Does Air Quality Matter for Mutual Funds' Tracking Errors?

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Abstract

Social science literature documents that air quality affects the cognitive dissonance of market participants including retail investors. In this paper, we examine the effect of air pollution on professional investors: mutual fund managers. We find air pollution affects managers' cognitive performance and behaviour bias, resulting in higher funds' tracking errors. In addition, we identify factors, which can improve fund managers' cognitive abilities, reducing the impact of air pollution.

JEL Classifications: Q5, G20, G23, G41

Keywords: Air Pollution, Tracking Error, Mutual Funds, Cognitive Biases, Managers' Behavioural Biases, Professional Investors.

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Section 1 Introduction

1.1 Motivation

Many prior medical studies examine the adverse impact of air pollution on mental health and cognition of individuals, which results in cognitive function impairment and probability of increasing anxiety and depression (Block & Calderon-Garciduenas, 2009; Calderon-Garciduenas et al., 2014; Fonken et al, 2011; Mohai, Kweon, Lee, & Ard, 2011; Weuve, 2012; Weir, 2012). The impairment of cognitive abilities triggers the rise of decision biases (Kahneman, Slovic & Tversky, 1982; Frederick, 2005; Hirshleifer 2015). According to Kahneman (2011), lack of cognitive function makes people have less control over their heuristic settings, which can lead to systematic errors with pronounced behavioural biases. We are confident that air pollution will negatively affect finance professionals like fund managers to exhibit noticeable behavioural biases and cognitive biases in their decision making. This notion originates from previous findings, the evidence of the impact of mental conditions on investors' trading (Kamstra, Kramer, & Levi, 2003).

On one hand, emerging literature finds that air pollution has been adversely influencing investors' decision making (Heyes, Neidell, & Saberian, 2016; Hirshleifer & Shumway 2003; Li, Massa, & Zhang, 2017). Huang, Xu, and Yu (2019) find evidence for significantly poor trading performance of retail investors in China due to the presence of air pollution. Not only Dehaan, Madsen, and Piotroski (2017) but also Kong, Lin, S. Liu, and Y.-J. Liu (2018) show that even experts or professionals, like financial analysts in capital markets lose the momentum of responding to earnings announcements quickly and forecasting accuracy as a result of bad weather. Li, Luo, & Soderstrom (2018) complement the findings of previous authors and add that air pollution affects analysts' productivity, accuracy in their role as information producers for financial markets.

However, many theoretical studies find that active fund managers, who have the skills of picking stocks, beat their benchmarks depending on the returns of fund holdings (Grinblatt & Titman 1989, 1993; Grinblatt, Titman, & Wermers, 1995; Daniel, Grinblatt, Titman, & Wermers, 1997; Wermers, 2000; Frank, Poterba, Shackelford, & Shoven, 2004). These managers get many restrictions in constructing an active portfolio because institutional investors set rules for managers to maintain acceptable alphas and a standard level of tracking errors (Jorion, 2003). Many previously mentioned authors work in developing approaches to mitigate tracking errors but those theoretical strategies in a mutual fund portfolio might consequently shore up the relentless trading volume, turnover ratio and trading costs (Sias, 2004). This state motivates us to ponder and discover the root of higher tracking error to examine an empirical question from a creative angle.

1.2 Contribution

In this study, we hypothesize that poor air quality can play a major part in increasing active mutual funds' volatility of active return. To our best knowledge, the influence of air pollution on the tracking errors and the cognitive ability of fund managers remains underexplored. Thus, we contribute to one of the first studies of the relationship between air quality and the tracking errors of mutual funds to bridge the existing gap. We also contribute a strategy in minimizing tracking errors of active mutual funds to the literature of mitigating tracking errors.

At this point, we provide a test to check whether poor air quality has significant impact on the tracking errors. The result of this test depends on the relationship between poor air quality and managers' cognitive function in decision-making. Such a relationship, if it exists, will offer a significant insight into managing sound air quality for mutual fund managers to constrain higher tracking errors of their funds to a minimum. Furthermore, financial industries can take precautions against poor air quality to avoid economic and mental health treatment costs for their stakeholders.

1.3 Research Questions

We formulate two foremost research questions for the investigation of our study. In this study, we would like to demonstrate the motivation for framing these questions, possible solutions and findings at the end. Research questions of our study are as follows:

1. Does air quality affect the tracking errors of mutual funds?
2. Do factors, which reduce or increase managers' psychological biases, weaken or strengthen the impact of poor air quality on the tracking errors?

We develop three hypotheses depending on the probable outcomes from our main research questions. We extensively discuss hypothesis development and feasible reasons for all the outcomes in details in section 2.

1.4 Preliminary Hypotheses and Findings

Our empirical methodology covers the hypothesis test on the link between air quality and the tracking errors of mutual funds. We build this hypothesis test on the premise from medical literature that poor air quality will affect mental health and cognitive function of mutual fund managers, and consequently affect the mutual fund performance along with their tracking errors. Our main hypothesis of baseline analysis is that poor air quality positively associates with the tracking errors of mutual funds. Our methodology also identifies that the tracking errors are the consequences of poor air quality even after considering the impacts of other crucial factors, such as fund, manager and market environment characteristics. Additionally, we examine the severity of the impact of air pollution on the tracking errors by exploring the factors that can help managers to control their psychological biases. We believe that the factors, strengthening cognitive abilities of fund managers, can reduce the tracking errors even in the presence of unsafe air pollutants in the atmosphere.

We choose China as an example to conduct our empirical tests, where air pollution is common and differs across time and place (Chen, Ebenstein, Greenstone, & Li, 2013). Our dataset covers 618 mutual funds along with 1339 fund managers from nine cities in China depending on their operation city during the period from January 2003 to February 2019. We, primarily, examine whether air quality matters for mutual funds. To extend further the validity of our findings from the first research question, we control three sets of characteristics to observe whether the impact of air quality on the tracking errors remains robust. We believe that certain characteristics or environments can get managers into a distinct mental state, which can boost or reduce the impact of air pollution on their decision-making. These factors can help fund managers to either improve or worsen their cognitive abilities. As a result, we will observe the extent of the impact of air pollution on the tracking errors, either higher or lower, in those specific environments.

That is why managers in funds with some special characteristics can be either immune or less resistant to air pollution. For example, managers working in old funds or in funds with higher fund flows have self-esteem and less anxiety in working for well-established funds so that they think deeply enough to use the system 2 part of their brains to counteract the air pollution effect. In addition, highly educated managers with a professional degree CFA, more experience, managing more funds, experience peace of mind and feel safe in their profession. They earn good salary and respect; as a result, they are confident and look for new opportunities to outperform the market. All these factors help them to reduce psychological biases, thus they have less exposure to the negative impact of air pollution. We, furthermore, can observe that mutual funds in certain market environments help managers with high cognitive abilities to be more aware of making mistakes and to take appropriate decisions to perform well in hazy days. Hence, these leading factors help fund managers to magnify or ease air pollution's impact on tracking errors.

On the contrary, poor air quality can disturb managers in bad market news or conditions and they perform poorly in investment decisions, resulting in higher tracking errors. We might observe declining, or no variation, in the relationship between tracking errors and air pollution in the presence of particular environments. For instance, fund managers can buy air purifiers to clean indoor air (Chen et al., 2015) as well as facemask to have less exposure to air pollutants (Zhang & Mu, 2018), and work remotely from the office under blue sky. They can also use their cognitive abilities to the fullest to be immune from the negative effect of air pollution. In addition to prior approaches, they can just simply replicate other mutual fund managers' fund management decisions (Malkiel, 2003). Nevertheless, we outline feasible results and reasons in detail for investigating both parts of the second research question in our later section, hypothesis development.

Our hypothesis tests provide us with solid and robust evidence that the tracking errors of mutual funds and poor air quality have a highly statistically significant positive association. It appears that managers in contact with unsafe air pollutants display cognitive as well as behavioural biases. This cognitive dysfunction results in unforeseen mistakes in decision-making (Huang et al., 2019). Thus, tracking errors of mutual funds tend to escalate whenever the level of air pollution rises. We find this result highly statistically significant after following a series of robust tests with controlling three sets of control variables. In addition, our channel analysis (Graham & Rogers, 2002; Li et al. 2017), with factors improving managers' cognitive abilities, shows us that managers are able to alleviate the impact of air pollution on their tracking errors. This result matches our theory behind our second research question as well. Finally, we introduce event study and difference-in-differences method (Brogaard, Li, & Xia, 2017) to capture the causal effect of air pollution on tracking errors. This study, here, employs an exogenous shock from the air pollution control regulations implemented for Beijing Olympic Games 2008 event (BOG08) (He, Fan, & Zhou, 2016; Chen, Jin, Kumar, & Shi, 2013, pp. 424–438). Our findings from these endogeneity tests show significant decline in tracking errors because air quality immediately and significantly improved in the regulated city, Beijing during the BOG08. All the tests, at this point, support our main conclusion that air quality influences managers' impairment of cognitive decisions, thus increasing tracking errors.

