrument of AQI in the first stage. When we regress the disposition effect on instrumented AQI in the second stage, we find a significantly positive relation. Moreover, this relationship is highly significant only in the heating seasons, when additional air pollution is created by the free heating policy in Northern China. This seasonality helps to alleviate concerns about omitted variables because known city characteristics should affect potential cognitive biases throughout the year. Finally, when we apply the same test to two artificial lines five degrees north and south of the Huai River line, we do not obtain significant results, suggesting that our tests have the proper power needed to reject nonexistent influences of air pollution.

Together, the results from the two identification tests support a causal interpretation of the influence of air pollution on investors' trading behavior in terms of the disposition effect. The influence also appears to be "on the spot" in that it weakens when pollution abates. Interestingly, trading volume and the fraction of high-disposition investors are not affected by air pollution in the DID or RD tests, suggesting that air pollution mainly induces investors to make more mistakes as opposed to engaging in more (or less) trading, and it achieves this effect by inducing an average investor to exhibit greater disposition (i.e., the intensive margin) rather than by attracting more initially biased investors to participate in the market.

The last step of our empirical analysis aims to extend our tests to obtain greater economic insights and to further assess the robustness as well as the potential economic grounds of our results. We first explore how investor characteristics may affect their exposure to air pollution. The influence of AQI attenuates when investors are older, better educated, and more experienced. We also find that AQI caused by particulate matter (PM2.5 and PM10) especially intensifies the disposition effect. These findings may shed new light on the influence of air pollution and even on the formation of cognitive heuristics in the first place.

We then provide two sets of account-level tests as robustness checks. In the first test, we define the (annual) disposition effect of an individual investor as the difference between the probability of selling winners and that of holding onto losers within a given year. We find that this variable is positively related to the average value of AQI in the same year even when we explicitly control for investor- and time-fixed effects. In the second test, we follow Ivković et al. (2005) and Ivković and Weisbenner (2009) and use Cox proportional hazard models to examine investors' selling behaviors, and we also find that air pollution augments the disposition effect. These tests support and complement the previous city-level analysis.

The remaining question is what the mechanism through which air pollution induces or intensifies the disposition effect might be. To shed light on this important yet challenging question, we notice that some state variables describing the mental well-being of investors, such as moods, may play a pivotal role according to recent studies in health science, psychology, and finance.[3] To see the intuition, recall that the psychology literature has long recognized that people often take action to self-regulate moods—i.e., to maintain good moods and particularly to eliminate bad ones (e.g., Morris and Reilly, 1987; Thayer, 1990; Wegner and Pennybaker, 1993)—and that such mood regulation may involve a variety of strategies ranging from shopping to cognitive restructuring (Thayer et al., 1994; Larsen, 2000; Bushman et al., 2001). Since realizing gains and losses can generate positive and negative bursts of utility according to the finance literature, such as the realization utility models of Shefrin and Statman (1985) and Barberis and Xiong (2012) and the neural experiments of Frydman et al. (2014), trading may be influenced by and be resorted to as a way to self-regulate moods.

As such, investors suffering from air pollution-induced mood disorders may find losses painful to realize. Instead, they resort to realizing gains as a potential therapy to offset the negative influence of bad moods, thereby exhibiting the disposition effect. Hence, mood regulation with the purpose of bringing back bad moods to comfortable levels (e.g., Thayer et al., 1994; Larsen, 2000) can potentially explain our main findings. Although mood regulation may also inspire people to take confirmative actions to maintain good moods (e.g., Mischel et al., 1973), such as to realize some small gains in no-pollution dates, this second effect is likely to be dominated by the mechanism of regulating AQI-initiated mood disorders in our data because severe mood disorders triggered in more polluted dates would require as a remedy the realization of more gains.[4] Nonetheless, the potential existence of alternative effects urges us to provide more evidence to further validate our proposed mechanism.

To achieve this goal, we notice that two important implications of the above mechanism can be derived and empirically examined. First, because air pollution-induced mood disorder incentivizes investors to realize more gains than losses, it may induce investors to sell more winners and subsequently lose more of the potential momentum profitability that can be generated by past winners. In other words, based on the theoretical ground of Grinblatt and Han (2005), air pollution and its associated mood disorder may intensify investors' trading mistakes by particularly strengthening their trading against momentum.

This implication can be tested based on the two momentum phenomena prominent in our data: time-series momentum in fund returns and postannouncement price drifts when fund policies are publicly released (e.g., on investments and dividends, etc.). And indeed we find that, while investors tend to sell past winners in general, this tendency is greatly intensified by (and in some cases, concentrated in) highly polluted dates. This influence of air pollution is suboptimal, however, because investors could have earned a much higher return by holding onto winners. The annualized counterfactual return that these winners can generate in a hypothetical 20-day period after their highly polluted selling date can be as high as 11.28% based on one standard deviation increases in both sell-date AQI and the presale return of past winners. Such evidence strongly supports the interpretation of the air pollution-induced disposition effect as a trading mistake originating from some sort of behavioral bias that pollution-related mood disorders may trigger.

However, what specific forms of behavioral bias may be triggered in haze? The second implication sketches a potential answer based on realization preference, a leading behavioral explanation of the disposition effect.[5] In general, utility bursts from both sign realization (i.e., the pleasure of realizing gains over losses) and magnitude realization (i.e., the deriving of more pleasure from realizing larger gains) may potentially help investors feel better on polluted days. But the goal of mood regulation to bring bad moods back to normal levels imposes some restrictions. In particular, more severe mood disorders introduced by worse air pollution may require investors to realize larger

[3] We thank the anonymous referee for pointing out this possible channel.

[4] In other words, the goal of achieving good moods requires more actions (such as the realization of more gains) when the initial mood condition is worse to begin with.

[5] Other popular behavioral explanations include mean-reverting beliefs (see, e.g., Odean, 1998; Kaustia, 2010) and the prospect theory (Kahneman and Tversky, 1979). Our mechanism tests are more closely related to realization utility due to the need for investors to seek utility bursts to offset the negative influence of air pollution.

gains as a remedy, which triggers a magnitude effect. Alternatively, a more frequent sign realization may also achieve a same goal. But this approach requires investors to trade more frequently in air pollution, which may not be appealing due to the aforementioned common symptoms of air pollution (e.g., anxiety, depression, and cognitive decline).

To empirically test this implication, we follow Ben-David and Hirshleifer (2012) to separately test the influence of air pollution on the sign and magnitude effects. We find mixed evidence on sign realization preference and an insignificant influence of air pollution on this form of behavioral bias in regression discontinuity analysis. By contrast, it is evident that investors indeed sell gains with larger magnitudes on more severely polluted days, particularly on funds that are most recently purchased.

Jointly, the above two tests lend support to the notion of air pollution-induced mood regulation in that investors sell winners and realize larger gains as a remedy for air pollution-induced mood disorder. The caveat on this interpretation is twofold. First, our evidence is indirect and the mechanism is not exclusive. Second, what we refer to as moods may be influenced by a variety of mental, psychological, and cognitive sources among which we cannot further differentiate. Regardless of such ambiguity, however, our results shed light on why air pollution could potentially trigger behavioral biases and how investors lose money trading this way.

Our paper provides some of the first evidence linking air pollution to behavioral finance. Pollution is among the most intriguing challenges faced by many countries (WHO, 2016), and identifying its associated economic and social costs has been the subject of substantial efforts. Recent studies indicate that pollution may adversely affect health conditions, human capital, and even crime.[6] Our contribution demonstrates that the effects of pollution can be extended to behavioral finance. The greater breadth of our data set also allows us to design two endogeneity tests to identify the causal impact of air pollution on the well-known behavioral bias of the disposition effect.

In doing so, we also contribute to the literature on the disposition effect.[7] Particularly, we provide new evidence that, consist with the analysis of Ivković and Weisbenner (2009), some mutual fund investors may exhibit a positive disposition effect when taxes are not a concern. Our findings also lend support to the notion that realized gains and losses may play a pivotal role in forming the disposition effect (e.g., Barberis and Xiong, 2012), and a common mistake behind this effect is to trade against momentum (Grinblatt and Han, 2005). In a broader sense, our paper illustrates that social factors seemingly unrelated to financial markets may influence investor behavior, echoing Hirshleifer's, (2015) call to expose behavioral finance to its far-reaching social background.

Our paper is also related to several other strands of the empirical literature. First, we build on and extend both scientific findings that air pollution is harmful to mental health and cognition (e.g., Fonken et al., 2011; Mohai et al., 2011; Weuve et al., 2012) and findings in the finance literature that investors' trading behavior can be associated with brain functioning and mental conditions (e.g., Frydman et al., 2014; Kamstra et al., 2003). Next, we compliment several recent papers examining the general relation between air pollution and stock market returns (e.g., Levy and Yagil, 2011; Lepori, 2016; Heyes et al., 2016; Huang et al., 2017) by using account-level data to provide detailed causal evidence and by establishing a micro foundation rooted in investor behavior and cognitive bias.

Finally, our study is also loosely related to the literature examining the relation between weather conditions and stock market returns.[8] Despite the similarity that both weather and pollution may affect investors' trading behavior, the latter type of influence has more explicit normative implications because policies aiming to reduce pollutions can more directly improve the health and welfare conditions of affected residents (e.g., Greenstone and Hanna, 2014; Isen et al., 2017). Our findings extend such normative implications to financial market participants. Since severe air pollution induces more suboptimal trading, which shifts wealth from more exposed investors (either because they are unaware of issue of pollution or because they cannot afford to sufficiently improve indoor air quality by purchasing air purification machines) to less exposed ones, good policies may largely improve not only the trading efficiency of financial markets but also the wealth distribution among retail investors.

The remainder of the paper is organized as follows. Section 2 presents our variables and summary statistics. Section 3 reports the baseline relation between air pollution and the disposition effect. Section 4 presents endogeneity tests, while Section 5 provides additional analysis and robustness checks. Section 6 concludes.

2. Data and variable construction

We now describe the sources of our data and the construction of our main variables.

2.1. Sample and data sources

Our data come from a confidential mutual fund family, located in Shanghai, China. It ranks among the top 30 mu-

[6] More explicitly, pollution may adversely affect health conditions indicated by life expectancy and mortality (e.g., Chay and Greenstone, 2003a,b; Chen et al., 2013; Greenstone and Hanna, 2014; Ebenstein et al., 2015; Deryugina et al., 2016; Ebenstein et al., 2017); human capital issues related to education, labor supply, and productivity (e.g., Currie et al., 2009; Hanna and Oliva, 2015; Mohai et al., 2011; Graff Zivin and Neidell, 2012; Chang et al., 2016a,b;Isen et al. 2017); and crime (Herrnstadt et al., 2016). Additionally, people are willing to pay for clean air and health insurance (Chay and Greenstone, 2005; Ito and Zhang, 2016; Chang et al. 2018).

[7] Starting from Shefrin and Statman (1985), the development of the literature is far reaching, both on empirical and theoretical sides (see, among others, Grinblatt and Han, 2005; Barberis and Xiong, 2009, 2012; Calvet et al., 2009; Ivković and Weisbenner, 2009; Kaustia, 2010; Ben-David and Hirshleifer, 2012; Henderson, 2012; Li and Yang, 2013; Frydman et al., 2014; An, 2016; Chang, Solomon, and Westerfield, 2016 for some of the most recent studies). As the literature is extensive, we refer to interested readers to Hirshleifer (2015) for a recent survey.

[8] See, among others, Saunders (1993), Hirshleifer and Shumway (2003), Kamstra, Kramer, and Levi (2003), Goetzmann and Zhu (2005), Goetzmann et al. (2014), and Kamstra et al. (2017).

tual fund families in China both in terms of the number of mutual funds offered and in terms of the total net assets (TNA) under management, with investors from all 31 provinces and more than 200 cities in mainland China. The fund family allows investors to open investment accounts either directly online or indirectly through brokerage firms or bank branches. Each investor is allowed to open only one account, registered under his or her national identity number (at any given time, each citizen in China has a unique national identity number) through these channels. After opening an account, an investor can buy shares of any fund offered by this family or redeem his or her existing shares. The investment rules on the operations side of a mutual fund investment are identical to those in the US.

For each account, the database allows us to retrieve information about a) investor profile, b) trading history, and c) dividend distributions. The investor profile contains an investor's personal information, including his or her unique national identity number, date of birth, gender, concurrent postcode, and distribution channel. For each transaction, the trading file provides the name of the mutual fund involved, the total number of shares purchased or redeemed, the total value of the purchase or redemption, the total transaction fees related to these transactions, and the total number of shares after the transaction. Finally, the dividend file provides information about the type and total amount of dividends distributed to each investor based on his or her shareholdings in the specific mutual fund. More detailed information about the data is provided in Internet Appendix 1.

For each investor, the unique national identity number enables us to trace the city of birth, whereas the postcode allows us to identify the city of trading. Moreover, based on account-level trading and dividend information, we can trace not only the entire trading history of each account but also its gains and losses. Occasionally, other types of transactions may be recorded, including swaps between different funds within the mutual fund family, the establishment of automatic purchase plans, and switches between dividend choices. We manually review all the records that may be treated as a buy or sell and transform them into purchase/redemption quantities and price data. Our results are not affected when we exclude these records.

We focus on open-end equity funds offered by the family. We require a fund operation history longer than five years to avoid the confounding effects that can arise from unsteady fund operations, such as Initial public offerings and vast early stage expansions (our results are robust if we include young funds). Our final sample includes 773,198 investment accounts in 247 cities trading seven equity funds from 2007–2015, which is larger than the sample of 128,829 accounts of mutual fund investors used in Chang et al. (2016a,b), based on the Odean (1998) data set.

Fig. 1 plots the geographic locations of these accounts. We can see that they are widely dispersed across China, covering a large sample of important cities (including nearly all provincial capitals and second-tier cities with large populations). The only two provinces in which few cities are covered in our sample are Xinjiang and Tibet—but these regions contain far fewer cities in the first place. Therefore, the investors in our sample are highly representative in terms of geographic distribution. The large coverage of the data set allows us to conduct endogeneity tests in later sections. Another benefit of our data is that investors do not pay taxes on capital gains or dividend payouts in China. This feature eliminates the confounding effects of tax-motivated selling activities (e.g., Ivković and Weisbenner 2009), which is a key difference between Chinese and US mutual fund investors.

We obtain daily information on air pollution (air quality index or AQI) from the official website of the Ministry of Environmental Protection of China (MEPC). Typically, for each city, MEPC has several monitoring points used to observe air quality. MEPC collects information from these points and derives the average local AQI for each city. We also obtain other weather information, such as temperature and wind speed, from the China Meteorological Administration and variables related to the local economy and developmental conditions from the China Economic Administration.

Information about pricing and equity mutual fund characteristics comes from two major sources: China Stock Market and Accounting Research (CSMAR), which is available from Wharton Research Data Services (WRDS), and the Wind Financial Database (WIND), another leading integrated service provider of financial data, information, and software. From these two databases, we retrieve not only daily prices (i.e., the net asset value or NAV), returns, and TNA for the seven equity funds but also characteristics such as fund fees and benchmarks. We cross-check the two databases to ensure the accuracy of all information. We check the quality of account-level data by aggregating the NAVs of all accounts at the fund level. We find that the aggregate asset value derived from individual accounts matches the TNA reported by CSMAR and WIND, confirming that we have complete information about all investors that trade these funds.

2.2. Main variables

We first describe our measure of air quality and then explain how we construct variables related to the disposition effect. Our main measure of air pollution is the daily AQI for each city (i.e., the average hourly AQI over a day), which synchronizes various contents of air pollution, including sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), and particulate matter (PM) such as dust, smoke, liquid drops, dirt, and other particles in the air. Recently, PM has attracted substantial public attention because particulate matter less than 2.5 micrometers in diameter (i.e., PM2.5) can collect in people's lungs and pose grave health risks. Internet Appendix 2 cites two recent health science blogs in explaining the direct influence of air pollution on cognition in humans. The first blog, for instance, indicates the pivotal role of microglia in air pollution: "Under normal conditions, microglia primarily serve as the defenders of the central nervous system.... But microglia can be dangerous when they are exceptionally 'angry' and are known to leave behind significant bystander damage to neighboring cells.

Fig. 1. Locations of cities and the Huai River in China. The figure plots the geographic location of the cities covered in our sample in China. Each city is represented by one dot on the map. The line in the middle of the map is the Huai River augmented by the Qinglin Mountains, which geographically divide China into its southern and northern parts.

This adverse behavior may lead to the development of any number of neurodegenerative diseases, including Parkinson's disease, Alzheimer's disease, or Gulf War Illness." According to this description, severe air pollution can have both an immediate influence and a long-term impact on mental and cognitive conditions.

The AQI ranges from 0–500 in China. The MEPC assesses air pollution in terms of AQI in accordance with the following seven categories: (1) excellent (air quality) corresponds to an AQI under 50; (2) good corresponds to an AQI between 50 and 100; (3) slightly polluted corresponds to an AQI between 101 and 150; (4) lightly polluted corresponds to an AQI between 151 and 200; (5) moderately polluted corresponds to an AQI between 201 and 250; (6) heavily polluted corresponds to an AQI between 251 and 300; and (7) severely polluted corresponds to an AQI above 300.[9] Although how constructive the MEPC standard has been debated, it is generally agreed that AQI values above 100 indicate unhealthy air conditions.

Fig. 2 graphically illustrates recent air pollution conditions in China. In Panel A, the solid curve plots the average AQI value in recent years for all the cities covered in our sample. To obtain this curve, we pool all city-day AQI observations within a year and then plot the average value during the year as a solid line and the 90-percentile confidence interval in the shaded area. In Panel B, we provide a special snapshot of air pollution conditions in Beijing, the capital of China. The solid line plots the average value of daily AQI within a given year, whereas the shaded areas indicate the 90-percentile confidence interval of daily AQI values within a year. We can see that air pollution remains a challenge in China. In Beijing, for instance, air quality in 2007 was unhealthy (i.e., above 100) to begin with. It then improved during the Olympic cycle, starting in 2008. However, the situation again worsened in more recent years. At the same time, the 90% quantile value of AQI indicates very unhealthy pollution levels throughout the period and shoots up to approximately 250 in more recent years. Therefore, even according to the MEPC standard, Beijing has experienced very heavy air pollution for more than 10% of days in these two years. These plots il-

[9] Although there are concerns that AQI reported by local governments and local branches of MEPC may be subject to a downward bias, especially when air pollution is severe, our tests based on quasi-experiments related to the Huai River Policy and wind conditions are largely immune to this potential bias.

