Behavioral Bias in Haze:

Evidence from Air Pollution and the Disposition Effect in China

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Abstract

Inspired by the recent health-science findings that air pollution reduces human cognitive skills, we examine whether air pollution can intensify cognitive bias observed in the financial markets. Based on a proprietary dataset obtained from a large mutual fund family in China, which contains the complete trading information of over 773,198 accounts covering more than 200 cities, we find that air pollution significantly increases the disposition effect of investors. Analysis based on two plausible exogenous variations in air quality (the Huai-river policy and the vast dissipation of air pollution due to strong winds) supports a causal interpretation. Our results have important normative implications that air pollutions may incur severe indirect (social) costs associated with enhanced cognitive biases.

Key words: Air Pollution, The Disposition Effect, Mutual Funds

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Introduction

Environmental issues are intriguing in a modern economy. On the one hand, industrial development and economic activities are often associated with severe pollutions in developing countries. Zheng and Kahn (2013), for instance, surveys the recent literature on China's urban pollution and concludes that economic growth has caused major environmental problems. On the other hand, pollutions are known to affect human health, which should hypothetically reduce the well-being and effectiveness of individuals participating economic activities and thus the pace of economic development itself (e.g., Graff Zivin and Neidell 2013). The relationship between environment and economic activities 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 round—say to understand how a steel mill pollutes the air. As a result, our knowledge regarding how widely and seriously pollution can affect our economy (other than health concerns) remains limited, with recent progresses mostly focusing on human capital measures related to education (e.g., Currie et al, 2009; Mohai et al., 2011), labor supply (e.g., Hanna and Oliva 2011) and productivity (Graff Zivin and Neidell, 2012; Chang, Graff Zivin and Neidell, 2016a,b).

This paper aims to contribute to the literature by a new intuition, a new dataset, and a set of new evidence on the causal influence of pollution. Our new intuition is built on the heuristic finding of the recent health-science literature that air pollution, which is regarded as "a major environmental risk to health" according to the World Health Organization (WHO, 2016)[1], could significantly damage the function of brains and reduce the cognitive skills of individuals (e.g., Block and Calderón-Garciduenñas, 2009; Fonken et al, 2011; Mohai et al., 2011; Weuve et al., 2012; see Figure 1 for visualized brain damages based on two science blogs—in addition to its better known impacts on respiratory, vascular, and mortality (e.g., Pope 1989; Pope et al., 2002; Pope et al., 2011). To the extent that cognitive ability is crucial for investors to properly make investment decisions in financial markets, we expect air pollution to also exert some influence therein. More explicitly, if air pollution does reduce human cognitive skills, it should induce investors to exhibit more behavioral bias in their trading.

To subject this intuition to falsification tests with the best data available, we obtain a new and unique proprietary dataset that contains complete account-level information for all investors in one of the largest mutual fund families (top 30) in China. It consists of 773,198 valid investment accounts trading seven equity

[1] http://www.who.int/mediacentre/factsheets/fs313/en/

funds from 2007 to 2015. Its investors come from all 31 provinces and more than 200 cities in mainland China. This dataset is ideal to examine the influence of air pollution for two reasons. First, air pollution is among the most challenging environmental problems in China. A proper assessment of air pollution therein could not only contribute to our general understanding about environmental issues but also have direct normative implications. Second, our dataset covers most major cities in China (our coverage is the largest in the literature). As we will see shortly, this large coverage is crucial in identifying the influence of air pollution based on quasi-experiments (e.g., the Huai-river Policy reported in Almond et al., 2009 and other endogeneity tests).

We then collect data on Air-quality Index (AQI; higher values mean more severe air pollution), and link it to one of the most important and robust cognitive bias reported in the finance literature—the disposition effect, or the tendency to sell winning assets while holding onto losers (Shefrin and Statman, 1985). Although its causes and consequences are still subject to debate (e.g., Barberis and Xiong 2009, 2012, Ben-David and Hirshleifer 2012, Henderson 2012, Li and Yang 2013, Frydman et al. 2014, and An 2016), the effect is typically interpreted as one of the most prominent trading mistakes of investors originated from cognitive bias (see Hirshleifer 2015 for a recent survey).

To better link the disposition effect to air pollution, which is available at the city level, we aggregate investor accounts at the same level. More explicitly, in each month, we first identify for each investor whether a position in a particular fund implies a capital gain or loss based on the entire trading history of that investor. Due to different 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") by investors in the same city as the fraction of investors in the city who sell their mutual funds at capital gains. 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.

In our sample, the PSW in a typical day is 0.382% at the regional level, which is much higher than the PSL (0.184%), confirming that investors in our sample exhibit a strong disposition effect (approximately 0.2%). Although we cannot directly compound this probability to monthly frequency, we have verified that the magnitude of monthly disposition is very close to Ben-David and Hirshleifer's (2012) estimation for the disposition effect among sales within 20 days of purchase (i.e., 0.49%). These summary statistics suggest that, different from U.S. mutual fund investors (e.g., Chang, Solomon and Westerfield 2016), Chinese mutual fund investors exhibit a normal disposition effect with its economic magnitude very close to that of U.S. stock investors.[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 relationship between the disposition effect and air pollution (the logarithm of AQI) in a pooled regression. We find that the disposition effect is positively associated with AQI, and that this effect mostly concentrates on the selling-winner side. Hence, severe air pollution is associated more with the cognitive bias of selling winners too soon. To quantify the effect, assume that AQI has increase from a slight-polluted level of 101 to the heavily-polluted level of 201 (which is very common change in cities like Beijing and around two-standard-deviation-change of daily AQI indices in our sample), the disposition effect increases by 5.8% compared to its average value.

To further explore whether the above relationship implies a causal impact of air pollution on behavioral bias, our second step of analysis provides two identification tests based on plausible exogenous variations in AQI. The first test exploits the quasi-experiment of "Huai-River policy" (Almond et al., 2009; Chen et al., 2013). More explicitly, Huai River, together with Mountain Qinling, 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 of homes and offices as a basic right *for and only for* the urban regions north of the Huai River. Since winter heating operates via the provision and burning of free coal for boilers, which releases air pollutants, this policy has unintendedly 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 across the river, which researchers have used to identify the plausible causal influence of air pollution on health issues such as life expectancy (e.g., Chen et al., 2013).

Our first identification test adopts a similar regression discontinuity (RD) methodology as Chen et al., (2013). We find that, across different empirical specifications, the disposition effect changes drastically across the discontinuity point. More explicitly, as graphically illustrated in Figure 2, cities located to the north of the Huai River exhibit significantly higher degree of the disposition effect. Regression-based analysis confirms the same conclusion. We then further use a two-stage specification, treating the location to the north of the river as an instrument to AQI index in the first stage. When we regress the disposition effect on instrumented AQI in the second stage, we find a significantly positive relationship.

