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Be nice to the air: Severe haze pollution and mutual fund risk

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A B S T R A C T

Motivated by the significant impacts of environmental risks on economic decisions and the increasing roles of mutual funds in financial markets in recent decades, this study examines the impact of ambient pollution on mutual funds' risk outcomes. Our fund fixed-effect regression estimates use manually collected propriety data from several datasets, showing that polluted air increases tracking errors and mutual fund return volatility. Adopting different identification strategies, including instrumental variable estimations and difference-in-difference analyses based on two natural experiments, suggests that the impact of air pollution on mutual funds' risk is causal. Our findings suggest that air pollution harms fund managers' cognitive abilities and impairs their investment efficiency, thereby increasing mutual funds' tracking errors and return volatility. Overall, our findings provide insights into the impact of climate change on social behavior by shedding new light on the impact of air quality on asset managers' behavior.

1. Introduction

Air pollution is one of the greatest environmental risks worldwide, affecting various aspects of life. Evidence from both sustainable finance, psychological and science literature suggests that poor air quality has far-reaching health, economic, and social consequences (Ebenstein et al., 2017; Künn et al., 2023; Liao et al., 2021; Wang & Lee, 2022). Recent studies suggest air quality significantly impacts financial market participants (Xu, 2022). Recent studies (Dong et al., 2021; Huang et al., 2020) focus on the impact of air pollution on the forecasting capacity of financial analysts and households' investment behavior; however, whether and the extent to which severe haze pollution influences professional asset managers remain under-investigated. Our paper addresses these gaps by investigating the impact of air quality on mutual funds' risks.

Our focus on mutual funds has important economic and social significance for two reasons. First, the mutual fund industry has played an increasing role in financial markets in recent decades. As Khorana and Servaes (2012) note, assets under management in the fund business have expanded from about 50 billion US dollars (USD) in 1976 to over 11 trillion USD in 2009, while the number of offering funds has quadrupled over the same period, based on the Investment Company Institute Fact Book. There were over 7700 US mutual funds with 13.4 trillion USD in assets in 2016 (Kostovetsky & Warner, 2020). The world mutual fund business handled over 26 trillion USD of financial holdings in 2007, compared to 6 trillion USD of assets handled in 1996 (Ferreira et al., 2013; Investment Company Institute, 2008). Second, managing a fund is a cognitively demanding activity. Polluted air has various negative externalities, such as cognitive impairment (Zhang et al., 2018), and behavioral biases lead to significant economic consequences (Coval & Shumway, 2005); therefore, understanding how air quality influences mutual fund managers and their investment decisions would provide more insights into the real economic consequences of one of the most significant environmental risks in the world.

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Air quality affects mutual funds' risk outcomes in several ways. *First*, fund managers often make stock investment decisions requiring significant cognitive efforts. Managers must gather information from various sources and utilize it to decide what stocks to buy or sell, how many stocks to trade, and when to execute trading decisions; thus, fund managers' inability to make the right choice at the right moment can raise the risk of the funds they manage (Agarwal & Mazumder, 2013; Benjamin et al., 2013; Frederick, 2005). As polluted air impairs cognitive function, air quality may impact fund managers' cognitive capacities, contributing to their funds' risk. *Second*, air pollution can accelerate attitude changes and sleep loss (Heyes & Zhu, 2019; Sass et al., 2017), resulting in considerable judgment mistakes and less information processing capacity, thereby intensifying mispricing in the financial markets (Nguyen & Pham, 2021). Therefore, we conjecture that air quality can impact fund managers' information processing by affecting their cognitive functioning and accelerating mood-induced judgments.

We employ two measures of fund risk to examine the impact of air quality on mutual fund managers' risk-taking behavior. First, tracking errors is a risk measure (Chen & Pennacchi, 2009; Huang et al., 2011) and active management (Cremers & Petajisto, 2009). An increase in fund risk also indicates fund managers' inferior ability (Huang et al., 2011). Furthermore, tracking errors matter for various economic decisions. The volatility of funds' deviation from their benchmark can impose multi-dimensional externalities, such as fund performance (Cremers et al., 2016; Cremers & Petajisto, 2009), fund flows (Spiegel & Zhang, 2013), fund managers' compensation (Huang et al., 2011), job security and career progression (Hu et al., 2011); thus, examining tracking errors is essential in mutual funds' risk management practices. Second, fund return volatility can measure fund risk (Huang et al., 2011; Shu et al., 2012); therefore, we employ tracking errors and fund return volatility as our dependent variables of interest. These measures can illustrate managers' intensely focused stock picks and their stance on systematic factors that can be potentially affected by air pollution. Additionally, examining the determinants of tracking errors and fund volatility has significant implications for practitioners and capital market regulators.[1]

China is considered one of the most polluted economies in the world, as specified by the Environmental Performance Index issued by the Yale Centre for Environmental Law and Policy.[2] While China's overall air pollution level is high, significant changes in air pollution levels are observed across times and cities in China (Chen, Ebenstein, et al., 2013; Chen, Jin, et al., 2013), providing an excellent setting for our empirical tests. Our sample covers 618 mutual funds and 1339 fund managers in China from January 2003 to February 2019. Our fund fixed-effect regression estimates show a positive relationship between air pollution and fund managers' risk-taking behavior. The magnitude of the effect is pronounced, with a shift from an air quality index (AQI) of 50 (the least hazardous level) to an AQI of 101 (a level that is hazardous for sensitive people), corresponding to a 7.93% (4.21%) increase in the sample median of tracking errors (return volatility). The findings suggest that mutual fund managers can encounter several side effects of hazardous air pollutants, such as cognitive dysfunction and lack of concentration. Consequently, fund managers tend to exhibit cognitive and behavioral biases in decision-making due to ambient pollution, leading to an increased tracking error and fund return volatility.

We acknowledge that the baseline specifications could suffer from potential omitted variables and reverse causality concerns. To address the endogeneity concerns, we exploit three identification strategies. First, following Arceo et al. (2016), Xue et al. (2021), and Chen et al. (2022), we employ a two-stage least squares (2SLS) regression with thermal inversion as an instrumental variable. A thermal inversion is a climatic and weather-related event that causes massive variations in air pollution. The results from the 2SLS models show that thermal inversion incidents produce critical levels of air pollution and that instrumented AQI is positively associated with active mutual funds' tracking errors and return volatility.

The second identification employs the Beijing Olympic Games 2008 (BOG08 hereafter) as an exogenous shock (Chen, Ebenstein, et al., 2013; Chen, Jin, et al., 2013; He et al., 2016). The Chinese Government executed numerous mandates for substantially reducing air pollution to ensure clean air throughout the BOG08; however, the Guardian reported that the Chinese Government's preliminary pollution control mandates were insufficient to clear air pollutants from the city.[3] Thus, additional traffic control regulations were implemented to improve air quality throughout the BOG08. This attempt reduced total automobile exhaust emissions by 60% at that time.[4] Our findings show that the risk of active mutual funds declined significantly during the BOG08 when air quality substantially improved in Beijing.

The third identification adopts the sporadic change in air quality along the Qinling-Huai (QH) River, resulting from China's heating policy (Ebenstein et al., 2017). Higher levels of air pollution are observed on the north side of the QH because the northern regions use coal-based hot water boilers for winter heating. Conversely, the southern side of the QH faces relatively less pollution due to this policy. This discontinuous disparity in ambient pollution is independent of fund managers' actions; therefore, we utilize this regional impact on air pollution as an instrumental variable (IV hereafter) to obtain fitted AQI. Our findings from the 2SLS model consistently support our hypothesis that hazardous air pollution increases the risk of active funds by reducing managers' cognitive abilities.

Furthermore, our third identification strategy is based on the QH heating policy, which adopts the widened variance in AQI between heating and non-heating zones in 2014. China's central heating system allows us to identify whether a change in air quality impacts mutual funds' risk-taking by influencing fund managers' cognitive function and behavioral biases. We run a difference-in-differences (DiD) specification to provide further evidence that mutual fund risk-taking is associated with air pollution. We find that funds in the northern regions of QH encounter 0.196 (0.064)% more in tracking errors (return volatility) compared to the other

[1] For example, managers may encounter legal issues and face penalties for reputational damage if violating these regulations (Penhall, 2015).
[2] The data is available at: https://epi.yale.edu/.
[3] The link can be found at: https://www.theguardian.com/world/2008/aug/07/china.olympics2008 (Retrieved on November 10, 2021).
[4] The information is sourced from https://aqli.epic.uchicago.edu/wp-content/uploads/2022/02/China-Report_FEB2022-2.pdf (Retrieved on July 10, 2022).

side of QH during higher air pollution years. Our results indicate that the impact of the central heating policy is pronounced once the gap in air quality between heating and non-heating zones broadens. Furthermore, we account for fund attributes, manager characteristics, market environment variations, and alternative measures of mutual fund risk, determining that our results are robust. Overall, different identification strategies and sensitivity analyses consistently indicate that air pollution impairs managers' cognitive decisions, thus increasing tracking errors and return volatility of their actively managed funds.

Our study adds two significant contributions to the literature. First, we contribute to the growing body of studies that examine the multi-dimensional externalities of air pollution. Among others, air pollution negatively impacts health (Ebenstein et al., 2017; Kampa & Castanas, 2008), mood (Zhang et al., 2017), contentment (Luechinger, 2010; Wang et al., 2021), respect for regulations (Burkhardt et al., 2019; Lu et al., 2018), driving safety (Sager, 2019), corporate reporting practices (Wu et al., 2022), worker productivity, and other economic consequences (Archsmith et al., 2018; Chang et al., 2019; Ebenstein et al., 2016; Gu et al., 2021; Hanna & Oliva, 2015). We complement several studies that show how exposure to hazardous air particles results in impaired brain function and cognitive skills in individuals, in general, and capital market participants, in particular.[5] For example, analysts exposed to higher levels of air pollution are unlikely to release correct forecasts on time (Dong et al., 2021; Li et al., 2020). Cho et al. (2022) show that air pollution damages business ethics and leads to higher earnings manipulation practices. We complement recent studies investigating the association between ambient pollution and retail investors' cognitive biases (Han et al., 2022; Huang et al., 2020; Li et al., 2021). To the best of our knowledge, ours is the first study to investigate the impact of air quality on professional asset managers' decision-making. Our findings suggest that poor air quality can harm fund managers' cognitive abilities, exposes them to behavioral biases, and impairs their investment efficiency, eventually leading to an increase in mutual fund risk; therefore, our results offer more insights into the impacts of climate change on social behavior by shedding new light on the impact of air quality on asset managers' behavior.