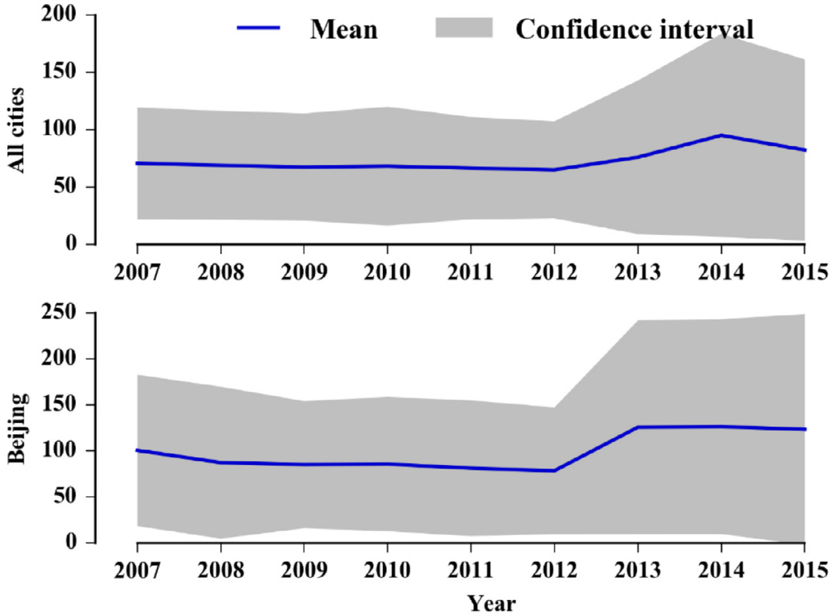

Fig. 2. AQI in recent years in China. The figure plots the mean and 90% confidence interval of the AQI for all cities in our sample (top) and those for Beijing (bottom) for the period from 2007 to 2015.

lustrate the importance of understanding the influence of air pollution.

We now describe the measurement of the disposition effect. To better link investor behavior to city-level AQI indices, we aggregate investors' trading activities for each equity mutual fund at the city level based on each investor's residential address. When there is no confusion, we refer to such accounts as city-level aggregate accounts or simply city accounts. Intuitively, each regional account describes the trading activities of a representative regional investor who buys and sells shares of a fund.

More explicitly, because the disposition effect is essentially the difference between the PSW and PSL, we construct these probabilities for our city accounts as follows. We first use the original data for each investor and compute the capital gains and losses that each investor could realize by trading a particular fund on a particular day. Specifically, for each investor-fund-day observation, we follow the literature (e.g., Odean, 1998; Frazzini, 2006; Ben-David and Hirshleifer, 2012) and calculate the purchasing cost of the inventory of each investor derived from his or her entire trading history in the fund.[10] We then compare this reference price with the market price of the fund reported by CSMAR. We flag an investor-fund-day observation as a capital gain if the current price is strictly above the reference price based on the investor's entire trading history. Similarly, an investor-fund-day is flagged as a capital loss if the current price is strictly below the reference price.

[10] We follow Frazzini (2006) and assume that investors use a cost-based mental accounting method (FIFO—first in, first out) to associate a quantity of shares in their trading account to the corresponding reference price.

Then, for each aggregate city account, we use the proportion of individual investors who sell shares of the fund conditional on capital gains to proxy for the PSW. In other words, PSW is the ratio between the number of investors realizing gains (by selling funds) and the total number of investors who have gains to potentially realize. Likewise, we use the proportion of investors who sell shares of the fund conditional on capital losses to proxy for the PSL. The final proxy for the disposition is then defined as follows:

$$Disp_{j,f,t} = PSW_{j,f,t} - PSL_{j,f,t}, \tag{1}$$

where $Disp_{j,f,t}$ is the proxy for the disposition effect for the aggregate account of city j, fund f in period t. In a similar manner, we can also pool all funds at the city level and create the variable $Disp_{j,t}$ to describe the disposition effect for investors in all equity funds offered by the fund family.

We also control for city- and fund-level variables that may be related to trading. At the city level, we control for the logarithm of GDP (*Log_GDP*), the logarithm of the local population (*Log_pop*), the logarithm of domestic firms (*Log_dom_firm*), and the logarithm of government income (*Log_gov_income*). The first three variables control for economic growth, whereas the fourth variable controls for the power of the government, which is also important in China's economy. Our results remain the same if we use different control variables related to the real economy.

2.3. Summary statistics

Table 1 presents summary statistics for our sample. Panel A1 tabulates the mean, median, standard deviation, and quantile distribution of the variables that describe trading behavior for city-level aggregate accounts. Panels A2 and A3 report similar statistics for AQI and economic growth-related local control variables, respectively. From

Table 1
Summary statistics.
This table presents summary statistics of the data from 2007 to 2015 used in this paper. Panel A reports numbers of observations, means, and standard deviations, along with the 5%, 25%, 50%, 75%, and 95% quantile values of the main variables, including measures of the city-level disposition effect in A1, the air quality index (AQI) in A2, and time-varying regional control variables in A3. Panel B presents the Spearman rank correlation coefficients of the variables. Coefficients that are significant at the 5% level are highlighted in bold.

Panel A: Summary statistics of main variables

	N	Mean	Std dev	5%	25%	Median	0.75	95%
A1: City-level disposition effect (city-day observations)								
Disposition effect,%	144,820	0.198	1.535	−0.662	0.000	0.000	0.000	1.867
PSW,%	144,820	0.382	1.376	0.000	0.000	0.000	0.125	2.083
PSL,%	144,820	0.184	0.857	0.000	0.000	0.000	0.011	0.952
A2: City-level air quality index								
AQI	144,239	80.265	44.250	34	54	70	94	159
A3: Time-varying local control variables								
Log_GDP	1540	15.890	1.168	14.244	15.057	15.742	16.624	18.019
Log_pop	1532	4.873	0.839	3.649	4.320	4.805	5.387	6.333
Log_num_domestic_firm	1532	5.733	1.325	3.691	4.852	5.684	6.475	7.965
Log_gov_income	1538	13.382	1.355	11.220	12.530	13.310	14.208	15.696

Panel B: The correlation matrix

	PSW	PSL	Disposition effect	Log_GDP	Log_pop	Log_num_domestic_firm	Log_gov_income	AQI
PSW	1							
PSL	**0.1153**	1						
Disposition effect	**0.8323**	−0.4548	1					
Log_GDP	**0.0083**	−0.0082	0.012	1				
Log_pop	−0.0042	**−0.0133**	0.0036	**0.8473**	1			
Log_num_domestic_firm	0.0016	−0.0083	0.006	**0.8268**	**0.7788**	1		
Log_gov_income	**0.0133**	−0.0038	**0.0141**	**0.902**	**0.77**	**0.7756**	1	
AQI	**0.0037**	**−0.0063**	**0.0068**	**0.0063**	**0.0256**	0.0051	**0.0171**	1

this table, we can see that the PSW in a typical trading day is 0.382% for aggregate city accounts, which is much higher than the PSL (0.184%). Therefore, investors, on average, exhibit a strong disposition effect in our sample. Unreported statistics show that the average intensity of the disposition effect at the monthly frequency is very close to the disposition effect of active, short-term trading (0.49% for sales made within 20 days of purchase) reported in Ben-David and Hirshleifer (2012) for US stock investors. Hence, in contrast to the reverse disposition effect observed among US mutual fund investors (e.g., Ivković and Weisbenner 2009; Chang et al., 2016a,b), Chinese mutual fund investors in our sample exhibit a positive disposition effect. We will discuss the difference between Chinese and U.S. mutual fund investors in later sections, where we report the results of account-level analysis.

Panel B reports the correlation matrix of the main variables. We find that AQI is positively correlated with the disposition effect. This observation, though preliminary, lends some support to the view that air pollution might affect investor behavior. Of course, these numbers could be spuriously related to many fund or regional characteristics. Therefore, in the next section, we will perform portfolio and regression analyses.

3. AQI and the disposition effect: baseline results

We start with a portfolio analysis to explore the general relation between AQI and the disposition effect. On each trading date, we independently double-sort city-level observations according to their AQI and disposition effect into nine portfolios (i.e., three AQI-based terciles by three disposition-effect-based terciles). Panel A1 first tabulates the fraction of observations that fall into each portfolio in the cross-section. We can immediately see that most observations are located at the diagonal elements. For instance, when the AQI of a city is low, the fractions of investors exhibiting low, medium, and high disposition effects are 22.56%, 5.08%, and 5.68%, respectively. In other words, when the AQI of a city is low, the probability that its investors will exhibit a low-disposition effect is about four times higher than that for medium or high disposition effects. Likewise, when the AQI of a city is high, the probability that its investors will display a high disposition effect is much higher than that for medium or high disposition effects. The diagonal distribution intuitively demonstrates that AQI and the disposition effect are highly correlated in our sample.

To quantify the magnitude of the effect, we note that the average values of AQI are 49.4 (low), 74.6 (medium), and 116.6 (high) in AQI sorting, while the disposition effect exhibits average values of −0.407% (low), 0.020% (medium), and 0.977% (high) in its sorted groups. Therefore, moving from the Low-tercile to the High tercile of the AQI, which amounts to a 1.52 standard deviation change in AQI, increases the disposition effect by an average of 1.38%, or 0.90 standard deviations of the disposition effect in our sample distribution. Roughly, in this case, a one-standard-deviation increase in AQI is associated with a 60% standard deviation increase in the disposition effect. Of course, we need to interpret this magnitude with caution because the impact is not linear—the impact of AQI moving from the medium to the high tercile is much larger than that of moving from the low to the medium tercile. Nevertheless, it clearly demonstrates that the influence of air pollution on the disposition effect is economically important.

Because most observations are concentrated in the diagonal elements, we can also quantify the economic impact of AQI-associated disposition effects based on the trading performance of investors located in these diagonal elements. Panel A2 implements this intuition by calculating the average trading performance (in basis points (bps) per day) of investors located in cities in each of these diagonal elements. In particular, we compute the (daily) return of a diagonal element as the date $t+1$ return of date-t buys minus that of date-t sells that we aggregate from all investors located in cities in that element. In this case, investors located in low-AQI/low-disposition effect cities and high-AQI/high-disposition effect cities generate a market-adjusted return of 0.901 bps and −0.823 bps per day, respectively. The first group of investors therefore-outperforms the second group by 1.724 bps per day, or 4.2% per year. More generally, the trading performance difference between the two groups can be as high as 8.97% (4.2% and 3.4%) per year for benchmark-adjusted (market-adjusted and three-factor-adjusted) returns. Hence, the AQI-associated disposition effect can indeed be regarded as a severe trading mistake.

Next, we conduct a multivariate specification to further verify the relation between air quality and investors' trading activities as follows:

$$Disp_{j,t} = \alpha + \beta \times AQI_{j,t} + C \times X_{j,t} + \varepsilon_{j,t}, \tag{2}$$

where $AQI_{j,t}$ is the air quality index value for city j on day t, and $Disp_{j,t}$ denotes the disposition effect of the aggregate account for city j on day t. The vector $X_{j,t}$ stacks a list of region-level control variables, including the regional gross domestic product (*Log_GDP)*, the total population in the region (*Log_pop*), the number of domestic firms (*Log_num_domesticfirm*) and local government revenue (*Log_gov_income)*. We also include city, day of the week, month of the year, and year-fixed effects, and we further follow Petersen (2009) to cluster standard errors at the city and date levels to control for within-cluster dependence uncaptured by fixed effects. The coefficient of interest is β, which is an estimate of the contemporaneous relation between air quality and the disposition effect.

The results are reported in Panel B of Table 2. Model (1) presents the baseline relation between AQI and the disposition effect, whereas in Model (2), we further include time-varying local control variables such as GDP. We can see that both models exhibit a significant relation between air pollution and the disposition effect—adding local variables such as GDP neither affects this relation nor changes its level of significance. Unreported tests also show that our results are robust with or without the aforementioned fixed effects.

We next provide two important robustness checks. In Model (3), we further control for one important weather condition—sunshine—that could potentially affect the market (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005). We find, however, that sunshine does not significantly affect the disposition effect in our sample, confirming that the influence of pollution is not spuriously correlated with sunshine. Given its insignificant role, we will not explicitly control for sunshine in later sections—we have verified that this weather condition remains insignificant in all these tests. The more important weather condition related to air pollution is wind, which we will specifically examine in later sections.

Model (4) further excludes dates of very important political events (such as top party meetings and top international summits)[11] and the largest metropolitan cities (the so-called tier-one cities, including Beijing, Shanghai, Guangzhou, and Shenzhen). The reason to remove these observations is as follows. Around important political events, small firms emitting air pollution could be temporarily shut down by the government to create a blue sky in Beijing for political reasons. In addition, tier-one cities typically consist of more migrants—investors therein might consequently differ from ordinary investors in terms of trading. Hence, air pollution could be spuriously correlated with the disposition effect due to omitted variables related to political considerations and metropolitan characteristics, as well as their potential interactions. Empirically, the influence of AQI on the disposition effect remains almost the same, if not more significant, after removing related observations, suggesting that our main results are not contaminated by political considerations or metropolitan characteristics.

The Internet Appendix further provides two robustness checks on our baseline analysis. We first verify that our results are robust to fund selection and to different channels of distribution (Table IN1). One interesting observation is that compared to other distribution channels (e.g., banks), the brokerage channel, which has attracted special attention from previous studies related to Chinese stock market investors (e.g., Seasholes and Zhu, 2010), is not associated with different investor behaviors in haze.[12] Later sections also show that account-level tests lead to very similar conclusions. In summary, the relation between air pollution and the disposition effect is highly robust regardless of the empirical specification used.

Secondly, we further examine the negative impact of air pollution on trading performance by conducting a path analysis (see Wright, 1934 for its statistical ground and Pevzner et al. (2015) for an example of application in the financial market), which allows us to explore whether this influence is directly achieved by air pollution or indirectly achieved through the mediation of the disposition effect. Our counterfactual analyses demonstrate that both direct and indirect influences are highly significant (Table IN2 of the Internet Appendix provides the details), which lend

[11] More explicitly, we exclude the Annual Meetings for the National People's Congress and the Chinese People's Political Consultative Congress, the 2008 Beijing Summer Olympics, World Expo 2010 Shanghai, APEC China 2014, and the 2015 China Victory Day Parade.

[12] In the early years, many investors physically visited brokerage firms to trade, in which case air pollution might reduce their willingness to pay the visit. The popularity of online and cell phone app-based trading among fund investors in the last decade (i.e., our testing period) may help eliminate the potential difference across different distribution channels.

Table 2
The impact of air quality on trading bias: baseline analysis.
This table presents the baseline relationship between AQI and the disposition effect in regression and portfolio analysis. More explicitly, Panel A tabulates the results for portfolio analysis. For each day t during our sample period, we independently double-sort all cities into nine groups, according to terciles of AQI (high, mid, low) and those of the disposition effect (high, mid, low) and then assess the trading performance of investors in these sorted groups. Panel A1 tabulates the average value of AQI and the disposition effect in each tercile as well as the proportion of observations that falls into each group. In Panel A2, we first aggregate all buy and sell trades by investors on day t in each of the nine groups to construct their buy and sell portfolios. We then compute their trading performance as the returns generated by the buy portfolio on day $t+1$ minus the returns of the sell portfolio on the same date. Such trading performance is further adjusted based on the CAPM model, Fama-French three-factor models, and the fund's benchmark. Panel B2 then reports trading performance for investors located in *Low-Low* cities (i.e., cities in the bottom tercile of AQI and the disposition effect) and those in *High-High* cities (i.e., cities in top tercile of AQI and the disposition effect), along with the difference between the two (denoted by *High-High minus Low-Low*). Panel B examines the following panel specification with city- and time-fixed effects: $Trading\ bias_{j,t} = \alpha_0 + \alpha_1 \times AQI_{j,t} + \alpha_2 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}$, where $AQI_{j,t}$ is the air quality index value for city j on day t, $Trading\ bias_{j,t}$ denotes disposition effect, and the vector $X_{j,t}$ stacks a list of region-level control variables, including the regional gross domestic product (*Log_GDP*), total population in the region (*Log_pop*), the number of domestic firms (*Log_num_domfirm*), and local government revenue (*Log_gov_income*). Model (3) further controls for sunshine conditions in each city. Model (4) excludes dates with major political events (such as large party meetings) and four tier-one cities (Beijing, Shanghai, Guangzhou, and Shenzhen). The sample period is from the year 2007 to 2015. Appendix A provides more detailed variable definitions. Robust t-statistics are reported in parentheses and are based on standard errors clustered by city and date. Superscripts of *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Portfolio analysis based on double sorting (AQI and disposition effect)

A1: Tercile values of AQI/disposition effect (in paranthesis) and the fraction of observation in each double-sorted group

	Disp_Low (−0.407%)	Disp_Mid (0.020%)	Disp_High (0.977%)
AQI_Low (49.439)	22.56%	5.08%	5.68%
AQI_Mid (74.573)	5.96%	20.37%	6.99%
AQI_High (116.622)	4.81%	7.86%	20.69%

A2: Trading performance of High-High and Low-Low AQI-associated disposition groups

	(1) Raw return(bp)	(2) Market-adjusted return(bp)	(3) 3-factor-model-adjusted return(bp)	(4) Benchmark-adjusted return(bp)
Low-Low	0.670	0.901	1.773	3.784
	(0.51)	(1.33)	(2.98)***	(2.48)**
High-High	−5.987	−0.823	0.399	0.026
	(−5.82)***	(−1.70)*	(0.76)	(0.02)
High-High minus Low-Low	−6.657	−1.724	−1.374	−3.758
	(4.02)***	(2.08)**	(1.71)*	(2.00)**

Panel B: Disposition effect regressed on Log(AQI)

	(1) Full sample	(2) Full sample	(3) With sunshine	(4) Excluding big events and cities
Log_AQI	0.037***	0.037***	0.037***	0.044***
	(3.91)	(3.85)	(3.86)	(4.30)
Log_GDP		−0.068*	−0.068*	−0.057
		(−1.73)	(−1.73)	(−1.40)
Log_pop		0.032	0.033	0.023
		(0.99)	(1.03)	(0.65)
Log_num_domestic_firm		0.036	0.035	0.044*
		(1.62)	(1.60)	(1.84)
Log_gov_income		0.035*	0.035*	0.040*
		(1.66)	(1.68)	(1.86)
Sunshine			0.000	
			(0.96)	
Constant	0.151***	0.373	0.364	0.125
	(3.28)	(0.65)	(0.63)	(0.21)
Fixed effects and clustering	City, day of the week, month of the year, and year fixed effets; S.E. clustered by city-day			
No. of obs	144,238	144,238	144,238	128,322
R-squared	0.02	0.02	0.02	0.02

further support to notion that the air pollution-related disposition effect should be regarded as a severe trading mistake originating from some sort of behavioral bias. Upon such evidence, we will refer to the disposition effect as a trading mistake or a behavioral bias when no confusion ensues. Exactly how—e.g., through which mechanisms or channels—air pollution may trigger the disposition effect and associated bias and mistakes becomes an interesting question that we will discuss in later sessions using account-level information.