Our findings are in harmony with the argument that poor air quality can increase economic costs of society (Hanna & Oliva, 2015; Chang, Zivin, Gross, and Neidell, 2016, 2019; Archsmith, Heyes, & Saberian, 2018). Our results contribute to the literature of the empirical findings of the positive association between poor air quality and mistakes of decision making from financial market participants (Hirshleifer & Shumway 2003; Heyes et al., 2016; Dehaan et al., 2017; Kong et al., 2018; Li et al., 2017; Huang et al., 2019). In particular, we contribute by examining the gap in the literature, the role of air pollution on professional investors like mutual fund managers.

1.5 Structure of Thesis

Our objective of this study is to examine the consequences of mutual fund managers' exposure to air pollution in the financial market. Many empirical studies in the field of medicine, economics, psychology and finance motivate us to think deeply and come up with the aforementioned research questions that we can investigate to contribute our findings to the existing literature.

We frame this study in a structure as following: Section 2 presents literature review; Section 3 presents data and variables; Section 4 presents methodology; Section 5 presents empirical results; Section 6 presents endogeneity test; Section 7 presents limitations of this study and Section 8 presents conclusions.

Section 2 Literature Review

2.1 Air Pollution and Cognitive Function

Air pollution contributes considerable evidence of adverse impacts on cognitive functioning to the literature of medical studies. In particular, as the upper respiratory (breathing) region transports high fine particulate matter (PM, an air pollutant) to the brain, an individual can experience cognitive deficiency and neuroinflammation (Pope & Dockery, 2006; Block & Calderon-Garciduenas, 2009). Additionally, air pollution inhibits the ability of red blood cells' haemoglobin to translocate oxygen and intensifies the scarcity of oxygen to the brain, thus a person loses the power of concentration and comprehension (Badman & Jaffe, 1996; Kampa & Castanas, 2008; Mills et al., 2009). In a worst-case scenario, people's immediate contact with air pollution can develop the chance of cerebrovascular diseases. For instance, Wellenius, Schwartz, and Mittleman (2005) document that it can increase the likelihood of ischemic stroke in an elevated level of fine PM in the air.

We formulate our new perception on the empirical findings of topical health science literature that unsafe air pollutants impose an adverse impact on the mental health and cognition of individuals. For instance, individuals will experience not only deterioration of cognitive ability and the chance of increasing risk of anxiety and depression (Block & Calderon-Garciduenas, 2009; Fonken et al, 2011; Mohai et al., 2011; Weuve, 2012; Weir, 2012) but also a negative effect on respiratory, vascular condition and their sense of wellbeing (Pope, 1989; Pope et al., 2002; Pope et al., 2011). World Health Organization (WHO) (2016) addresses air pollution as a key environmental threat to health. We follow the literature of the influence of mental conditions on investors' trading (Kamstra et al., 2003), the activities of brain (Frydman 2014) and the unfitting cognitive properties triggering the rise of decision biases (Kahneman et al., 1982; Hirshleifer 2015). Consequently, we are confident that air pollution will induce some influence especially on finance professionals like fund managers to display cognitive biases in their decision making.

Along with medical studies, social studies find a similar negative association between air pollution and cognitive performance in several activities, which demand mental insight. According to Ebenstein, Lavy, and Roth (2016), exam performance of students of an Israeli high school, in immediate exposure to air pollution, tends to negatively associate with the level of air pollution. Similarly, Chang et al. (2019) find that workers in call centres require to do jobs with cognitive effort perform poorly on hazy (poor air quality) days. Given these studies, the impact of air pollution on the cognitive performance of indoor workers is quite noteworthy. Therefore, office workers cannot just relax in indoor offices because outdoor ambient pollutants can effortlessly pierce interior places (Thatcher & Layton, 1995; Vette et al., 2001; Braniš, Řezáčová, & Domasová, 2005). As per the findings of Vette et al. (2001), 50% - 90% of open-air pollutants typically pierce indoors.

To go along with these findings, several studies (Calderon-Garciduenas et al., 2003; Sorensen et al., 2003; MohanKumar, Campbell, Block, & Veronesi, 2008) document systematic or oxidative stress and inflammation, which lead to significant impairment to cytokine signalling in the brain due to air pollution (Salim, Chugh, & Asghar, 2012). Cytokines contribute a major part in monitoring the activities of the brain along with the neural system of mood. Abnormality or impairment in cytokine signalling might increase the likelihood of incidents like depression, apprehension, and cognitive disruption (Salim et al., 2012). If people face these issues, they usually rely on the heuristic approach in decision-making. Kahneman (2011) defines heuristic setting of human beings as system 1, which is quite convenient until it leads to extreme systematic errors. He also says that system 2, function of cognitive abilities, is in control of overcoming compulsions of system 1. Therefore, if our cognitive function depletes due to air pollution, we lose control over system 1 and cause severe undesirable biases in decision-making. Given that we hypothesize that poor air quality will induce cognitive dysfunction of mutual fund managers. Consequently, this condition negatively correlates with mutual fund performance, leading to higher tracking errors of funds.

2.2 Impact of Air Pollution on Capital Markets

Very few studies explore the significance of air pollution on capital markets, instead only looking at its affiliation with analyst and retail investors. This, despite its significant impact on cognitive ability and anxiety (Lavy, Ebenstein, & Roth, 2014; Pun, Manjourides, & Suh, 2017; Zhang, Chen, & Zhang, 2018). As a result, we are missing out significant information on the behaviour of professional capital market participants like active mutual fund managers. For example, the negative impact on their abilities to process, investigate information and act on it while they are in contact with poor air quality. Therefore, we examine the consequences of air pollution on mutual fund managers, the specialists or professionals in such capital markets, and its effect on mutual fund performance to fill the gap in the literature.

Few scholars conduct their studies on the impacts of air pollution on capital markets. Among them, Heyes et al. (2016) put on record that air pollution weakens the stock returns and allows the volatility of stocks to increase in The New York Stock Exchange. In addition to this finding, Huang et al. (2019) document significantly poor trading performance of retail investors in China due to the presence of air pollution. Furthermore, Dehaan et al., (2017) find that even experts or professionals, like financial analysts, lose the momentum of responding to earnings announcements quickly as a result of bad weather effect in U.S. capital markets. Kong et al. (2018) investigate the relationship between air pollution and the accuracy of analyst forecast and conclude that poor air quality significantly decreases the accuracy of analyst forecast in reaction to earnings announcement in China. Li et al. (2018) also shed lights on previous findings by showing that air pollution affects analysts' productivity and accuracy in their role as information producers for financial markets.

From these findings, we motivate ourselves to study mutual fund managers, professional investors, and investigate the role of air pollution on managers' tracking errors. Fund managers of actively managed stocks constantly takes stock trading decisions, which require cognitive effort to reflect good fund performance in mutual funds. To maintain positive active returns and tolerable tracking errors of mutual funds, fund managers must both collect information from numerous sources and process information to take decisions, such as what stocks to buy or sell, how many stocks to buy or sell and when to execute trading decisions. As stock prices are quite volatile over time, active fund managers of stock mutual funds constantly need to process vast volumes of information associated with stocks and take prompt actions. More than a few recent findings confirm not only the effect of cognitive aptitudes on stock trading performance but also the negative association between behavioural mistakes in decision making and cognitive abilities (Grinblatt, Keloharju, & Linnainmaa, 2012; Frederick, 2005; Oechssler, Roider, & Schmitz, 2009; Benjamin, Brown, & Shapiro, 2013; Agarwal & Mazumder, 2013). For instance, Grinblatt et al. (2012) document that the disposition effect does not affect high-IQ investors. Therefore, they execute trades better and outperform low-IQ investors in terms of return. Consequently, lack of cognitive functions in investors can lead to the consequences of depending on heuristics for the decision-making process and behavioural biases in executing trades (Huang et al, 2019).

Until now, our study on the literature hints at the negative impacts of air pollution on activities and decisions, which require mental efforts. We regard taking decisions on trading in diversified holdings and managing mutual funds as cognitive functions. These cognitive functions have huge financial impacts on the economy as many individual, professional and institutional investors engage in them. To our best knowledge, the influence of air pollution on mutual fund performance and cognitive ability of fund managers remains underexplored. Thus, we contribute to one of the first studies of the association between air quality and the tracking errors of mutual funds. From this moment, we would like to explore more on mutual fund performance and tracking errors so that we understand their importance to fund managers.

2.3 Mutual Fund Performance and Tracking Errors

Studying this literature, we perceive what fund managers want to achieve, and why they want to minimize tracking errors throughout fund management. There is extensive literature on mutual fund performance in the past several decades. The majority settles with mutual funds' incapacity of generating outperforming returns relative to their benchmark indices (Jensen, 1968; Lehmann & Modest, 1987; Grinblatt & Titman, 1987, 1989; Malkiel, 1995; Gruber, 1996; Carhart, 1997). We see consistent findings of similar results in studies on mutual fund performance from other countries (Cai et al., 1997; Hallahan & Faff, 1999; Sawicki & Ong, 2000; Bauer et al., 2006). Nevertheless, many studies find that active fund managers, who have stock-choosing skills, beat their benchmarks depending on the returns of fund holdings (Grinblatt & Titman 1989, 1993; Grinblatt et al., 1995; Daniel, Grinblatt, Titman, & Wermers, 1997; Wermers, 2000; Frank et al., 2004). It seems that active portfolio managers are the wheels of mutual funds, which set their destiny.