Second, our study contributes to a strand of literature exploring determinants of mutual fund performance and risk outcomes (Cuthbertson et al., 2016; Kim et al., 2021; Mateus et al., 2019). For example, Brown et al. (1996) find that under-achieving executives from the earliest part of the year tend to buy and sell more stocks than the remaining part of the year, resulting in higher risk in their funds. Koski and Pontiff (1999) indicate that the past performance of funds affects their risk. Managers increase fund risk when motivated by agency issues such as occupation risk, corporate benefit, and incentives (Huang et al., 2011; Kempf et al., 2009). Guo et al. (2022) find fossil fuel divestments can foster low energy transitions on mutual funds. Cullen et al. (2012) suggest that more assets are traded to lower tracking errors than to increase them. Our paper adds to the literature by suggesting that poor air quality significantly drives mutual funds' risk.

We further contribute to the literature on how mental conditions influence investors' trading and decision biases (Frydman et al., 2014; Hirshleifer & Shumway, 2003; Kahneman & Slovic, 1982; Kamstra et al., 2003; Staniewski & Awruk, 2022). To the best of our knowledge, the influence of air pollution on the cognitive capacities of fund managers and funds' risk-taking remains under-explored. Our paper bridges the inconvenient gaps in the literature and delivers the first comprehensive empirical study on the relation between air quality and mutual fund managers' preferences for risk-taking attitude. We also show that fund managers' experience and higher education help moderate the effect of air pollution on their managed funds' risk.

The rest of the paper is structured as follows. Section 2 discusses the related literature review and empirical predictions, Section 3 presents the data and sample, and Section 4 presents our methodology and main findings. Section 5 discusses identification strategies and other results, while Section 6 concludes our study.

2. Related literature and empirical predictions

Our paper relates to psychological and health economics literature that assesses air pollution's cognitive, behavioral, and physical health consequences (Schlenker & Walker, 2016). This section briefly discusses related literature on the association between air pollution, cognitive function, and financial market outcomes.

2.1. Air pollution and cognitive function

Medical studies have contributed substantial evidence of the harmful effects of air pollution on cognitive performance. An individual can suffer cognitive flaws and inflammation of neurons when the respiratory (breathing) system carries extreme amounts of hazardous air particles to the brain (Block & Calderón-Garcidueñas, 2009; Pope & Dockery, 2006). Furthermore, air pollution creates a shortage of oxygen in the brain; thus, affected individuals can lack concentration and understanding ability (Badman & Jaffé, 1996; Kampa & Castanas, 2008; Mills et al., 2009). Medical research consistently shows that polluted air decreases reasoning function and the possibility of growing concern and low spirits (Fonken et al., 2011; Zhang et al., 2017). Impaired cognitive abilities reduce people's power over their investigative systems, leading to logical inaccuracies with evident behavioral biases (Frederick, 2005; Kahneman, 2012; Kahneman & Slovic, 1982). Social science research observes the adverse impacts of poor air quality on cognitive function in several actions requiring intellectual acumen; for example, students exposed directly to air pollution perform poorly in the exam

[5] These include the impacts of air quality on a firm's productivity (Wang et al., 2018), courier productivity (Wang et al., 2022), permit trading (Wang, 2018), movie theater admissions (He et al., 2022), child absences at schools (Liu & Salvo, 2018), trust in government (Yao et al., 2022), child growth (Balietti et al., 2022), high blood pressure risk (Pullabhotla & Souza, 2022), water and electricity consumption (Agarwal et al., 2020; Yi et al., 2020), the spread and severity of COVID-19 (Isphording & Pestel, 2021), medical expenses (Liao et al., 2021; Xia et al., 2022), and mispricing in the stock market (Nguyen & Pham, 2021).

(Ebenstein et al., 2016). Likewise, Chang et al. (2019) show that call-center workers, who undertake tasks requiring cognitive skill, tend to underperform with higher air pollution. A central message among these findings is that poor air quality noticeably affects the cognitive or reasoning function of individuals with indoor jobs.

2.2. Air pollution and financial market participants

Our paper contributes to a growing body of literature documenting that air pollution can cause cognitive dysfunction and behavioral biases in decision-making among financial market participants. For example, Kamstra et al. (2003) analyze the influence of mental conditions on investors' trading, suggesting that an absence of cognitive acumen in investors can result in dependence on heuristics for decision-making and behavioral biases in buying or selling securities (Kamstra et al., 2003). Cho et al. (2022) find that air pollution can damage business ethics, leading to higher earnings manipulation practices. Furthermore, critical levels of air pollution can trigger investors' disposition bias and substantial weak trading performance (Huang et al., 2020; Li et al., 2021). Li et al. (2020) suggest that the adverse effects of air pollution persist for analysts regarding their productivity and accuracy in producing information, while Dong et al. (2021) observe more pessimistic earnings forecasts from analysts visiting corporate sites amid air pollution. We complement these findings by considering the impact of air quality on the cognitive capacities of professional asset managers.

2.3. Empirical predictions

Previous literature offers mixed implications on the relationship between air pollution and fund managers' behavior. Research in psychological and economic fields suggests that investors do not always behave rationally (Feng & Seasholes, 2005; Kahneman & Tversky, 1979; Odean, 1998; Shapira & Venezia, 2001). Poor air quality facilitates cognitive impairment and, thus, can initiate senselessness, resulting in elevated decision-making biases. Conversely, though behavioral biases exist in many retail investors (Barberis & Thaler, 2003), specialized investors, such as fund managers, act differently than other investors (Ekholm, 2006; Ekholm & Pasternack, 2007); this perspective indicates either no (or a positive) relationship between air pollution and fund managers' behavioral biases. Additionally, poor outdoor air quality may not influence individuals' behavioral biases and investment decisions if they work indoors. Furthermore, fund managers, who have a high level of cognitive abilities and intelligence compared to individual investors, can be mindful of the adverse outcomes of air pollution. They can employ System 2 Thinking, which requires concentration and more effortful thinking when assessing investment opportunities (Kahneman, 2012). To that extent, either no or weak association can be expected between air pollution and mutual fund managers' behavioral biases. Given mixed predictions from prior studies, the relationship between air pollution and fund managers' behavioral biases is an important yet unanswered question. The subsequent sections discuss our empirical analyses of this possible relationship between air quality and mutual fund risk-taking.

3. Data and sample

To construct our sample, we start with the intersection of AQI and mutual fund data from the Morningstar database and the Chinese Air Quality Study Platform.[6] We source mutual fund data from the Morningstar database. Our sample includes daily returns of 618 active mutual funds. Following Appel et al. (2016), we identify and exclude passively managed funds, as the Morningstar database indicates.[7] Our sample begins in 2003 (when Morningstar started providing mutual fund data in China) and ends in 2019 (the latest accessible data when writing the paper). Furthermore, we collect sentiment variables data from Global Financial Data and Bloomberg.

We obtain mutual funds' key benchmark names from the Morningstar database and calculate the benchmark return for each fund based on the weights of the primary benchmark indices assigned by fund managers.[8] While the Morningstar database does not have daily benchmark return data of mutual funds, it provides each fund's benchmark name. We use the Morningstar benchmark names for each fund and collect the corresponding benchmark return data from Bloomberg. We hand-collect a fund's location information and that of the fund management company from Morningstar and Bloomberg, using Google search as the last resource. As our study focuses on local air quality, we cross-check the location information from these data sources to ensure the accuracy of the location data. Mutual fund managing companies are located across nine cities in China.

We obtain thermal inversions and climate data, such as humidity, wind speed, cloudiness, precipitation, clear sky, and temperature measures, from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2), which the US National Aeronautics and Space Administration release every 6 h for each 0.5-degree × 0.625-degree latitude by longitude region.[9] We aggregate the data at a monthly level for each city and collect fund attributes from Morningstar. To construct data on managers' characteristics, we manually collect information from three data sources, including Morningstar's mutual fund prospectus, Bloomberg, and a website that provides mutual fund managers' profiles in China.[10] The combination of these three different datasets allows us to

[6] The data is available at www.aqistudy.cn.

[7] We manually read funds' prospectuses and mark a fund as passively managed if it covers an index fund identifying string (Appel et al., 2016). For example, we exclude fund names with “Index,” “IND,” “Inx,” “Idx,” “ETF,” “SSE-SZSE 300,” and fund names with integers such as “500,” “600,” “800.”

[8] The primary benchmark in our sample comprises a minimum of two aggregated indices.

[9] We collect data from https://power.larc.nasa.gov/data-access-viewer.

[10] We collect mutual fund managers' profiles from: http://fund.eastmoney.com.

compile comprehensive data on fund attributes (e.g., fund size, fund age, fund flow, management team, and managing funds) and managerial characteristics (e.g., managers' gender and educational backgrounds, such as bachelor, master or Ph.D. degrees or professional qualifications, such as CFA certificates). Appendix A presents detailed information on the variable construction.

4. Key variables and baseline results

This section presents the key variable construction process and summary statistics. We start by investigating the univariate analyses between AQI and fund risk, then contemplate a multivariate regression framework that lets us account for other AQI and mutual fund risk determinants. The following sections discuss our empirical analyses in detail.

4.1. Key variables and summary statistics

Following Chevalier and Ellison (1997), Roll (1992), and Huang et al. (2011), we employ tracking error and fund return volatility as measures of mutual fund risk. Fund return volatility (*RetVol* hereafter) is the standard deviation of the daily fund returns. Tracking error (*TracErr* hereafter) is the difference between the daily fund and benchmark returns in a month (Grinold & Kahn, 2000; Shu et al., 2012).[11] Our estimations of tracking errors and return volatility are as follows:

$$TracErr_{i,t} = \sqrt{\frac{1}{n-1}\sum_{d=1}^{n}\left(e_{i,d} - \overline{e}_i\right)^2} \tag{1.1}$$

$$\text{and } RetVol_{i,t} = \sqrt{\frac{1}{n-1}\sum_{d=1}^{n}\left(r_{i,d} - \overline{r}_i\right)^2} \tag{1.2}$$

where $e_{i,d} = R_{i,d} - R_{b,d}$, $R_{i,d}$ is the return of the active fund i on day d. $R_{b,d}$ is the return of the benchmark index b on day d, and $\overline{e}_i$ is the average return of $e_{i,d}$ for fund i over n days; n is the number of days, and $TracErr_{i,t}$ is the tracking error (in percentage) of the active fund i in month t. Furthermore, we use fund return volatility as an alternative fund risk proxy for a further robustness check. In Eq. (1.2), $r_{i,d}$ is the return of the mutual fund i on day d, $\overline{r}_i$ is the average return of $r_{i,d}$ for fund I over n days, n is the number of days in a month t, and $RetVol_{i,t}$ is the return volatility (in percentage) of the active mutual fund i in the month t.