4. Two endogeneity tests

One concern about our previous results is that the disposition effect and air pollution may be spuriously correlated because of either unobserved regional characteristics or omitted time-varying variables related to economic development. Cities in the northern part of China, for instance, are associated with both a higher level of air pollution and a relatively lower pace of economic growth in the last decade. If the investors therein make more trading mistakes due to their decreased exposure to the benefits of rapid economic development, a positive relation may spuriously arise between the disposition effect and air pollution. Therefore, in this section, we formally address this issue of spurious correlation using two endogeneity tests.

4.1. Vast dissipation of air pollution, especially because of strong winds

We first explore exogenous variations in AQI, building on knowledge obtained from the atmospheric environment literature. In that literature, researchers show that the formation and dissipation of air pollution are heavily influenced by meteorological conditions in general and wind conditions in particular (e.g., Seaman, 2000; Arain et al., 2007; Su et al., 2015).[13] In particular, dramatic reductions in air pollution, typically driven by windy weather, are largely exogenous to financial markets, allowing us to use DID tests to identify (and also to intuitively demonstrate) the influence of air pollution.

We design two different versions of DID tests to utilize different forms of air pollution reduction that are exogenous to the financial markets. The first version focuses on drastic AQI decrease of more than two standard deviations (which is 88 in AQI values)—this magnitude of intra-day AQI change will not occur as a result of natural dissipation without drastic meteorological conditions. The second version explores a more explicit meteorological condition, which is also the leading meteorological condition to dissipate air pollutants in China: strong winds (of more than five meters/second in speed). In other words, the first version depicts the more general influence of AQI decreases on investor behavior, whereas the second version aims to exploit more explicit and exogenous meteorological shocks to validate the direction of causality. Exploring the two versions of the DID tests therefore allows us both to understand the general influence of air pollution and to address related endogeneity concerns.

Because trading occurs only on weekdays, to conduct the first version of the test, we first identify the treatment group by focusing on cities that have experienced (1) air pollution at the beginning of a week (i.e., an AQI above 100 before the treatment event) and (2) the treatment event of drastic AQI drops in mid-week (i.e., Wednesday or Thursday). Drastic AQI drops are defined as AQI drops larger than two standard deviations of the AQI distribution (roughly a drop in AQI of more than 88—our results are robust to this threshold). We choose this threshold because once severe air pollution is formed, this magnitude of AQI change will not occur as a result of natural dissipation without exogenous weather changes such as strong wind or snow/rain. In this regard, large AQI drops are already quite exogenous with respect to financial markets. Moreover, we restrict the event days to either Wednesday or Thursday so that we have a valid number of pre- (i.e., weekdays before the AQI drop within the same week) and post-treatment observations (i.e., weekdays after the AQI drop within the same week, including the event date—our results are robust if we exclude the event date) for analysis. The typical weekday pattern for the treatment group, in this case, features a high AQI at the beginning of a week, followed by a sudden drop in AQI in mid-week, after which the pollution level often remains low until the end of the week.

For each city in the treatment group, the valid control group includes cities that (1) have similar degrees of pollution at the beginning of the week (we require the AQI difference between the two groups of cities to be smaller than 30) and (2) do not experience large AQI changes on Wednesday/Thursday. To implement the second condition, we focus on cities with absolute changes in AQI of less than one standard deviation. From the sample of cities that satisfy the two conditions, we then choose the city that has the closest pretreatment average of AQI values within the same week as the control sample of the treatment city. Our results are robust to the various thresholds noted above.

We then examine potential changes in the disposition effect of the treatment group attributable to large AQI changes in the following difference-in-difference specification with time- and city-fixed effects:

$$Disp_{j,t} = \rho_0 + \rho_1 \times Treated_{j,t} + \rho_2 \times Treated_{j,t} \times After_{j,t} + \rho_3 \times After_{j,t} + \rho_4 \times X_{j,t} + \varepsilon_{j,t}, \tag{3}$$

where $Treated_{j,t}$ is a dummy variable that takes a value of one if city j on day t is in the treatment group, and $After_{j,t}$ is a dummy variable that takes a value of one if day t is in the post treatment period, and zero if day t is in the pretreatment period. The vector $X_{j,t}$ contains region-level control variables. The coefficient of interest is ρ_2 before the interaction term, which captures the difference in the disposition effect between the treatment and control groups induced by the drop in AQI in the treated cities.

The results are reported in Panel A of Table 3. We first tabulate the level of AQI for the treatment and control groups before and after the treatment event (i.e., the big drop in AQI in the treated cities) in Panel A1. We can see that both groups have an AQI of approximately 160 at the beginning of the week. In addition, we can also easily verify that the disposition effect is similar in the two groups on Monday (approximately 0.3). To the extent that both AQI and the disposition effect do not vary much before the treatment event, our specification satisfies the parallel trend assumption. Next, the AQI of the treatment group then drops to approximately 85, whereas that of the control group remains largely unchanged. Interestingly, similar changes are observed for the disposition effect, suggesting that the effect could indeed be influenced by air pollution.

Panel A2 reports the results of the multivariate analysis. Specifically, Model (1) controls for time- and city-fixed effects, whereas Model (2) also includes local

[13] The vast dissipation of air pollution due to strong winds in China was also reported by the official Xinhua News Agency: http://news.xinhuanet.com/local/2014-12/09/c_127287409.htm. Consistent with this notion, Su et al. (2015) show that the reduction in wind speeds in north China from 1973–2012 was a leading meteorological trend contributing to the escalating frequency and intensity of haze. Some recent studies (e.g., Herrnstadt et al., 2016) have used the direction of the wind to identify the causal influence of air pollution within a small number of cities. In contrast, the extensive coverage of our sample allows us to use wind speed, which is the leading meteorological condition dissipating air pollutants in China, to identify the causal influence of air pollution on potential bias.

control variables. We can see that across all empirical specifications, changes in AQI significantly reduce the disposition effect of the treatment group, as the interaction term $Treated_{j,t} \times After_{j,t}$ is significantly negative. Moreover, the coefficients for $Treated_{j,t}$ and $After_{j,t}$ are largely insignificant, suggesting that the influence of air pollution concentrates on the treatment effect.

As for economic magnitude, because AQI drops by 80.9 under the treatment effect in Panel A1 (which is 1.83 standard deviations of AQI) and the disposition effect drops by 0.234% in Model 2 of Panel A2 (i.e., 15.2% standard deviations of the disposition effect), a one standard deviation drop in AQI results in an 8.34% standard deviation decrease in the disposition effect. Note that this magni-

Table 3

DID on AQI drops.

The table presents the results of two versions of difference-in-difference tests associated with drastic AQI drops. In Panel A, we first identify the treatment group by focusing on cities that have experienced (1) air pollution at the beginning of the week (i.e., an AQI above 100 before a drastic AQI drop) and (2) the treatment event of a drastic AQI drop (i.e., larger than two standard deviations) on Wednesday or Thursday. For each city in the treatment group, we identify as control group cities those that 1) have similar degrees of pollution at the beginning of a week (i.e., an AQI difference smaller than 30) and 2) do not experience abrupt AQI changes on Wednesday/Thursday (i.e., AQI changes less than one standard deviation). Panel A1 tabulates the level of AQI for the treatment and control groups before and after the treatment effect. Panel A2 presents the results of the following multivariate specification:

$$Disp_{j,t} = \rho_0 + \rho_1 \times Treated_{j,t} + \rho_2 \times Treated_{j,t} \times After_{j,t} + \rho_3 \times After_{j,t} + \rho_4 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t},$$

where $Disp_{j,t}$ is the disposition effect of all investors in city j on day t, $Treated_{j,t}$ is a dummy variable that takes a value of one if city j on day t is in the treatment group, and $After_{j,t}$ is a dummy variable that takes a value of one if day t is in the posttreatment period and zero in the pretreatment period. The vector $X_{j,t}$ contains region-level control variables. In Panel B, we identify the treatment group as cities that have experienced (1) air pollution at the beginning of a week, as in Panel A and (2) the treatment event of strong wind on Wednesday or Thursday (wind speed > 5 m/s). The control group is identified similar to that above. We then apply the same multivariate specification to these two samples of city-level observations. Finally, in Panel C, we identify the treatment group as cities that have experienced 1) no air pollution at the beginning of a week (i.e., AQI < 100) and 2) the treatment event of strong wind on Wednesday or Thursday (wind speed > 5 m/s), and we apply the same multivariate specification as a placebo test in Panel B. All specifications include city and time-fixed effects, with standard errors clustered at the city level. Robust t-statistics are reported in parentheses and are based on standard errors clustered by city and date. Superscripts of *, **, and *** indicate significance levels.

Panel A: DID test using large drops in AQI as the treatment event

A1: Univariate analysis

		Before event	After event	After-before
AQI	Treated	165.92	84.99	−80.93***
	Control	156.8	153.03	−3.77
	Treated-Control	9.12	−68.04***	−77.16***
				(−24.71)
Disposition	Treated	0.348	0.084	−0.264**
	Control	0.301	0.278	−0.023
	Treated-Control	0.047	−0.194**	−0.241**
				(−2.49)

A2: Multivariate analysis on disposition effect and investor composition

	(1)	(2)	(3)	(4)
	y = Disposition effect		y = Log(Trading vol)	y = Fraction_HighDisp
Treated*After	−0.234**	−0.234**	−0.051	0.024
	(−2.29)	(−2.29)	(−0.25)	(0.53)
Treated	0.137*	0.136	−0.250	0.056
	(1.69)	(1.65)	(−0.86)	(1.16)
After	0.121	0.121	−0.073	−0.011
	(1.44)	(1.44)	(−0.41)	(−0.30)
Log_GDP	−0.277	−0.366*	−0.309	−0.396*
	(−1.54)	(−1.83)	(−0.33)	(−1.67)
Log_pop	0.025	−0.015	0.276	0.481*
	(0.26)	(−0.14)	(0.30)	(1.71)
Log_num_domestic_firm		0.071	−0.046	−0.097*
		(1.17)	(−0.20)	(−1.81)
Log_gov_income		0.003	0.448**	0.000
		(0.04)	(2.10)	(0.00)
Constant	4.186	5.278*	8.821	5.158
	(1.56)	(1.67)	(0.64)	(1.52)
Time and city FE	Yes	Yes	Yes	Yes
Observations	2740	2740	2740	2740
R-squared	0.15	0.16	0.58	0.27

(*continued on next page*)

Table 3
(*continued*)

Panel B: DID test using strong wind as the treatment event

y = Disposition effect	(1) Strong wind with pollution	(2)	(3) Placebo tests: strong wind without pollution	(4)
Treated*After	−0.384**	−0.391***	0.011	0.013
	(−2.41)	(−2.85)	(0.15)	(0.17)
Treated	0.245	0.232	−0.006	−0.003
	(1.53)	(1.58)	(−0.09)	(−0.05)
After	0.11	0.113	−0.061	−0.061
	(0.93)	(1.38)	(−1.10)	(−1.10)
Log_GDP	−2.295	−2.097	−0.274	−0.482*
	(−1.29)	(−0.92)	(−1.03)	(−1.92)
Log_pop	0.173	0.206	0.457**	0.183
	(0.18)	(0.21)	(2.28)	(0.90)
Log_num_domestic_firm		0.004		0.333*
		(0.02)		(1.82)
Log_gov_income		−0.288**		0.200
		(−2.40)		(1.36)
Constant	34.579	35.009	2.551	2.562
	(1.45)	(1.09)	(0.70)	(0.79)
Time and city FE	Yes	Yes	Yes	Yes
Observations	1522	1522	13,284	13,284
R-squared	0.17	0.18	0.07	0.07

tude is smaller than in previous tests. This reduction in economic magnitude is reasonable because the DID test is intended to identify the very short term, if not immediate, influence of air pollution on trading behavior. Overall, however, these results clearly demonstrate that investors in treated cities exhibit significantly less disposition effects once air pollution has been reduced.

To shed more light on this result, Models (3) and (4) are used to further analyze the influence of AQI drops on trading volume and the fraction of investors who exhibit a stronger disposition effect in their previous trading histories (i.e., their individual-account-level disposition effect is above median when measured six months prior to the treatment event—using different thresholds, such as the top quartile, does not change our results). Both variables are not affected by AQI drops. The insignificant trading volume suggesting that the influence of air pollution on the disposition effect is not contaminated by investors' willingness or reluctance to trade.[14]

To interpret the result with regard to high-disposition investors, recall that in general, the city-level disposition effect can be influenced by air pollution in two ways: air pollution can either induce existing investors to exhibit greater bias and thus stronger disposition effect (which creates an average effect at the intensive margin) or induce more biased investors to participate in trading (which changes the composition of investors at the extensive margin). Because these two effects manifest two potential causal influences of air pollution, it will be helpful to further differentiate the two. Model (4) achieves this goal: to the extent that the participation ratio of more biased investors does not change during the treatment event, the first effect dominates in our tests.

Next, in the second version of the DID test, we identify cities with high AQI at the beginning of a week as before but use strong wind (of more than five meters/second in speed) on Wednesday and Thursday as the treatment event to identify the impact of reduced air pollution. In other words, we replace large AQI drops with strong wind in Eq. (3) and keep other conditions unchanged. To save space, we omit the univariate results (they are very similar to those in Panel A1) and directly report the multivariate results in Models (1) and (2) of Panel B (in a similar layout as the first two columns in Panel A2). We first notice that the number of observations decreases in this DID test. This reduction is reasonable because not all large AQI drops are caused by strong wind (although strong wind typically reduces AQI dramatically). The main results of the DID test, however, remain unchanged: investors in the treatment group start to exhibit significantly lower levels of the disposition effect once strong wind starts to blow away air pollution. Unreported tests further confirm that trading volume and the composition of investors do not change during the treatment event.

Could it be, however, that strong wind itself, not air pollution, affects the disposition effect? To differentiate the effect of wind from that of wind-induced AQI changes, we design a placebo test in which both treatment and control cities have no air pollution at the beginning of a week. Then, similar to the second version of the DID test, strong wind starts to blow in mid-week, separating treatment cities from control cities. The results are reported in Models (3) and (4) of Panel B. We find that wind alone does not affect the disposition effect. Jointly, this panel suggests that it is AQI and its changes introduced by strong

[14] Meyer and Pagel (2016) found that air pollution has a significantly negative effect on the willingness of individual investors in Germany to sit down, log in, and trade using their brokerage accounts. Severe air pollution in China, however, could induce retail investors to spend more time indoors, offsetting their reluctance to trade. Using stock accounts in China, Huang et al. (2017) also found little evidence that air pollution significantly affects trading volume.

wind—but not wind itself or related meteorological conditions—that affect the disposition effect.

Table 4 presents additional robustness checks and analyses. We first assess the robustness of our results by adopting a different identification approach: the instrumental variable approach. The intuition is that, to the extent that strong winds can exogenously dissipate air pollution, we can also treat strong winds as an instrument to introduce exogenous variations into our main independent variable of air pollution. This idea can be specifically examined in the following two-stage specification:

$$\text{1st stage}: \ AQI_{j,t} = b_1 \times D(Strong\ wind)_{j,t} + b_2 \times X_{j,t} + \eta_{j,t}, \quad (4)$$

$$\text{2nd stage}: \ Disp_{j,t} = \alpha + \beta \times \widehat{AQI}_{j,t} + C \times X_{j,t} + \varepsilon_{j,t}, \quad (5)$$

where $D(Strong\ wind)_{j,t}$ is the dummy variable that takes the value of one if a strong wind occurs in city j on day t, $\widehat{AQI}_{j,t}$ is the projected value of ln(AQI) based on the first stage regression, and other specifications are the same as in Eq. (1).

The results are reported in Panel A of Table 4. Models (1) and (3) report the results of the first stage regression, whereas Models (2) and (4) tabulate those of the second stage analysis. We can see that, consistent with the previous DID test, strong winds lead to significant reductions in air pollution in the first stage. In other words, although there might be other meteorological effects that also influence air pollution (e.g., those related to wind directions), strong winds suffice to provide a reasonable instrument to introduce exogenous shocks into air pollution as a first order effect. Importantly, instrumented AQI in the second stage significantly reduces the disposition effect. This result lends further support that air pollution can causally influence investors' bias in their trading.

Next, Panels B1 and B2 provide robustness checks for the two versions of the DID test. In the first version reported in the previous table, we have required the treatment group to have drastic AQI drops of more than two standard deviations of the AQI sample distribution. In Panel B1 of this table, we first increase this threshold to three standard deviations. We then require that treatment cities have high AQI values (above 180). Next, we exclude the event date (Wednesday or Thursday) in computing the post treatment disposition effect. Finally, we relax the control group to allow the AQI difference between the treatment and control groups to be smaller than 50 at the beginning of the week (the threshold is 30 in our main tests). In all these alternative specifications, reported in Models (1)–(4), our results remain robust. In Panel B2, we introduce similar changes, except that in Model (1), we alter the required wind speed (now 7 m/s). In all these tests, our main conclusion remains valid.

Panel C further complements the above test by focusing on the influence of AQI changes with the opposite sign. Models (1) and (2) present DID tests in which AQI starts at a low level at the beginning of the week and then suddenly increases in treatment cities but not in control cities. Consistent with the first version of the DID test in Table 3, we can see that the disposition effect is significantly enhanced when air pollution is drastically increased in treated cities. Models (3) and (4) provide further tests in the spirit of the second version of our main DID test, replacing drastic AQI increases with low wind speed in mid-week among the increasing sample. We see that the disposition effect again increases among investors in treated cities. Although increases in AQI could be less exogenous than large reductions because the formation of air pollution could be introduced by economic activities such as heating and mining, the economic intuition of this table is consistent with that of the previous DID tests. Interestingly, all our results suggest that the influence could be observable over a very short time horizon—i.e., at a daily frequency.

4.2. RD tests based on the Huai River policy

We now examine the quasi-experiment of the "Huai-River policy," as reported in Almond et al. (2009), Chen et al. (2013), and Ebenstein et al. (2017). As noted, the Huai River splits China into northern and southern parts, and China's central government provides free winter heating of homes and offices as a basic right for and only for the urban regions north of the Huai River, typically between November 15 and March 15 each year. Because winter heating operates via the provision and burning of free coal for boilers, which release air pollutants (they especially increase total suspended particulates, or TSP, in the air) because of technical inefficiency, this policy has unintentionally worsened air quality in cities located north of the river (Almond et al., 2009), creating a discontinuity in terms of AQI for cities located on the two sides of the river (i.e., "across" the river). This discontinuity allows Chen et al. (2013) to use RD to identify the plausible causal influence of air pollution on life expectancy. We adopt the same methodology to determine the influence of AQI on the disposition effect.