In addition to the above quasi-experiment in which government policies generate endogenous variation in air pollution in the (geographical) cross section, we further examine exogenous variations in AQI caused by weather conditions such as winds. It is well known in the atmospheric environment literature that the

[2] In other words, U.S. and Chinese mutual fund investors could be subject to different types of behavioral biases. A potential explanation on this difference goes beyond the scope of this paper. Interested readers may refer to Li, Massa, and Zhang (2016) for some discussions.

formation and dissipation of air pollution are heavily influenced by weather conditions in general and wind conditions in particular (e.g., Seaman, 2000; Arain et al., 2007). China is no exemption (Su et al., 2015): drastic improvements in air quality are usually caused by strong winds, whereas drastic deteriorations in air quality often occur in opposite weather conditions favoring accumulations as opposed to dissipations of air pollutants. In this regard, drastic drops in AQI are especially 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 from two cities—call them A and B. Investors in both cities trade a same financial asset. Assume that both cities are exposed to similarly severe air pollutions early in a week. Further assume that strong wind blows away air pollution for city A on Wednesday (i.e., its AQI drops sharply on Wednesday and stays there for the rest of the week), while the AQI of city B remains unchanged. In this case, we can use the trading bias 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 on cognitive behavior, behavior bias of the treatment group (city A's investors) should decrease in the post-wind period (Wed to Friday in this example), compared to that of the control group (city B's investors) and the treatment-group bias in the pre-wind period (Monday to Tuesday).

To implement this test, we identify all city-level observations of sharp AQI drops on Wednesday and Thursday in our data (we include Thursday to allow for more observations—using Wednesday only will not change the results), and then create a control group similar to aforementioned city B. Empirically, we first verify that the disposition effect does not differ between the two cities in the pre-wind period of the week—hence our specification satisfies the parallel trend assumption. We then conduct the DID test, and find that the disposition effect gets significantly attenuated for the treatment group after the drastic reduction in AQI. These results, together with that of the Huai-River test, strongly support a causal interpretation on the influence of air pollution. The two tests also suggest that air pollution can have both long-term and short-term influences on investors' trading bias.

Our last step of empirical analysis aims to further assess the robustness of our major findings. To further assess the testing power of the Huai-River policy, we conduct a Placebo test in which we apply the same RD and two-stage tests to an artificial line which is 5-degree north to the Huai River as well as one 5-degree south to the river. We do not find any significant changes across these lines, suggesting that our tests have the proper power of rejecting none-existing influences of air pollution. Next, we use alternative specifications of RD in the Huai River test and different thresholds to define drastic changes and different length to measure the disposition effect in the difference-in-difference test. Finally, we also conduct tests on the opposite variation of the main difference-in-difference test—i.e., when city A's AQI increases drastically—and find that the disposition effect is significantly enhanced when air pollution is drastically increased in this case. In all these tests, our main conclusion remains valid.

To the best of our knowledge, we are among the first to document that pollution may significantly influence the behavior of individual investors. The closest paper to ours is Huang, Xu, and Yu (2016), which explores how air pollution affects the trading profitability of investors in China based on a brokerage dataset. Both studies demonstrate that air pollution adversely affect stock market investors. Our study differs by focusing on the influence of air pollution on cognitive bias. The larger coverage of our dataset also allows us to design two endogeneity tests to identify the causal impact of air pollution.

In doing so, we extend the literature on the disposition effect (Shefrin & Statman 1985, Barberis & Xiong 2009, 2012, Ben-David & Hirshleifer 2012, Henderson 2012, Li & Yang 2013, Frydman et al. 2014, An 2016, Chang, Solomon and Westerfield 2016; Hirshleifer 2015 provides a recent survey). Specifically, our results indicate that external environment could affect behavioral bias. Based on the recent finding of health science studies that air pollution hurts human cognitive ability (e.g., Fonken et al, 2011; Mohai et al., 2011; Weuve et al., 2012) and that from the finance literature that investors' trading behavior is associated with brain functions (e.g., Frydman 2014), it is reasonable to conjecture that air pollution affects trading behavior of investors through its influence on investors' cognitive heuristics as documented in the literature. The caveat here is that we do not directly observe the pivotal role played by cognitive heuristics of investors in our test, and cannot rule out the alternative that air pollution may affect trading behavioral bias through some other channels.

Finally, our paper also contributes to the emerging literature in understanding the influence of pollution and thus its associated economic and social costs. Existing studies indicate that pollution may adversely affect the health conditions of residence, such as life expectancy (e.g., Chen et al., 2013; Greenstone and Hanna 2014; Ebenstein et al, 2015), and human capital measures related to education, labor supply and productivity (e.g., Currie et al, 2009; Hanna and Oliva 2011; Mohai et al., 2011; Graff Zivin and Neidell, 2012; Chang, Graff Zivin and Neidell, 2016a,b). Our results suggest that the influence can be extended to financial markets as well. This finding has important normative implications in developing countries like China, because financial markets are important institutions for such countries to obtain sustainable growth.

The remainder of the paper is organized as follows. Section II presents our variables and summary statistics. Section III reports the baseline relationship between air pollution and the disposition effect. Section IV explores the endogeneity tests. Section V discusses additional robustness checks. Finally, Section VI concludes.

II. Data and Variable Construction

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

A. Sample and Data Sources

Our data comes from a confidential mutual fund family in China. The mutual fund family is located in Shanghai. It ranks top 30 in China, both in terms of the number of mutual funds offered and in terms of 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. It is common practice for Chinese fund families to use all three distribution channels. Each investor is allowed to open only one account through these channels, which is registered under his or her National Identity Number (at any given time, each citizen in China has a unique National Identity Number). After opening the account, investors can buy shares of any fund offered by this family and/or redeem their existing shares. The investment rules on the operations side of mutual fund investment are identical to those in the U.S.

For each account, the database allows us to retrieve information about the a) investor profile, b) trading history, and c) dividend distributions. The investor profile contains the personal information about an investor, including his or her unique National Identity Number, date of birth, gender, postcode and distribution channel. The trading file provides, for each transaction, 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 regarding the type and total amount of dividends distributed to each investor based on his/her share holdings in the specific mutual fund. Detailed information about the data is provided in Appendix B.

For each investor, the unique National Identity Number allows us to trace the region (i.e., the province) of birth, whereas the postcode allows us to verify the region of residence. Moreover, from account-level trading and dividend information, we can trace the entire trading history of each account, as well as 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 quantity and price data. Our results are not affected when we exclude these records.

We focus on the open-end equity funds offered by the family. We require a fund operations history that is longer than five years so that we can have a long period over which to examine the disposition effect. Our final sample includes 773,198 investment accounts trading seven equity funds from 2007 to 2015, which is larger than the sample of 128,829 accounts of mutual fund investors reported in Chang, Solomon and Westerfield (2016) based on the Odean (1998) dataset. The large coverage of dataset allows us to conduct endogeneity tests in later sections. Another benefit of our data is that investors do not pay taxes on capital gain or dividend payouts in China. This feature eliminates the confounding effects of tax-motivated selling activities.