The AQI synchronizes various measures of air pollution, ranging from 0 to 500; an AQI of above 100 is hazardous to human beings (Li et al., 2021; Nguyen & Pham, 2021). We estimate the monthly mean of AQI (denoted *AQI*) because the effect of air quality on managers' cognitive performance can become evident within a month rather than a day. We create a dummy variable (denoted *DAQI*) that equals 1 if the AQI is >100 in a month and zero otherwise.[12] Following Li et al. (2021), we also use the natural logarithm of AQI, denoted *LOG_AQI*.

A typical mutual fund's tracking error (return volatility) is 0.75% (1.35%) monthly. The median of the tracking error (return volatility) is 64.40% (1.21%). Poor air quality persists in 14.5% of the months in our sample. These results are consistent with those in prior studies (Blitz et al., 2012; Cremers & Petajisto, 2009). The mean (median) values of *AQI* are 76.03 (72.83). Our air pollution measures are highly consistent with the literature (Huang et al., 2020; Li et al., 2021).

4.2. Univariate analyses

We start our empirical analysis by conducting a univariate analysis, considering four subsamples based on the quartile of *AQI*. We sort all funds into four monthly groups based on the *AQI* in each city location. A subsample of *AQI* within the lower quartile or Q1 (i.e., $AQI \leq 59.233$) falls under the low *AQI* group. A subsample of *AQI* above Q1 but within the second quartile or Q2 (i.e., $AQI > 59.233$ & $AQI \leq 72.833$) falls under the second *AQI* group. A subsample of *AQI* above Q2 but under the third quartile or Q3 (i.e., $AQI > 72.833$ & $AQI < 89.871$) falls under the third *AQI* group. Finally, a subsample of *AQI* within the third quartile or Q3 (i.e., $AQI \geq 89.871$) falls under the high *AQI* group. We consider the impact of higher levels of air pollution on mutual fund managers by computing the fund risk difference between high and low *AQI* groups. We sort the subsamples in Table 2 depending on the lag of *AQI* and calculate the mean (and median) of *TracErr* and *RetVol* in the current month. Table 2 presents summary statistics for the *TracErr* and *RetVol* across AQI-sorted subsamples.

Mutual fund risk increases monotonically with *AQI* except in column (2) of Table 2. Funds in the poor air quality subsamples have higher *TracErr* (*RetVol*). Table 2 shows that most air pollution-affected fund managers' funds, those in the highest *AQI* group, are 0.186% (0.133%) (with p-value = 0.00) more likely to face *TracErr* (*RetVol*) in the following month compared with the funds in the lowest *AQI* group. The differences in medians for *TracErr* (*RetVol*) in the highest and lowest *AQI* group from Table 2 are 0.191%

[11] We also employ two alternative measures of mutual fund risk, discussed in Section 5.4. Our findings are robust and not sensitive to a specific measure of mutual fund risk.

[12] As Appendix B suggests, an AQI of above 100 is hazardous for human beings.

Table 1
Summary Statistics.

Variables	Nobs	Mean	Std	Pctl.25th	Median	Pctl.75th
Panel A: Fund Risk and AQI						
TracErr	45,142	0.745	0.398	0.452	0.644	0.943
RetVol	45,142	1.349	0.672	0.900	1.210	1.656
AQI	45,142	76.039	24.318	59.233	72.833	89.871
LOG_AQI	45,142	4.285	0.314	4.081	4.293	4.504
DAQI	45,142	0.145	0.353	0.000	0.000	0.000
Panel B: Weather Conditions						
Humidity	45,142	73.816	12.674	71.060	78.120	82.250
WindSpeed	45,142	13.389	3.428	11.280	13.030	15.090
Cloudiness	45,142	63.380	14.128	54.120	64.170	74.060
Precipitation	45,142	3.359	3.030	1.020	2.660	4.960
ClearSky	45,142	5.403	1.500	4.180	5.520	6.790
Temperature	45,142	18.308	6.648	13.770	17.590	22.920
ThermInver	45,142	6.381	9.055	0.000	0.000	12.100
Panel C: Fund Characteristics						
FundAge	45,142	3.643	0.969	3.091	3.807	4.394
MngrTurn	45,142	3.832	17.776	0.000	0.000	0.000
FundFlow	45,142	0.062	1.683	−0.145	−0.054	0.054
FundSize	45,142	6.713	1.602	5.486	6.863	7.938
FundTurn	45,142	360.939	306.054	162.570	274.870	453.630
ExpRatio	45,142	1.849	0.200	1.764	1.790	1.878
MngTeam	45,142	1.298	0.523	1.000	1.000	2.000
Panel D: Managers' Characteristics						
MngrExper	45,142	42.079	29.450	20.500	35.333	57.000
MngrFund	41,947	2.527	1.574	1.000	2.000	3.000
MngrMale	45,142	88.233	29.657	100.000	100.000	100.000
MngrBachelor	45,142	99.857	2.976	100.000	100.000	100.000
MngrMaster	45,142	96.427	17.344	100.000	100.000	100.000
MngrPhD	45,142	12.730	30.733	0.000	0.000	0.000
MngrCfa	45,142	7.622	24.884	0.000	0.000	0.000
Panel E: Market Characteristics						
IntSpread	45,142	0.004	0.002	0.003	0.004	0.006
MktVol	45,142	1.439	0.698	1.012	1.248	1.605
Inflation	45,142	0.189	0.505	−0.200	0.100	0.500
OledInd	45,142	−0.018	0.161	−0.091	−0.020	0.054
BusConfid	45,142	−0.012	0.285	−0.109	−0.013	0.089
ConsuConfid	45,142	0.050	0.307	−0.111	0.035	0.168
PPI	45,142	−0.003	0.869	−0.574	0.000	0.563
UnemplRate	45,142	4.027	0.125	3.950	4.050	4.100

Table 1 presents the summary statistics of our sample data and variables in this table. We winsorize all continuous variables at the 1st and 99th percentiles to address potential outliers across pooled data. The sample period is from 2003 to 2019. Our sample includes 45,142 fund-month observations from 618 unique active mutual funds. Appendix A provides variable descriptions.

(0.179%) (with p-value = 0.00). The differences in mean and median distributions for fund risk in the highest and lowest *AQI* groups are statistically significant at the 1% level.[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15]

These findings confirm a positive relationship between air pollution and mutual fund risk at the univariate level, suggesting that poor air quality influences mutual fund managers' cognitive performance and enhances behavioral biases. This situation can hinder their ability to manage their funds' returns compared to their benchmarks; however, some differences in fund risk could be due to other weather conditions, fund, or manager characteristics, which we consider in the subsequent sections.

4.3. Multivariate analyses

We expand the evaluation of our prediction to a multivariate specification. We utilize the following regression model to test the effect of critical levels of air pollution on mutual funds' risk through tracking errors and return volatility:

[13] We observe similar results if we consider three or five subsamples based on the tercile or quintile of *AQI*. These results are available upon request.

Table 2
Univariate Analyses on Tracking Errors and Return Volatility by Air Quality Index Groups.

	Mean		Median		
Decile	*TracErr*	*RetVol*	*TracErr*	*RetVol*	Average AQI
Low *AQI*	0.660***	1.221***	0.583***	1.113***	52.223
	(0.00)	(0.00)	(0.00)	(0.00)	
2	0.682***	1.322***	0.602***	1.179***	66.534
	(0.00)	(0.00)	(0.00)	(0.00)	
3	0.788***	1.331***	0.701***	1.205***	79.970
	(0.00)	(0.00)	(0.00)	(0.00)	
High *AQI*	0.823***	1.306***	0.77***	1.218***	103.835
	(0.00)	(0.00)	(0.00)	(0.00)	
High - Low	0.186***	0.133***	0.191***	0.179***	
p-value	(0.00)	(0.00)	(0.00)	(0.00)	

Table 2 reports the univariate analyses across groups of funds, formed on air quality index (AQI) measure from 2003 to 2019. This table reports the distribution of fund risk (*TracErr* and *RetVol)* in each quartile group. The low AQI group (High AQI group) refers to AQI being the lower quartile (higher quartile) of each month in our sample, respectively. This table reports the mean and median of *TracErr*, *RetVol*, and the average *AQI* of each quartile. It also reports the difference between the mean and median of *TracErr* and *RetVol* across high and low *AQI* groups. The *p*-value for the mean and median *TracErr* group based on the *t*-test and Wilcoxon signed rank test, respectively, are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

$$FundRisk_{i,j,t} = \alpha_0 + \alpha_1 AQI_{i,j,t-1} + \epsilon_{i,j,t} \tag{2}$$

where $FundRisk_{i,j,t}$ refers to *TracErr* (*RetVol*) of fund *i* in city *j* in month *t*. $AQI_{i,j,t-1}$ represents the AQI designated to fund *i* based on funds' operation in city *j* in month $t-1$. We control for fund characteristics and weather conditions. Following Busse et al. (2021) and Elton et al. (1993), we consider the following fund-level characteristic: fund age (FundAge), manager turnover (*MngrTur)*, fund flow (*FundFlow*), fund size (*FundSize*), turnover ratio (*FundTurn*), management expense (*ExpRatio*), and the number of members in a fund's management team (*MngTeam*). Furthermore, previous studies suggest that investors' moods and trading behavior can be associated with weather conditions (Cao & Wei, 2005; Dehaan et al., 2017; Goetzmann et al., 2015; Hirshleifer & Shumway, 2003; Loughran & Schultz, 2004; Saunders, 1993).; therefore, we include several weather controls, including humidity, wind speed, cloudiness, precipitation, clear sky, and temperature. Appendix A presents a comprehensive definition of the variables used in this paper. We calculate tracking error and return volatility from daily observations each month and transform them into monthly variables to maintain consistency with the other monthly variables. We lag right-hand side variables by one month to minimize the reverse causality concern. Additionally, we employ fund-, city-, and time-fixed effects to control for our robust standard errors are clustered by funds (Petersen, 2009).

Panels A and B in Table 3 present the result for multivariate analyses with fund characteristics and weather controls, respectively. Our baseline specification shows that air pollution influences mutual fund risk, indicating that air pollution impairs fund managers' cognitive abilities. This impairment causes the upswing of decision biases and eventually leads to higher tracking error and return volatility for their funds.