Following Chen et al. (2013), we first investigate whether the Huai River policy can lead to a discontinuous change in AQI and investor behavioral bias using the following specifications:

$$AQI_{j,t}\ or\ Disp_{j,t} = \beta_0 + \beta_1 \times D(North)_j + f\left(R_j\right) + \beta_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}, \quad (6)$$

where $AQI_{j,t}$ and $Disp_{j,t}$ refer to the AQI index and the disposition effect, respectively, for all investors in city j in year t (i.e., the average daily AQI during the year—we adopt this testing frequency following Chen et al., 2013); $D(North)_j$ is an indicator variable that takes a value of one if city j is located north of the Huai River line and zero otherwise; R_j represents the degree of the northern latitude of city j relative to that of the Huai River line; $f(R_j)$ is parameterized as a k-order polynomial function of R_j on either side of the Huai River line; and the vector $X_{j,t}$ contains a set of time-varying region-level control variables, as described above. We also include year-fixed effects, δ_t, to address the possibility that the results are driven by particular years. There are two technical points to note with respect to the function $f(R_j)$. First, in our main results, k equals one or two (i.e., linear and quadratic) because Gelman and Imbens (2018) demonstrate that causal effects

Table 4
Additional analysis related to the DID test.
This table provides various robustness checks of tests related to drastic AQI drops. Panel A examines an alternative specification in which strong wind is used as an instrument to proxy for exogenous variations of AQI. More specifically, we estimate the following specifications: 1st stage : $AQI_{j,t} = b_1 \times D(Strong\ Wind)_{j,t} + b_2 \times X_{j,t} + \eta_{j,t}$, and 2nd stage: $Disp_{j,t} = \alpha + \beta \times \widehat{AQI}_{j,t} + C \times X_{j,t} + \varepsilon_{j,t}$, where $D(Strong\ Wind)_{j,t}$ is a dummy variable that takes the value of one if a strong wind as defined in Table 3 occurs in for city j on day t, and $\widehat{AQI}_{j,t}$ is the projected value of ln(AQI) based on the first stage regression. Other specifications are the same as in Model (2) from Panel B in Table 2. Next, Panel B1 includes similar robustness checks that apply the following new thresholds to the first version of the DID test (i.e., as seen in Panel A of Table 3): (1) the treatment group is identified based on drastic AQI drops of more than three standard deviations (instead of two standard deviations); (2) pretreatment AQI is required to be higher than 180 (instead of 100); (3) information about the treatment event day—i.e., the date when drastic AQI drops occur—in computing the posttreatment disposition effect is excluded (instead of including the event-day disposition effect); and (4) a maximum of 50 for the AQI gap between the control group and the treatment group is allowed in the first period of the week when we identify the control group (instead of capping the difference at 30). Panel B2 includes similar robustness checks when we apply these new thresholds to the second version of the DID test (i.e., as we have seen in Panel B of Table 3), except for Model (1) in which we require strong wind to have a speed of more than 7 m/s (instead of more than 5 m/s). Panel C explores the reverse scenario of Table 3, with AQI mild at the beginning of the week and then increasing drastically in general or due to a lack of wind in particular (i.e., weak wind). To conduct a test of such treatment events, we first identify the treatment group by focusing on cities that have experienced (1) little or mild air pollution at the beginning of a week (i.e., AQI < 150 on Monday and Tuesday) and (2) a treatment event of drastic AQI increases (i.e., larger than two standard deviations) or weak wind (wind speed < 2 m/s among the AQI increases sample) on Wednesday or Thursday. For each city in the treatment group, we identify as a control group cities that (1) have a similar degree of pollution at the beginning of a week (i.e., an AQI difference smaller than 30) and (2) do not experience abrupt AQI changes on Wednesday/Thursday (i.e., AQI changes less than one standard deviation). Robust t-statistics are reported in parentheses and are based on standard errors clustered by city and date. Superscripts of *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Alternative specifications (strong wind as an instrument)

	(1) 1st-stage *Log(AQI)*	(2) 2nd-stage *Disposition*	(3) 1st-stage *Log(AQI)*	(4) 2nd-stage *Disposition*
D(Strong wind)	−0.128***		−0.128***	
	(−56.93)		(−56.88)	
Log_AQI_Hat		0.094**		0.097**
		(2.08)		(2.13)
Log_GDP			−0.051***	0.070***
			(−4.79)	(2.81)
Log_pop			0.055***	−0.039*
			(6.03)	(−1.68)
Log_num_domestic_firm			0.042***	−0.027*
			(7.46)	(−1.82)
Log_gov_income			−0.044***	−0.018
			(−7.07)	(−1.23)
Sunshine			0.000	−0.000
			(0.49)	(−0.89)
Constant	4.486***	−0.604***	5.361***	−1.124***
	(341.54)	(−2.93)	(36.12)	(−2.60)
Fixed effects	City, day of the week, month of the year, and year fixed effets; S.E. clustered by city-day			
Observations	144,238	144,238	144,238	144,238
R-squared	0.27	0.02	0.27	0.02

Panel B1: Robustness checks of the DID test (abrupt drops in AQI)

	(1) Change in AQI,3sd	(2) AQI(−1)>=180	(3) Excluding event day	(4) Pre-event AQI Diff<50
Treated*After	−0.582***	−0.481***	−0.248**	−0.256**
	(−2.69)	(−2.74)	(−2.57)	(−2.58)
Treated	0.185	0.187	0.239***	0.140*
	(0.95)	(1.60)	(2.82)	(1.68)
After	0.248*	0.314**	0.071	0.140*
	(1.74)	(2.05)	(1.01)	(1.70)
Log_GDP	1.154	0.197	−0.775***	−0.445**
	(1.10)	(0.39)	(−2.84)	(−2.11)
Log_pop	−0.113	0.095	0.036	0.066
	(−0.10)	(0.13)	(0.24)	(0.84)
Log_num_domestic_firm	0.251	−0.592	0.126	0.071
	(0.30)	(−1.20)	(1.60)	(1.34)
Log_gov_income	−3.130**	−0.875***	−0.173	0.001
	(−2.01)	(−2.65)	(−1.14)	(0.01)
Constant	21.243**	10.925	13.247***	6.112**
	(2.42)	(1.46)	(3.18)	(1.98)
Time and city FE	Yes	Yes	Yes	Yes
Observations	879	1233	2221	3160
R-squared	0.20	0.17	0.17	0.14

(*continued on next page*)

Table 4
(*continued*)

Panel B2: Robustness checks of the DID test (strong wind)

	Wind > =7 m/s	AQI(−1)> = 180	Excluding event day	Pre-event AQI Diff < 50
Treated*After	−0.505***	−0.360***	−0.357**	−0.385***
	(−3.49)	(−2.72)	(−2.31)	(−3.88)
Treated	0.253	0.183	0.285**	0.261***
	(1.11)	(0.76)	(2.07)	(2.86)
After	0.272**	0.136*	0.067	0.193***
	(2.56)	(1.82)	(0.81)	(2.89)
Log_GDP	−0.534	−0.318	−1.473	−1.422
	(−0.65)	(−0.15)	(−0.52)	(−1.20)
Log_pop	0.717	1.232	−0.149	0.570
	(1.54)	(0.51)	(−0.13)	(1.03)
Log_num_domestic_firm	0.173	−2.445	0.054	−0.368
	(0.60)	(−1.45)	(0.23)	(−1.28)
Log_gov_income	−0.172*	−0.119	−0.318**	−0.192**
	(−1.93)	(−0.73)	(−2.28)	(−2.06)
Constant	5.497	14.555	27.125	23.857
	(0.46)	(0.79)	(0.68)	(1.32)
Time and city FE	Yes	Yes	Yes	Yes
Observations	1018	762	1241	2492
R-squared	0.20	0.41	0.21	0.16

Panel C: DID test for the reverse case of AQI increases

	Abrupt increases in AQI as the treatment event		Weak wind as the treatment event	
Treated*After	0.231***	0.227***	0.245**	0.243**
	(2.83)	(2.81)	(2.54)	(2.53)
Treated	−0.082	−0.095	−0.011	−0.019
	(−1.12)	(−1.29)	(−0.09)	(−0.16)
After	−0.057	−0.055	−0.049	−0.047
	(−0.87)	(−0.83)	(−0.71)	(−0.69)
Log_GDP	−0.048	0.119	−0.119	−0.074
	(−0.26)	(0.67)	(−0.67)	(−0.38)
Log_pop	−0.045	0.021	0.085	0.155
	(−0.28)	(0.14)	(0.46)	(0.88)
Log_num_domestic_firm		−0.237***		−0.077**
		(−3.41)		(−2.00)
Log_gov_income		0.125**		−0.066
		(2.18)		(−0.55)
Constant	0.450	−2.702	0.807	1.046
	(0.18)	(−1.06)	(0.36)	(0.36)
Time and city FE	Yes	Yes	Yes	Yes
Observations	3683	3683	1858	1858
R-squared	0.13	0.13	0.21	0.21

based on higher polynomials can be misleading and recommend the use of local linear or quadratic polynomials. Second, we require that $|R_j| < 10°$ in our main test and provide robustness checks at this threshold in later sections.[15] Our results are robust to these technical issues.

The main results of this system of equations are tabulated in Table 5, Panel A for a linear specification, and Panel B, for a quadratic specification. In each panel, Models (1) and (2) report the results of Eq. (6) with different control variables for AQI, and Models (3) and (4) tabulate the results for the disposition effect. We can first observe from Models (1) and (2) that in both specifications, the Huai River policy has created a discontinuity in air pollution, as documented in the literature. More importantly for our analysis, Models (3) and (4) suggest that investors' trading behavior also exhibits an interesting jump across the river. In terms of magnitude, the disposition effect increases approximately 0.205–0.189 (Models 3 and 4) in moving across the Huai River, depending on the empirical specification. Compared to the mean and standard deviation (0.198 and 1.535, respectively) of the disposition effect in our sample, the magnitude of the "jump" is quite sizable (e.g., it is almost on a par with the sample mean of the disposition effect and is approximately 13% of a standard deviation). This effect is therefore highly significant both statistically and economically.

This discontinuity in the disposition effect is illustrated in a more intuitive way in Fig. 3. In this figure, Panels A

[15] This bandwidth restriction (i.e., the range of $|R_j|$) indicates that we only include cities located within 10° of latitude (both to the north and the south) of the Huai River line. In general, larger bandwidth allows more cities to be included in the sample, although cities located farther from the Huai River might be less influenced by the river. For the main body of the RD analysis, we choose a bandwidth of ten degrees (approximately 1000 km) around the Huai River line, which we believe is sufficient broad for our sample. As later robustness checks will show, our main results are qualitatively the same when narrower bandwidths are used.

Table 5
RD test based on the Huai River policy.
This table presents the results of the following test to examine the influence of the Huai River policy:.

$$AQI_{j,t} = \beta_0 + \beta_1 \times D(North)_j + f\left(R_j\right) + \beta_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}.$$

$$Trading\ bias_{j,t} = \theta_0 + \theta_1 \times D(North)_j + f\left(R_j\right) + \theta_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}.$$

where $AQI_{j,t}$ and $Trading\ bias_{j,t}$ measure the degree of air pollution and the disposition effect for city j in year t, $D(North)_j$ is an indicator variable equal to one if city j is located north of the Huai River (augmented by the Quinling Mountains), R_j represents the degree of northern latitude of city j relative to that of the Huai River, $f(R_j)$ is parameterized as a k-order polynomial function of R_j on either side of the Huai River, and vector $X_{j,t}$ contains a set of time-varying region-level control variables. Appendix A provides detailed definitions of all variables. Panels A and B present the results when $f(R_j)$ is estimated as a linear ($k = 1$) and quadratic function ($k = 2$), respectively. We further require $|R_j| < 10°$ in our main test. All specifications include year-fixed effects, with standard errors clustered at the city level. The testing period is from 2007 to 2015. Robust t-statistics are reported in parentheses and are based on standard errors clustered by city and year. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Linear specification

	(1)	(2)	(3)	(4)
	AQI		Disposition effect	
D(North)	8.845**	8.628***	0.205***	0.189***
	(2.58)	(3.08)	(2.86)	(3.79)
Degree north	0.349	0.214	−0.004	−0.002
	(0.89)	(1.12)	(−1.15)	(−0.40)
Log_GDP		−3.684*		−0.046
		(−1.69)		(−0.95)
Log_pop		14.602***		0.037*
		(3.13)		(1.74)
Log_num_domestic_firm		−3.267		0.030
		(−1.56)		(0.72)
Log_gov_income		−0.093		−0.030
		(−0.06)		(−0.46)
Constant	69.784***	74.399***	0.157***	0.909
	(44.05)	(3.07)	(5.06)	(1.46)
Year fixed effect	Yes	Yes	Yes	Yes
No. of obs	709	709	709	709
R-squared	0.26	0.30	0.04	0.05

Panel B: Quadratic specification

	(1)	(2)	(3)	(4)
	AQI		Disposition effect	
D(North)	10.741***	9.814***	0.207***	0.188***
	(2.83)	(3.40)	(3.01)	(4.07)
Degree north	0.010	−0.049	−0.005	−0.002
	(0.02)	(−0.22)	(−1.26)	(−0.34)
Degree north squared	−0.187***	−0.163***	0.000	0.000
	(−4.56)	(−5.75)	(−0.38)	(0.20)
Log_GDP		−1.498		−0.048
		(−0.56)		(−0.97)
Log_pop		12.148***		0.040
		(2.79)		(1.30)
Log_num_domestic_firm		−4.184*		0.031
		(−1.87)		(0.68)
Log_gov_income		0.057		−0.030
		(0.04)		(−0.46)
Constant	73.714***	59.880*	0.160***	0.921
	(91.10)	(1.95)	(4.32)	(1.38)
Year fixed effect	Yes	Yes	Yes	Yes
No. of obs	709	709	709	709
R-squared	0.29	0.32	0.04	0.05

and B graphically illustrate the general trend of the disposition effect based on linear and quadratic specifications, respectively. The x-axis indicates a city's degree of latitude with respect to the Huai River, whereas the y-axis plots the disposition effect. Both graphs clearly demonstrate that the disposition effect jumps across the Huai River. The economic magnitude of the jump is highly visible, especially compared to the average disposition effect to the south (left) of the river.

Next, because the potential cognitive bias of urban investors is unlikely to drastically change across a river except through the influence of a jump in air pollution, we can further rely on a two-stage least-square specification to estimate the effect of AQI on investors' disposition

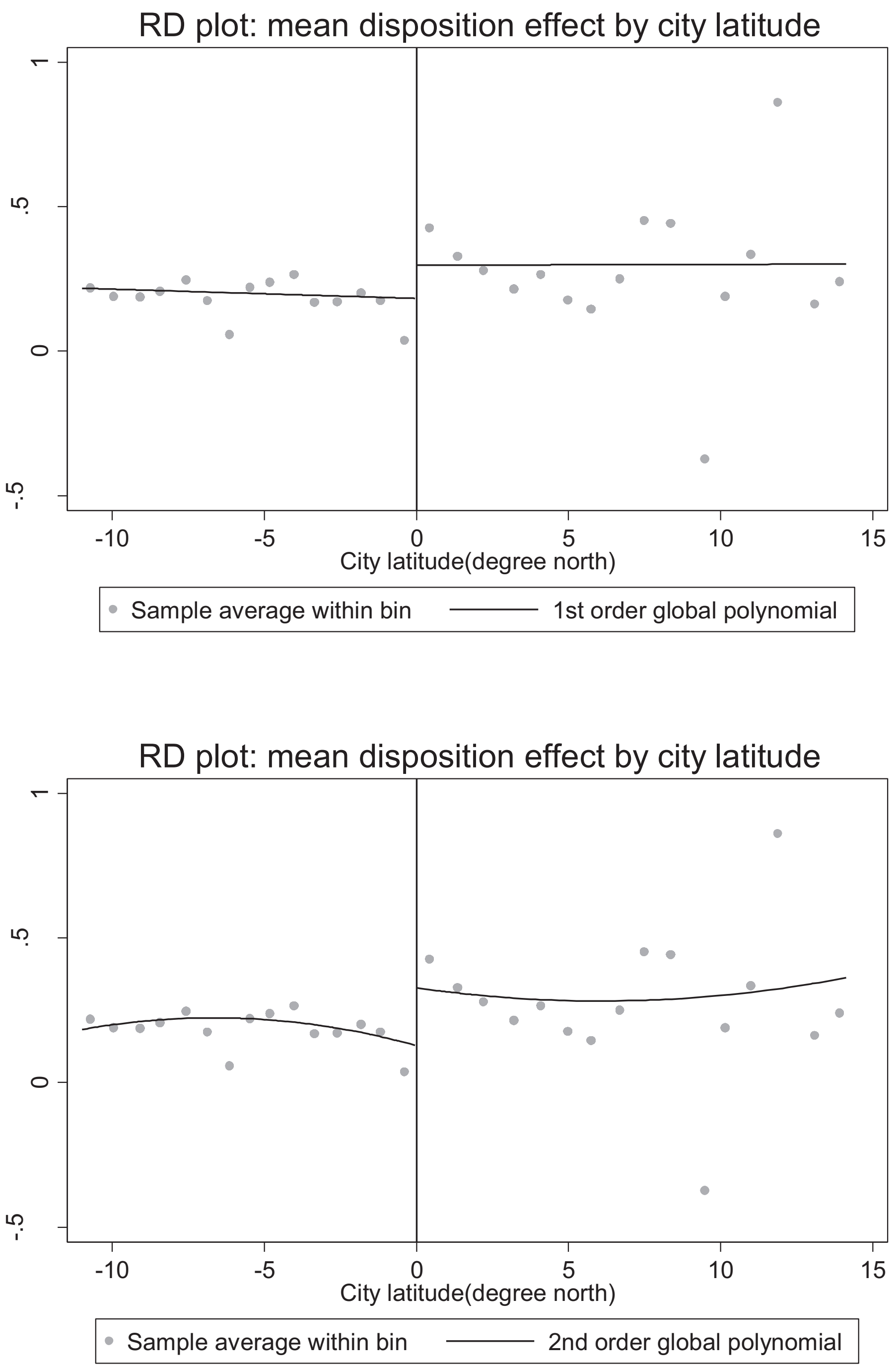

Fig. 3. Disposition effect across Huai River. The figure plots trading bias aggregated at the city level against degrees north of the Huai River line, which is drawn at 33.6° (the middle of the latitude range covered by the Huai River). Each dot represents the average over each bin, and the number of bins is selected based on the mimicking variance evenly spaced method, using spacing estimators (Calonico et al., 2015).

effect. The first stage is the same as Eq. (6) with AQI as its dependent variable. In the second stage, we regress the disposition effect on Huai River policy instrumented air pollution as follows:

$$Disp_{j,t} = \gamma_0 + \gamma_1 \times \widehat{AQI_{j,t}} + f\left(R_j\right) + \gamma_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}, \quad (7)$$

where $\widehat{AQI_{j,t}}$ refers to the fitted value from estimating Eq. (6), R_j represents the degree of northern latitude of city j relative to that of the Huai River, and $f(R_j)$ is parameterized as a k-order polynomial of R_j on either side of the Huai River line, as above. Other variables are similar to those in previous equations.