Elton, Gruber, Brown, and Goetzmann (2003) document that the greatest number of investment textbooks extensively explain tracking errors in a passive portfolio management scenario rather than in an active one. Thus, we consider the standard error as the typical definition of tracking errors. This standard error comes from a regression between passively managed funds and their benchmark returns; nonetheless, the beta of both must be equal to one to avoid overstating tracking errors (Treynor & Black, 1973). Ammann and Zimmermann (2001) document the similar issue in correlation analysis between them. Hence, we outline tracking errors of active funds as the square root of the second moment deviation of returns of actively managed funds and their benchmarks. On the other hand, we can define active funds' tracking errors as the average of absolute difference between returns of actively managed funds and their benchmarks (Satchell & Hwang, 2001). Pope and Yadav (1994) propose these three types of tracking error definitions in examining a study of determining errors in tracking errors. Thomas et al. (2013) address return optimization as a key driver for the cause of tracking errors. In addition, they complement management fees, operation or transaction fees, taxes, all types of factor tilts, funds' cash management process to the list of determinants of tracking errors.

Roll (1992) and Cornell and Roll (2005) mention frequent money management of institutional investors, where active managers always look for opportunities to outperform the benchmark with a constraint on tracking errors. Riddles (2015) says that institutional investors expect their hired active managers to outperform their assigned funds' benchmark indices and they track the likelihood of underperforming of their managers by tracking errors. Therefore, if an active portfolio manager surpasses tracking error constraint, it means that they are not performing in alignment with their investment company objectives. Pope and Yadav (1994) suggest that tracking errors are critical in optimizing and handling index funds. In agreement with the previous statement, Roll (1992) imposes tracking error as the medium of inspection to check whether managers' investment styles are in line with the objectives of the funds or not.

That is why we find interest in reviewing active fund managers' tracking errors. Starting with Rudd (1980), Chan and Lakonishok (1993) and Chan, Karceski, and Lakonishok (1999), most prior academic studies serve passive tracking managers well but very few studies apply similar attention to active tracking managers. Roll (1992) and Jorion (2003) are novices in this field of studying tracking error constraint and utilizing it to find comprehensively the answers for active portfolio allocation. Clarke, de Silva, and Thorley (2002) also examine several active strategies with tracking error constraints and weights so that they can identify the best investment option by not compromising projected excess returns. They also mention that institutional investors restrict active portfolio managers with constructing an active portfolio. These active managers must maintain acceptable betas or alphas as well as a standard level of tracking errors (Clarke et al., 2002). If they violate these regulations, they may have serious legal issues and face penalties of reputational damage (Penhall, 2015). Investment companies consider tracking error an eminent constraint on their active fund managers. Thus, an investment company does not appreciate unconventional deviation in tracking error while managing a fund. For instance, Merrill Lynch used to manage the pension fund of Uniliver's management and attempted to outperform the FTSE All-Share Index by relatively 1% per year. In a consequence, Merrill Lynch faced a lawsuit against them due to underperforming the benchmark index by around 10% over a fifteen-month period.[1]

With reference to the above literature, we comprehend the significance of tracking errors to mutual fund managers. They consistently employ their cognitive abilities to focus on improving their fund performance as well as reducing tracking errors. In tracking error literature, many authors consider different active trading strategies to reduce tracking errors. Jorion (2003) and El-Hassan & Kofman (2003) focus on applying active portfolio allocation approaches. They exploit an efficient frontier for constrained tracking-error to predict conditional variance-covariance matrix of asset returns. Along with them, Burmeister, Mausser, and Mendoza (2005) look at developing analytical tools to assess different active trading methods to minimize tracking errors. Recently, Maxwell, Daly, Thomson, and Vuuren (2018) add different tracking error constraints to maximize the risk adjusted return in contrast to Jorion (2003). Theoretically, their techniques

[1] Merrill Lynch had to settle the case by compensating the client $105 million in agreement. They also incur huge loss to the similar agreement with Sainsbury. Please see The Wall Street Journal, December 7, 2001, p. C1.

of rebalancing portfolios based on the variance-covariance matrix appear efficient in minimizing tracking errors but trades, practically, are dynamic and require more cognitive abilities from a manager to have them executed. Employing those theoretical strategies in a mutual fund portfolio might shore up the relentless trading volume and turnover ratio. We, therefore, will see a subsequent increase in trading costs for the mutual fund, resulting in poor fund performance. This state also motivates us to ponder and discover the root of this issue to examine an empirical question and establish a relationship between air pollution and fund managers. Our study illustrates how managers can reduce tracking errors with a new tactic by realizing factors that improve their cognitive abilities and reduce the impact of poor air quality on them.

2.4 Cognitive and Behavioural Biases in Fund Managers

It follows that since air pollution minimizes cognitive abilities, it should increase the likelihood of revealing behavioural biases, thereby causing fund managers to perform poorly. Exploring these biases will help us understand the significance of the negative effect of air pollution on cognitive abilities. Previous studies in capital markets document the existence of several behavioural biases in mutual fund managers, for instance: biases of risk taking, extreme trading, familiarity, extreme optimism, a disposition effect. On the other hand, other factors like employability risk, fund ownership and incentives on fund performance also influence the behaviour of fund managers who require cognitive effort to perform decision making in their jobs. Oechssler et al. (2009) find that people with low cognitive abilities surge up their biases in decision making significantly. Medicine literature documents that air pollution has adverse impacts on cognitive functioning, which leads to minimal cognitive abilities (Pope & Dockery, 2006; Block & Calderon-Garciduenas, 2009; Badman & Jaffe, 1996; Kampa & Castanas, 2008; Mills et al., 2009; Wellenius et al., 2005). Therefore, we dive into the literature of mutual fund managers’ behavioural biases to comprehend their impacts, which associate with cognitive abilities and air pollution.

Fund managers often adopt the strategies that the market follows (Sias, 2004). It means that, because they are under pressure, they replicate peer funds or cannot utilise their cognitive effort. Negative market factors can affect the impact of air pollution on cognitive abilities. As a result, managers rely on the heuristic approach and operate their funds with the flow. Past studies find that herding funds underperform in the long run, whereas funds that follow different measures to deviate themselves from the crowd outperform the other funds (Cremers & Petajisto, 2009; Kacperczyk, Sialm, & Zheng, 2005; Kacperczyk & Seru, 2007). Herding and intolerant behaviour by institutional investors also could amplify the volatility of stock prices, increase market fragility and destabilise corporate valuation (Sias, 2004).

On the other hand, Kahneman (2011) delineates system 1 as a common process of decision-making. He says that decision-making is immediate, instinctive and comes from prior learning, experience as well as familiarity. We think this heuristic setting increases the fund managers' familiarity and home biases as managers lose their cognitive abilities due to air pollution. According to Pool, Stoffman, and Yonker (2012), managers overweight the average fund by its home states funds by 18.8%. Ke, Ng and Wang (2010) document that familiar or home-name stock holdings underperform compared to the other stock holdings in funds. It implies that familiarity encourages fund managers to trade with home bias rather than informed trading. Pool et al. (2012) find that managers who are in their early profession display stronger familiarity and home bias than managers who are in their late profession.

However, Jin and Scherbina (2011) find in their comprehensive study that new managers sell significantly higher number of loser stocks than ongoing managers because the new managers get less emotionally involved with these holdings, pointing a direction to a disposition effect. Wermers (2003) investigates fund investors' responses to fund performance and fund managers' consequential behaviour after net inflows. He wants to see how momentum strategies work towards the position of managers' fund holdings. He finds that losing managers hold on to their low return stocks, reflecting a disposition effect and winning managers do the opposite using momentum strategies stronger than the others. Examining the disposition effect, not only Grinblatt et al. (2012) find the negative association between poor trading performance and cognitive abilities but also Huang et al. (2019) observe similar results under the circumstances of poor air quality. Following these studies, we add managers' experience in our robustness tests to see how it can manipulate air pollution's impact on cognitive abilities.

In addition, managers, run by over confidence bias, believe that their past successful performance comes from their own skills instead of luck. Subsequently, they overestimate their trading decision making skills following good performance, whilst ignoring bad performance (Gervais & Odean, 2001). Losing control of cognitive function can enable managers to display these biases, as they do not think hard enough to employ their system 2 part of the brain. According to Puetz and Ruenzi (2011), overconfident investors consequently rely on their wrong theories regarding their abilities, as a result, executing too many trades. We see the similarity of these findings with a detailed elaboration in the chapter of overconfidence in the Nobel laureate Kahneman's book (2011).

From medical literature, we get evidence of pronounced depression and anxiety in hazy days (Calderon-Garciduenas et al., 2003; Sorensen et al., 2003; MohanKumar et al., 2008; Salim et al., 2012). That is why fund managers often execute their trading choices depending on career concern.