Panel A of Table 3 presents the coefficients on *AQI* for tracking errors, 0.001 (*t*-statistic = 7.05) and return volatility 0.001 (*t*-statistic = 4.89); we observe similar robust results after controlling for weather conditions. Our findings are both statistically and economically significant. Appendix B reports that an *AQI* of >100 is hazardous for human beings, and *AQI* ranging from 0 to 50 is considered acceptable; thus, the magnitude of the coefficients on *AQI* demonstrates that a shift from *AQI* 50 to *AQI* 101 increases *TracErr* and *RetVol* by 0.051 (i.e., 0.001 × [101–50])%. If we consider the magnitude of 0.051 relative to the median of tracking errors and return volatility, it corresponds to 7.93% (i.e., 0.051/0.644) and 4.21% (i.e., 0.051/ 1.21) of the sample median of *TracErr* and *RetVol*, respectively. These results indicate the economic significance of our findings.

Based on the magnitude of the AQI coefficients in Panel B, moving from the 25th to 75th percentile of *AQI* increases *TracErr* and *RetVol* by 0.031 (i.e., 0.001 × [89.871–59.233])%. If we consider the magnitude of 0.031 relative to the median of tracking errors and return volatility, it accounts for 4.81% (i.e., 0.031/ 0.644) and 2.56% (i.e., 0.031/ 1.21) of the sample median of *TracErr* and *RetVol*, respectively. These findings indicate the economic significance of our results. Thus, a higher *AQI*, which indicates a hazardous health signal, is associated with higher fund risk.

Overall, the findings from the multivariate specifications validate our results from the univariate analyses in Section 4.2. The positive association between poor air quality and tracking errors (return volatility) holds even when considering fund and manager characteristics and weather conditions, which can be correlated with tracking errors and return volatility.

5. Identification strategies

Section 4 discusses the relationship among air pollution, tracking errors, and return volatility; however, univariate and multivariate analyses do not address the potential omitted variable and reverse causality concerns. Therefore, we exploit three identification strategies in this part. *First*, we utilize a two-stage least squares (2SLS) specification with thermal inversion as an instrumental variable. *Second*, we employ an exogenous shock to air pollution using the BOG08 event. *Third*, we utilize a discontinuous variation in air

Table 3
Regressions of Air Pollution on Tracking Errors and Return Volatility.

Panel A: Multivariate analysis with fund characteristics						
	TracErr			*RetVol*		
AQI	0.001***			0.001***		
	(7.05)			(4.89)		
LOG_AQI		0.057***			0.028*	
		(6.47)			(1.89)	
DAQI			0.031***			0.093***
			(4.33)			(7.66)
FundAge	−0.027***	−0.028***	−0.029***	0.006	0.005	0.007
	(−2.77)	(−2.82)	(−2.93)	(0.55)	(0.41)	(0.58)
MngrTurn	0.001	0.001	0.001	0.001***	0.001***	0.001***
	(0.99)	(0.98)	(0.96)	(3.28)	(3.26)	(3.30)
FundFlow	0.002*	0.002*	0.002*	−0.011***	−0.011***	−0.011***
	(1.65)	(1.65)	(1.69)	(−5.89)	(−5.91)	(−5.86)
FundSize	0.016**	0.016***	0.017***	0.016*	0.016**	0.015*
	(2.57)	(2.62)	(2.71)	(1.93)	(2.03)	(1.92)
FundTurn	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(5.48)	(5.49)	(5.55)	(7.00)	(7.03)	(7.06)
ExpRatio	0.020	0.020	0.021	0.014	0.016	0.013
	(0.48)	(0.48)	(0.52)	(0.27)	(0.30)	(0.25)
MngTeam	0.005	0.005	0.005	−0.001	0.001	−0.001
	(0.59)	(0.62)	(0.62)	(−0.09)	(−0.04)	(−0.16)
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,071	40,071	40,071	40,071	40,071	40,071
Adj. R-squared	48.04%	48.00%	47.97%	42.18%	42.14%	42.29%
Panel B: Multivariate analysis with weather conditions						
	TracErr			*RetVol*		
AQI	0.001***			0.001***		
	(5.13)			(5.40)		
LOG_AQI		0.034***			0.051***	
		(3.40)			(2.84)	
DAQI			0.026***			0.092***
			(3.61)			(7.10)
Humidity	0.001	0.001	0.001	−0.003***	−0.003***	−0.003***
	(−0.20)	(−0.39)	(−0.34)	(−7.59)	(−7.83)	(−6.65)
WindSpeed	0.003***	0.003***	0.003***	0.017***	0.017***	0.017***
	(8.30)	(8.20)	(8.22)	(23.50)	(23.15)	(23.91)
Cloudiness	0.001	0.001	0.001	0.002***	0.003***	0.002***
	(0.47)	(0.88)	(0.70)	(12.40)	(12.76)	(11.46)
Precipitation	0.005***	0.004***	0.004***	0.006***	0.005***	0.006***
	(7.75)	(7.24)	(6.76)	(5.50)	(5.01)	(4.93)
ClearSky	−0.011***	−0.011***	−0.011***	−0.023***	−0.023***	−0.023***
	(−9.68)	(−9.92)	(−10.39)	(−16.67)	(−16.84)	(−17.44)
Temperature	0.004***	0.004***	0.004***	−0.004***	−0.004***	−0.004***
	(9.51)	(9.45)	(9.51)	(−5.12)	(−5.16)	(−4.50)
Fund characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,065	40,065	40,065	40,065	40,065	40,065
Adj. R-squared	48.43%	48.39%	48.40%	43.12%	43.08%	43.20%

Table 3 presents ordinary least squares regressions of mutual funds' tracking errors and return volatility on air pollution measures. *AQI* refers to the air quality index. *LOG_AQI* is the natural logarithm of the air quality index. *DAQI* indicates zero if *AQI* is within 100 and one otherwise. *TracErr* refers to the standard deviation between the daily fund and benchmark returns in a month. *RetVol* refers to the standard deviation of daily fund returns in a month. Panel A reports the results from multivariate analysis with fund characteristics. Panel B reports the results from multivariate analysis with weather conditions and fund characteristics. All independent variables are lagged by one month relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by fund. All regressions include fund, city, and year-fixed effects to account for the fund-, region-, and time-specific invariant omitted variables. The sample period is from 2003 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

pollution between northern and southern regions during winter caused by the Chinese central heating policy. With this approach, we aim to prove that the causal effect of air pollution on mutual fund risk is not spurious. The distinct difference in air pollution in the two regions during winter allows us to employ the 2SLS and DiD analyses to analyze the impact of air pollution on fund managers through their fund risk management. We perform several identification tests to investigate the influence of air pollution on mutual fund risk in the subsequent sessions.

5.1. 2SLS model with thermal inversion

In this analysis stage, we continuously investigate whether changes in air pollution matter for mutual fund risk. Following Arceo et al. (2016) and Xue et al. (2021), we employ thermal inversion strength as an instrumental variable (IV) for air pollution in the 2SLS model. The above-ground temperature is higher than the ground-level temperature, creating thermal inversion, which traps air pollutants near the ground by moving air from hot to cool places. Thermal inversions cause country-level deviation in air pollution intensities independent of fundamental causes of air pollution (Chen et al., 2022). Thermal inversion is also independent of fund risk and a joint climatic and weather-related event; therefore, we assume that employing thermal inversion as our instrument fulfills the relevance and exclusion requirements for an identification test (Roberts & Whited, 2013).

We exploit thermal inversion strength as an IV to capture changes in air pollution. Following the extant literature, we develop the 2SLS model as follows:

$$AQI_{i,j,t} = \alpha_0 + \alpha_1 TI_{i,j,t-1} + \epsilon_{i,j,t} \tag{3.1}$$

$$FundRisk_{i,j,t} = \gamma_0 + \gamma_1 \widehat{AQI}_{i,j,t-1} + \zeta_{i,j,t} \tag{3.2}$$

where $\widehat{AQI}_{i,j,t-1}$ is the fitted value of $AQI_{i,j,t}$. $TI_{i,j,t-1}$ is the thermal inversion depth in city j where fund management company i is located in $t-1$ month. Following Xue et al. (2021), we calculate thermal inversions by subtracting the ground temperature from the above-ground temperature. $TI_{i,j,t-1}$ takes a zero value if the ground-level temperature exceeds the above-ground temperature. We also account for weather conditions and fund characteristics consistent with prior analyses.

Table 4 presents the outcomes of the above 2SLS model, where columns (1) and (2) report the first-stage estimated effects. We observe a robust positive association between *AQI* and *TI*, consistent with the prior literature (Xue et al., 2021). The *F*-statistics from the first-stage regressions pass the Stock and Yogo (2005) weak identification tests at the 1% level, indicating the validity of the IV. The

Table 4
2SLS Analysis with Thermal Inversion.

	AQI		*TracErr*		*RetVol*	
	(1)	(2)	(3)	(4)	(5)	(6)
ThermInver	0.053***	0.086***				
	(4.03)	(6.38)				
InstrumAQI			0.006***	0.007***	0.018***	0.014***
			(18.05)	(22.00)	(33.28)	(29.68)
FundAge		1.113***		−0.015		−0.005
		(3.42)		(−1.44)		(−0.42)
MngrTurn		−0.013***		0.001		0.001***
		(−2.88)		(0.87)		(3.50)
FundFlow		0.030		0.001		−0.011***
		(0.64)		(1.33)		(−6.41)
FundSize		0.236		0.011*		0.010
		(1.22)		(1.87)		(1.20)
FundTurn		−0.001		0.001***		0.001***
		(−1.06)		(5.43)		(6.75)
ExpRatio		−0.175		0.011		0.009
		(−0.15)		(0.27)		(0.17)
MngTeam		0.673**		0.001		−0.011
		(2.26)		(0.14)		(−1.27)
Weather conditions	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Weak identification test:						
(F-Statistic)			60.87***	67.72***	60.87***	66.41***
Hausman endogeneity test:						
(p-value)			0.00	0.00	0.00	0.00
Observations	44,492	40,065	44,447	39,448	44,447	39,448

Table 4 presents the results from the 2SLS model estimation and shows the impact of air pollution on mutual fund risk. *TracErr* refers to the standard deviation between the daily fund and benchmark returns in a month. *RetVol* refers to the standard deviation of daily fund returns in a month. Air pollution is measured by monthly raw *AQI*. The instrumental variable (IV) for *AQI* is the thermal inversion strength (*ThermInver*), which is the daily average of max (above-ground temperature minus ground temperature, 0) in a region in a month. Columns (1) and (2) represent first-stage estimated results, whereas columns (3), (4), (5), and (6) represent second-stage estimated results. All independent variables are lagged by one month relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by fund. All regressions include fund, city, and year-fixed effects to account for fund-, region-, and time-specific invariant omitted variables. The sample period is from 2003 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Hausman endogeneity test statistics substantiate our endogeneity concern. The coefficients on *InstrumAQI*, as shown in columns (3), (4), (5), and (6), are significantly positive at the 1% level, indicating that fund managers are more likely to face adverse side effects when air pollution in their location rises, thereby increasing tracking errors and fund return volatility. These results confirm that air pollution significantly impacts professional asset managers.