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 to observe air quality. MEPC then collects information from these points based upon which it derives the average local AQI of the city. We also obtain other weather information, such as temperature and wind speed from China Meteorological Administration, and variables about local economy and development conditions from China Economic Administration.

Pricing information and equity mutual fund characteristics come from two major sources: China Stock Market and Accounting Research (CSMAR), which is available from the 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 daily prices (i.e., the net asset value or NAV), returns, and TNA for the seven equity funds, as well as characteristics such as fund fees and benchmarks. We crosscheck the two databases to ensure the accuracy of all the information. We check the quality of account-level data by aggregating the NAV 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.

B. Main Variables

We first describe our measure for air quality and then explain how we construct variables related to the disposition effect. Our main measure for air pollution is the daily AQI for each city, which synchronizes various contents of air pollutions, including sulfur dioxide (SO2), nitrogen dioxide (NO2), carbon monoxide (CO), ozone (O3), and particulate matter such as dust, smoke, liquid drops, dirt and other particles in the air (PM). Recently, PM has especially attracted public attention, because particulate matters less than 2.5 micrometers in diameter (i.e., PM2.5) can deposit in people's lungs and pose grave health risks. The AQI ranges from 0 to 500 in China. According to MEPC, air pollution in general increase in AQI according to the following seven categories:(1) Excellent (air quality) when AQI is under 50; (2) Good for AQI between 50 and 100; (3) Slightly polluted for AQI between 101 and 150; (4) Lightly polluted for AQI between 151 and 200; (5)Moderately polluted for AQI between 201 and 250; (6) Heavily polluted for AQI between 201 and 250; (7) Severely polluted for AQI above 300.[3]

We now move on to describe the construction of 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 the residential address of each investor. 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 particular fund via a specific distribution channel.

More explicitly, since the disposition effect is essentially the difference between the probability of selling winners (PSW) and that of selling losers (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.[4] 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.

Then, for each aggregate city account, we use the proportion of individual investors therein who sell shares of the fund conditional on capital gains to proxy for the probability of selling winners (PSW). 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:

$$Disp_{j,f,t} = PSW_{g,f,t} - PSL_{j,f,t},$$

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 of all the equity funds offered by the fund family.

We also control for city- and fund- level variables that can related with trading. At the city level, we control for the logarithm of GDP (*Log_GDP*), the logarithm of local population (*Log_pop*), the logarithm of domestic firms (*Log_dom_firm*), as well as the logarithm of government income (*Log_gov_income*). The

[3] 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 of the Huai-River Policy and wind blows are largely immune to this potential bias.

[4] 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.

first three variables mean to control economic growth, whereas the last controls for the power of 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.

At the fund level, *Ret* refers to the benchmark-adjusted fund return, which is calculated as the difference between the after-fee return of a fund in a month and its benchmark return. Next, different distribution channels may result in varying flow-performance sensitivity. For instance, investors could value their relationships with banks the most and therefore be reluctant to withdraw capital even when a fund performs poorly. Accordingly, we define the *Channel* variable to capture this effect. The variable takes the values 0, 1, and 2 for the bank branch, brokerage firm, and direct online account distribution channels, respectively. *Log(TNA)* is the logarithm of the mutual fund's total net assets in millions of RMB. *Mfee* is the percentage of the management fee as a share of fund TNA. *Fundage* is the number of days of operation since a fund's inception.

C. Summary Statistics

Table 1 presents summary statistics for our sample. Panel A tabulates the mean, median, standard deviation, and quantile distribution of the variables that describe trading behavior for individual and city-level accounts. Panels B, C report similar statistics for AQI, and economic growth related regional control variables, respectively. Especially, we can see that the PSW in a typical trading date is 0.382% for aggregate city accounts, which is much higher than the PSL (0.184%). Hence, 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-run trading (0.49% for sales made within 20 days of purchase) reported in Ben-David and Hirshleifer (2012). Although we examine two very different samples of investors, this similar finding suggests that Chinese and U.S. investors share common factors in terms of the disposition effect.

Panel D reports the correlation matrix of the main variables (the Internet Appendix provides a correlation matrix for all the 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 perform formal multivariate tests.

III. AQI and the Disposition Effect: Baseline Results

We start with a conventional strategy to estimate the relationship between air quality and investor's trading bias as follows:

$$Disp_{j,t} = \alpha_0 + \alpha_1 \times AQI_{j,t} + \alpha_2 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}, \quad (1)$$

where $AQI_{j,t}$ is the air quality index value for city j in period t; $Disp_{j,t}$ denotes the disposition effect of the aggregate account for city j in period t. 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_doemsticfirm*) and local government revenue (*Log_gov_income).* We also include region and time fixed effects to control for time-invariant characteristics that can affect investor's trading behaviors. The coefficient of interest is α_1, which estimates the potential impact of air quality on investor's trading bias after taking account of the relevant covariates.

The results are reported in Table 2. In Models (1) to (3), we examine the relationship between AQI and the disposition effect using alternative controls. In Models (4) to (6) and Models (7) to (9), we separately test the impact of air pollution on PSW and PSL, respectively, in order to understand the specific types of cognitive heuristic that air quality can have impact on.

The first three models illustrate a significant relationship between air pollution and the disposition effect. We can see that the coefficients of AQI are highly significantly positive across all the three specifications. The economic magnitude can be quantified as follows. Assume that AQI has increased from a slight-polluted level of 101 to the heavily-polluted level of 201—this change is very common change in cities like Beijing, and is about two-standard-deviation-change of daily AQI indices in our sample. The disposition effect increases by 5.8% compared to its average value.[5] Hence, the relationship is both statistically significant and economically relevant.

The next six models show that the effect concentrates more on selling-winners than on holding-onto-losers. This asymmetry could imply that investors compensate the cognitive suffering from air pollution by capital gains. This result, however, needs to be interpreted with caution, because we yet to prove whether air pollution is the reason for investors to alter their trading behavior or not. Our next section, therefore, moves on to explore whether air pollution has a causal influence on behavior bias.

IV. Two Plausibly Exogenous Tests

One concern related to our previous results is that the disposition effect and air pollution may be spuriously

[5] For the regression of $y = \beta \times X$, where y and X refers to the disposition effect and the logarithm of AQI, respectively, the economic magnitude of the marginal impact of AQI is estimated as $\beta \times \Delta X/\bar{y} = 0.038 \times [log(201) - log(101)]/0.198 = 5.8\%$.

correlated due to unobserved regional characteristics or reverse causality. In this section, we formally address this issue based on two endogeneity tests.