According to Khorana (1996), managers lose their jobs because of their poor performance, consistent for up to two years preceding their dismissal. Hu, Kale, Pagani and Subramanian (2011) documents a U-shaped correlation between managers' risk-taking decisions and previous performance. They also find that managers incline to display 40% higher risk in that situation. Additionally, they are prone to window dress as they have past poor performance, which can result in their employability termination (Barras, Scaillet, & Wermers, 2010). Wang (2012) documents 9.4% window dressing transactions out of nearly 54,000 dealings in the sample of their false discovery procedure. Wang (2012) also finds that fund managers mislead investors with their window dressed funds, which enjoy more successive cash inflows.

We include funds' expense ratio to proxy for managers' self-interest in managing funds. This factor can improve managers' cognitive abilities as they intensely utilize their mental effort to make a profit in their investment. Given that, almost 50% of all mutual fund managers in the US hold personal ownership of their managed funds (Khorana, Servaes, & Wedge, 2007). Khorona et al. (2007) believe that these factors can change managers' behaviour and fund performance. Each basis point increase in ownership improves the future risk-adjusted performance by near 3 basis points (Khorona et al., 2007). Ownership is typically in small percentage, less than 5% according to their observation. Carpenter (2000) finds a strong evidence of influenced managerial behaviour by incentive fees. Concurring with that statement, Elton, Gruber, and Blake (2003) establish that incentivised managers are prone to take more risk, having significantly higher market betas, and diverge from their given benchmark to outperform the market. After investigating the US market, Dass, Massa, and Patgiri (2008) document the managers' holdings deviation from the stated benchmark, for instance, each percentage of incentives increase causes a 3% decline in portfolio weight.

Overall, the study of empirical findings firmly depicts the exhibition of several behavioural biases from mutual fund managers. Managers' feeble cognitive abilities induce these behavioural biases and make them even stronger. After following prior literature, we know poor air quality lessens cognitive abilities and increases many behavioural biases. Thus, understanding these causes of behavioural biases helps us to frame our study to prove their economic costs in financial markets.

2.5 Related Literature

We relate some other literature to our study to understand the significance of poor air quality's outcome. Following emerging literature, we find that air pollution adversely influences investors' decision-making (Heyes et al., 2016; Hirshleifer, & Shumway, 2003; Li et al, 2017). Having theoretical connection between air pollution and decision-making, former studies also recognize the negative mood due to air pollution (Bakian et al., 2015; Calderon-Garciduenas et al., 2015; Lim et al., 2012; Power et al., 2015; Szyszkowicz, 2007). In addition, preceding literature attributes agents' weakening performance to their health issues because of air pollution (Chang et al., 2016, 2019; Lavy et al., 2014; Suglia, Gryparis, Wright, Schwartz, & Wright, 2007; Graff Zivin & Neidell, 2013).

Though there are some important findings regarding poor air quality, it might have negative correlation with investor moods (Hu, Li, & Lin, 2014; Heyes et al. 2016). However, the impact of negative mood on mutual fund performance is indistinct according to psychological studies. If we look at the findings, poor trading decision induced by an unpleasant mood (Isen, Means, Patrick, & Nowicki, 1982; Murray, Sujan, Hirt, & Sujan, 1990; Isen, Rosenzweig, & Young, 1991), we see the lack of cognitive functionality in processing essential information. Conversely, we observe the vice-versa result as some studies document that individuals, experiencing an unpleasant mood, are highly unlikely to show heuristic behaviours (Schwartz & Clore, 1983; Wyer, Clore, & Isbell, 1999). Therefore, there is less likelihood of observing any clarification on a strong forecast on the association between air pollution and mutual fund performance by investor moods.

Our study also helps understanding of the emerging literature; the association of air quality with social and economic costs. Past studies show how life expectancy of individuals is shortened due to the impact of air pollution on physical conditions (Chen, Ebenstein, Greenstone, & Li, 2013; Greenstone & Hanna, 2014; Ebenstein, Fan, Greebstone, He, Yin, & Zhou, 2015). Arceo, Hanna, and Oliva (2016) find that poor quality positively associates with infant mortality. Moreover, air pollution costs our human capital by influencing education, labour supply, migration and worker productivity (Currie, Hanushek, Kahn, Neidell, & Rivkin, 2009; Hanna & Oliva, 2015; Mohai et al., 2011; Zivin & Neidell, 2012; Chang et al., 2016, 2019; Chen, Oliva, & Zhang, 2017). On the other hand, we attribute the rapid economic growth in China to ignorance of the impact of air pollution by following the survey on China's urban pollution (Zheng & Kahn, 2013). China has been enhancing its economic growth by sacrificing environmental quality for a decade (Christmann & Taylor, 2001). Both Environmental Performance Index (Hsu & Zomer, 2016) and WHO standards indicate that the risky level of air pollution causes 20% of daily deaths. That is why they classify it as the third most hazardous risk factor in China, exposing more than half of its population. However, we find that proof of rising concern from people towards air pollution. Ito and Zhang (2016) document that people understand the significance of clean air in society and economy, therefore, are willing to pay for it. Zhang and Mu (2018) shows that people spend $187 million to buy facemasks in China and it can only partly minimize the negative effects of air pollution.

2.6 Hypothesis Development

Many prior studies examine the adverse impact of air pollution on mental health and cognition of individuals. This results in cognitive function impairment and probability of increasing anxiety and depression (Block & Calderon-Garciduenas, 2009; Calderon-Garciduenas et al., 2015; Fonken et al, 2011; Mohai et al., 2011; Weuve, 2012; Weir, 2012). The impairment of cognitive abilities triggers the rise of decision biases (Kahneman et al., 1982; Hirshleifer 2015). We believe that air pollution negatively affects professional investors like fund managers to exhibit cognitive biases in their decision making. This notion comes from the evidence of the impact of mental conditions on investors' trading (Kamstra et al., 2003).

Prior medical literature attributes air pollution to the resultant disruption of concentration and comprehension (Badman & Jaffe, 1996; Kampa & Castanas, 2008; Mills et al., 2009), cognitive dysfunction and neuroinflammation (Pope & Dockery, 2006; Block & Calderon-Garciduenas, 2009). Suglia et al. (2007) specify that air pollutants like black carbon reduce the intellectual level along with cognitive abilities. Szyszkowicz (2007) shows that emergency appointments for depression have a similar positive correlation with PM after controlling for weather conditions. Similarly, both Lim et al. (2012) and Power et al. (2015) document that PM in air positively associates with the signs of depression and anxiety.

With reference to the prior findings, we find that unpleasant mood causes poor trading decisions (Isen et al., 1982; Murray et al., 1990; Isen et al., 1991). We believe that the lack of cognitive functionality in processing relevant information is the main reason behind them. We find the effect of cognitive aptitudes on stock trading performance in the following studies. In addition to that, the negative association between behavioural mistakes in decision-making and cognitive abilities are in the findings of many prominent studies (Grinblatt et al., 2012; Frederick, 2005; Oechssler et al., 2009; Benjamin et al., 2013; Agarwal & Mazumder, 2013). For instance, Grinblatt et al. (2012) document that high-IQ investors execute trades better and outperform low-IQ investors in terms of return. Therefore, managers' lack of cognitive functions can lead to the consequences of depending on heuristics for their decision-making process. They can even show behavioural biases in executing trades. According to Kahneman (2011), lack of cognitive function makes people have less control over their heuristic settings, which can lead to systematic errors with many behavioural biases.

Previous studies in capital markets document the existence of several behavioural biases in mutual fund managers and we mention them in our literature review section. For instance, biases of risk taking, extreme trading, familiarity, extreme optimism, disposition effect are common in fund managers. Nevertheless, Oechssler et al. (2009) find that individuals with low cognitive abilities are prone to be impatient and are significantly risk averse in good situations. Their results suggest that individuals, who possess higher cognitive abilities, can gain higher projected returns and attain better position in financial markets than other market contestants with lower cognitive abilities. Therefore, we would like to explore the relationship between tracking errors of mutual funds and air quality. This notion will tell us how severe the impact of poor air quality is on mutual fund managers. In addition, we will be able to identify their psychological biases, which strengthen or ease that impact of poor air quality on the tracking errors.

Building upon this idea, we study more literature on the relationship between worker productivity and air pollution. The productivity of both indoor and outdoor workers negatively correlates with air pollution as per previous studies. For instance, an association of increasing ozone (O_3) in the air significantly harms farmers' productivity (Zivin & Neidell, 2012). Chang et al. (2016) stretch this study by inspecting pear-packer productivity in association with PM pollution. They find a negative correlation between indoor worker productivity and PM pollution. According to Archsmith et al. (2018), there is a positive correlation between carbon monoxide pollution in air and professional baseball umpires' likelihood of making incorrect decisions. Chang et al. (2019) document the reluctance to work during highly polluted days. Given these studies, the impact of air pollution on the cognitive performance of indoor workers is quite noteworthy. To go along with these findings, we also find that outdoor ambient pollutants can effortlessly pierce interior places (Thatcher & Layton, 1995; Vette et al., 2001; Braniš et al., 2005). For instance, 50% - 90% of open-air pollutants pierce indoors as per the findings of Vette et al. (2001).