5.2. Natural experiments with BOG08

The BOG08 substantially reduced air pollution (Chen, Ebenstein, et al., 2013; Chen, Jin, et al., 2013), representing an opportunity to utilize this setting as an exogenous shock. We report that tracking error and return volatility decreased throughout the BOG08. The Chinese Government executed numerous mandates for reducing air pollution to host the BOG08 from July 20 to September 20, 2008. Following He et al. (2016), we use the BOG08 as an exogenous shock that regulated AQI. We choose April and May 2008 as our pre-match period and August and September 2008 as the post-match period. Air quality improved in July and was excellent in August and September 2008; therefore, we expect a drop in tracking errors and return volatility in August and September 2008. Fig. 1 presents the index of air quality distribution pre, post, and throughout the BOG08. We follow the probit regression specification on a pre-match sample as follows:

$$Treat_{i,t} = \beta_0 + \beta_1 FundAge_{i,t} + \beta_2 MngrTurn_{i,t} + \beta_3 FundFlow_{i,t} + \beta_4 FundSize_{i,t} + \beta_5 FundTurn_{i,t} + \beta_6 ExpRatio_{i,t} + \beta_7 MngTeam_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $Treat_i$ equals one if a fund management firm is based in Beijing or Tianjin (a treatment group) and zero if a fund management firm is based in the other cities or a control group in month *t*. Panel A of Table 5 examines the relationship between the likelihood of being a treated group and fund characteristics, as shown in Eq. (4). The column "Pre-match" result in Panel A of Table 5 shows that a fund with a larger size and higher turnover is more likely to be a treated fund. This finding suggests that the treatment and the control group have different characteristics in the pre-matched sample, especially regarding fund size and turnover.

We then calculate the propensity score and construct the one-to-one matched pair from the treatment and control groups. We then use the post-match sample and run the probit regression analysis in Eq. (4) again. The "Post-match" column result in Panel A of Table 5 shows that both the treated and control groups have similar fund characteristics, as none of the fund characteristics in Eq. (4) is statistically significant. This result shows that matching can effectively create comparable treatment and control pairs. The approach in Panel A of Table 5 generates treatment and control groups with closely comparable fund characteristics but a unique level of variation in air quality during BOG08.

The matching process yields 76 treatment-control pairs. We report the probit regression results in Table 5, Panel A, column (1). The

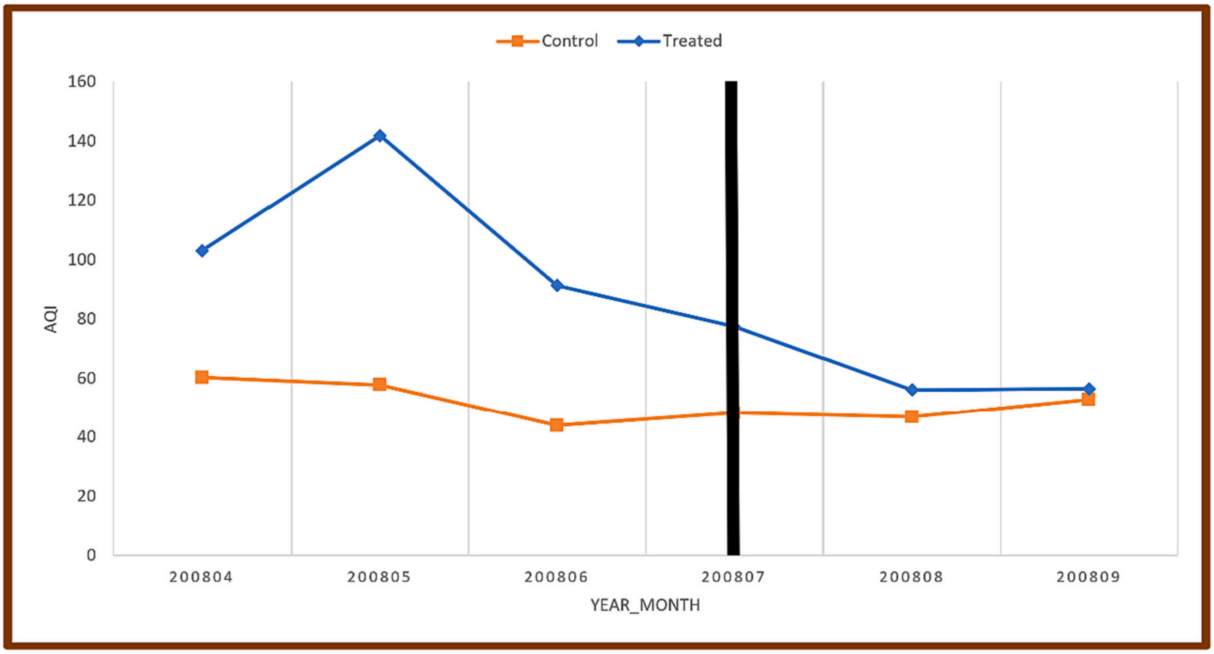

Fig. 1. Air Pollution Distribution for Pre, Post, and During Beijing Olympic Games 2008.
Fig. 1 presents the monthly average of air quality index (AQI) of the treated city (i.e., Beijing) and other control cities. There are a couple of observations. First, the treated city's AQI dropped during the Beijing Olympic Games 2008 (BOG08) event when the Chinese Government implemented many additional pollution control regulations. Second, we do not see any significant change in the control of cities' AQI before and during the BOG08, as the government did not enforce these regulations in these cities.

Table 5
Difference-in-Differences Analysis during BOG08.

Panel A: Probit Regressions with pre- and post-matched samples						
		Pre-match			Post-match	
FundAge		0.060			−0.017	
		(0.46)			(−0.11)	
MngrTurn		−0.001			−0.003	
		(−0.23)			(−0.74)	
FundFlow		0.013			0.024	
		(0.04)			(0.02)	
FundSize		0.328***			−0.170	
		(2.60)			(−1.14)	
FundTurn		0.004***			0.001	
		(4.17)			(0.02)	
ExpRatio		3.496*			1.033	
		(1.82)			(1.19)	
MngTeam		0.280*			−0.158	
		(1.95)			(−0.93)	
Observations		367			152	
p-value of $\chi 2$		0.002			0.697	
Pseudo R2		0.092			0.041	
Panel B: Propensity scores distribution						
Group	Nobs	Mean	Min.	Median	Max.	Std Dev
Treatment	76	0.251	0.090	0.249	0.447	0.093
Control	76	0.250	0.089	0.248	0.435	0.091
Difference	76	0.001	0.001	0.000	0.012	0.002
Panel C: Difference-in-differences regression						
		TracErr			*RetVol*	
*Treatment*After*		−0.226**			−0.146	
		(−2.45)			(−1.50)	
After		0.245**			0.817***	
		(2.49)			(6.86)	
Treatment		−0.097**			−7.483***	
		(−0.13)			(−8.63)	
Fund characteristics		Yes			Yes	
Fund fixed effect		Yes			Yes	
City fixed effect		Yes			Yes	
Observations		152			152	
Adj. R-squared		98.66%			98.86%	

Table 5 presents a difference-in-differences (DiD) air quality analysis on mutual fund risk during BOG08. Panel A reports the results of a probit model (4), depending on pre-matched and post-matched funds in the treatment and control groups. The dependent variable of the probit model equals one if the fund fits in the treatment group and aero if the fund belongs to the control group. We use fund characteristics as control variables in this regression. We report the statistical distribution of the propensity scores of the funds in both treatment and control groups, along with their differences. DiD regression (5) based on the matched sample reports results in Panel C. *After* equals one if our data fall into the BOG08 period, August and September; otherwise, it is zero. Our robust standard errors are clustered by fund. We parenthesize *t*-statistics under each coefficient below. *, **, and *** designate statistical significance at the 10%, 5%, and 1% levels, respectively.

probit specification generates a pseudo-R-squared of 0.092 and a chi-square p-value <0.002, implying that the regression setting portrays a substantial quantity of difference in the option variables. Fund characteristics are insignificant in column (2) from Panel A of Table 5. Additionally, the pseudo-R-squared falls significantly from 0.092 before pairing to 0.041. The chi-square test has a p-value of 0.697 in column (2) from Panel A of Table 5, signaling that the coefficients of the explanatory variables do not significantly differ statistically from zero. Table 5, Panel B, presents the summary statistics of the propensity scores of the treatment and control groups and their difference, showing that the gap between the propensity scores in the two groups is marginal.

For the “Pre-match” result, we use Eq. (4) to examine whether some fund characteristics could explain the propensity of being a treated sample compared to a control sample. The results show that larger fund sizes and higher fund turnover increase the likelihood of being in the treatment group, indicating that the treatment and control groups are not yet comparable in the unmatched sample. We then apply the propensity score matching where each treated sample is matched with the control sample with the closest propensity score, and the difference in the propensity score is <0.01. After we obtain the matched sample, we repeat the probit regression in Eq. (4) and report the result in the “Post-match” column in the Panel A of Table 5. The results show that the matching process can obtain comparable treatment and control samples because none of the fund characteristics can explain the likelihood of being in the treatment group after the matching; therefore, we can use the matched pair sample to apply the DiD regression, as shown in Panel C of Table 5.

Constructing two comparable groups based on fund characteristics allow us to investigate whether a radical reduction in air pollution can influence fund managers' behavioral biases and reasoning in treated cities. Following Brogaard et al. (2017), we form treatment and control group funds centered on propensity score matching and run a DiD analysis in a regression framework as follows:

$$FundRisk_{i,t} = \beta_0 + \beta_1 Treat_i \times After_t + \beta_2 After_t + \beta_3 Treat_i + \varepsilon_{i,t} \quad (5)$$

where $FundRisk_{i,t}$ refers to the mutual fund risk (*TracErr* and *RetVol*) of fund *i* in a month *t*. $Treat_i$ equals one if a fund management firm is based in Beijing or Tianjin, and *After* refers to one for the period in July, August, and September of 2008; otherwise, it is zero. We account for fund characteristics used in Table 5, Panel A; we add fund, city, and time-fixed effects to control for fund-, region-, and time-specific invariant omitted variables.