A. RD Tests based on the Huai-River Policy

The first test exploits the quasi-experiment of "Huai-River policy" as reported in Almond et al., (2009) and Chen et al., (2013). As mentioned, the Huai River splits China into northern and southern parts, and the central government of China 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 of a year. Since winter heating operates via the provision and burning of free coal for boilers, which releases air pollutants (it especially increases total suspended particulates or TSP in the air) because of technically inefficiency, this policy has unintendedly worsened air quality for cities located to the north of the river (Almond et al., 2009) and creates a "discontinuity" in terms of AQI across the river. This discontinuity allows Chen et al., (2013) to use regression discontinuity (RD) to identify the plausible causal influence of air pollution on life expectancy. We adopt the same methodology to understand the influence of AQI on behavioral bias.

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

$$AQI_{j,t} = \beta_0 + \beta_1 \times D(North)_j + f(R_j) + \beta_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t} \quad (2)$$

$$Disp_{j,t} = \theta_0 + \theta_1 \times D(North)_j + f(R_j) + \theta_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t} \quad (3)$$

where $AQI_{j,t}$ and $Disp_{j,t}$ refer to the AQI index and the disposition effect of all investors in city j in year t, $D(North)_j$ is an indicator variable that takes the value of one if city *j* is located north of the Huai River line and zero otherwise, R_j represents the degrees north of the Huai River for city *j*. The function *f* is parameterized as k-order a polynomial of $R_j$on either side of the Huai River Line. The vector $X_{j,t}$ contains a set of time-varying region-level control variables as described above. We include year fixed effects, δ_t, to address the possibility that the results are being driven by any particular years. We report our main results with *k* equaling 1 and 2 because Gelman and Imbens (2014) demonstrate that casual effects based on higher polynomials can be misleading and recommend the use of local linear or quadratic polynomials.

The main results of this system of equations are tabulated in Table 3, Panel A for a linear specification and Panel B for a quadratic specification. In each panel, Models (1) and (2) report the results of Equation (2) with different control variables, and Models (3) and (4) tabulate the results for Equation (3). 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 important to our analysis, Models (3) and (4) suggest that investors' trading behavior also exhibit an interesting jump across the river. This effect is highly significant.

This "discontinuity" effect in the disposition effect is more intuitively illustrated in Figure 2. In this figure, Panels A and B visualize the general trend of the disposition effect based on linear and quadratic specifications, respectively. The x-axis indicates the degree of latitude of a city with respective to the Huai River, while 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 when compared to the average disposition effect to the south (left) of the river.

Next, based on the results of this system of equations, we can further rely on a two-stage least-square specification to estimate the casual effect of AQI on investor's trading bias. The first stage is the same as Equation (2). In the second stage, instead of Equation (3) we regress the disposition effect on Huai-River Policy instrumented air pollution as follows:

$$Disp_{j,t} = \gamma_0 + \gamma_1 \times \widehat{AQI_{J,t}} + f\left(R_j\right) + \gamma_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}, \qquad (4)$$

where $\widehat{AQI_{J,t}}$ is the fitted value from estimating Equation (2), R_j represents the degrees north of the Huai River for city j. The function *f* is parameterized as k-order a polynomial of R_j on either side of the Huai River Line.

The results are reported in Table 4. Panel A for a linear specification and Panel B for a quadratic specification. We can see that instrumented air pollution positively affect the trading bias. This effect is highly significant across all specifications, lending strong support to a causal interpretation of the general relationship between air pollution and behavioral bias of investors.

Before we move on to the next test, we want to also mention one technical issue of the RD estimation. For the main body of the RD analysis, we choose bandwidth = 10 degrees (around 1000 km) around the Huai River Line. Essentially, we face a trade-off between bias and variance in choosing the bandwidth: larger bandwidth will give us higher testing power but lower accuracy and vice versa. As later robustness checks will show, our main results are qualitatively the same using alternative bandwidth choices. The large city coverage of our dataset contributes to the accuracy of our analysis in this test.

B. Vast Dissipation of Air Pollution due to Strong Winds

In addition to the above quasi-experiment, we further examine exogenous variations in AQI building on the knowledge obtained from the atmospheric environment literature. In that literature, researchers show that the formation and dissipation of air pollution are heavily influenced by weather conditions in general and wind conditions in particular (e.g., Seaman, 2000; Arain et al., 2007). China is no exemption (Su et al., 2015): drastic improvements in air quality (or large drops in AQI) are usually caused by strong winds, whereas drastic deteriorations in air quality (or large increases in AQI) often occur in opposite unfavorable weather conditions. Especially, drastic dissipation of air pollution, which are typically driven by a windy weather, are largely exogenous to financial markets, allowing us to use difference-in-difference tests to identify the influence of air pollution.

To design difference-in-difference tests utilizing drastic dissipation of air pollution, we first identify the treatment group by focusing on all city-day events in which AQI sharply drops for more than two standard deviations of AQI distribution (roughly a drop of AQI for more than 88). We choose this threshold because, once a severe air pollution is formed, this magnitude of AQI change will not occur simply based on natural dissipation without exogenous weather changes—strong winds and similar weather conditions are typically the reason to drive such big AQI changes—but our results are robust to this threshold. Since trading only occurs during weekdays, we restrict the event days to be either Wednesday or Thursday so that we can have 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. Once the treatment group is identified, we match it (by searching in the non-treated sample of cities) with cities that have the closest pre-treatment average of AQI values within the same week without large changes in AQI. These matched cities become our control group.

We then examine the potential changes in the disposition effect of the treatment group due to large AQI changes in the following difference-in-difference specification:

$$Disp_{j,t} = \rho_0 + \rho_1 \times Treated_{j,t} + \rho_2 \times Treated_{j,t} \times After_{j,t} + \rho_3 \times After + \rho_4 \times X_{j,t} + \delta_t + \varepsilon_{j,t} \quad (5)$$

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

The results are reported in Table 5. In univariate tests, we see that the disposition effect does not have any significant difference between the two groups of investors in pre-wind periods, and that the control group investors have consistent disposition effects throughout the week. Significant results come from the treated group as well the difference-in-difference term: when AQI drops drastically in treated cities, investors therein demonstrate significantly less behavioral bias either on its own or when compared to investors located in the control cities that are exposed to as severe air pollution as the treated cities all over the week. The multivariate analysis generates very similar results. While the coefficients before $Treated_{j,t}$ and $After_{j,t}$ are both insignificant, the interaction term of $Treated_{j,t} \times After_{j,t}$ is significantly negative. This result suggests that investors in the treated cities exhibit significantly less degree of behavioral bias once the air pollution has been reduced. This result not only supports the existence of a causal influence of air pollution on behavioral bias, but also suggests that the influence is observable at least at the daily frequency. Hence, the influence of air pollution on cognitive bias can occur in a very short horizon.