Afterwards, we attempt to understand the influence of poor air quality in capital markets. Emerging literature finds that air pollution has been adversely influencing investors' decision-making (Heyes et al. 2016; Hirshleifer & Shumway 2003; Li et al., 2017). In addition to these findings, Huang et al. (2019) find the evidence of significantly poor trading performance of investors in China due to the presence of air pollution. Both Dehaan et al. (2017) and Kong et al. (2018) show that even professional researchers, like financial analysts in capital markets, lose the momentum of responding to earnings announcements quickly and forecasting accuracy as a result of bad weather. Li et al. (2018) complement the findings of previous authors and add that air pollution affects analysts' productivity and accuracy in their role as information producers for financial markets. Therefore, we examine the consequences of air pollution on mutual fund managers, the specialists or professional investors in such capital markets, and its effect on mutual fund performance to fill the gap in the literature.

Expanding on the above literature and considering mutual fund managers' exposure to air pollution, we believe that at least one of the penalties, such as health issues, cognitive dysfunction, pronounced behavioural biases and negative mood will affect fund managers. In consequence, we will see poor mutual fund performance and high volatility in active return. Conversely, we might experience a different scenario depending on the level of managers' cognitive abilities because managers with high cognitive abilities can be immune to air pollution. Therefore, we develop our first hypothesis considering the answer to the first research question in this study as following:

Hypothesis 1(H_1) : Poor air quality positively associates with tracking errors.

Contemplating our literature review, we are confident that our first answer to the question (R_1) will line up with the first hypothesis(H_1). It implies that, if air pollution increases, we experience higher tracking errors as mutual fund managers' decision-making abilities get affected. However, we may see some different scenarios. For instance, some mutual fund managers can have immunity to the exposure of air pollution due to their higher cognitive abilities and intelligence. They can be more conscious as well as aware of the negative consequences of air pollution and take help from system 2 in the event of air pollution. As a result, we will observe a negative relationship between them meaning that the tracking errors will decline in the occurrence of air pollution. Additionally, if mutual fund managers usually take decisions in indoor offices and buy air purifiers to clean indoor air (Chen et al., 2015), they get less exposure to air pollutants. They can also buy facemasks to avoid the negative effect of air pollution. Zhang and Mu (2018) observe a positive association between AQI and the consumption of all kinds of masks. These factors indicate managers' tracking errors have little correlation with air pollution. This slight correlation can also continue if fund managers simply replicate other mutual fund managers' fund management decisions (Malkiel, 2003).

We formulate our next hypothesis in terms of looking at a robustness test to the result of our first research question(R_1). If our first hypothesis to the question (R_1) holds, we would like to investigate whether poor air quality is the main reason behind higher tracking errors, or some other variables are the key factors. We test the link between air pollution and tracking errors by controlling for three sets of characteristics separately so that we can determine the magnitude of the impact from a particular set of characteristics. Thus, our second hypothesis in this study is as follows:

Hypothesis 2(H_2) : The results of positive correlation between tracking errors and poor air quality remain robust across fund, manager and market environment characteristics.

Firstly, we consider controlling for fund characteristics to find an answer partly for our second hypothesis. Prior literature presents the crucial impacts of fund characteristics on determining mutual fund performance (Sharpe, 1966; Prather, Bertin, & Henker, 2004; Detzel, & Weigand, 1998). We believe that air pollution positively correlates with the tracking errors of mutual funds even after controlling for fund characteristics. Our second hypothesis will remain robust, as our literature review directs our attention to the positive relationship between tracking errors and air pollution. This hypothesis can unfold different outcomes if other variables, such as fund characteristics, are the key factors to impact tracking errors, rather than air pollution. Mutual fund managers, holders of cognitive abilities and intelligence, can act rationally and become more mindful of the situation in the event of poor air quality.

Secondly, we check whether the impact of air pollution on tracking errors also remains robust after controlling for manager characteristics. Existing literature proves that manager characteristics influence mutual fund performance (Golec, 1996; Chevalier & Ellison, 1999; Prather et al., 2004; Babalos, Caporale, & Philippas, 2015; Yuhong & Mazumder, 2017). We also hypothesize a positive correlation between tracking errors and poor air quality even after controlling for manager characteristics. We can observe either upward or downward trending in tracking errors. It depends on how severely air pollution affects managers' cognitive function. For instance, managers with high cognitive abilities can suppress the negative impact of air pollution on them or find a solution to tackle the air pollution in their workplaces, relative to managers with low cognitive abilities. It is highly unlikely to obtain unexpected results, such as poor air quality not explaining tracking errors of mutual funds rather than manager characteristics do.

In this stage, we frame our final test in respect of revisiting the final part of the second hypothesis. We follow previous studies (Chan, Chen, & Hsieh, 1985; Chen, Roll, & Ross, 1986; Burnmeister & Wall, 1986; Burnmeister & MacElroy, 1988; Kryzanowski & Zhang, 1992; Chen & Jordan, 1993; Clare & Thomas, 1994; Cheng, 1995; Ozcam, 1997; Altay, 2003; Rjoub, Türsoy, & Günsel, 2009) to explore macroeconomic factors that influence stock return and different asset classes. After doing that, we believe that market environment characteristics surely have an impact on tracking errors. So, we control for many market environment characteristics to explore whether poor air quality is the one explaining tracking errors' movement or not. We are confident to obtain a positive relationship between tracking errors and poor air quality after controlling for market environment characteristics.

Building upon our assumptions from above research questions, hypotheses and preceding literature, we believe that all our above hypotheses will prevail. If they do, then we would like to ask different questions. We want to raise questions to check whether the impact of poor air quality on the tracking errors severe or less in terms of interacting with fund, manager and market environment characteristics.

Extending our research question(R_1), we would like to investigate how these three sets of factors, which reduce or increase managers' psychological biases, weaken or strengthen the impact of poor air quality on tracking errors. Building up models to find the answers for the second research question(R_2), we can observe some positive, negative and even no relationship among air pollution and all the characteristics interacted with AQI. Therefore, our final hypothesis to answer the research question (R_2) is as follows:

Hypothesis $3(H_3)$: Factors that strengthen (weaken) cognitive abilities of fund managers can reduce (increase) tracking errors.

We believe that certain characteristics or environments can get managers into a distinct mental state, which can boost or reduce the impact of air pollution on their decision-making. These factors can help fund managers to either improve or worsen their cognitive abilities. As a result, we will observe the extent of the impact of air pollution on tracking errors, either higher or lower, in those specific environments. Air pollution is unlikely to affect managers with those characteristics that support their cognitive function. On the other hand, they can be less resistant to the unsafe air pollutants if those factors weaken their cognitive abilities. For example, managers working in old funds or in funds with higher fund flows have self-esteem and are less anxious in working for well-established funds so that they think deeply enough to use the system 2 part of their brains to counteract the air pollution effect. Thus, air pollution magnifies or alleviates its impact on tracking errors of mutual fund managers, when the aforementioned factors dominate them.

In the next step, we can observe a similar situation if managers have skills to improve their cognitive abilities. Consequently, the managers with those abilities are able to expand or ease the tracking errors of their managed funds in the contact of unsafe air pollutants. For instance, highly educated managers, with a professional degree CFA, more experience, managing more funds, experience security and feel safe in their profession. All the factors help them reduce psychological biases, and as a result, air pollution will be highly unlikely to have a negative impact on tracking errors. We, additionally, can observe that mutual funds in certain market environments help managers with high cognitive abilities to be more aware of making mistakes and to take appropriate decisions in hazy days. Conversely, air pollution can affect fund managers in bad market news or conditions, resulting in highly undesirable decisions.

We expect a lot of determinants to pull the strings of these results, such as managers' cognitive abilities, mental state, health, behavioural biases, using indoor air purifiers and facemasks (Chen et al., 2015; Zhang & Mu, 2018), and replicating others' investment strategies (Malkiel, 2003) as well as the regulations for controlling air pollution. We report the methodology and result of these parts in later sections.

Section 3 Data and Variables

3.1 Data Collection

3.1.1 AQI (Air Quality Index)

We collect daily observation data of Air Quality Index (AQI), which contains the average of hourly AQI values over a day for each day value, to use them as proxies to measure air quality of some of the cities in China. Many authors in recent studies use AQI as a proxy for measuring the effect of air pollution (Li et al., 2017; Zhang & Mu, 2018; Li et al., 2018; Huang et al., 2019). So, we obtain AQI data (2014 to 2018) from the government official website of the Ministry of Environmental Protection of China and the data centre of Ministry of Ecology and Environment of the People's Republic of China.[2] We obtain AQI data from 2002 to 2012 uploaded by an AQI data collector in a website source with a help of a friend from China.[3] Unfortunately, we detect some missing AQI data in 2013 from our sample dataset. We reach out to authors, who have been working on this AQI variable, to obtain the missing data.[4]. We provide the distribution of AQI and AQI trend (Wooldridge, 2016, p. 329) across all cities to understand the gap in our data and trend in them in figure section and in Appendix D. We find from Appendix D that around 70% cities in our sample have a significant trend of increasing AQI. Both Vidal (2006) and Walsh (2016) address this rising issue of air pollution and mention that unsafe open-air particulate matter (PM) pollution has been experiencing an 8% rise in past years. Given anecdotal evidence that hazards to health from outdoor air pollution induce sombre economic growth, Ebenstein, Fan, Greebstone, He, Yin, and Zhou (2015) attribute reduced life expectancy to a high level of air pollution.