Table 5, Panel C, presents the results of the DiD analyses. In column (1), the statistically significant and negative coefficient of −0.226 for *Treatment*After* suggests that the treated funds suffer a greater decline of 0.226% in tracking errors during the BOG08 relative to the control group. For the return volatility column (2), the coefficient level drops to −0.148. The results show some weak evidence that improving air quality lowers fund risk. The coefficient for "*After*" is positive; however, this is offset by the two negative coefficients from an interaction "*Treat*After*" and a "*Treat*" variable. The net impact for the tracking error is −0.226 + 0.245–0.097 = −0.078, and the net result for the return volatility is −0.146 + 0.817–7.483 = −6.812. As a result, we can conclude that the fall in air pollution in Beijing and Tianjin during BOG08 reduced mutual fund risk.

Table 6
Impact of Air Quality on Fund Risk through QH Heating Policy.

Panel A: Impact of air quality in 2SLS

	Full Sample	
	TracErr	*RetVol*
fitted_AQI	0.007***	0.015***
	(23.08)	(30.25)
Polynomial	Yes	Yes
Fund characteristics	Yes	Yes
Weather conditions	Yes	Yes
Fund fixed effect	Yes	Yes
City fixed effect	Yes	Yes
Year-fixed effect	Yes	Yes
Observations	40,044	40,044
Adj. R-squared	88.56%	89.12%

Panel B: Impact of air quality in DiD

	Full Sample	
	TracErr	RetVol
QH × Post	0.151***	0.061**
	(4.10)	(2.09)
QH	−51.749***	−39.93
	(−6.65)	(−1.39)
Polynomial	Yes	Yes
Fund characteristics	Yes	Yes
Weather conditions	Yes	Yes
Fund fixed effect	Yes	Yes
City fixed effect	Yes	Yes
Observations	13,388	13,388
Adj. R-squared	48.05%	35.94%

Table 6 reports the results of the 2SLS estimation of the effect of air pollution on fund risk. *TracErr* refers to the standard deviation between the daily fund and monthly benchmark returns. *RetVol* refers to the standard deviation of daily fund returns in a month. Air pollution is measured by monthly raw *AQI*. *AQI* refers to the raw air quality index. In the first stage, we regress *AQI* on *QH*, which indicates whether a fund management company is in a region where the Qinling-Huai (QH) River heating policy operates (yes: one, no: zero). In the second-stage model (6.2), the *fitted_AQI* from the first-stage model (6.1) is regressed with the fund risk (*TracErr* and *RetVol*) along with fund characteristics. Panel B reports the results from DiD analysis by employing the radically broadened difference in AQI between heating and non-heating areas in 2014 from 2011 to 2015. Post equals one for years 2014 and 2015 (the post period of the broadened difference) and zero for years 2011 and 2012 (the pre-period of broadened difference). *QH* equals one if a fund management company is in a region where the Qinling-Huai River heating policy applies and zero otherwise. Polynomial is $f(Lat_{j,t})$, which represents a smooth control function for the latitude of the fund management company location, permitting diverse polynomials of the space between the fund management company location and the QH boundary. Our robust standard errors are clustered by fund. We parenthesize *t*-statistics under each coefficient below. *, **, and *** designate statistical significance at the 10%, 5%, and 1% levels, respectively.

5.3. Discontinuous variation in AQI with Qinling-Huai River heating policy

The Qinling Mountains and the Huai River divide China into northern and southern regions. The Chinese Government introduced a heating policy to provide free winter heating to the northern region of the Huai River by burning free coal for heating boilers, consequently deteriorating the air quality of the northern region (Almond et al., 2009). A probable correlation between *AQI* and unobservable fund characteristics with city factors—which can also affect mutual fund risk—can cast doubt on the causal impact of air pollution on tracking errors and fund return volatility. To mitigate this identification issue, we utilize the irregular change in air quality along the Huai River due to this policy (Chen, Ebenstein, et al., 2013; Chen, Jin, et al., 2013; Ebenstein et al., 2017).

5.3.1. 2SLS specification with Qinling-Huai River heating policy

Following Xue et al. (2021), we apply the following 2SLS regressions to assess the policy-related impact of air quality on fund risk:

$$AQI_{i,j,t} = \gamma_0 + \gamma_1 QH_{j,t} + f\left(Lat_{j,t}\right) + \varepsilon_{i,j,t} \tag{6.1}$$

$$FundRisk_{i,j,t} = \theta_0 + \theta_1 \widehat{AQI}_{i,j,t-1} + f\left(Lat_{j,t}\right) + \mu_{i,j,t} \tag{6.2}$$

where $QH_{j,t}$ equals one if city j is in the heating area created by the QH boundary in month t and zero otherwise. $f\left(Lat_{j,t}\right)$ represents a smooth control function for the latitude of the fund management company's location, permitting diverse polynomials of the space between the fund management company location and the QH boundary. Following Xue et al. (2021), we employ the cubic polynomial of the space between the fund management company location and the QH boundary. We run models (6.1) and (6.2) to observe the variation in the AQI when the heating policy impacts the fund risk by affecting air quality. Following Chen, Ebenstein, et al., 2013, Chen, Jin, et al. (2013), Ebenstein et al. (2017), and Xue et al. (2021), we include $f\left(Lat_{j,t}\right)$ for both first-stage regression (6.1) and second-stage regression (6.2). In the first stage of the 2SLS regression, we include the $f\left(Lat_{j,t}\right)$, or the distance from the river variable, to control for variations in coal consumption and types that can affect the AQI. This situation means that different kinds of coal and consumption levels change geographically because the Chinese free-of-charge heating system burns coal to heat water and sends it through pipes to households in different northern locations (Almond et al., 2009). Furthermore, substantial energy loss arises in carrying heat water over long distances, requiring different kinds of coal and levels of coal usage. We control for $f\left(Lat_{j,t}\right)$ in the second-stage regression because we assume that the QH River policy only affects fund risk through its impact on air pollution; therefore, our second-stage regression also includes the control variables used in the first-stage regression. This assumption is commonly used in many related studies that use the Huai River policy in their 2SLS analysis (Chen, Ebenstein, et al., 2013; Chen, Jin, et al., 2013; Ebenstein et al., 2017; Xue et al., 2021). We include fund characteristics and weather conditions in the model to control for observable fund characteristics and weather. Notably, the 2SLS regression provides the projected amount of the AQI effect on mutual funds' tracking errors and return volatility.

Table 6, Panel A, reports highly statistically significant positive coefficients on fitted_AQI for tracking errors and return volatility in the total sample group. Mutual funds experience 0.007% (0.015%) of higher tracking errors (return volatility) following air pollution. We also observe significant results using the samples of the heating season (October, November, December, January, February, and March) and non-heating season (April, May, June, July, August, and September).[14] These findings indicate that fund management companies in cities with critical levels of air pollution most presumably experience higher tracking errors and return volatility for their funds because poor air quality hampers their fund managers' cognitive functions.

5.3.2. DiD analyses with Qinling-Huai River heating policy

Xue et al. (2021) and Cho et al. (2022) observe that the central heating policy in China triggers a discontinuous variation in air pollution. They also observe a sudden broadening AQI between heating and non-heating regions since 2014. This setting allows us to identify whether a change in air quality impacts funds' tracking errors and return volatility by influencing fund managers' cognitive function and behavioral bias. Following Xue et al. (2021), we run subsequent DiD analyses to provide further evidence that higher tracking error and return volatility are associated with air pollution:

$$FundRisk_{i,j,t} = \rho_0 + \rho_2 QH_{j,t} {}^{*} Post + \rho_2 QH_{j,t} + f\left(Lat_{j,t}\right) + \omega_{i,j,t} \tag{7}$$

These analyses run from 2011 to 2015 (we exclude 2013 due to missing AQI values). We utilize the widened variation in AQI between heating and non-heating areas in 2014, depicted in Fig. 2. The post variable is equivalent to one for 2014 and 2015 (the post-period of the broadened AQI difference) and zero for 2011 and 2012 (the pre-period of the broadened AQI difference). We employ an interaction term, Post and $QH_{(j,t)}$, to investigate how air quality changes affect fund risk.

We next investigate how the variation in air quality affects fund risk. Utilizing the suddenly broadened difference in AQI between heating and non-heating areas in 2014 and 2015 (as shown in Fig. 2), we employ model (7) to run DiD regressions from 2011 to 2015. We find that funds in the northern regions of QH increase by 0.151% (0.061%) in tracking errors (return volatility) compared to the other side of QH during years with higher air pollution. The interaction term, *QH*Post*, indicates that the model provides positive

[14] These results are reported in Appendix C.

Table 7
Air Pollution Impact on Fund Risk with Market Characteristics.

	TracErr			*RetVol*		
AQI	0.001***			0.001***		
	(4.87)			(6.27)		
LOG_AQI		0.037***			0.060***	
		(3.83)			(3.57)	
DAQI			0.032***			0.106***
			(4.70)			(9.23)
IntSpread	48.078***	48.217***	48.937***	76.734***	77.104***	78.998***
	(19.95)	(20.00)	(20.21)	(26.97)	(27.20)	(28.01)
MktVol	0.056***	0.056***	0.057***	0.236***	0.236***	0.237***
	(13.23)	(13.20)	(13.38)	(33.34)	(33.34)	(33.46)
Infla	0.014***	0.013***	0.013***	0.065***	0.063***	0.065***
	(6.57)	(6.27)	(6.30)	(22.34)	(21.96)	(22.14)
OledInd	−0.042*	−0.040*	−0.042**	0.042	0.047	0.034
	(−1.96)	(−1.87)	(−1.96)	(1.15)	(1.30)	(0.94)
BusConfid	−0.041***	−0.041***	−0.039***	−0.080***	−0.080***	−0.074***
	(−6.88)	(−6.87)	(−6.60)	(−6.32)	(−6.28)	(−6.01)
ConsuConfid	−0.194***	−0.196***	−0.197***	−0.310***	−0.315***	−0.313***
	(−43.00)	(−43.86)	(−43.70)	(−54.16)	(−55.02)	(−53.76)
PPI	−0.045***	−0.045***	−0.045***	−0.077***	−0.076***	−0.077***
	(−28.07)	(−27.87)	(−28.23)	(−38.51)	(−37.70)	(−39.61)
UnemplRate	−0.420***	−0.411***	−0.389***	−1.320***	−1.296***	−1.259***
	(−12.18)	(−11.96)	(−11.55)	(−23.97)	(−23.72)	(−24.19)
Fund characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Weather conditions	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,057	40,057	40,057	40,057	40,057	40,057
Adj. R-squared	52.19%	52.16%	52.19%	50.12%	50.07%	50.24%

Table 7 presents a multivariate analysis of fund risk on air pollution measures after considering market environment variations. *AQI* refers to the air quality index. *LOG_AQI* denotes the natural logarithm of the air quality index denotes. A dummy variable, *DAQI,* indicates zero if *AQI* is within 100 and one otherwise. *TracErr* refers to the standard deviation between the daily fund and benchmark returns in a month. *RetVol* refers to the standard deviation of daily fund returns in a month. All independent variables are lagged by one month relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by fund. All regressions include fund, city, and year-fixed effects to account for fund-, region-, and time-specific invariant omitted variables. The sample period is from 2003 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

coefficients for tracking errors and return volatility at a 1% significance level in all columns of Table 6, Panel B.[15]

These results imply that the impact of the central heating policy becomes more evident when the gap in AQI between heating and non-heating areas broadens. Our findings suggest that a significant drop in air quality is associated with more fund managers' behavioral biases and decision-making mistakes, leading to higher tracking errors and return volatility of their funds.