Table 6
The impact of AQI on two-stage least square RD estimations.
This table provides results of a two-stage least-square specification used to estimate the effect of AQI on investors' trading bias in the period from 2007 to 2015. The first stage is reported in Model (2) of Table 3. In the second stage, we estimate the following specification: $Disp_{j,t} = \gamma_0 + \gamma_1 \times \widehat{AQI_{j,t}} + f(R_j) + \gamma_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}$, where $Disp_{j,t}$ refers to the disposition effect of all investors in city j in year t, $\widehat{AQI_{j,t}}$ is the fitted value of AQI from the first-stage estimation, $D(North)_j$ is an indicator variable that takes a value of one if city j is located north of the Huai River line and zero otherwise, R_j represents the degree of northern latitude of city j relative to that of the Huai River, $f(R_j)$ is parameterized as a k-order polynomial function of R_j on either side of the Huai River (linear in Models 1 and 2 and quadratic in Models 3 and 4), and vector $X_{j,t}$ contains a set of time-varying region-level control variables. Appendix A provides detailed definitions of all variables. All specifications include year-fixed effects, with standard errors clustered at the city level. Panel A presents the results of the second-stage estimations. Panel B further splits each year into heating and nonheating seasons and reports the results of the above estimation in these two subperiods. All Cragg-Donald Wald F-statistics exceed the Stock-Yogo weak instrument thresholds. Robust t-statistics are reported in parentheses and are based on standard errors clustered by city and year. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Disposition effect regressed on instrumented AQI (full sample analysis)

	(1)	(2)	(3)	(4)
	Linear specification		Quadratic specification	
AQI_hat	0.024**	0.022**	0.020***	0.019**
	(2.54)	(2.08)	(2.70)	(2.17)
Degree north	−0.013	−0.007	−0.005	−0.001
	(−0.72)	(−0.94)	(−0.52)	(−0.18)
Degree north squared			0.003**	0.003**
			(2.04)	(2.22)
Log_GDP		0.036		−0.017
		(0.46)		(−0.22)
Log_pop		−0.280***		−0.191***
		(−3.17)		(−3.29)
Log_num_domestic_firm		0.101*		0.111*
		(1.80)		(1.70)
Log_gov_income		−0.032		−0.035
		(−0.43)		(−0.50)
Constant	−1.499	−0.707	−1.283	−0.217
	(−1.31)	(−0.64)	(−1.44)	(−0.21)
Year fixed effect	Yes	Yes	Yes	Yes
No. of obs	709	709	709	709

Panel B: Disposition effect regressed on instrumented AQI in heating vs nonheating seasons

	Heating season	Nonheating season	Heating season	Nonheating season
	Linear specification		Quadratic specification	
AQI_hat	0.065**	0.015	0.053***	0.010
	(2.32)	(0.75)	(2.80)	(0.83)
Degree north	−0.031**	−0.011	−0.009	−0.004
	(−2.32)	(−0.81)	(−0.98)	(−0.95)
Degree north squared			0.009***	0.001
			(3.22)	(0.73)
Log_GDP	0.243	−0.021	0.049	−0.055***
	(0.88)	(−0.46)	(0.22)	(−4.05)
Log_pop	−1.097**	−0.129	−0.749***	−0.053
	(−2.36)	(−0.69)	(−2.60)	(−0.62)
Log_num_domestic_firm	0.223*	0.092	0.234**	0.085
	(1.67)	(0.91)	(2.19)	(0.90)
Log_gov_income	0.071	−0.044	0.060	−0.045
	(0.60)	(−0.55)	(0.58)	(−0.58)
Constant	−4.918	0.186	−2.947	0.698*
	(−1.31)	(0.19)	(−1.05)	(1.88)
Year fixed effect	Yes	Yes	Yes	Yes
No. of obs	709	709	709	709
P-value of F-test				
Heating vs. nonheating	0.0274		0.0120	

The results are reported in Panel A of Table 6, with Models (1) and (2) providing a linear specification of $f(R_j)$ and Models (3) and (4) providing a quadratic specification. We can see that instrumented air pollution positively affects the disposition effect. This effect is highly significant across all specifications, lending strong support to a causal interpretation of the general relation between air pollution and the behavioral bias of investors. To interpret the economic magnitude of this test, we first recall from Table 5 that the Huai River discontinuity is associated with an increase in AQI of approximately 8.63 (e.g., Model 2). If we treat this as the magnitude of instrumented air pollution, then its influence on the disposition effect can be computed as 8.63 $\times$ 0.022 = 0.19, where 0.022 is the regression parameter. This economic magnitude is on par with what we observed in Table 5.

To further validate the economic interpretation of the Huai River policy—i.e., that air pollution is caused by coal burning in the heating season—we conduct subperiod tests to examine the above relation in heating and nonheating seasons. The results are reported in Panel B. Interestingly, whereas Models (1) and (3) show that the influence of instrumented air pollution is highly significant in heating seasons, Models (2) and (4) suggest that the influence becomes insignificant in nonheating seasons. The difference between heating and nonheating seasons is revealing. It alleviates concerns about omitted variables because any time-invariant city-level characteristics should affect potential cognitive biases in both seasons. Moreover, it also reveals that the influence of air pollution on behavioral bias could be on the spot; i.e., the influence occurs when AQI is high in heating seasons and dissipates when pollution diminishes in nonheating seasons.

In addition to the above tests, we have conducted various robustness checks and additional analyses. To save space, we tabulate the results in Table IN3 of the Internet Appendix and mention only the main findings here. In the first set of tests, we further assess the testing power of the Huai River policy by conducting a placebo test in which we apply the same RD and two-stage tests to two artificial lines that are five degrees north and five degrees south of the geographic location of the Huai River. Intuitively, the RD test should not yield any significant results because the heating policy applies to the actual river, not these two artificial lines. Consistent with this intuition, we do not find any significant changes across these lines, suggesting that our tests have sufficient power to reject the nonexistent influences of air pollution.

Next, we verify that our results are robust to different bandwidths of the RD test (6° and 8°), further controlling for sunshine, further excluding important political event dates or tier-one cities, and applying the test to a special group of investors who migrate from the southern part of China and trade on both the southern and northern sides of the Huai River. Among these tests, the exclusion of tier-one cities could be especially helpful for the RD test because it might be arguably more difficult to balance the influence of these large cities across the Huai River.

The test of migrant investors is also revealing: even within the subsample of investors whose birth regions are relatively homogeneous, residence north of the Huai River still predicts a greater disposition effect, suggesting that the issue of air pollution is not attenuated by having similar cultural roots, as characterized by investors' birth regions, or by selection/matching issues, in which investors self-select cities with appropriate levels of pollution (e.g., investors use migration as an opportunity to minimize the potential adverse influence of air pollution on them). In particular, self-selection is not a concern because, empirically, investors migrating to the northern part of China do not appear to be less influenced by AQI in terms of the disposition effect. Moreover, unreported tests show that long-term residence (for the person whose birth city is his or her current residence city) exhibits similar exposure to air pollution. A later section provides more tests showing this similarity. Together, air pollution significantly influences the current residence of a city, regardless of a person's past location.

Finally, when we apply the RD test to trading volume and the fraction of selling orders, we do not find any differences between the two sides of the river. Unreported tests further show that consistent with the literature (Almond et al., 2009; Chen et al., 2013; Ebenstein et al., 2017), city-level variables such as GDP do not significantly differ on the two sides of the river. These findings are important in completing the picture, as they suggest that the observed higher disposition effect in high-polluting regions is neither correlated with investors' general trading frequency nor attributable to fundamentals of the cities (other than pollution).

5. Additional analysis

In this section, we extend our analysis to investor characteristics, particular matter, and account-level trading to uncover more insights into the influence of air pollution on investor behavior.

5.1. Investor characteristics

As a second extension, Table 7 explores how investors' characteristics can affect—i.e., exaggerate or mitigate—the influence of air pollution on the disposition effect. In particular, we interact AQI with various investor characteristics at the city level, including the average age of investors in a city, the fraction of female investors in a city, the average education level and trading experience (in years) of investors in a city, and the fraction of migrant investors in a city. We find that the influence of AQI is smaller when investors are older, proportionately more male, better educated, and have more trading experience.

The first observation is in general consistent with the health science observation on the influence of air pollution across ages as summarized in Weir (2012). More explicitly, air pollution often exerts a U-shaped influence on the neural systems of people at different ages. Drawing on a sample of emergency visits for air pollution-induced depression among different age groups of the Korean population, for instance, Cho et al. (2014) show that small particulate matter (PM10 in their study) is likely to induce the highest likelihood of depression for people in the age group 19–39. The likelihood declines for the age group 40–64 and increases again for the people aged 65 and above (but the effect in people aged 65 and above is lower than the effect for the 19–29 age group). Since most investors in our sample are between 22 and 64 years old (they present the 5%–95% quantile values of the age distribution), it is perhaps not surprising to see that the air pollution-induced disposition effect is more prominent among younger investors in our sample with its truncated age distribution.[16]

[16] It is often found that air pollution may have an even larger influence for children (e.g., Weir, 2012; Cho et al., 2014). We cannot directly test this implication, as the investors in our sample are mostly adults.

Table 7
The impact of haze and investor characteristics: heterogeneity test.
This table explores how investors' characteristics affect the influence of air pollution on cognitive bias. In particular, we expand the baseline specification in Model 4 of Table 2 to interact AQI with a list of variables that capture the characteristics of investors in each city. *Old_High* is a dummy variable that equals one if the ratio of investors older than 40 in a city is above the median value of the ratio in the cross-section. *Female_High* is a dummy variable equal to one if the ratio of female investors in a city is higher than the median value. *Migrant_High* is a dummy variable equal to one if the ratio of migrant investors in a city is higher than the median value. *Education_High* is a dummy variable equal to one if the ratio of more educated investors in a city (based on city census data) is higher than the median of the distribution. Following Korniotis and Kumar (2011), we classify new and experienced investors based on the number of months between the account opening date and the trading date, and we construct a dummy variable, *Experience_High*, equal to one if the ratio of experienced investors in a city is higher than the median of the distribution. *D(PM2.5/10)* is a dummy variable if the primary pollutant is PM2.5 or PM10 (more likely to penetrate into indoor environments) on day t in city i. Robust t-statistics are reported in parentheses and are based on standard errors clustered by city and date. Superscripts of *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log_AQI	0.063***	0.059***	0.024**	0.024**	0.038**	0.038**	0.080***	0.081***	0.059***	0.058***	0.029***	0.028***
	(3.77)	(3.52)	(2.49)	(2.44)	(2.40)	(2.41)	(4.28)	(4.27)	(4.24)	(4.15)	(2.90)	(2.84)
Log_AQI*Old_High	−0.041**	−0.035*										
	(−2.08)	(−1.79)										
Log_AQI* Female_High			0.067**	0.067**								
			(2.42)	(2.41)								
Log_AQI*Migrant_High					−0.006	−0.007						
					(−0.15)	(−0.17)						
Log_AQI* Education_High							−0.060***	−0.061***				
							(−2.81)	(−2.85)				
Log_AQI*Experience_High									−0.051***	−0.050***		
									(−2.93)	(−2.84)		
Log_AQI*D(PM2.5/10)											0.010***	0.010***
											(3.13)	(3.12)
D(PM2.5/10)											0.031**	0.032**
											(1.97)	(2.02)
Log_GDP		−0.065*		−0.064		−0.067		−0.067*		−0.065*		−0.070*
		(−1.68)		(−1.64)		(−1.20)		(−1.72)		(−1.66)		(−1.78)
Log_pop		0.032		0.031		0.033		0.033		0.033		0.037
		(1.00)		(0.96)		(1.19)		(1.04)		(1.03)		(1.16)
Log_num_domestic_firm		0.035		0.037*		0.035		0.035		0.035		0.034
		(1.56)		(1.67)		(0.70)		(1.57)		(1.57)		(1.55)
Log_gov_income		0.034		0.034		0.035		0.035*		0.033		0.033
		(1.59)		(1.63)		(1.09)		(1.68)		(1.57)		(1.59)
Sunshine		0.000		0.000		0.000		0.000		0.000		0.000
		(0.96)		(0.94)		(1.04)		(0.96)		(0.95)		(1.02)
Constant	0.154***	0.367	0.150***	0.327	0.151	0.360	0.152***	0.365	0.154***	0.359	0.188***	0.453
	(3.36)	(0.64)	(3.25)	(0.57)	(1.63)	(0.46)	(3.30)	(0.63)	(3.36)	(0.62)	(4.01)	(0.78)
Fixed effects and clustering	City, day of the week, month of the year, and year fixed effets; S.E. clustered by city-day											
No. of obs	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238
R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

The second observation appears to suggest that air pollution has a stronger influence on female investors than on male investors. We may need to interpret this result with caution, however, because females in different cities may have different participation ratios for economic and cultural reasons. Together, the first two observations suggest that air pollution has heterogeneous effects on different types of investors. The latter two effects suggest that investors more exposed to the disposition effect (i.e., less educated or experienced) are also more vulnerable to the influence of AQI in exaggerating their existing effect.[17] These properties, together with the tests of PSW and PWL, not only help us assess the adverse influence of air pollution but also shed new light on the origin of the disposition effect in the first place.

In contrast, migrant investors (e.g., those who have moved from the southern part of China to the northern part of China) are subject to the effect of AQI as much as local investors are. This result is consistent with the RD test, suggesting that the influence of air pollution is again quite on the spot in the sense that originating from a low-pollution hometown neither reduces nor enhances the influence of air pollution on investor behavior. Note that, if air pollution is an important consideration when investors make migrating decisions, its adverse influence should be mitigated. In other words, compared to the bulk of urban residents who face migrating restrictions or friction (e.g., the "*hukou*" issue), migrant investors should be better allocated to cities with various levels of air pollution so that these investors will, on average, be less adversely influenced by air pollution. Between the RD test and this test, however, we find little evidence supporting this notion. In this regard, migration in China is not yet endogenously driven by pollution-related cognitive vulnerability in our sample.

[17] The age of professional fund managers can be used as a proxy for their investment experience (e.g., Greenwood and Nagel, 2009). Interestingly, we see here that the two characteristics can be positively correlated for retail investors as well.

5.2. Particulate matter

Some components of air pollution, such as small particulate matter (PM2.5 and PM10), are more capable of penetrating into indoor environments than others, such as sulfur dioxide. Therefore, among all of the sources contributing to air pollution, therefore, we should expect particulate matter to have a greater influence on the trading behaviors of investors because the majority of trading is performed indoors.

In our sample period, the MEPC does not report density of PM2.5 and/or PM10 at the city level. However, the MEPC indicates the major components of AQI when it reports the value of AQI, including combined PM2.5 and PM10 as one category. This feature allows us to construct a dummy variable, *D(PM2.5/10)*, which takes the value of one if the MEPC reports that PM2.5 and PM10 are the major components of AQI and zero otherwise. We can then interact this dummy variable with the main independent variable of AQI in our tests. If particulate matter has a greater influence on the trading behavior of investors, then the coefficient for this interaction term should be positive.

The tests are reported in the last two columns of Table 7. We find that the influence of air pollution is indeed significantly enhanced if the source of pollution is particulate matter (PM2.5 and PM10), confirming an especially adverse influence of particulate matter on investor behavior. These findings could have important normative implications for the design of policies to reduce air pollution and its damaging effects.

5.3. Account-level robustness checks

Since air pollution is observed at the city level, our main tests focus on city-level aggregate accounts, allowing us to achieve a balanced sampling distribution between air pollution and investor behavior. However, could the relationship between AQI and the disposition effect be somehow distorted by our aggregation procedure? Although, conceptually, our aggregation procedure-based probability weighting is unlikely to introduce systematic distortions, we construct two account-level tests below to directly address this potential concern.

In the first test, we exploit the time-series information of each individual in defining his or her own PSW and PSL. Without loss of generality, we can define the disposition effect of an individual investor as the difference between the PSW and that of holding onto PSL in a given year, and we link this average behavior to the average condition of air pollution to which the investor is exposed within the same year (the average daily values within one year). Panel A of Table 8 provides such a test, in which we further control for account- and time-fixed effects, as well as a list of city and/or weather variables. Standard errors are further clustered at the account and year levels. The layout of this panel resembles Panel B in Table 2.

We can see that the positive relation between AQI and the disposition effect remains highly significant at the account level. Indeed, both the magnitude of the effect and its statistical significance level slightly increase, potentially due to the larger sample for this test. Moreover, one advantage of this empirical approach is that account- and time-fixed effects are explicitly controlled for. In this case, what drives the positive relation between AQI and the disposition effect is time-varying air pollution and its corresponding time-varying disposition effect, i.e., the intensive margin. This observation further supports the interpretation that air pollution causally influences investor behavior because it is unlikely to be driven by spurious correlations with any time-invariant characteristics of investors.

Next, we explore a different specification focusing on the propensity to sell a fund after its initial purchase by an investor. The literature shows that the probability of selling can be examined in Cox proportional hazards models (e.g., Ivković et al., 2005; Ivković and Weisbenner 2009). We therefore estimate the following Cox proportional hazards model at the account level:

$$h_i(t) = \gamma(t) \times exp\{\beta_1 \times Gain_{i,t-1} + \beta_2 \times Gain_{i,t-1} \times \ln(AQI_t) + \beta_3 \times \ln(AQI_t)\}, \quad (8)$$

where $h_i(t)$ is the hazard function for the sale of the asset for investor *i*, *t* days after the purchase; $\gamma(t)$ is the baseline hazard rate; and $Gain_{i,t-1}$ is a dummy variable that takes the value of one if the underlying asset of investor *i* infers capital gains prior to date *t* (and zero if it indicates capital losses). If investors, on average, exhibit the disposition effect, then the parameter of β_1 should be positive (i.e., investors are more likely to sell upon capital gains than upon capital losses). The influence of air pollution is captured by the coefficient of β_2. If air pollution enhances the disposition effect, as we have seen from other tests, this coefficient should be positive.