However, after the completion of the AQI data collection process, our primary AQI data consists of 369 cities' data. Afterwards, we translate those city names through Google translation platform. Additionally, we take the help of a Chinese friend to crosscheck all English versions of Chinese

[2] The official website of the data centre of Ministry of Ecology and Environment of the people's republic of China is http://datacenter.mee.gov.cn. We would like to thank our friend, Yabai Li by acknowledging his help to open an account. As a result, we successfully download AQI data from this website.
[3] The website source, https://pan.baidu.com/s/1hMmUM. Similarly, we are also grateful to Will Chen to help me understand this website process and download the data by translating information.
[4] We are thankful to Jin-hui Luo, Department of Accounting, School of Management, Xiamen University, for helping us with a year (2013) missing data in our collected AQI data set. We still observe some missing data (not more than 9 months data) for some of the cities in 2013, which we show in the figures of AQI dispersion at the end in our sample over the years. We leave the missing data blank in our dataset as it is.

city names.[5] However, we use only nine cities' air quality index, because our sample mutual funds operate only in those nine cities. For most of the years in our sample, the AQI level comprises of the level of three air pollutants, namely sulfur dioxide (SO2), nitrogen dioxide (NO2), and fine particulate matter smaller than 10 micrometres (PM10) measured throughout each day. AQI ranges from 0 to 500, with a larger value indicating worse air quality.

Ministry of Environmental Protection of China classifies AQI into six classes depending on the probable impact of AQI on human health. We show a list in our Appendix A, ordering the six categories with grades for air pollution level and heights of health issues that an individual can face, by coming into contact with those categorized air pollutants. Environment Agency (2015) grades air pollution as the "single largest environmental health risk" in Europe. AQI from 0 to 100 puts a notion of blue-sky days into people's mind and most of the people know these days with this range as sanitary days. Conversely, AQI more than 300 in days embodies severe air pollutants, hazardous to health for most people. We find this information and AQI category explanation from a US government website source.[6] The Marine Environment Protection Committee (MEPC) also confirms it with an AQI category list, which we present in Appendix A later. Even though there are arguments about the standard of the list, people usually accept AQI over 100 as an unhygienic air condition. Relying on this information on AQI categories, we develop some AQI category variables from our sample data to have different AQI models so that we can test the variation of our result across those models. We discuss thoroughly the construction process of these AQI category variables later, in the variable construction section.

3.1.2 Mutual Funds

We collect mutual fund data, initially mutual fund names from Morningstar.[7] We follow prior studies to collect our mutual fund data from Morningstar database (Chevalier & Ellison, 1999; Blake & Morey, 2000; Elton, Gruber, & Blake, 2001; Chen & Pennacchi, 2009). To begin our data collection process, we first choose the domicile of China and deselect index and enhanced index funds in the filtering option in Morningstar platform as these funds do not require a proactive role of continuous movement of security holdings by mutual fund managers. We get more than 6,000 funds, which we filter manually by going through each fund's name. We look for key words (Index, Idx, CSI, IND, SSE-SZSE 300, Inx, ETF and name with integers like 300,

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[5] We would like to show our gratitude to Hui Zeng to crosscheck the validity of translating all names of 369 cities into English and to revise the AQI data by updating them.

[6] Notes on AQI and classification from https://airnow.gov/index.cfm?action=aqibasics.aqi.

[7] Morningstar,Inc. is a financial services company to provide investment research and investment management services along with different arrays of data of mutual fund , ETFs, Indices etc. globally. Website: www.morningstar.com.

700 as well as 800) to exclude index funds or funds replicating other indices in case some of them remain in the list after the filtering process. Additionally, we manually read the prospectus of each fund to check the fund objective to make sure the objective of each fund is in line with our filtering process. We also examine each fund's prospectus to make sure that we are not picking any funds holding investments more than 20% in other assets, for instance, fixed income securities or other assets classified by Morningstar. The reason behind this is to select equity funds and avoid long-term fixed investment funds. In addition, we look at the turnover ratio of each fund and make sure none of the funds have less than 50% turnover ratio.

We read each fund's prospectus to understand their fund strategy and objective so that we can squeeze the remaining index funds out of equity funds. Finally, although we get 653 actively managed mutual funds due to all the above filtering and screening processes, we curtail the list and come up with 618 funds at the end. This is because some of the funds have an inception date after March 2018, which will prevent us from getting at least one-year daily observations for each fund. Another reason is that we cannot find appropriate benchmark data for some funds from our source, which we will discuss shortly after this section.

We also obtain mutual fund data from Bloomberg platform to crosscheck mutual fund names and other information like managers' city names (places of managers' operation), funds' benchmark names with Morningstar data to ensure their accuracy. Firstly, we sort open-end mutual funds by Chinese domicile and then filter them by setting fund objective, fund asset class focus and fund allocation in equity in Bloomberg. In addition, we select the exclusion option of index fund in general attribute setting so that we can collect actively managed equity funds by fund managers. Our intention here is to scrutinize funds managed by fund managers who are actively engaged in the decision-making process of equity turnover. We end up with 577 funds and start filtering fund names to look for certain key words as previously (Index, Idx, CSI, IND, SSE-SZSE 300, Inx, ETF and name with integers like 300, 700 as well as 800) to exclude index funds or funds imitating other indices.

Our final step is to select mutual funds to make sure we have as many observations as possible to examine our research questions, so we proceed with Morningstar mutual fund data. To begin our primary data collection, we specifically get fund ID, mutual fund names, management company, firm city, which is the location of management company, and primary benchmark names for our 618 mutual funds. We also crosscheck "City" information from Morningstar's "firm city" variable information after matching fund names and double-check them in Bloomberg and Google.

3.1.2.1 Daily Fund Return

In our second step, we look for the daily return of 618 mutual funds, as our research questions require us to examine daily observations. We collect the daily return index of those funds, which also consider any gain from dividend. We calculate the daily fund return for each fund in our sample by simply computing logarithm change of mutual funds' ending market values. We calculate this change considering the ending market value of the current day relative to the ending market value of the previous day. We manage to collect this data from January 2003 to February 2019. Morningstar does not have this data prior to 2003 for our sample mutual funds so we stick to this period to construct our daily fund return sample data. We multiply the daily fund returns expressed in decimal points by 10,000 to transform them into basis points.

3.1.2.2 Funds' Benchmarks

After obtaining primary benchmark names for our 618 sample mutual funds from Morningstar, we look for each benchmark index in Bloomberg. The reason behind this is that Morningstar does not provide daily return data of mutual funds' benchmarks. Therefore, we need to manually search benchmark names one by one in Bloomberg and concurrently note the Bloomberg ticker for each benchmark index. Each mutual fund from our sample data has at least two indices combined as its primary benchmark. Thus, we note each benchmark's weight and constitute a primary benchmark out of stated indices for distinct funds after calculating the daily return of each index. We collect total return index data of all indices to calculate benchmark return by computing the daily change of index returns, similar to the daily return calculation process. We compare both intended days' close price to previous days' close price to calculate the logarithm change of all benchmark indices for those days.

Afterwards, we calculate the primary benchmark return from these indices by summing up their return as stated by their weights assigned by fund managers. This weight varies from fund to fund based on how a fund manager assigns weights to the index component for a fund's benchmark. Not only do we collect equity indices but also, we collect different types of bond indices along with six-month and one-year interbank deposit rates from Bloomberg.

These choices are because Chinese mutual fund managers construct their funds' benchmarks using both types of indices, but the weights of bond indices and interbank deposit rates are usually one-third or less that of the benchmark for our sample data. The number of indices in each main benchmark return depends on fund managers' choices. We follow the process consecutively to calculate every single fund's benchmark return. Subsequently, we multiply the benchmark returns calculated in decimal points by 10,000 to convert them into basis points. We end up with 618 individual benchmark data for our 618 sample mutual funds. We then add them to our data set as per to our fund IDs.

3.1.3 Control Variables

3.1.3.1 Fund Characteristics

Prior literature presents the crucial impacts of fund characteristics on determining mutual fund performance (Sharpe, 1966; Prather, Bertin, & Henker, 2004; Detzel, & Weigand, 1998; Thomas et al., 2013). Thus, we consider using these fund characteristics to check their impacts on tracking errors. These studies, along with our literature review on the determinants of tracking errors, motivate us to get the notion of collecting the data. Firstly, we want to collect management team data throughout the life span of a mutual fund. Our intention here is to determine the number of members in a fund's management team on a certain day of a month in a year. Morningstar does not have this continuous variable for management time, so we want to manually collect this information and create management-team continuous variables for the mutual funds in our sample. We manually go through each fund's prospectus, especially in the section of management's history. We then note each manager's tenure with the fund on a year-month basis. This process continues for all the funds in our sample. After completion of the data collecting process, we calculate management team members on a rolling window of a month in a year for the whole sample in SAS. Afterwards, we transform this dataset into daily observations by assuming that the participation of a manager in a month means the participation of that manager from day one to the end of that month. We, finally, merge them into our dataset by matching with our mutual funds' fund IDs. In the next stage, we calculate manager turnover in percentage from management team members' data. Firstly, we compute the percentage change of the members in the management team monthly and then use absolute function to get the final variable of manager turnover in percentage. We similarly transform them to daily observations by the process used for the management team.