V. Additional Tests and Robustness Checks

In this section, we first conduct a list of robustness checks to further validate our previous results. In the first set of tests, we further assess the testing power of the Huai-River policy. Especially, we conduct a Placebo test in which we apply the same RD and two-stage tests to an artificial line which is 5-degree north to the Huai River as well as one 5-degree south to the river. The results are tabulated in Table 6. We do not find any significant changes across these lines, suggesting that our tests have the proper power of rejecting none-existing influences of air pollution. In addition, we find that residence to the north of Huai-River exhibits higher disposition effect in winter times, consistent with the notion that air quality therein during the heating period is especially deteriorating due to the Huai-River policy. Finally, alternative specifications of RD in the Huai River test lead to similar results as reported in Table 7.

In the second set of tests, we examine the robustness of the difference-in-difference test. We first conduct tests on the opposite variation of the main difference-in-difference test—i.e., when city A's AQI increases drastically—and find that the disposition effect is significantly enhanced when air pollution is drastically increased in this case. Next, we use different thresholds to define drastic changes and different length of treatment period to measure the disposition effect in the DID tests. In all these tests, our main conclusion remains valid.

Conclusion

Inspired by the recent health science findings that air pollution can significantly damage the function of brains and reduce the cognitive skills of individuals in addition to its better known impacts on respiratory, vascular, and mortality, we examine whether air pollution can significantly intensify cognitive bias observed in the financial markets.

Based on a proprietary dataset obtained from a large mutual fund family in China, which contains the complete trading information of 773,198 accounts covering more than 200 cities, we find that air pollution significantly increases the disposition effect of investors. We further examine two plausible exogenous variations in air quality. In the first quasi-experiment, the Huai-River heating policy of the central government in China had unintendedly created a discontinuity in AQI across the Huai River. In the second test, strong winds lead to vast dissipations of air pollution. In both tests, we find that exogenous variations in air quality lead to changes behavior bias. These tests suggest that air pollution has a causal influence on the cognitive bias observed in the financial markets.

Our results have important normative implications regarding the role of environment played in developing countries like China. We show that air pollutions may incur severe indirect (social) costs associated with enhanced cognitive biases in financial markets. Hence the cost of air pollution could be much higher than recognized before. Our study thus calls for more attention and actions from the regulators and researchers to better protect the environment of our modern society.

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Appendix A

Panel A: Aggregated Account-level Variables	
Aggregate Account	City-level
Region	247 cities in China
Channel	Distribution channels of mutual funds (0, 1, and 2 represent the bank, broker, and direct channels, respectively)
AQI	The measure is intended measurement of harmful content in the air including namely sulfur dioxide (SO2), nitrogen dioxide (NO2), carbon monoxide (CO), and ozone (O3) as well as particulate matter (PM).
The Disposition Effect	The disposition effect 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: Fund-level Variables	
Ret	Benchmark-adjusted return: Difference between the fund monthly net return and its benchmark return.
Log(TNA)	Log total net assets of the mutual funds in millions of RMB
Mfee	Percentage of management fee as a share of total net assets of the fund
Fundage	Number of years since the fund launch
NAV	Daily net asset value of the fund
Panel C: Region-level Variables	
Log_GDP	Log of gross domestic product at year end in billions of RMB
Log_pop	Log of total population in the 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	Squares of Latitude degree north of the Huai River line for the region

Appendix B

The dataset consists of three main parts, investor account-level information, dividend distribution information and investor trade information. The investor account-level information describes an individual investor's account, including the investor's unique national identity (e.g., date of birth, age, gender, education, vocation and location) and the account status (e.g., application date, confirmation date, Internet service and bonus type). Dividend distribution information includes the amount distributed to each investor based on his/her fund holdings, and this table includes the fund code, investor ID, investor location, dividend date and bonus type. Finally, investor trade information includes all the necessary information regarding an investor's purchases and sales of the fund, which includes an investor's trade type, trade fees and channel used to purchase shares. For a complete review of the data, please refer to the following table.

Panel A: Investor Account-level Information	
CustID	Investor's ID
Birth	Investor's date of birth
Education	Investor's education level
Vocation	Investor's vocation
Confirm Date	Account confirmation date
Call Service	Whether telephone service is open
Internet Service	Whether Internet service is open
Channel*	Business channel
Region	Investor province location
Postcode	Investor location postcode
BusinFlag*	Business type
Panel B: Dividend Distribution Information	
CustID	Investor's ID
FundID	Fund code
Regdate	Registration date for the dividend
Exdate	Ex-dividend date
PayDate	Date of payment
Bonustype	0=Dividend reinvested 1=Cash dividend
Totalshare	Investor holding of the fund for dividend
Unitprofit	Dividend per share
Totalprofit	Total dividend proceed
Panel C: Investor Trading Information	
BusinFlag*	Transaction type
Cdate	Confirmation date
Balance	Application amount (cash)
Shares	Application amount (shares)
Confirmbalance	Confirmation amount (cash)
Netvalue	Net value per share (based on date)
Transactionfee*	Total transaction fees
AGIO	Discount percentage on transaction fees
Channel	Business channel
Agency No.	The channel agency code
Region	Investor province location
City	Investor city location
Postcode	Investor location postcode

Table 1: Summary Statistics

This table presents summary statistics for the data used in the paper from 2007 to 2015. Panel A reports the aggregate account level statistics while Panel B and C are for air quality and regional controls. Panel D presents the Spearman Rank Correlation Coefficient of the variables used for this paper. Coefficients significant at 5% level are in bold.

	N	Mean	SD	min	5%	25%	Median	75%	95%	max
Panel A Aggregate Account-Level Variables										
Disposition Effect,%	144820	0.198	1.535	-87.611	-0.662	0.000	0.000	0.000	1.867	57.692
PSW,%	144820	0.382	1.376	0.000	0.000	0.000	0.000	0.125	2.083	57.692
PSL,%	144820	0.184	0.857	0.000	0.000	0.000	0.000	0.011	0.952	87.611
Panel B Air Quality Index										
AQI	144239	80.265	44.250	0	34	54	70	94	159	500
Panel C Region Control										
Log_GDP	1540	15.890	1.168	12.436	14.244	15.057	15.742	16.624	18.019	19.441
Log_pop	1532	4.873	0.839	1.629	3.649	4.320	4.805	5.387	6.333	7.741
Log_num_dom_firm	1532	5.733	1.325	2.177	3.691	4.852	5.684	6.475	7.965	14.846
Log_gov_income	1538	13.382	1.355	8.692	11.220	12.530	13.310	14.208	15.696	17.850

Panel D Variable Correlation

		1	2	3	4	5	6	7	8
1	PSW	1							
2	PSL	**0.1153**	1						
3	Disposition Effect	**0.8323**	-0.4548	1					
4	Log_GDP	**0.0083**	-0.0082	0.012	1				
5	Log_pop	-0.0042	**-0.0133**	0.0036	**0.8473**	1			
6	Log_num_domestic_firm	0.0016	-0.0083	0.006	**0.8268**	**0.7788**	1		
7	Log_gov_income	**0.0133**	-0.0038	**0.0141**	**0.902**	**0.77**	**0.7756**	1	
8	AQI	**0.0037**	**-0.0063**	**0.0068**	**0.0063**	**0.0256**	0.0051	**0.0171**	1