5.4. Additional robustness tests

We perform a myriad of sensitivity tests, which we discuss in this section. First, we further control for market environment variations to verify our results from the baseline specification. Prior literature (Chen et al., 1986) shows that market environment characteristics affect fund performance and stock returns. We test whether funds maintain consistently higher tracking errors and return volatility during critical levels of air pollution after accounting for the effects of market environment variations, fund characteristics, and weather conditions. Thus, we re-estimate Eq. (2) by adding market environment characteristics.

Our findings are robust after accounting for market environment characteristics, fund characteristics, and weather conditions. Coefficients on both *AQI* and *LOG_AQI* are positive for *TracErr* and *RetVol* at the 1% significance level. The tracking errors and fund return volatility increase by 0.032% and 0.106%, respectively, as soon as AQI rises >100. These results suggest a robust statistical relation between air pollution and mutual fund risk.

We further employ additional statistical approaches to capture mutual fund risk to ensure the robustness of our results from baseline specification. Following Rudolf et al. (1999), we calculate fund risk (denoted *AbsExcret*) as the absolute value of the difference between the fund return and benchmark return. Following Treynor and Black (1973), we calculate an alternative fund risk measure as the standard deviation of the residuals of a linear regression between the return of the active fund and those of the benchmark index's return (denoted *RretVol*). We re-estimate Eq. (2) using *AbsExcret* and *RretVol* and run regression individually after controlling for fund characteristics, weather conditions, manager characteristics, and market environment variations, determining that our key findings in

[15] We observe similar results using the same methodology for heating and non-heating seasons and report them in Appendix C.

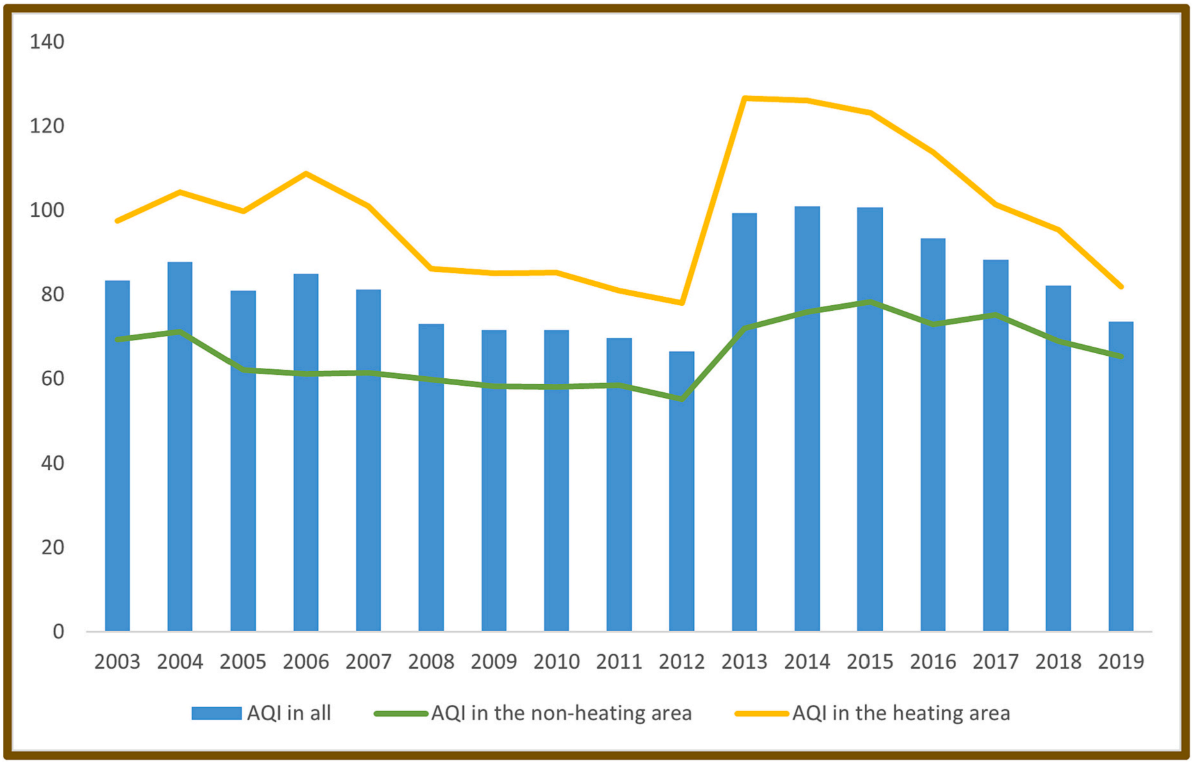

Fig. 2. Annual Distribution of Air Pollution.
In Fig. 2, the blocks refer to the average air quality index (AQI) across all cities in China by year. The yellow-solid (green-solid) line denotes the average AQI on the heating (non-heating) region of the Qinling-Huai River. We observe a broadened difference between these two regions in 2014 and 2015, compared to 2011 and 2012.

Section 4 are robust. The dependent variable is alternative measures of mutual fund risk (*AbsExcret* and *RretVol*), and the coefficients on *AQI* are positive and statistically significant. These results suggest that mutual fund managing firms in cities with critical levels of air pollution have higher levels of mutual fund risk. We do not report these results in this paper; however, they are available upon request.

In a final set of sensitivity analyses, we consider several subsample analyses. Following Raffestin (2017), we test whether our findings are driven by excessive variations during uncertain periods. We explicitly omit observations during the 2008 Global Financial Crisis and the Chinese Stock Market Turbulence of 2015–2016 to minimize this concern. We re-estimate Eq. (2) with air quality as the independent variable of interest and a similar set of control variables for each subsample. We observe that the results align with the key findings presented in Table 3; therefore, we conclude that air pollution causes mutual fund managers' tracking errors and fund return volatility to increase. We do not report these results in this paper; however, they are available upon request.

Overall, our findings support prior studies in that air pollution can influence retail investors' decision-making (Huang et al., 2020; Li, Massa, Zhang and Zhang, 2021) and that professional asset managers, such as mutual fund managers, are subject to these externalities. Our study suggests that managers can experience behavioral biases and mistakes in decision-making amid poor air quality, leading to upward-trending fund risk.

5.5. *The moderating effects of managerial attributes on cognitive abilities*

This section examines whether managerial attributes can lessen the impact of air pollution on fund managers' cognitive abilities. This analysis is motivated by a growing literature showing the roles of managers in shaping various corporate outcomes (Bertrand & Schoar, 2003; Cronqvist & Yu, 2017; Golec, 1996; Malmendier et al., 2011; Pham et al., 2022). If managers' characteristics can enhance (deteriorate) their cognitive abilities, we should observe lower (higher) fund risk from their actively managed funds. To test this possibility, we hand-collected a range of fund managers' attributes from http://fund.eastmoney.com/, the largest Chinese fund website. Our manual collection allows us to construct propriety data of fund managers' characteristics, including managerial experience, gender, educational background, and professional certifications. To test whether managers' characteristics can lessen the impact of air pollution on their actively managed mutual fund risk, we re-estimate our baseline models—Eq. (2)—and include the interaction terms between managers' characteristics and air quality indicator (*DAQI*). Table 8 presents the results of these analyses, indicating that managers with more experience and higher education are associated with lower tracking errors and fund return volatility caused by ambient air pollution. Thus, managers' experience and higher education (i.e., Master's or Ph.D. degrees) can lessen

Table 8
The Moderating Effects of Managerial Characteristics.

Panel A: The effect of manager characteristics on tracking errors							
	TracErr						
*DAQI*MngrExper*	−0.001***						
	(−3.83)						
*DAQI*MngrFund*		0.002					
		(0.47)					
*DAQI*MngrMale*			0.001				
			(1.38)				
*DAQI*MngrBachelor*				−0.004***			
				(−9.92)			
*DAQI*MngrMaster*					−0.001**		
					(−2.50)		
*DAQI*MngrPhD*						−0.001**	
						(−2.06)	
*DAQI*MngrCfa*							0.001
							(0.52)
DAQI	0.072***	0.024*	0.001	0.473***	0.15***	0.036***	0.028***
	(5.48)	(1.71)	(0.04)	(10.82)	(3.04)	(4.18)	(3.35)
Fund characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,718	34,718	34,718	34,718	34,718	34,718	34,718
Adj. R-squared	49.04%	48.98%	48.99%	49.01%	49.01%	49.00%	4.65%
Panel B: The effect of manager characteristics on return volatility							
	RetVol						
*DAQI*MngrExper*	−0.002***						
	(−4.67)						
*DAQI*MngrFund*		−0.003					
		(−0.40)					
*DAQI*MngrMale*			0.001				
			(0.64)				
*DAQI*MngrBachelor*				0.001			
				(−0.27)			
*DAQI*MngrMaster*					−0.002**		
					(−2.38)		
*DAQI*MngrPhD*						−0.001***	
						(−2.76)	
*DAQI*MngrCfa*							0.001
							(0.17)
DAQI	0.172***	0.099***	0.071**	0.134	0.299***	0.105***	0.092***
	(6.93)	(4.36)	(2.02)	(0.87)	(3.34)	(6.79)	(6.03)
Fund characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,718	34,718	34,718	34,718	34,718	34,718	34,718
Adj. R-squared	43.33%	43.26%	43.26%	43.26%	43.29%	43.28%	43.26%

Table 8 presents the results for the moderating effects of fund managers' characteristics. Our main variable of interest is the interaction term of *DAQI* and each managerial characteristic. We test whether manager characteristics can alleviate the impact of air pollution on fund risk. A dummy variable, *DAQI,* indicates 0 if *AQI* is below 100 and 1 otherwise. *TracErr* refers to the standard deviation between the daily fund and benchmark returns in a month. *RetVol* refers to the standard deviation of daily fund returns in a month. This table reports the results after controlling for fund characteristics, manager characteristics, and weather conditions. All independent variables are lagged by one month relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by fund. All regressions include fund, city, and year-fixed effects to account for fund-, region-, and time-specific invariant omitted variables. The sample period is from 2003 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

their psychological biases and alleviate poor air quality's impact on their funds' risk outcomes.