We can collect non-continuous fund age data for all the mutual funds in our sample directly from Morningstar. However, we would like to observe the continuous effect of older funds on the tracking error, so we manually collect the funds' operation period from the description part of their prospectus in Morningstar. We calculate their operation period monthly and then add them to our daily data by assuming that funds are in operation for all days in that month.

Additionally, we obtain fund size data in quarterly frequency from Morningstar, as we cannot get more than that frequency from Morningstar for our Chinese mutual fund sample. We distribute the value of the last known month to last unknown months. As a result, we get monthly observations of fund size, which we transform into daily observations assuming all the days of a month have same size value. Finally, we divide daily fund size observations by one million and merge them to our sample dataset by fund ID.

As we obtain the quarterly fund size data, we primarily calculate the change rate of fund size and fund flow by following the formula assumed in Sirri and Tufano (1998). We proceed with this method in two steps to get daily fund flow. In the first step, we compute the quarterly change in fund size by comparing each quarterly's fund size to its previous quarter's. In the second step, we allocate the value of the last known month to last unknown months and transform them into daily observations assuming all the days of a month have the same change rate in fund size. Subsequently, we multiply the daily change in fund size by (1 + fund return), which is our daily fund return calculated above and obtain daily fund flow for each fund in our sample. We, lastly, get daily fund flow data in decimal points, which we also merge into our sample data set by fund ID.

Finally, we obtain net expense and turnover ratio data in yearly frequency in percentage from Morningstar. Expense ratio refers to the management expenses or fund operating costs as a percentage of average value of fund assets invested in a mutual fund. On the other hand, turnover ratio represents a percentage of a fund's replacement of all its holdings over a year.

3.1.3.2 Manager Characteristics

Existing literature proves that manager characteristics influence the mutual fund performance (Golec, 1996; Chevalier & Ellison, 1999; Prather et al., 2004; Babalos et al., 2015; Yuhong & Mazumder, 2017). Therefore, we follow the characteristics that they use in their study and obtain a concept of constructing variables for this section. Next, we would like to explore how many funds a mutual fund manager manages in a given month. We want to use this variable as a proxy for fund managers' reliability measurement. The more funds a manager manages, the more reliability that manager has. We believe if the number of managing funds increases at a given period for a manager, the situation requires a manager to utilize more mental effort and cognitive abilities. We cannot find any continuous variable for our intended variable in Morningstar, so we manually go through the manager history section in each fund's prospectus. We note each fund manager's engagement in a fund on a year-month basis. We collect all funds' names that a manager works in his or her whole career up to the end of our sample date. Next, we calculate the number of funds a manager manages in a given month in SAS like a continuous variable. We name the variable as managing fund. Finally, we have distinct 1339 managers for our sample data set. To merge this data with our daily data set, we transform monthly managing fund data to daily by assuming that managing a fund for a month means managing that fund for that entire month.

Next, we collect managers' education information manually from Morningstar. We divide this education information into four segments, for instance, Bachelor's degree, Master's degree, PhD and CFA. We check managers' history in the prospectus of each fund and manually note each manager's education information. Due to some missing information, we crosscheck and fill up the information with Bloomberg and a Chinese website containing mutual fund managers' profile data.[8] We create four categorical variables to obtain this data. Our first categorical variable "Bachelor", referring to a manager's bachelor's degree holding, is equivalent to "1" if a manager has a bachelor's degree, master's degree or PhD. Otherwise we take "0" if our first statement is not true. Here, we assume a manager, who has a master's degree and PhD, has a bachelor's degree as well. Similarly, second education categorical variable "Master", representing a manager's master's degree holding, equals to "1" if a manager has a master's degree or PhD. Otherwise we take "0" if our first statement is not true. Here, we assume a manager, who has PhD, also has a master's degree. Likewise, third education categorical variable is "PhD", which refers to a manager holding a PhD and is equivalent to 1 if he or she has one, otherwise "0". Finally, we set CFA as the education categorical variable. If a manager is a Chartered Financial Analyst, then we assign "1" value to this variable, otherwise "0". Knowing the impact of managers' education on mutual fund performance motivates us to collect this data (Yuhong & Mazumder, 2017). The purpose of creating these categorical variables is to have proxies for measuring managers' mental agility.

The literature about effect of gender on mutual fund performance (Babalos et al., 2015) motivates us to collect gender identity data. We obtain this data manually as before from Morningstar. We read the description about individual managers in a fund's prospectus and note male and female, gender identity by looking at their pronouns, as Morningstar does not have this variable for managers. Afterwards, we create a dummy variable for this Gender variable. We assign "1" value if a manager is male and "0" if she is female. We create this variable as a proxy for measuring managers' confidence and risk-aversion tendency by following prior literature (Sunden & Surette, 1998; Barber & Odean, 2001; Sanders, 2003).

[8] The link of the Chinese website for mutual fund managers' profile is http://fund.eastmoney.com.

3.1.3.3 Market Environment Characteristics

We follow previous studies (Chan, Chen, & Hsieh, 1985; Chen, Roll, & Ross, 1986; Burnmeister & Wall, 1986; Burnmeister & MacElroy, 1988; Kryzanowski & Zhang, 1992; Chen & Jordan, 1993; Clare & Thomas, 1994; Cheng, 1995; Ozcam, 1997; Altay, 2003; Rjoub, Türsoy, & Günsel, 2009) to explore macroeconomic factors that influence stock return and different asset classes. After doing that, we believe that market environment characteristics surely have an impact on tracking errors. We obtain 6-month interbank deposit rates and 10-year Treasury bond yields from Global Financial Data as proxies for current interest rate and long-term interest rate consecutively.[9] We get daily frequency data for both annualized interest rates, so we divide daily-annualized interest rates by 365 days to convert the rates into daily interest rates. After that, we calculate interest rate spread by subtracting the daily current interest rate from daily long-term interest rate. We use this variable as a proxy for measuring the market risk in an investment period.

Afterwards, we obtain CSI 300 capitalization-weighted stock market index data from Bloomberg, which is the measurement of imitating the performance of the top 300 stocks traded in the Shanghai and Shenzhen stock exchanges. We, primarily, calculate the daily return of CSI 300 index by following the same formula we use to calculate fund daily return in decimal points. Next, we want to find the volatility of daily return of CSI 300 to use it as a proxy for market volatility. Thus, we use GARCH (1, 1) model, developed by Engle (1982), to estimate the daily volatility of the return of CSI 300. The formula is

$$r_t = \alpha r_{t-1} + \varepsilon_t - - - - - - - - - - -(1)$$

$$\sigma^2 = w + \beta_0 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 - - - - - (2)$$

Where r_t refers to the return of CSI 300 in day t, and r_{t-1} is 1 lag daily return of CSI 300 in equation (1). In equation(2), we regress conditional variance σ^2, obtained from equation (1), with 1 lag of the square of error term ε_t, obtained from equation (1) and 1 lag of conditional variance σ^2. From the second equation, we get daily estimated conditional variance, σ^2 and then we use square root of variance, σ^2 to get daily Standard deviation, σ of CSI 300. We consider this σ of Shanghai Shenzhen CSI 300 as a proxy of market volatility. Finally, we multiply calculated daily market volatility by 10,000 to transform the value from decimal points into basis points.

[9] Website source of global financial data is http://www.globalfinancialdata.com

Additionally, we collect sentiment variables, for instance, OLED leading indicator index, consumer confidence index, business confidence index, producer price index, consumer price index, and unemployment rate from Global Financial Data except OLED leading indicator index, which we collect from Bloomberg. OLED leading indicator consists of economic variables that give a sense of the future state of an economy. We get all the aforementioned sentiment data in monthly frequency except the unemployment rate, which is in quarterly frequency. Firstly, we calculate the monthly change in percentage using the natural logarithm function for the sentiment index data. We get inflation rate from the monthly change of consumer price index. We then assign all the monthly values of sentiment variables along with the unemployment rate to the days of each month, by assuming that monthly values are constant for all the days in each month. We express all the values of these variables in percentage. Afterwards, we merge these variables with our sample data set by dates.

To consider trade volume as proxy for market risk, we obtain market value traded data of both Shanghai Stock Exchange and Shenzhen Stock Exchange from the World Federation of Exchanges.[10] We sum up the value of traded volume, which is in local currency in billions. The reason for this is that fund managers usually invest in stocks listed in both stock exchange markets, to capture the influence of both markets. Similarly, we transform this monthly trading volume data to daily; assuming monthly values are constant for all the days in each month.