Table 2: The Impact of Air Quality on Trading Bias: Baseline Analysis

This table presents the baseline relationship between air quality and trading bias based on the following specification:

$$Trading\ Bias_{j,t} = \alpha_0 + \alpha_1 \times AQI_{j,t} + \alpha_2 \times X_{j,t} + \delta_t + \theta_j + \varepsilon_{j,t}$$

where $AQI_{j,t}$ is the air quality index value for city j at day t; $Trading\ Bias_{j,t}$ denotes the disposition effect of the aggregate account of region j in day t. We also report the impact on PSW and PSL in Column 4-9. 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*). The sample period is from year 2007 to 2015. Appendix A provides more detailed variable definition. We control for region and time fixed effects in all specifications except for Column 1, 4 and 7. Robust t-statistics are reported in parenthesis and based on standard errors clustered by year. *,**,*** denotes significance at the 10%,5% and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Disposition Effect			PSW			PSL		
Log_AQI	0.023***	0.038**	0.038**	0.016**	0.033***	0.033***	-0.007	-0.005	-0.005
	(2.79)	(2.05)	(2.05)	(2.19)	(2.80)	(2.85)	(-1.51)	(-0.43)	(-0.39)
Log_GDP			-0.068			-0.051			0.016
			(-1.21)			(-0.86)			(0.47)
Log_pop			0.032			0.021			-0.011
			(1.16)			(0.50)			(-0.60)
Log_num_domfirm			0.036			0.013			-0.023**
			(0.71)			(0.25)			(-2.32)
Log_gov_income			0.035			0.040			0.005
			(1.09)			(1.52)			(0.35)
Constant	0.100***	-0.088	0.147	0.313***	0.165	0.259	0.212***	0.253**	0.112
	(2.84)	(-0.61)	(0.18)	(9.73)	(1.39)	(0.30)	(11.35)	(3.08)	(0.19)
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
R-Sqr	0.00	0.02	0.02	0.00	0.04	0.04	0.00	0.02	0.02
N	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238	144,238

Table 3: Discontinuity Test for AQI and Trading Bias using the Huai River Policy

This table presents the discontinuity test for the effect of Huai River Policy on the AQI and trading bias. Speicifically, we estimate the following two specification on the city and yearly basis from 2007 to 2015 around the Huai River Line

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

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

where for $|R_j|$<10, $D(North)_j$ is an indicator variable that equals one if city *j* is located north of the Huai River line, R_j represents the degrees north of the Huai River for city j. The function *f* is parameterized as k-order a polynomial of R_j on either side of the Huai River Line. Other variables are defined in the same as Table 2. Panel A and B present estimates whereby we vary the order of polynomial, with Panel A for linear (k=1) and Panel B for quadratic (k=2) form respectively. Year fixed effect are included in all specifications. Robust t-statistics are reported in parenthesis and based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AQI		Disposition Effect		PSW		PSL	
Panel A : Linear								
D(North)	9.351**	9.845***	0.597***	0.646**	0.440	0.461	-0.319	-0.326
	(2.52)	(3.73)	(3.59)	(3.00)	(1.44)	(1.27)	(-1.48)	(-1.36)
Degree North	0.392	0.211	-0.023***	-0.024**	-0.021	-0.020	0.026*	0.026
	(0.90)	(0.82)	(-2.81)	(-2.05)	(-0.90)	(-0.82)	(1.76)	(1.63)
Log_GDP		-3.717		-0.157		-0.233		-0.063
		(-1.55)		(-1.29)		(-1.46)		(-1.21)
Log_pop		14.563**		-0.114		0.037		0.073
		(3.27)		(-1.28)		(0.49)		(0.85)
Log_num_domfirm		-2.658		0.131		0.093		-0.034
		(-1.46)		(1.49)		(0.67)		(-0.43)
Log_gov_income		-0.333		0.045		0.057		0.049*
		(-0.42)		(0.93)		(1.38)		(1.93)
Constant	69.524***	73.649***	0.079	1.707	0.290**	2.434*	0.301***	0.477
	(37.96)	(3.25)	(1.03)	(1.57)	(1.97)	(1.79)	(2.90)	(0.75)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
R-Sqr	0.27	0.31	0.06	0.07	0.06	0.06	0.04	0.04
N	678	678	678	678	678	678	678	678
Panel B : Quadratic								
D(North)	12.062***	11.689***	0.604***	0.649***	0.458	0.470	-0.306	-0.317
	(2.86)	(3.76)	(3.75)	(3.12)	(1.50)	(1.30)	(-1.37)	(-1.29)
Degree North	0.011	-0.086	-0.024***	-0.024**	-0.024	-0.022	0.025	0.025
	(0.02)	(-0.29)	(-3.10)	(-2.30)	(-1.06)	(-0.92)	(1.52)	(1.46)
Degree North Squared	-0.179***	-0.156***	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001
	(-4.71)	(-5.57)	(-0.37)	(-0.24)	(-0.69)	(-0.59)	(-0.97)	(-1.05)
Log_GDP		-1.843		-0.153		-0.225		-0.053
		(-0.61)		(-1.24)		(-1.46)		(-1.14)
Log_pop		12.377***		-0.118		0.027		0.062
		(2.84)		(-1.49)		(0.46)		(0.69)
Log_num_domfirm		-3.486*		0.129		0.090		-0.038
		(-1.77)		(1.44)		(0.66)		(-0.50)
Log_gov_income		-0.090		0.046		0.059		0.051**
		(-0.12)		(0.96)		(1.44)		(1.97)
Constant	72.716***	60.311**	0.088	1.682	0.312**	2.373*	0.316***	0.409
	(62.37)	(2.07)	(1.03)	(1.55)	(2.07)	(1.81)	(3.29)	(0.69)