Panel B of Table 8 tabulates the results based on the subsample of transactions for which we can unambiguously match the purchase and sale dates. Specifically, we follow Ivković et al. (2005) and Ivković and Weisbenner (2009) to exclude sales preceded by multiple purchases, and we include only the first sale in our sample if a single purchase is followed by multiple sales. Model (1) reports the basic specification in which capital gains/losses are the only determinant in the hazard model. Model (2) further introduces air pollution into the analysis. Since we pool all selling decisions in the cross- section to estimate the hazard function, we also control for quarter-fixed effects to remove potential time-series effects (our conclusions are robust without this additional control). Finally, standard errors are clustered by accounts and selling dates to control for within-cluster dependence.

From the first two models, we can see that investors, on average, exhibit a disposition effect. Including additional regional characteristics as controls does not affect the magnitude of this effect or its statistical significance. We can compare this behavior of Chinese investors to that of US investors estimated in similar models. It is known that US mutual fund investors typically exhibit a reverse disposition effect (e.g., Ivković and Weisbenner 2009; Chang et al., 2016a,b). One noticeable difference between Chinese and US mutual fund investors, however, is that Chinese investors do not pay taxes on capital gains or dividend payouts. Hence, we should expect Chinese investors to behave more like US investors

Table 8

Robustness checks conducted at the account level.

This table presents robustness checks at the account level. In Panel A, we define the annual disposition effect of an individual investor as the difference between the fraction/probability of selling winners (PSW) and that of holding onto losers (PSL) in a given year, and we link it to the annualized AQI (the average of daily values within a year) to which the investor is exposed, following the baseline regression model presented in Table 2. Robust t-statistics are reported in parentheses and are based on standard errors clustered by investor and year. In Panel B, we estimate the following Cox proportional hazards model at the account level: $h_i(t) = \gamma(t) \times exp\{\beta_1 \times Gain_{i,t-1} + \beta_2 \times Gain_{i,t-1} \times \ln(AQI_t) + \beta_3 \times \ln(AQI_t)\}$, where $h_i(t)$ is the hazard function describing the selling decision of an investor since the purchase of the asset, $\gamma(t)$ is the baseline hazard, and $Gain_{i,t-1}$ is a dummy variable that takes the value of one if the underlining asset of investor i infers capital gains on date t (and zero if it indicates capital losses). We follow the restrictions in Ivković et al. (2005) to select a trade with which we can unambiguously match the purchase and sale dates. Specifically, we exclude sales preceded by multiple purchases and include only the first sale in our sample if a single purchase is followed by multiple sales. Models (1) and (2) are estimated based on the full sample. Models (3) and (4) are further estimated based on two subsamples according to whether the selling dates are associated with fundamental fund-level news. In particular, we classify days around fund announcements (from the announcement date to three days later) as news dates, where announcements include quarterly reports, dividends, turnovers of the management team, and changes in investment policies, etc. Other days are accordingly classified as no-news dates. In all models, we control for quarter fixed-effects. Robust t-statistics are reported in parentheses and are based on standard errors clustered by account and sale date. The sample period is from 2007 to 2015. Superscripts of *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: The effect of AQI on account-year disposition effect (account-level analysis for the baseline specification)

	(1) Full Sample	(2) Full Sample	(3) With sunshine	(4) Excluding big events and cities
Log_AQI	0.066***	0.069***	0.069***	0.105***
	(2.72)	(2.70)	(2.73)	(4.16)
Log_GDP		−0.224***	−0.226***	−0.187***
		(−5.17)	(−5.22)	(−5.24)
Log_pop		−0.051	−0.051	−0.051
		(−1.52)	(−1.54)	(−1.52)
Log_num_domestic_firm		0.067***	0.068***	0.049***
		(5.24)	(5.29)	(3.74)
Log_gov_income		0.016*	0.015	0.025***
		(1.66)	(1.60)	(2.86)
Sunshine			−0.002	
			(−1.50)	
Constant	0.449***	3.762***	3.813***	2.953***
	(4.07)	(5.01)	(5.08)	(5.42)
Fixed effects and clustering	Investor, year-fixed effets (S.E. clustered by investor-year)			
No. of obs	549,211	549,211	549,211	425,403
R-squared	0.85	0.85	0.85	0.85

Panel B: The effect of AQI in Cox proportional hazards models (account-level analysis on selling decisions)

	(1)	(2)	(3)	(4)
	Full Sample		Subsamples of selling dates with/without news	
			No-news dates	News dates (Day 0–3)
Gain	0.298***	0.115**	0.150***	−0.138
	(54.90)	(2.34)	(2.66)	(−1.50)
Gain*Log(AQI)		0.043***	0.078***	0.015
		(3.71)	(5.85)	(0.70)
Log(AQI)		−0.078***	−0.111***	−0.037**
		(−7.46)	(−9.29)	(−1.97)
Log_GDP	−0.073***	−0.074***	−0.091***	0.003
	(−11.81)	(−11.96)	(−11.76)	(0.28)
Log_pop	0.027***	0.035***	0.059***	−0.083***
	(5.50)	(6.89)	(9.92)	(−8.57)
Log_num_domestic_firm	0.031***	0.027***	0.026***	0.023***
	(8.13)	(7.10)	(5.51)	(3.28)
Log_gov_income	0.035***	0.035***	0.024***	0.064***
	(8.17)	(8.28)	(4.56)	(8.40)
Fixed effects and clustering	Y	Y	Y	Y
No. of obs	252,541	252,541	197,549	54,992

with tax-deferred accounts. Indeed, Ivković and Weisbenner (2009) found that the propensity to sell in hazard models is negatively related to fund returns for taxable accounts, indicating a reverse disposition effect especially related to tax-motivated trading. In contrast, the relation becomes positive (although insignificant) for tax-deferred accounts, inferring an insignificant disposition effect. Similarly, households in Sweden exhibit a positive yet insignificant disposition effect in selling mutual funds (Calvet et al., 2009). The positive sign for Chinese fund investors is therefore consistent with that for US tax-deferred accounts, although the remaining gap in statistical significance indicates that Chinese investors might nonetheless exhibit more behavioral biases. How to explain this remaining difference could be an interesting topic for future research.

Importantly, our focus is whether air pollution could enhance the disposition effect among investors at the account level. Model (2) indicates that the answer is yes, in that the interaction term has a significant coefficient (i.e., β_2). In this model, the coefficient β_1 is 0.115, whereas the coefficient of β_2 is 0.043. From the first coefficient, we can estimate the baseline hazard rate of selling at capital gains as 0.122 in this case (i.e., $e^{\beta_1 \times Gain}|_{Gain=1} - e^{\beta_1 \times Gain}|_{Gain=0} = e^{0.115} - 1 = 0.122$). To roughly estimate the economic magnitude of the impact of air pollution, we can perform a simple back-of-the-envelope calculation based on the second coefficient, exploring how hazard rates change for a hypothetical investor experiencing a transition of AQI from one standard deviation less than the mean value of AQI to the mean value of AQI. According to Table 1, the mean value of AQI is approximately 80, whereas a one standard deviation increase in AQI is approximately 44. The hazard rate change in this case can be computed as follows: $(e^{0.043\ \times ln80} - 1) - (e^{0.043\ \times ln(80-44)} - 1) = 0.016$. This change is economically sizable with respect to the baseline hazard rate of 0.122 (i.e., approximately 13%).

Models (3) and (4) further split the sample according to whether the selling dates are associated with some sort of fundamental news about the fund. In particular, we hand collect all dates on which funds announce their quarterly reports, dividends, turnovers of the management team, and changes in investment policies related to management fees, front load, and redemptions, etc. For each announcement, we classify news dates as the period from the announcement date to three days later. Note that we allow for three more days because it may take a few days for retail investors to notice such events (our results are robust to this threshold). Other days are accordingly classified as no-news dates. Approximately 22% of trading dates are classified as news dates in this approach.

Since trading in no-news days is less motivated by fund fundamentals, we expect investors to be more influenced by factors unrelated to the fundamentals of their invested assets—such as air pollution—in exercising their trading. Indeed, we see that the adverse influence of air pollution on the disposition effect is concentrated on no-news dates in Model 3, whereas the effect becomes insignificant on news dates, as indicated in Model 4 (though the sign still indicates the same direction). The hazard rate change associated with a one standard deviation change in AQI and the baseline hazard rate on no-news dates become 0.031 and 0.16, respectively, indicating a larger influence of AQI on hazard rates in this case (approximately 19.4%). Additional tests (tabulated in the Internet Appendix, Table IN4) show that our results are robust when we further control for investor characteristics, when we adopt an alternative time window for the classification of news dates (from the announcement day to five days after), and when we split news dates into different types of news. Our later tests will further show that one reason for investors to exhibit a higher disposition effect on no-news days is that they sell winners too soon in postannouncement periods on highly polluted days.

Of course, since hazard models are nonlinear, we must interpret the above calculation with care. Nonetheless, estimations based on Cox hazards model and yearly estimated disposition effects clearly demonstrate that the relation between air pollution and the disposition effect remains highly robust at the account level.

5.4. A potential channel and related tests

We lastly examine one potential mechanism through which air pollution may introduce behavioral bias into investors' trading activities in terms of the disposition effect. Although it is difficult to provide direct evidence, this section examines two implications of the mechanism that may shed light on how investors trade and lose money on polluted days.

More specifically, cross-referencing the psychology, health science, and finance literature suggests that moods, the diffuse and global feeling states of people as defined in Morris and Reilly (1987), may help pass on the influence of air pollution to trading behavior. First of all, the psychology literature provides vast evidence that people take actions to self-regulate moods. Between the two goals of mood regulation, i.e., to maintain good moods and bring back bad moods to comfortable levels, the literature typically emphasizes the importance of the latter (e.g., Morris and Reilly, 1987; Thayer, 1990; Wegner and Pennybaker, 1993; Larsen, 2000) and proposes a spectrum of strategies to achieve the latter goal, such as a combination of shopping, relaxation, stress management, cognitive, and exercise techniques (e.g., Thayer et al., 1994; Bushman et al., 2001; Larsen, 2000).

The health science literature, on the other hand, demonstrates that air pollution can negatively influence moods, cognition, and mental well-being (e.g., Block and Calderón-Garcidueñas, 2009; Fonken et al., 2011; Mohai et al., 2011; Weuve et al., 2012; Weir, 2012 summarizes recent findings). Hence, air pollution creates mood disorders or negative mood swings that require people to self-regulate.

Last but not least, realization utility models in the finance literature (e.g., Shefrin and Statman, 1985; Barberis and Xiong, 2012; Frydman et al., 2014 provides experimental evidence) suggest that realized gains and losses may directly affect utility (in addition to consumptions), suggesting that trading may be both influenced by air pollution-induced mood disorders and/or resorted to as a remedy to offset pollution-initiated bad moods. In some sense, if utility gains from shopping (i.e., some sort of consumption) can help regulate bad moods, so do utility bursts that investors can achieve via realizing trading gains.[18]

Jointly, the above evidence suggests that air pollution-induced mood disorder may incentivize investors to realize more gains than losses to bring back their moods to comfortable levels, which gives rise to the disposition effect. Note that this mechanism implicitly assumes that investors use normal days (i.e., with no or low pollution) as the

[18] The mutual influences between utility and moods are widely documented in the psychology literature (see, e.g., Isen et al., 1988; Rick and Loewenstein, 2008). The idea can be dated back to Jeremy Bentham, the founder of modern utilitarianism, who views utility as being rooted in the felt experience of pain and pleasure (see, e.g., Bentham, 1968). Following Bentham's view, the pleasure of utility gains can offset the pain of bad moods.

target comfortable level—or the set point of mood regulation, as discussed in Larsen (2000)—to eliminate pollution-induced bad moods. This assumption is reasonable given the health science evidence that air pollution creates mood disorder and the meteorological observation that normal or low pollution dates (e.g., AQI < 100) dominate in our sample.

We also recognize the possibility that a different disposition effect may arise in no/low pollution dates, when the goal of maintaining the good moods on these days makes losses more painful (see, e.g., Isen et al., 1988) and induces people to take confirmative actions (Mischel et al., 1973) such as realizing gains. This effect is likely to be dominated by the mechanism of regulating air pollution-induced mood disorders in our data because offsetting bad moods is relatively more difficult—and therefore requires more actions (such as the realization of more gains)—than maintaining good ones. In other words, investors need to realize more gains as a remedy to offset the negative impact of mood disorders that are more deviated from their target comfortable level (i.e., in more polluted dates), whereas the maintenance of good moods does not require as much. In the extreme case when severe air pollution becomes a "normal" (although still bad) mood state, however, the goal of maintaining good moods might become important and dominate investors' behavior. In other words, although we expect air pollution to mainly influence investors' trading behavior by creating negative mood swings on highly polluted days, the reverse influence can nonetheless occur if air pollution becomes too prevalent.

To further differentiate these two cases and to subject the mechanism of moods to the best (if indirect) falsification test available, we derive two implications of the mechanism that can be examined in the data. First, if air pollution-induced mood disorder incentivizes investors to realize more gains as opposed to losses, it should induce investors to sell more winners on polluted days and subsequently lose the potential momentum profitability that can be generated by these winners. If so, this mechanism not only explains why air pollution-induced disposition effect should be interpreted as a behavioral bias (i.e., investors lose money trading this way) but also strongly supports the insight of Grinblatt and Han (2005) on the relation between the disposition effect and momentum: air pollution in our setup intensifies the disposition effect of investors by particularly strengthening their trading against momentum.

Second, from the perspective of realization utility models (e.g., Barberis and Xiong, 2012), although utility gains from both sign realization (i.e., the pleasure of realizing gains over losses) and magnitude realization (i.e., to derive more pleasure from realizing larger gains) may help investors to feel better under pollution, the two effects may play a different role in air pollution-induced mood regulation. Indeed, the goal of self-regulating moods, i.e., to bring bad moods back to normal or comfortable levels (Thayer et al., 1994; Larsen, 2000), suggests that investors need to realize larger gains in order to offset the more negative mood-related influence of worse air pollution. In contrast, although a more frequent sign realization can also achieve the goal, it requires investors to trade more often in air pollution, which may not be appealing due to air pollution-induced symptoms of anxiety, depression, and cognitive decline. In other words, mood-regulating investors may resort more to magnitude realization than to sign realization to address the impact of severe air pollutions.

We next move on to empirically examine these two implications. The first implication can be tested based on the two momentum phenomena that are prominent in our data: time-series momentum in fund returns and postannouncement price drifts when fund policies are publicly released. As demonstrated in our Internet Appendix (Table IN5, Panel C), both types of momentum can generate significant returns for investors. Hence, we take a two-step analysis on the influence of air pollution vis-à-vis momentum. In the first step, we examine whether air pollution intensifies the tendency of selling winners in the following pooled logit regressions:

$$D_{i,t} = \beta_1 \times MOM_{-t} + \beta_2 \times MOM_{-t} \times \ln(AQI_{i,t}) + \beta_3 \times \ln(AQI_{i,t}), \tag{9}$$

where $D_{i,t}$ denotes the dummy variable that takes the value of one if investor i sells a fund on any date t that belongs to the first ten working days (i.e., first two weeks) of a calendar month and zero otherwise,[19] MOM_{-t} is the return of the fund in the previous calendar month, and $\ln(AQI_{i,t})$ measures the level of air pollution faced by investor i on date t. Market return and its potential interaction with air pollution are controlled.

The results are reported in Models (1) and (2) in Panel A1 of Table 9. Model (1) confirms that investors tend to sell winners in general, in that the probability of selling a fund increases after the fund has realized good calendar-month returns. Model (2) further shows that air pollution significantly intensifies the tendency of selling winners. To assess the economic magnitude of the intensifying effect, we notice that the coefficients of β_1 and β_2 are 2.402 and 0.359, respectively, in Model (2). A one standard deviation influence of AQI on the tendency of selling winners can be approximated as $\Delta \ln(AQI) \times \beta_2/\beta_1 = 0.801 \times 0.359/2.402 = 12.0\%$, where $\Delta \ln(AQI) = 0.801$ is the corresponding change in AQI on $\ln(AQI)$.[20] Roughly speaking, in this linear extrapolation, the marginal contribution of air pollution is to intensify the tendency of selling winner by approximately 12%. Models (3) and (4) expand the selling decision dates to include all feasible trading dates, whereby MOM_{-t} is as the fund return realized in the one-month period prior to date t. The effect of air pollution on intensifying the tendency of selling winners remains highly robust.

Models (5) and (6) in Panel A2 adopt a similar methodology to examine how investors sell funds following fund-level news announcements, except that $D_{i,t}$ now

[19] In other words, all account-fund-date observations (for all dates that belong to the first two weeks of a calendar month) are pooled in this regression.

[20] More specifically, $\Delta \ln(AQI)$ can be estimated from the difference between the logarithm of the average level of AQI and that of AQI one-standard-deviation below its mean value (i.e., $\Delta \ln(AQI) = ln(\mu_{AQI}) - ln(\mu_{AQI} - \sigma_{AQI}) = 0.801$, where μ_{AQI} and σ_{AQI} refer to the mean value and the standard deviation of AQI in our sample).