6. Conclusion

Over the last few decades, the impacts of environmental problems on health, economic, and social outcomes have received increasing attention (Bolton & Kacperczyk, 2021; Krueger et al., 2020; Marshall et al., 2021; Stroebel & Wurgler, 2021). This paper focuses on one of the greatest environmental risks: air pollution. The impacts of air pollution on health outcomes and various economic costs are well established; however, the severity of air pollution's influence on the trading behavior of capital market participants remains under-investigated. Our paper addresses these gaps by examining the impact of air pollution on professional asset managers, such as mutual fund managers. Fund managers are of significant interest as they manage a large proportion of financial assets worldwide, and their behavior is distinct from other investors (Ekholm, 2006; Ekholm & Pasternack, 2007). Our findings suggest that poor air quality plays a significant role in understanding the risk outcomes of active mutual funds.

Our multivariate tests confirm the statistically significant positive association between air pollution and mutual fund risk after accounting for the fund, manager, market environment characteristics, and weather conditions. We utilize three identification approaches to explore this association, including (1) air pollution changes due to thermal inversion, (2) drastic improvement in air quality because of the BOG08 event, and (3) discontinuous variation in air pollution because of QH River heating policy. We observe consistent evidence that air pollution, a critical non-economic factor, harms managers' cognitive capacities and increases their funds' tracking errors and return volatility in each setting. Our results are consistent with the notion that air pollution accelerates society's economic costs. This paper contributes to the literature on the association between air quality and behavioral biases among financial market participants. Our findings suggest that professional asset managers (such as mutual fund managers, who generally have higher cognitive abilities and intelligence than retail investors) are not immune from the negative externalities caused by air pollution. Therefore, our findings carry significant implications for fund management practices to relieve the consequences of air quality and behavioral biases in financial markets.

CRediT authorship contribution statement

Suvra Roy: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization. **Harvey Nguyen:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Nuttawat Visaltanachoti:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

Suvra Roy, Harvey Nguyen, and Nuttawat Visaltanachoti do not have any conflicting interests.

Data availability

Data are available from the data sources identified in the paper.

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Appendix A. Appendix

Variable definition

Variables	Description
TracErr	The standard deviation between the daily fund and benchmark returns in a month. The *TracErr* formula follows as $TracErr_{i,t} = \sqrt{\frac{1}{n-1}\sum_{d=1}^{n}\left(e_{i,d} - \bar{e}_i\right)^2}$ where $e_{i,d} = R_{i,d} - R_{b,d}$, $R_{i,d}$ is the return of the active fund i in the day d. $R_{b,d}$ is the return of the benchmark index b in the day d, n is the number of days in a month t and $\bar{e}_i$ the average return of $e_{i,d}$ for fund i over n days. $TracErr_{i,t}$ is the tracking error of the active fund i in the month t in percentage.

(*continued on next page*)

(*continued*)

Variables	Description
RetVol	The standard deviation of daily fund returns in a month. The *RetVol* formula follows as $RetVol_{i,t} = \sqrt{\frac{1}{n-1}\sum_{d=1}^{n}\left(r_{i,d} - \bar{r}_i\right)^2}$ where $r_{i,d}$ is the return of the mutual fund *i* in the day *d*, $\bar{r}_i$ the average return of $r_{i,d}$ for fund *i* over *n* days, *n* is the number of days in a month *t* and $RetVol_{i,t}$ is the return volatility of the active mutual fund *i* in the month *t* in percentage.
AbsExcret	The absolute value of the difference between the fund returns and benchmark returns in percentage
RretVol	The standard deviation of the residuals of a linear regression between the return of the active fund and those of the benchmark index's return in percentage.
AQI	Average of the raw value of daily observation data of Air Quality Index (AQI) in a month
LOG_AQI	Refers to the natural logarithm of *AQI*
DAQI	Refers to 0 if *AQI* is within 100 and 1 if *AQI* is >100
FundAge	Represents the time of mutual funds' operation in months
MngrTurn	This is the percentage change of the fund managers in the team every month; the outcome comes through applying the absolute function of manager turnover.
FundFlow	Represents the monthly variation in fund size multiplied by (1 + fund return) in percentage
FundSize	Refers to the natural logarithm of the size of mutual funds
FundTurn	Refers to the substitution of funds' holdings over a year in percentage, allocated equally over each month
ExpRatio	Refers to management expenses or fund operating costs as a percentage of the average value of investment fund assets in a fund
MngTeam	Refers to the number of managers in a fund management team in a month
MngrExper	Indicates the duration of managers' fund management activity, and this is an average monthly experience for each fund across all fund managers.
MngrFund	Refers to the number of funds that managers manage in a month
MngrMale	The percentage of male members in a fund management team in a month
MngrBachelor	Referring to the percentage of bachelor's degree holders in a fund management team
MngrMaster	Referring to the percentage of master's degree holders in a fund management team
MngrPhD	Referring to the percentage of Ph.D. degree holders in a fund management team
MngrCfa	Referring to the percentage of CFA degree holders in a fund management team
IntSpread	Referring to subtracting 10-year Treasury bond yield from 6-month interbank deposit rate in percentage
MktVol	The volatility of the monthly return in the percentage of CSI 300
Inflation	Representing the monthly variation of the consumer price index in percentage
OledInd	Representing the monthly potential state of an economy in percentage
ConsuConfid	Referring to the monthly consumer confidence about spending and savings in percentage
BusConfid	Referring to the potential monthly growth in percentage
PPI	Referring to the sale price of goods and services from producers in percentage
UnemplRate	The quarterly unemployment rate in percentage
ThermInver	Referring to the average of max (daily above-ground temperature minus ground temperature, 0) in a city in a month
Humidity	The average daily humidity (%) in a city in a month
WindSpeed	The daily average wind speed in a city is 2 m per second monthly.
Cloudiness	The average cloud amount in a city in a month in percentage
Precipitation	The monthly average precipitation (mm) in a city
ClearSky	Clear Sky is the monthly average of surface shortwave downward irradiance (kW-hr/m^2/day).
Temperature	The monthly average temperature (°C) in a region
Treatment	Equals one if a fund management firm is based in Beijing or Tianjin
After	Equals one if our data fall into the BOG08 period, August and September, and zero otherwise
QH	Equals one if a fund management company resides where the city's latitude distance from the line of Qinling-Huai River is positive and zero otherwise
Post	Refers to one for the years 2014 and 2015 and '0' for the years 2011 and 2012

Appendix B. Appendix

List of Health Issues Air Pollution Producing

AQI Range	Air Quality Level	Health Issues
From 0 to 50	Least hazardous	No health issues
From 51 to 100	Decent	Few health issues
From 101 to 150	Low pollution	Hazardous for sensitive people
From 151 to 200	Medium pollution	Hazardous to most people
From 201 to 300	Heavy pollution	More health problems for all people
From 300 to the highest value	Most hazardous	Severe health problems for all people

The Chinese Ministry of Environmental Protection classifies air quality index (AQI) into six groups to show the severity of poor air quality. AQI under 100 indicates no or little health risk. AQI over 300 is considered the most hazardous risk. Generally, people consider days with an AQI of >100 as hazy days and <100 as blue-sky days.

Appendix C. Appendix

Impact of Air Quality on Fund Risk with Heating and Non-heating Season

Panel A: Impact of air quality in 2SLS				
	Heating Season		Non-heating Season	
	TracErr	RetVol	TracErr	RetVol
fitted_AQI	0.006***	0.009***	0.006***	0.013***
	(16.7)	(16.24)	(16.88)	(23.64)
Polynomial	Yes	Yes	Yes	Yes
Fund characteristics	Yes	Yes	Yes	Yes
Weather conditions	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
No. of Obs	20,162	20,162	19,882	19,882
Adj. R-squared	87.77%	87.52%	52.67%	71.64%

Panel B: Impact of air quality in DiD				
	Heating Season		Non-heating Season	
	TracErr	RetVol	TracErr	RetVol
QH*Post	0.196***	0.064*	0.194***	0.062
	(5.63)	(1.75)	(5.54)	(1.64)
QH	−46.677***	−9.296	−61.351***	−27.078***
	(−7.16)	(−1.24)	(−11.3)	(−4.51)
Polynomial	Yes	Yes	Yes	Yes
Fund characteristics	Yes	Yes	Yes	Yes
Weather conditions	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
No. of Obs	6891	6891	6497	6497
Adj. R-squared	51.00%	26.83%	49.84%	25.75%

Appendix C reports the results of the 2SLS estimation of the effect of air pollution on fund risk and DiD analyses on the heating and non-heating season. *TracErr* refers to the standard deviation between the daily fund and benchmark returns in a month. *RetVol* refers to the standard deviation of daily fund returns in a month. Air pollution is measured by monthly raw *AQI*. *AQI* refers to the raw air quality index. In the first stage, we regress *AQI* on *QH*, which indicates whether a fund management company is in a region where the Qinling-Huai (QH) River heating policy operates (yes: one, no: zero). In the second-stage model (6.2), the *fitted_AQI* from the first-stage model (6.1) is regressed with the fund risk (*TracErr* and *RetVol*) along with fund characteristics. Panel B reports the results from DiD analysis by employing the radically broadened difference in AQI between heating and non-heating areas in 2014 from 2011 to 2015. Post equals one for 2014 and 2015 (the post-period of the broadened difference) and zero for 2011 and 2012 (the pre-period of broadened difference). *QH* equals one if a fund management company is in a region where the Qinling-Huai River heating policy applies and zero otherwise. Polynomial is $f(Lat_{j,t})$, which represents a smooth control function for the latitude of the fund management company location, permitting diverse polynomials of the space between the fund management company location and the QH boundary. Our robust standard errors are clustered by fund. We parenthesize *t*-statistics under each coefficient below. *, **, and *** designate statistical significance at the 10%, 5%, and 1% levels, respectively.

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