Time FE	YES	YES	YES	YES	YES	YES	YES	YES
R-Sqr	0.29	0.33	0.06	0.07	0.06	0.07	0.04	0.04
N	678	678	678	678	678	678	678	678

Table 4: The Impact of AQI on Trading Bias: Two-staged Least Squares

This table provides panel regression estimates of the effect of AQI, instrumented by the location relative to the Huai River Line, on trading bias between 2007 and 2015. The results are from estimating the following specification around the Huai River Line:

$$Trading\ Bias_{j,t} = \gamma_0 + \gamma_1 \times \widehat{AQI_{j,t}} + f(R_j) + \gamma_2 \times X_{j,t} + \delta_t + \varepsilon_{j,t}$$

where for $|R_j|$<10, $\widehat{AQI_{j,t}}$ is the fitted value from estimating Equation (2), R_j represents the degrees north of the Huai River for city j. The function *f* is parameterized as k-order a polynomial of $R_j$on either side of the Huai River Line. Other variables are defined in the same as Table 2. Panel A and B present estimates whereby we vary the order of polynomial, with Panel A for linear (k=1) and Panel B for quadratic (k=2) form respectively. All Cragg-Donald Wald F-statistics exceed the Stock-Yogo weak instrument thresholds. Year fixed effect are included in all specifications. Robust t-statistics are reported in parenthesis and based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Disposition Effect		PSW		PSL	
Panel A Linear						
D(North)	0.065**	0.066**	0.045	0.046	-0.034**	-0.034*
	(2.42)	(2.45)	(1.19)	(1.11)	(-2.07)	(-1.84)
Degree North	-0.049	-0.038*	-0.038	-0.030	0.040*	0.033*
	(-1.45)	(-1.66)	(-1.20)	(-1.06)	(1.69)	(1.68)
Log_GDP		0.106		-0.063		-0.193*
		(0.56)		(-0.42)		(-1.73)
Log_pop		-1.096***		-0.645		0.567
		(-2.76)		(-1.18)		(1.47)
Log_num_domfirm		0.307*		0.225		-0.124
		(1.82)		(1.14)		(-0.78)
Log_gov_income		0.063		0.075		0.039
		(0.89)		(1.26)		(1.32)
Constant	-4.418**	-3.279	-2.859	-0.965	2.695**	3.017**
	(-2.23)	(-1.52)	(-1.01)	(-0.38)	(2.18)	(2.03)
Time FE	YES	YES	YES	YES	YES	YES
N	678	678	678	678	678	678
Panel B Quadratic						
D(North)	0.051**	0.056**	0.037	0.039	-0.026*	-0.028*
	(2.53)	(2.47)	(1.21)	(1.12)	(-1.93)	(-1.74)
Degree North	-0.025	-0.020	-0.023	-0.018	0.025	0.022
	(-1.00)	(-1.19)	(-1.10)	(-0.98)	(1.52)	(1.57)
Degree North Squared	0.009***	0.008**	0.005	0.006	-0.005**	-0.005*
	(2.81)	(2.16)	(1.22)	(1.12)	(-2.14)	(-1.83)
Log_GDP		-0.033		-0.155		-0.110
		(-0.15)		(-0.94)		(-1.04)
Log_pop		-0.831***		-0.469		0.408
		(-2.70)		(-1.20)		(1.31)
Log_num_domfirm		0.325*		0.237		-0.134
		(1.75)		(1.09)		(-0.84)
Log_gov_income		0.046		0.064		0.049
		(0.75)		(1.30)		(1.59)
Constant	-3.606**	-1.817	-2.339	0.008	2.186**	2.141*
	(-2.33)	(-0.96)	(-1.00)	(0.00)	(2.08)	(1.66)
Time FE	YES	YES	YES	YES	YES	YES
N	678	678	678	678	678	678

Table 5: The Impact of AQI on Trading Bias: Abrupt Change in Weather

This table reports estimate based on a difference-in-difference test. Large change in AQI value is often due to abrupt weather change that can be viewed as an exogenous treatment. So we first create the treated sample by selecting all city-day observations, that AQI experience a big rise or drop with the magnitude larger than two times of the standard deviation, roughly 88. Since trading only occurs during weekdays, we restrict the treatment days to be either Wednesday or Thursday so that we can have valid number of pre- and post-treatment observations for analysis. Then, for each treated city j at day t, we search in the non-treated sample and matched with the city-day that has the closest pre-treatment average of AQI values within the same week. Panel A and B present the multivariate results for big rise and drop sample. Robust t-statistics are reported in parenthesis and based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AQI		Disposition Effect		PSW		PSL	
Panel A Big Rise in AQI								
Treated*After	90.104***	89.995***	0.173**	0.162*	0.113	0.110	-0.060	-0.052
	(24.08)	(24.21)	(2.10)	(1.91)	(1.60)	(1.52)	(-1.23)	(-1.04)
Treated	6.986***	5.303**	-0.122*	-0.134*	-0.129**	-0.147**	-0.007	-0.014
	(3.28)	(2.49)	(-1.83)	(-1.94)	(-2.23)	(-2.46)	(-0.17)	(-0.35)
After	-2.616	-2.476	-0.035	-0.039	-0.049	-0.053	-0.015	-0.013
	(-1.47)	(-1.40)	(-0.53)	(-0.57)	(-0.89)	(-0.92)	(-0.38)	(-0.34)
Log_GDP		-10.051***		-0.074		-0.037		0.037
		(-3.55)		(-1.31)		(-0.78)		(0.83)
Log_pop		26.200***		0.073		-0.001		-0.074
		(8.90)		(1.15)		(-0.02)		(-1.43)
Log_num_domfirm		-4.500***		-0.009		-0.015		-0.006
		(-2.74)		(-0.28)		(-0.55)		(-0.33)
Log_gov_income		-4.908**		0.071***		0.087***		0.016
		(-2.34)		(3.10)		(4.28)		(1.31)
Constant	93.896***	207.191***	0.076	-0.023	0.468**	0.009	0.392**	0.032
	(22.28)	(8.64)	(0.26)	(-0.04)	(2.08)	(0.02)	(2.13)	(0.07)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
R-Sqr	3,355	3,271	3,355	3,271	3,355	3,271	3,355	3,271
N	0.32	0.34	0.01	0.01	0.01	0.01	0.01	0.01
Panel B Big Drop in AQI								
Treated*After	-90.924***	-89.896***	-0.173**	-0.195**	-0.132*	-0.151**	0.041	0.044
	(-25.62)	(-25.80)	(-2.22)	(-2.50)	(-1.85)	(-2.12)	(0.91)	(0.99)
Treated	77.307***	77.777***	0.070	0.076	0.054	0.055	-0.016	-0.021
	(27.85)	(28.07)	(1.39)	(1.56)	(1.16)	(1.22)	(-0.66)	(-0.85)
After	-16.394***	-17.553***	0.053	0.075	0.049	0.067	-0.004	-0.008
	(-10.10)	(-11.28)	(0.98)	(1.37)	(0.92)	(1.26)	(-0.15)	(-0.29)
Log_GDP		-20.824***		-0.107*		0.008		0.115***
		(-8.11)		(-1.92)		(0.16)		(3.15)
Log_pop		20.995***		0.091		0.077		-0.014
		(6.31)		(1.38)		(1.35)		(-0.33)
Log_num_domfirm		0.950		-0.008		-0.073**		-0.065***
		(0.64)		(-0.24)		(-2.37)		(-4.54)
Log_gov_income		1.295		0.092***		0.052		-0.040*
		(0.79)		(2.59)		(1.64)		(-1.73)
Constant	108.858***	308.319***	0.080	0.077	0.243***	-0.593	0.163***	-0.669**
	(23.24)	(13.45)	(1.16)	(0.16)	(4.51)	(-1.43)	(3.19)	(-2.42)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
R-Sqr	3,500	3,460	3,500	3,460	3,500	3,460	3,500	3,460
N	0.40	0.42	0.02	0.02	0.02	0.02	0.01	0.02