Table 9
Selling upon momentum and counterfactual return.
Panels A1 and A2 examine how air pollution affects investors' selling decision conditioning on calendar-month momentum and fund announcements. More explicitly, Models (1) and (2) present the results of the following pooled logit regressions: $D_{i,t} = \beta_1 \times MOM_{-t} + \beta_2 \times MOM_{-t} \times \ln(AQI_{i,t}) + \beta_3 \times \ln(AQI_{i,t})$, where $D_{i,t}$ denotes the dummy variable that takes the value of one if investor i sells a fund on any date t that belongs to the first ten working days (i.e., first two weeks) of a calendar month and zero otherwise (i.e., all account-fund-date observations are pooled in this regression, as long as the date of the observation belongs to the first two weeks of a calendar month); MOM_{-t} is the return of the fund in the previous month; and $\ln(AQI_{i,t})$ measures the level of air pollution faced by investor i on date t. Market return and its potential interaction with air pollution are explicitly controlled. Models (3) and (4) expand the selling decision dates to include all feasible trading dates, whereby MOM_{-t} is defined in this case as fund returns in the one-month period prior to date t. Panel A2 further applies a similar specification to the selling decision of investors after fund announcement (more specifically during the first and second ten working days of the postannouncement period) by regressing pooled selling dummy variables on the corresponding announcement-period return interacted with air pollution. Finally, for actual sales occurring during the first 10 days of a calendar month or the first 10 days of any postannouncement period, Panels B1 and B2 provide a counterfactual analysis of what investors could have earned if they had retained the asset for another 20 working days (i.e., approximately one month). More explicitly, we examine the following specification: $Ret_{i,t+1\sim t+20} = \beta_1 \times MOM_{-t} + \beta_2 \times MOM_{-t} \times \ln(AQI_t) + \beta_3 \times \ln(AQI_t)$, where $Ret_{i,t+1\sim t+20}$ is the counterfactual return that can be generated by the asset in a hypothetical period of 20 working days right after the actual selling date, MOM_{-t} refers to the preselling momentum in Panel B1 and announcement-period return in Panel B2, and $\ln(AQI_t)$ measures air pollution of the actual selling date t. Superscripts of *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

A. Selling decision of investors vs. past momentum (logistic model)

	A1. Selling decision vs. past-month momentum					A2. Selling decision vs. announcement momentum			
	Selling on the first 10 days of each calendar month		Selling on all dates			Selling on the first 10 days after the announcement period		Selling on 11–20D after the announcement period	
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Mom (last month return)	3.949***	2.402***	3.782***	3.074***	Announcement period ret	11.691***	−2.088	7.659***	5.075***
	(140.23)	(9.03)	(203.42)	(17.59)		(36.67)	(−1.45)	(22.93)	(3.47)
Mom*AQI		0.359***		0.163***	Ann-period ret*AQI		2.759***		0.335
		(5.80)		(4.02)			(8.58)		(1.01)
AQI		0.058***		0.076***	AQI		0.226***		0.189***
		(10.03)		(18.26)			(18.87)		(15.15)
Lagged market ret	Yes	Yes	Yes	Yes	Ann-period market ret	Yes	Yes	Yes	Yes
Lagged market*AQI	No	Yes	No	Yes	Ann-period market*AQI	No	Yes	No	Yes
Observations	55,115,198		11,25,80,000		Observations	1,43,67,157		1,41,00,073	

B. Counterfactual returns generated by winners sold by investors in polluted days (in a hypothetical 20D period right after the actual selling date)

	B1. Counterfactural 20-D return (%) vs. MOM				B2. Counterfactural 20-D return (%) vs. Announcement MOM		
	(if investors do not sell in the first 10 days of a month)				(if investors do not sell in the first 10 days immediately after the announcement period)		
	(1)	(2)	(3)		(4)	(5)	(6)
Selling day AQI	1.231***		0.666***	Selling day AQI	2.782***		1.223***
	(26.79)		(13.99)		(26.43)		(11.95)
Mom (prior to selling)		5.541***	−49.081***	Ann-period ret (prior to selling)		70.322***	−218.990***
		(16.45)	(−15.86)			(20.93)	(−13.53)
Mom*AQI			12.717***	Ann-period ret*AQI			65.042***
			(17.74)				(17.88)
Constant	−6.001***	−0.921***	−3.865***	Constant	−9.664***	1.804***	−3.546***
	(−24.86)	(−6.46)	(−16.06)		(−20.92)	(37.11)	(−8.07)
Lagged market ret	Yes	Yes	Yes	Ann-period market ret	Yes	Yes	Yes
Lagged market*AQI	No	No	Yes	Ann-period market*AQI	No	No	Yes
Fund FE	Yes	Yes	Yes	Fund FE	Yes	Yes	Yes
Observations	193,989	193,989	193,989	Observations	46,241	46,241	46,241
R-squared	0.075	0.074	0.080	*R*-squared	0.325	0.323	0.336

denotes the dummy variable that takes the value of one if investor i sells a fund on any date t that belongs to the first ten working days of a postannouncement period and zero otherwise, and MOM_{-t} refers to the announcement period return, or the return that can be generated by the fund during the news period as defined in Table 8. Model (5) confirms that investors still tend to sell winners that have realized high announcement-period returns. Moreover, when Model (6) includes the influence of air pollution, the interaction between AQI and MOM_{-t} not only is highly significant but also absorbs the significance of β_1. In other words, the tendency of selling winners now is concentrated on highly polluted days in the first two weeks of the postannouncement period, highlighting an even more prominent role of air pollution in influencing investors' trading behavior in this case. Interestingly, the influence spans only a short period of time. When we examine the second ten working-day window in the postannouncement period in Models (7) and (8), air pollution no longer intensifies the tendency of selling winners.

Overall, we find that air pollution can strongly intensify the tendency to sell winners during a short period of time right after the underlining assets have realized high calendar month returns or high announcement-period returns. This conclusion is also highly robust when we use alternative ordinary least squares (OLS) specifications to explicitly control for fund- and time-fixed effects (see Table IN5 in the Internet Appendix).

We next examine whether the air pollution-intensified tendency of selling winners makes investors worse off, an important question for gauging the interpretation of air pollution-induced disposition effect. To provide a potential answer, we conduct a counterfactual analysis on what investors could have earned from the winners they sold—if they could hold onto winners for a few more weeks—in the following specification:

$$Ret_{i,t+1\sim t+20} = \beta_1 \times MOM_{-t} + \beta_2 \times MOM_{-t} \times \ln(AQI_t) + \beta_3 \times \ln(AQI_t), \quad (10)$$

where $Ret_{i,t+1\sim t+20}$ refers to the counterfactual return that can be generated by a fund sold by investor i on date t during a hypothetical 20-working-day (or four-week) period immediately after the actual selling date (our results are robust to the length of the counterfactual holding period); MOM_{-t} refers to the pre-selling calendar month momentum or announcement-period return; and $\ln(AQI_t)$ measures the air pollution of actual sale date t. The results are tabulated in Panels B1 and B2 of Table 9.

Model (1) of Panel B1 reports that assets sold on highly polluted days can, on average, generate highly significant counterfactual returns in the postsale period (i.e., $\beta_3 > 0$). Likewise, Model (2) suggests that the general tendency of selling winners is not optimal, as winners sold by investors can generate high counterfactual returns in the future. Most importantly, Model (3) suggests that winners sold on severely polluted days can generate highly positive returns in the future. To assess the economic magnitude of the joint effect, we notice that $\beta_2 = 12.7$ in Model (3). Hence, a one standard deviation increase in both AQI and MOM_{-t} can be associated with an annualized counterfactual return of as high as 11.28% (i.e., $12.7 \times 0.0853 \times 0.801 \times (260/20) = 11.28\%$, where 0.0853 is the standard deviation of MOM_{-t} in our sample, 0.801 is the one standard deviation change in the logarithm of air pollution, and the ratio 260/20 roughly translates 20-working-day returns into annualized ones based on the assumption that there are approximately 260 working days in a year). Although the joint effect is not solely due to air pollution, it is evident that investors face significant financial disadvantages when they sell winners on polluted days.[21]

Models (4)–(6) conduct similar counterfactual analyses on the potential return that investors forgo by selling winners with high announcement-period returns during haze. We again find that riding momentum, or more precisely, riding the postannouncement price drifts, could leave investors better off. In addition, we also expand the counterfactual analysis to funds sold on all days and to those sold during an extended 20 working day period of the postannouncement period. Since the results are very similar, we report them in Table IN 5 of the Internet Appendix in the interest of space.

Because the above tests confirm that air pollution induces trading mistakes, which are likely to originate from some sort of behavioral bias, we next move on to explore the specific forms of realization preference that air pollution may trigger in giving rise to the disposition effect. As discussed in the second implication, all forms of realization preferences are not the same in terms of regulating air pollution-induced mood disorder. To examine this implication, we separately test the influence of air pollution on the sign and magnitude effects as follows. We first apply the regression discontinuity approach of Ben-David and Hirshleifer (2012) to sign realization preference. The main idea is to examine whether the likelihood of selling an asset (proxied by a selling indicator multiplied by 100) increases in an indicator function of whether the return since purchase is positive (i.e., $I(ret > 0)$) when the magnitude of the return since purchase is refined in a small region around zero. A positive relation between the two variables confirms a jump in selling at zero, which is implied by the sign realization preference.

In Panel A of Table 10, we apply this regression discontinuity analysis to our sample. We focus on the narrow region with 0.1 standard deviations from zero and the use of third-degree polynomials to fit to the probability of selling for both the positive and negative ranges of returns. Control variables and other specifications are the same as those in Table 2 in Ben-David and Hirshleifer (2012).[22] We also follow Ben-David and Hirshleifer (2012) and split the sample according to different lengths of prior holding horizon. More specifically, Models (1) and (2) present the results for short prior holding horizons (between 1 and 20 working days), whereas Models (3)–(6) tabulate those based on mid-range (from 21–250 working days) and long-prior holding horizons (above 250 days). Within each prior holding horizon sample, we first report the sign effect of $I(ret > 0)$ and then examine whether air pollution could affect the sign effect by interacting AQI with $I(ret > 0)$.

[21] One way to estimate the marginal influence of AQI is to apply the inference of Panel A1—i.e., air pollution marginally enhances the tendency of selling winners by approximately 12%—to this joint effect, in which case air pollution could be associated with $11.28\% \times 12\% = 1.35\%$ of counterfactual returns. Another way is to compare the joint influence form both AQI and momentum to that from momentum only. The latter (momentum only) influence can be estimated from Model (2), in which a one standard deviation increase in MOM_{-t} is associated with an annualized counterfactual return of 6.15% (i.e., $5.54 \times 0.0853 \times (260/20) = 6.15\%$, where 5.54 is the coefficient β_1), which is smaller than the AQI/Momentum joint influence, 11.28%. Although these estimations are not accurate, as we do not explicitly identify how air pollution and momentum intertwine in influencing investor behavior, they are on par with the trading loss reported in Table 2 and confirm that air pollution induces trading mistakes.

[22] Ben-David and Hirshleifer (2012) use third-, fourth-, and fifth-degree of polynomials in regression discontinuity. Additional tests reported in Table IN6 in the Internet Appendix show that the latter two specifications will not change our main results.

Table 10
Trading responses to past return and the influence of air pollution.
This table examines realization preferences related to the disposition effect as well as how air pollution influences them. We first apply the regression discontinuity analysis of Ben-David and Hirshleifer (2012, Table 2) to the selling decision of investors for various holding horizons, when returns since purchase are in a small region around zero. Panel A focuses on the region with 0.1 standard deviations from zero with third-degree polynomials. Panel B conducts the magnitude test of Ben-David and Hirshleifer (2012; in their Table 4), in which investors' selling decisions are regressed on $Ret- = \text{Min}\{0,\ \text{return since purchase}\}$ and $\text{Ret}+ = \text{Max}\{0,\ \text{return since purchase}\}$ and a list of control variables in a probit specification. Both panels further report the influence of air pollution by interacting air pollution with the corresponding return characteristics of interest (i.e., $I\{ret > 0\}$ in Panel A and *Ret*−/ Ret+ in Panel B). The Internet Appendix provides related summary statistics and more robustness checks for both tests. Robust *t*-statistics are reported in parentheses and are based on standard errors clustered by investor. Superscripts of *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Panel A. Discontinuity analysis on sign realization preference (dependent variable = $I\{\text{Sell}\} \times 100$; range = 0.1 stdev around zero; 3rd polynomials)

	Short-term periods (1 to 20 days)		Mid-term periods (21 to 250 days)		Longer periods (> 250 days)	
	(1)	(2)	(3)	(4)	(5)	(6)
I(ret>0)	0.333***	0.775**	−0.017	0.004	−0.046**	0.018
	(4.21)	(2.21)	(−0.56)	(0.05)	(−2.02)	(0.31)
I(ret=0)	−0.284***	−2.526***	−0.229***	−0.228***	−0.127***	−0.022
	(−5.55)	(−10.00)	(−10.90)	(−3.51)	(−7.24)	(−0.51)
I(ret>0)*Logaqi		−0.095		−0.005		−0.015
		(−1.19)		(−0.24)		(−1.20)
I(ret=0)*Logaqi		0.525***		−0.000		−0.024***
		(8.93)		(−0.02)		(−2.61)
Logaqi		−0.515***		−0.004		0.027***
		(−8.80)		(−0.31)		(3.04)
Sqrt(Time)	−0.043***	−0.039***	−0.024***	−0.024***	0.002***	0.002***
	(−5.47)	(−4.98)	(−19.42)	(−19.46)	(4.26)	(4.11)
Polynomials	Yes	Yes	Yes	Yes	Yes	Yes
Polynomials with sqrt(time)	Yes	Yes	Yes	Yes	Yes	Yes
Polynomials with positve and negative indicator	Yes	Yes	Yes	Yes	Yes	Yes
Observations	963,721	963,721	1854,455	1854,455	1366,419	1366,419
R-squared	0.012	0.012	0.001	0.001	0.000	0.000

Panel B: The Ben-David and Hirshleifer (2012) magnitude test (dependent variable = $I\{\text{Sell}\} \times 100$)

	Short-term periods (1 to 20 days)		Mid-term periods (21 to 250 days)		Longer periods (> 250 days)	
	(1)	(2)	(3)	(4)	(5)	(6)
Ret+	5.108***	−4.237***	4.749***	5.395***	2.044***	0.890
	(58.52)	(−4.80)	(86.12)	(10.69)	(21.97)	(1.07)
Ret-	1.616***	1.428	−0.376***	3.269***	−0.596***	−3.710***
	(8.96)	(0.86)	(−5.21)	(4.65)	(−5.92)	(−4.13)
I(ret>0)	0.090***	0.009	0.236***	−0.041	0.050***	0.472***
	(7.15)	(0.14)	(30.83)	(−0.99)	(3.80)	(6.78)
I(ret=0)	−0.676***	−1.462***	−0.812***	−2.304***	−0.568***	−0.537
	(−26.13)	(−5.24)	(−23.45)	(−6.58)	(−8.82)	(−0.77)
Ret+*Logaqi		2.221***		0.605***		0.594***
		(11.74)		(5.53)		(3.24)
Ret-*Logaqi		−0.511		−0.926***		0.199
		(−1.36)		(−6.14)		(0.95)
I(ret>0)*Logaqi		−0.005		0.031***		−0.052***
		(−0.31)		(3.50)		(−3.35)
I(ret=0)*Logaqi		0.130**		0.189**		0.132
		(2.11)		(2.56)		(1.37)
Logaqi		−0.102***		−0.051***		0.034***
		(−7.56)		(−7.19)		(2.82)
Control variables	Same as Table 4 in Ben-david and Hirshleifer (2012). Models (2),(4),(6) include sqrt(Time) and interactions.					
Observations	4357,608	4357,608	16,326,851	16,326,851	20,158,791	20,158,791
Pseudo *R2*	0.0321	0.0330	0.0317	0.0322	0.00948	0.0100

The striking finding is that the sign effect differs drastically in different ranges of prior holding horizon. While the effect is highly significant for returns with a short prior holding horizon in Model (1), it becomes insignificant in the mid-horizon and even reverts in the long horizon, as reported in Models (3) and (5), respectively. Hence, unlike the behavior of Finnish household investors examined in Kaustia (2010), evidence on sign realization preference is quite mixed among our sample of Chinese mutual fund investors.[23] The interaction between AQI and $I(ret > 0)$, by contrast, is consistently insignificant across all prior holding horizons. Therefore, consistent with the second

[23] In terms of the average effect of sign realization preference, Chinese fund investors seem, if anything, to be more similar to US stock investors as examined in Ben-David and Hirshleifer (2012).

implication, investors do not seem to resort to this particular form of realization preference in dealing with the negative influence of air pollution.

In Panel B of Table 10, we apply another test of Ben-David and Hirshleifer (2012, Table 4) to assess the potential influence of air pollution on the magnitude of gains and losses. Different from regression discontinuity, in this magnitude test we include all ranges of returns and link the selling indicator of investors to the magnitude of gains and losses in a probit specification. The magnitude of gains and losses are measured by $\text{Ret+} = \text{Max}\{0,\ \text{return since purchase}\}$ and $Ret- = \text{Min}\{0,\ \text{return since purchase}\}$, respectively. A list of control variables, including the indicator variable for sign realization preference, are explicitly controlled (the list of control variables and other specifications are the same as Table 4 in Ben-David and Hirshleifer, 2012).

We again examine the magnitude effect in three different ranges of prior holding horizon. For each prior holding horizon, we first examine the magnitude effect without air pollution. We then ask whether air pollution affects the magnitude effect by interacting AQI with Ret+ and $Ret-$. Note that since our control variable includes $I(ret > 0)$, we also interact air pollution with $I(ret > 0)$ in this specification as a control and a robustness check to our previous test on the sign effect. In the interest of space, we report only the coefficients of return- and air pollution-related variables here and leave the full specification of the regression to be tabulated in Table IN6 of the Internet Appendix.

The results in Model (1) demonstrate that when the holding horizon is short, the selling likelihood increases in both Ret+ and $Ret-$. Because $Ret-$ becomes more negative for larger losses, these results suggest that investors prefer to realize larger gains over smaller gains and smaller losses over larger losses. In other words, investors exhibit a strong magnitude realization preference, which refers to the preference of investors to prefer larger gains over smaller gains and smaller losses over larger losses in Ben-David and Hirshleifer (2012). Interestingly, in Models (3) and (5), the coefficient for $Ret-$ becomes negative with longer holding horizons, whereas that for Ret+ remains positive. Hence, investors start to exhibit a V-shaped disposition effect, as documented in Ben-David and Hirshleifer (2012) for longer holding horizons.

Across all prior holding horizons, however, the influence of air pollution is unambiguous. In Models (2), (4), and (6), the interaction between AQI and Ret+ is significantly positive, suggesting in all these cases air pollution enhances the magnitude of gains that investors realize. Consistent with the second implication, investors therefore realize larger gains on highly polluted days. Moreover, this effect is the strongest in short holding horizons in terms of the magnitude of the coefficient for the interaction term (i.e., the coefficient is 2.22 in short horizons since purchase, compared to 0.605 and 0.594 for the case of mid- and long-prior holding horizons, respectively).[24] In other words, investors tend to realize larger gains especially from their most recent purchases to self-regulate the negative mood influences of air pollution. Recall that air pollution also intensifies selling against momentum in a short span of time in our pervious tests. Jointly, then, these results suggest that air pollution-induced mood disorder may particularly attract investors' attention to the most recent events or trading activities in self-regulating their moods.

By contrast, we do not find consistent results on the interaction term between air pollution and $Ret-$. If we focus on the most important case of short prior holding horizon in Model (2), air pollution has an insignificant influence on the magnitude of losses being sold even when it can significantly enhance the magnitude of gains being realized. Hence, air pollution exerts asymmetric influences on the magnitude realization of gains and losses. Interestingly, this asymmetry is consistent with the realization utility model of Barberis and Xiong (2012), in that their model can generate a positive relation between the probability of selling and the magnitude of gains and a flat relation between selling and the magnitude of losses.[25] This consistency could arise due to an appealing similarity between mood regulation and realization utility models: in Barberis and Xiong (2012), it suffices for the disposition effect to arise when investors derive linear utility from realizing gains and when investors are impatient over time. In the channel of mood regulation, the need to regulate mood disorder essentially creates impatience when investors resort to realizing gains as a therapy to regulate air pollution-induced mood disorder.