Table 6: A Placebo Test on the Huai-River Policy

This table reports the placebo tests using the latitude of 28.6 and 38.6 as cutoff points, which are 5 degrees south and north of the Huai River Line. Variables are defined in the same as Table 2. Appendix A provides more detailed variable definition. We present estimates whereby we vary the order of polynomial, with Column 1 and 2 for linear (k=1) and Column 3 and 4 for quadratic (k=2) form respectively. Year fixed effect are included in all specifications. Robust t-statistics are reported in parenthesis and based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Linear		Quadratic	
	OLS	IV	OLS	IV
Panel A Latitude of 28.6 degree				
D(North)	-0.199		-0.208	
	(-0.83)		(-0.74)	
$\widehat{AQI_{J,t}}$		0.083		0.082
		(0.11)		(0.53)
Control	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
N	639	639	639	639
Panel B Latitude of 38.6 degree				
D(North)	-0.230		-0.156	
	(-1.36)		(-0.76)	
$\widehat{AQI_{J,t}}$		0.018		0.032
		(0.96)		(0.88)
Control	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
N	639	639	639	639

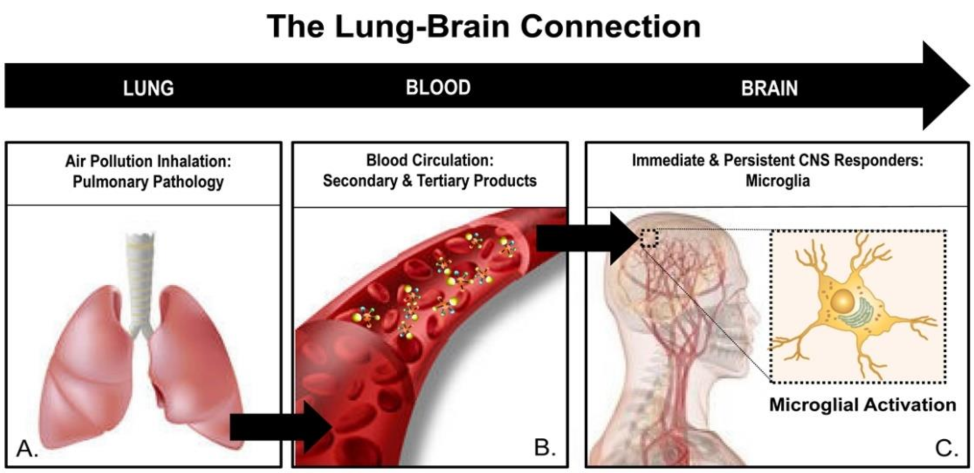
Table 7: Alternative Specifications for the RD test

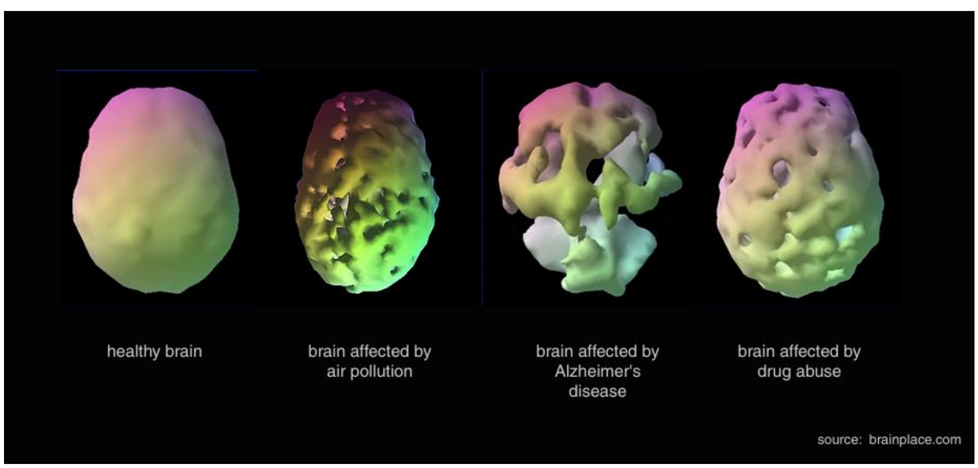
This table presents the robustness test for the regression discontinuity design. Specifically, we report the results for different bandwidth choice: 5 and 8 around the Huai River Line. Variables are defined in the same as Table 2. Appendix A provides more detailed variable definition. Panel A and B present estimates whereby we vary the order of polynomial, with Panel A for linear (k=1) and Panel B for quadratic (k=2) form respectively. Column 1 and 3 reports OLS estimates similar to Table 3 while Column 2 and 4 presents results based on Equation 4. Year fixed effect are included in all specifications. Robust t-statistics are reported in parenthesis and based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	$\lvert R_j \rvert$<8		$\lvert R_j \rvert$<5	
	OLS	IV	OLS	IV
Panel A Linear				
D(North)	0.814***		1.291**	
	(2.59)		(2.23)	
$\widehat{AQI_{J,t}}$		0.072***		0.179
		(2.70)		(1.51)
Control				
Time FE	YES	YES	YES	YES
N	587	587	430	430
Panel B Quadratic				
D(North)	0.827***		1.236**	
	(2.63)		(2.26)	
Degree North		0.083**		0.161*
		(2.54)		(1.68)
Control				
Time FE	YES	YES	YES	YES
N	587	587	430	430

Figure 1. Illustrations of Brain Damages from Science Blogs

The figure cites two blogs and their posted figures to demonstrate the influence of air pollution on human brains. The first blog (top figure), “Urban air pollution exposure may trigger toxic responses in brain cells and impact neurodegenerative disease pathways” (February 18, 2014)[1], explains the pivotal role microglia plays through which air pollution can immediately affect human brains: “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. 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.” The second blog (with the figure below), “Can air pollution cause permanent brain damage?” (June 3, 2016)[2], compares the SPECT scan of a brain of a person exposed to air pollution to those of Alzheimer’s disease or drug abuse.





[1] https://medicalxpress.com/news/2014-02-urban-air-pollution-exposure-trigger.html
[2] https://u-earthblog.com/2016/06/03/can-air-pollution-cause-permanent-brain-damage/

Figure 2. RD Plots of AQI and the Disposition Effect Across the Huai-River Line

The figure plots cities' AQI and trading bias against its degrees north of the Huai River Line, which is drawn at 33.6 (roughly the middle of the latitude range covered by the Huai River line). Each dot represents the average over each bin and number of bins are selected based on mimicking variance evenly-spaced method using spacing estimators.