Last but not least, the coefficient on $I(ret > 0)$ becomes significant in this panel, which may appear at odds with the insignificance of sign realization in regression discontinuity. This inconsistency, however, is not a concern. As pointed out by Ben-David and Hirshleifer (2012), a spurious jump may easily occur when ranges of returns get widened because sign realization will be mixed with other interfering effects in this case. Hence, the sign realization effect should be more reliably tested over a very narrow return range in regression discontinuity. Meanwhile, the interaction between AQI and $I(ret > 0)$ remains insignificant in this specification, consistent with the conclusion of the regression discontinuity analysis that investors do not exhibit more frequent sign realization in air pollution.

Overall, Table 10 portraits the influence of air pollution on investor behavior as follows. Air pollution can significantly enhance the magnitude of gains realized by investors. By contrast, air pollution does not seem to induce a stronger sign realization effect or a larger magnitude of losses (at least for the important case of short prior holding horizons). This picture of investor behavior lends support to the second implication that more severe

[24] Interestingly, when air pollution is included, the original relation between selling and Ret+ becomes negative in Model (2), remains positive in Model (4) and becomes insignificant in Model (6). This pattern also confirms that air pollution has a particularly strong influence on magnitude realization when the holding horizon is short.

[25] Note that this asymmetric influence of air pollution also applies to the long prior holding horizon, as reported in Model (6), and is thus quite robust in our sample. In between (mid-horizon), investors also seem to exhibit a V-shaped disposition effect in Model (4) and can be subject to additional trading motivations. See Ben-David and Hirshleifer (2012) for the potential motivations that can give rise to a V-shaped disposition effect.

mood disorders introduced by worse air pollution need to be compensated by the realization of larger gains. Therefore, together with Table 9, tests conducted in this section are consistent with our proposed mechanism of air pollution-induced mood regulation. The caveat is that these tests do not provide direct evidence on the role of moods or mood regulation in bridging air pollution and trading mistakes. Instead, the mechanism we propose here may be better interpreted in a broader sense, in that there could exist some state variable describing the mental well-being of people, which receives the impact of air pollution from a variety of (e.g., mental, psychological, and cognitive) sources on one hand and influences the behavior of investors on the other hand in a way similar to mood regulation. Even with this broader interpretation, we do not think that this channel is exclusive. Regardless of this layer of ambiguity, however, this session further validates the importance of air pollution in shaping investor behavior.

6. Conclusion

In this paper, we examine whether air pollution can significantly intensify cognitive bias observed in the financial markets based on a proprietary data set obtained from a large Chinese mutual fund family that contains complete trading information on more than 773,198 accounts in 247 cities. We find that air pollution significantly increases the disposition effect of investors.

We further examine two plausible exogenous variations in air quality. The first test exploits that strong winds lead to vast dissipations of air pollution. The second quasi-experiment exploits the fact that the Huai River heating policy of the central government of China unintentionally created a discontinuity in AQI along the Huai River. In both tests, we find that exogenous variations in air quality lead to changes in behavioral bias. These tests suggest that air pollution has a causal influence on cognitive bias observed in financial markets. We also propose that air pollution-induced mood regulation may help explain how such influence is achieved and what specific form of behavioral preference could be triggered.

Our results have important normative implications regarding the role of the environment in developing countries such as China. We show that air pollution may incur trading inefficiency and the redistribution of wealth associated with enhanced cognitive biases in financial markets. Accordingly, the issue of air pollution could give rise to much broader consequences than previously recognized. Our study thus calls for more attention and action from regulators and researchers to better protect the environment in our modern society.

Appendix A. Variable definition

Panel A: Aggregated account-level variables	
Aggregate account	City level (covering 247 cities in China)
AQI	A measure of harmful content in the air, including sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), and particulate matter (PM) (Ministry of Environmental Protection)
Disposition effect	The disposition effect is calculated by the method of Ben-David and Hirshleifer (2012): the probability of selling winners minus the probability of selling losers
PSW	The probability of selling winners aggregated at the region account level
PSL	The probability of selling losers aggregated at the region account level
Panel B: Region-level variables	
Log_GDP	Log of gross domestic product at year end in billions of RMB
Log_pop	Log of total population in a region
Log_num_domestic_firm	Log of the number of domestic firms
Log_gov_income	Log of total government revenue at year end in billions of RMB
D(North)	An indicator variable that equals one if the region is located north of the Huai River line
Degree north	Latitude degree north of the Huai River line for the region
Degree north squared	Square of latitude degree north of the Huai River line for the region
Old_High	Dummy variable that equals one if the ratio of aged investors in a city is above the median of the distribution (aged investors is defined as older than 40)
Female_High	Dummy variable equal to one if the ratio of female investors in a city is higher than the median of the distribution
Migrant_High	Dummy variable equal to one if the ratio of migrant investors in a city is higher than the median of the distribution. We use national identity numbers to trace the regions of birth of investors
Education_High	Dummy variable equal to one if the ratio of more educated investors a city is higher than the median of the distribution. We use city census data to infer the education level of an investor
Experience_High	Dummy variable equal to one if the ratio of experienced investors in a city is higher than the median of the distribution. Following Korniotis and Kumar (2011), we classify new and experienced investors based the number of months between the account opening date and the trading date
Panel C: Fund-level variables	
Raw return	The fund's daily raw return
Market-adjusted return	The fund's daily abnormal returns obtained using the CAPM
Three-factor adjusted return	The fund's daily abnormal returns obtained using the Fama-French three-factor model
Benchmark-adjusted return	The fund's daily abnormal adjusted by the benchmark return

References

An, L., 2015. Asset pricing when traders sell extreme winners and losers. Rev. Finan. Stud. 29, 823–861.

Almond, D., Chen, Y., Greenstone, M., Hongbin, L., 2009. Winter heating or clean air? unintended impacts of China's Huai river policy. Am. Econ. Rev. Pap. Proc. 99, 184–190.

Arain, M.A., Blair, R., Finkelstein, N., Brook, J.R., Sahsuvaroglu, T., Beckerman, B., Zhang, L., Jerrett, M., 2007. The use of wind fields in a land use regression model to predict air pollution concentrations for health exposure studies. Atmos. Environ. 41, 3453–3464.

Barberis, N., Xiong, W., 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. J. Finance 64, 751–784.

Barberis, N., Xiong, W., 2012. Realization utility. J. Financ. Econ. 104, 251–271.

Ben-David, I., Hirshleifer, D., 2012. Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. Rev. Finan. Stud. 25, 2485–2532.

Bentham, J., 1968. An introduction to the principles of morals and legislation. In: Page, A.L. (Ed.), Utility Theory. A Book of Readings Willey, New York pp. 3–29 (Original work published 1823.).

Block, M.L., Calderón-Garcidueñas, L., 2009. Air pollution: mechanisms of neuroinflammation and CNS disease. Trends Neurosci. 32, 506–516.

Bushman, B.J., Baumeister, R.F., Phillips, C.M., 2001. Do people aggress to improve their mood? catharsis beliefs, affect regulation opportunity, and aggressive responding. J. Pers. Soc. Psychol. 81, 17–32.

Calonico, S., Cattaneo, M.D., Titiunik, R., 2015. Optimal data-driven regression discontinuity plots. J. Am. Stat. Assoc. 110, 1753–1769.

Calvet, L.E., Campbell, J.Y., Sodini, P., 2009. Fight or flight? Portfolio rebalancing by individual investors. Quart. J. Econ. 124, 301–348.

Chang, T., Graff Zivin, J., Gross, T., Neidell, M.J., 2016a. Particulate pollution and the productivity of pear packers. Am. Econ. J. Econ. Pol. 8, 141–169.

Chang, T., Graff Zivin, J., Gross, T., Neidell, M., 2016b. The Effect of Pollution On Worker productivity: Evidence from Call-Center Workers in China. National Bureau of Economic Research Unpublished working paper.

Chang, T.Y., Huang, W., Wang, Y., 2018. Something in the air: projection bias and the demand for health insurance. Rev. Econ. Stud. 85, 1609–1634.

Chang, T.Y., Solomon, D.H., Westerfield, M.M., 2016. Looking for someone to blame: delegation, cognitive dissonance, and the disposition effect. J. Finance 71, 267–302.

Chay, K.Y., Greenstone, M., 2003a. Air Quality, Infant Mortality, and the Clean Air Act of 1970. National Bureau of Economic Research Unpublished working paper.

Chay, K.Y., Greenstone, M., 2003b. The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. Quart. J. Econ. 118, 1121–1167.

Chay, K.Y., Greenstone, M., 2005. Does air quality matter? Evidence from the housing market. J. Polit. Econ. 113, 376–424.

Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from china's huai river policy. Proc. Natl. Acad. Sci. 110, 12936–12941.

Cho, J., Choi, Y.J., Suh, M., Sohn, J., Kim, H., Cho, S.K., Ha, K.H., Kim, C., Shin, D.C., 2014. Air pollution as a risk factor for depressive episode in patients with cardiovascular disease, diabetes mellitus, or asthma. J. Affect. Disord. 157, 45–51.

Currie, J., Hanushek, E.A., Kahn, E.M., Neidell, M., Rivkin, S.G., 2009. Does pollution increase school absences? Rev. Econ. Stat. 91, 682–694.

Deryugina, T., Heutel, G., Miller, N.H., Molitor, D., Reif, J., 2016. The Mortality and Medical Costs of Air pollution: Evidence from Changes in Wind Direction. National Bureau of Economic Research Unpublished Working Paper.

Ebenstein, A., Fan, M., Greenstone, M., He, G., Yin, P., Zhou, M., 2015. Growth, pollution, and life expectancy: China from 1991–2012. Am. Econ. Rev. 105, 226–231.

Ebenstein, A., Fan, M., Greenstone, M., He, G., Zhou, M., 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proc. Natl. Acad. Sci. 114, 10384–10389.

Fonken, L.K., Xu, X., Weil, Z.M., Chen, G., Sun, Q., Rajagopalan, S., Nelson, R.J., 2011. Air pollution impairs cognition, provokes depressive–like behaviors and alters hippocampal cytokine expression and morphology. Mol. Psych. 16, 987–995.

Frazzini, A., 2006. The disposition effect and underreaction to news. J. Finance 61, 2017–2046.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P., Rangel, A., 2014. Using neural data to test a theory of investor behavior: an application to realization utility. J. Finance 69, 907–946.

Gelman, A., Imbens, G., 2018. Why high-order polynomials should not be used in regression discontinuity designs. J. Bus. Econ. Stat. 113, 1–10.

Grinblatt, M., Han, B., 2005. Prospect theory, mental accounting, and momentum. J. Financ. Econ. 78, 311–339.

Goetzmann, W.N., Kim, D., Kumar, A., Wang, Q., 2014. Weather-induced mood, institutional investors, and stock returns. Rev. Financ. Stud. 28, 73–111.

Goetzmann, W.N., Zhu, N., 2005. Rain or shine: where is the weather effect? Eur. Finan. Manag. 11, 559–578.

Graff Zivin, J., Neidell, M., 2012. The impact of pollution on worker productivity. Am. Econ. Rev. 102, 3652–3673.

Graff Zivin, J., Neidell, M., 2013. Environment, health, and human capital. J. Econ. Lit. 51, 689–730.

Greenstone, M., Hanna, R., 2014. Environmental regulations, air and water pollution, and infant mortality in India. Am. Econ. Rev. 104, 3038–3072.

Greenwood, R., Nagel, S., 2009. Inexperienced investors and bubbles. J. Financ. Econ. 93, 239–258.

Hanna, R., Oliva, P., 2015. The effect of pollution on labor supply: evidence from a natural experiment in Mexico city. J. Publ. Econ. 122, 68–79.

Henderson, V., 2012. Prospect theory, liquidation, and the disposition effect. Manag. Sci. 58, 445–460.

Herrnstadt, E., Heyes, A., Muehlegger, E., Saberian, S., 2016. Air Pollution As a Cause of Violent Crime: Evidence from Los Angeles and Chicago. University of California at Davis, University of Otawa, and Harvard University Unpublished working paper.

Heyes, A., Neidell, M., Saberian, S., 2016. The Effect of Air Pollution On Investor behavior: Evidence from the S&P 500. National Bureau of Economic Research Unpublished working paper.

Hirshleifer, D., 2015. Behavioral finance. Ann. Rev. Financ. Econ. 7, 133–159.

Hirshleifer, D., Shumway, T., 2003. Good day sunshine: stock returns and the weather. J. Finance 58, 1009–1032.

Huang, J., Xu, N., Yu, H., 2017. Pollution and Performance: Do Investors Make Worse Trades On Hazy Days? Unpublished working paper. Renmin University of China, University of Illinois at Urbana-Champaign, and Najing University.

Isen, A.M., Nygren, T.E., Ashby, F.G., 1988. Influence of positive affect on the subjective utility of gains and losses: it is just not worth the risk. J. Pers. Soc. Psychol. 55, 710–717.

Isen, A., Rossin-Slater, M., Walker, W.R., 2017. Every breath you take—every dollar you'll make: the long-term consequences of the clean air act of 1970. J. Polit. Econ. 125, 848–902.

Ito, K., Zhang, S., 2016. Willingness to pay for clean air: evidence from air purifier markets in China. J. Polit. Econ. forthcoming.

Ivković, Z., Poterba, J., Weisbenner, S., 2005. Tax-motivated trading by individual investors. Am. Econ. Rev. 95, 1605–1630.

Ivković, Z., Weisbenner, S., 2009. Individual investor mutual fund flows. J. Financ. Econ. 92, 223–237.

Kahneman, D., Slovic, P., Tversky, A., 1982. Judgement Under Uncertainty: Heuristics and Biases. Cambridge University Press, New York.

Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–291.

Kamstra, M.J., Kramer, L.A., Levi, M.D., 2003. Winter blues: a sad stock market cycle. Am. Econ. Rev. 93 (1), 324–343.

Kamstra, M.J., Kramer, L.A., Levi, M.D., Wermers, R., 2017. Seasonal asset allocation: evidence from mutual fund flows. J. Financ. Quant. Anal. 52, 71–109.

Kaustia, M., 2010. Prospect theory and the disposition effect. J. Financ. Quant. Anal. 45, 791–812.

Korniotis, G.M., Kumar, A., 2011. Do older investors make better investment decisions? Rev. Econ. Stat. 93, 244–265.

Larsen, R.J., 2000. Toward a science of mood regulation. Psychol. Inq. 11, 129–141.

Lepori, G.M., 2016. Air pollution and stock returns: evidence from a natural experiment. J. Emp. Finan. 35, 25–42.

Levy, T., Yagil, J., 2011. Air pollution and stock returns in the US. J. Econ. Psychol. 32, 374–383.

Li, Y., Yang, L., 2013. Prospect theory, the disposition effect, and asset prices. J. Financ. Econ. 107, 715–739.

Meyer, S., Pagel, M., 2016. Fresh Air Eases Work—The Effect of Air Quality On Individual Investor Activity. National Bureau of Economic Research Unpublished working paper.

Mischel, W., Ebbesen, E.B., Zeiss, A.R., 1973. Selective attention to the self: situational and dispositional determinants. J. Pers. Soc. Psychol. 27, 129–142.

Mohai, P., Kweon, B., Lee, S., Ard, K., 2011. Air pollution around schools

is linked to poorer student health and academic performance. Health Aff. 30, 852–862.
Morris, W.N., Reilly, N.P., 1987. Toward the self-regulation of mood: theory and research. Motiv. Emot. 11, 215–249.
Odean, T., 1998. Are investors reluctant to realize their losses? J. Finance 53, 1775–1798.
Petersen, M., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22, 435–480.
Pevzner, M., Xie, F., Xin, X., 2015. When firms talk, do investors listen? the role of trust in stock market reactions to corporate earnings announcements. J. Financ. Econ. 117, 190–223.
Pope III, C.A., 1989. Respiratory disease associated with community air pollution and a steel mill, Utah valley. Am. J. Publ. Health 79, 623–628.
Pope III, C.A., Burnett, R.T., Thun, M.J., Calle, E.E., Krewski, D., Ito, K., Thurston, G.D., 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA 287, 1132–1141.
Pope III, C.A., Hansen, J.C., Kuprov, R., Sanders, M.D., Anderson, M.N., Eatough, D.J., 2011. Vascular function and short-term exposure to fine particulate air pollution. J. Air Waste Manag. Assoc. 61, 858–863.
Rick, S., Loewenstein, G., 2008. The role of emotion in economic behavior. Handb. Emot. 3, 138–158.
Saunders, E.M., 1993. Stock prices and wall street weather. Am. Econ. Rev. 83, 1337–1345.
Seaman, N.L., 2000. Meteorological modeling for air-quality assessments. Atmos. Environ. 34, 2231–2259.
Seasholes, M.S., Zhu, N., 2010. Individual investors and local bias. J. Finance 65, 1987–2010.
Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and ride losers too long: theory and evidence. J. Finance 40, 777–790.
Su, S., Song, M., Wu, C., Chen, X., 2015. Potential impacts of temperature and wind on winter haze in north china. Chin. J. Environ. Eng. 9, 3928–3936.
Thayer, R.E., 1990. The Biopsychology of Mood and Arousal. Oxford University Press, Oxford.
Thayer, R.E., Newman, J.R., McClain, T.M., 1994. Self-regulation of mood: strategies for changing a bad mood, raising energy, and reducing tension. J. Pers. Soc. Psychol. 67, 910–925.
Wegner, D.M., Pennebaker, J.W., 1993. Handbook of Mental Control. Prentice Hall, Upper Saddle River.
Weir, K., 2012. Smog in our brains. Am. Psychol. Assoc. 43, 42.
Weuve, J., Puett, R.C., Schwartz, J., Yanosky, J.D., Laden, F., Grodstein, F., 2012. Exposure to particulate air pollution and cognitive decline in older women. Arch. Intern. Med. 172, 219–227.
World Health Organization, 2016, Ambient (outdoor) air quality and health available at: https://apps.who.int/iris/bitstream/handle/10665/250141/9789241511353-eng.pdf.
Wright, S., 1934. The method of path coefficients. Ann. Math. Stat. 5, 161–215.
Zheng, S., Kahn, M.E., 2013. Understanding china's urban pollution dynamics. J. Econ. Lit. 51, 731–772.