3.2 Main Variable Construction

3.2.1 Tracking Error

To look for the answer to the research question of our study, we start our journey with finding the tracking error of mutual funds in our sample. As we have already collected active return of our funds in the sample, we want to find out the daily volatility of the active return. We use GARCH (1, 1) model to forecast daily volatility of the active return. The ARCH model and its several progenies by Engle (1982) have been dominant in academic portfolio literature for the last two decades. He develops his assumption that volatility of returns of a stock and its beta, change over time. These models make considerable progress in accomplishing better fitting conditions for univariate time series. In practice, portfolio managers frequently employ forecasted risk models rather than applying forecasted return models based on the assumption of changing stocks' volatility and beta over time (Blair, 2002). Thus, the formula of calculating tracking error of the active return for our sample mutual funds is as follows:

[10] The website of WFE is https://www.world-exchanges.org

$$ar_{(i,t)} = \rho ar_{(i,t-1)} + \varepsilon_{(i,t)} ------------(3)$$

$$\sigma^2_{(i,t)} = w + \beta_0 \varepsilon^2_{(i,t-1)} + \beta_1 \sigma^2_{(i,t-1)} ------(4)$$

$ar_{(i,t)}$ refers to the daily active return of our sample fund i in day t, and $ar_{(i,t-1)}$ is 1 lag daily active return of our sample fund i in equation (3). In equation (4), we regress conditional variance $\sigma^2_{(i,t)}$, obtained from equation (3), with 1 lag of the square of error term $\varepsilon_{(i,t-1)}$, obtained from equation (3) and 1 lag of conditional variance σ^2. From the second equation, we get daily estimated conditional variance, $\sigma^2_{(i,t-1)}$ and then we use square root of variance, $\sigma^2_{(i,t)}$ to get daily Standard deviation $\sigma_{(i,t)}$, of the active return. We consider this $\sigma_{(i,t)}$ of the active return as the daily volatility, thus, estimated daily tracking errors, of our sample mutual fund i. Finally, we multiply estimated daily tracking errors by 10,000 to transform the value from decimal points into basis points.

3.2.2 AQI Categories

As our focus is to find the effect of AQI (Air Quality Index) on TE (Tracking Error), we use several formats of AQI in our models to test our hypotheses. Many authors in recent studies on air pollution (Li et al., 2017; Li et al., 2018; Huang et al., 2019) use different AQI models to investigate their hypotheses like raw or base AQI model, log of AQI model, AQI category model. In each model using their methods, we assign different formats of AQI to check the variation of the result so that we can justify whether our hypotheses are going to hold across all formats of AQI. We consider raw value of AQI as our base AQI variable. Then, we calculate log of AQI, log (AQI), as our second AQI variable to solve the problem of skewness in daily data points.

In the next step, we calculate Abnormal AQI as our third variable. The reason behind constructing this new variable is that managers can be accustomed to certain amount of air quality. We would like to measure the excess value of the air quality index to measure the impact of abnormal AQI on tracking errors. To do that, we calculate a mean of AQI per city and then subtract from daily observations of AQI for each city. Then, we name the variable as abnormal AQI.

We mention that an AQI of more than 100 is hazardous to the health of human beings. Thus, we construct a dummy variable for AQI. If AQI is less than 101 then Dummy AQI value is "0" and if AQI is more than 100 then Dummy AQI value is "1". We would like to capture the variation of detrimental and non-detrimental effect on managers from AQI.

We also consider creating a category variable for AQI. As per MPEC, AQI falls into six categories; therefore, we assign values for each category consecutively starting from value one.[11] AQI (1-50) is categorized as 1, AQI (51-100) as 2, AQI (101–150) as 3, AQI (151–200) as 4, AQI (201–300) as 5, and AQI (300+) as 6. The purpose here is to capture the magnitude of AQI impact more closely based on the categorical impact of AQI on health. We merge all the AQI data of cities into our dataset by the operation city of each fund, firm city or management city of a fund, with our sample dataset.

3.2.3 Funds' Manager Characteristics

In the sample, we observe that there are more than one manager managing funds in a specific month in many cases. Therefore, we want to compute managers' characteristic variables in a proportion of management team in a month. We check how many managers manage funds in a specific month and then compute an average of their characteristics, such as managers' experience and managing funds, for that month in each fund. Similarly, we count the number of management team members per month along with the number of male members, bachelor's degree holders, master's degree holders, PhD degree holders, CFA degree holders. Afterwards, we compute all of those previously mentioned proportions in percentage per month. We, in the last step, transform all the manager characteristic variables in daily observations where each month's value is equal to all of the days for that month.

3.2.4 Demeaning of Control Variables

We follow calculation process of demeaning control variables (Wooldridge, 2016). We call them abnormal characteristics, as they are proxies for measuring abnormality in these characteristics. Firstly, we calculate average of all fund characteristics by each fund and then deduct the average of fund characteristics from daily-observed fund characteristics. We continue this process for 7 fund characteristic variables to investigate further how the excess variations in those characteristics increase or decrease the impact of air pollution on the tracking errors of mutual funds.

Secondly, we calculate average of all manager characteristics by each manager and then deduct the average of manger characteristics from daily-observed manager characteristics. Our intention to construct these 7 manager characteristic variables is the same as above portion.

[11] Please find the details of these six AQI categories by MPEC in Appendix A.

In the last stage of calculating demean value of characteristics; we calculate demeaning of market environment characteristics, which is not regional but nationwide. We, similarly, compute average of each market environment characteristics and subtract each of them from their daily-observed 7 market environment characteristics. As a result, we form new 7 abnormal market environment characteristics to measure excess impact of these variables on the tracking errors in the presence of air pollution.

We merge all the demean control variables with the main dataset. We match the data with funds based on fund ID and dates for fund characteristics, managers ID in each fund and dates for manager characteristics, and dates for market environment characteristics as these nationwide market environment characteristics are same for all funds across all cities.

3.3 Summary Statistics

3.3.1 AQI

The most topical key variable in our sample is AQI (Air Quality Index) reported in Panel B of Table 1. In our sample, 618 mutual funds are scattered across nine cities in China. It means that main operation centres or firm cities of those funds are limited to nine cities. We examine these AQI data regionally as we would like to see the effect of poor air quality on mutual fund managers, who are running their fund management operation in those nine cities. The mean and median of AQI in Beijing are 98.79 and 87.00, which look quite high and close to the dangerous level of 100 AQI. In Beijing, 32.11% of our observation days are holding more than 100 AQI. On the other hand, Zhuhai has the lowest mean of 49.72 and median of 47 out of all nine cities. Besides, we examine the AQI data in our sample and find the number of days AQI is higher than 100. Out of 4,217 observation days for each city in our sample, 1354, 865, 441, 823, 620, 122, 1042, 58, 145 days are the hazy days (poor air quality days) for Beijing, Chongqing, Guangzhou, Hangzhou, Shanghai, Shenzhen, Tianjin, Xiamen and Zhuhai respectively.

In total, 5470 days out of 37,953 days in our sample for all cities are hazy days, which accounts for 14.42% air polluted days. However, two cities, Xiamen and Zhuhai, skew down this value, where we have less than 10 funds operating their businesses from our sample. After excluding these two cities, we get around 20% of observation days in our sample, which are considered as hazy days and hazardous for mutual fund managers to act on their roles. This state of AQI brings us an insight to take precaution against this air pollution and have us ponder about its significant impact on the financial markets. Mean and median of AQI for nine cities account for 72.60 and

65, which values are highly comparable to those previous study on AQI, though their dataset covers different cities and period (Heyes et al., 2016; Dehaan et al., 2017, Kong et al., 2018; Li et al., 2018; Huang et al., 2019).

3.3.2 Mutual Funds

In table 1, we present summary statistics of our sample variables and other important data. We start with Panel A and show fund returns, active returns and tracking errors of 618 funds from our sample. We have 978,434 observations for both fund returns and active returns from January 2003 to February 2019. We estimate tracking error with 977,820 observations from GARCH (1, 1), shown in variable construction section. Average fund return of our sample is 2.41 basis points per day, which is close to the median return of 2.80 basis points. If we look at the volatility of our sample funds, we expect 160.60 basis points up or down from our daily fund return on average. In Fund return data distribution, we find fund return is negative as 2039.37 basis points or 20.39% in a day. On the other hand, the return upsurges to 1462.86 basis points or 14.63% in a day.

[Please insert Table 1 here]

Moreover, the active return, difference between fund return and benchmark return, is negative .11 basis points on average but the median is positive .87 basis points. This tells us that the magnitude of negative active returns of funds in our sample are pulling down the average return to the territory of underperformance. This situation confirms the most empirical findings that mutual funds constantly underperform relative to their benchmark indices with the US evidence (Jensen, 1968; Lehmann & Modest, 1987; Grinblatt & Titman, 1987, 1989; Malkiel, 1995; Gruber, 1996; Carhart, 1997). We see consistent findings of the similar results in studies on mutual fund performance with the evidence of the other countries (Cai et al., 1997; Hallahan & Faff, 1999; Sawicki & Ong, 2000; Bauer et al., 2006).

Tracking error is one of the key variables in our sample. It reports the daily volatility of active returns of our sample mutual funds. Panel A reports 80.86 basis points tracking error on average in our sample. However, the median of the tracking error is 67.81 basis points, which indicates the outliers in the mounting side. In our tracking error observations, we find that tracking error is as low as 5.73 basis points and as high as 788.08 basis points in a day. Looking at the Panel A, we can expect 46.35 basis points up and down in our daily tracking error estimation in our sample.

3.3.3 Control Variables

Panel C reports the summary statistics of 618 funds' fund characteristics. Among them, we report fund flows in decimal points in the table. Mean and median of fund flows are 6% and negative 5% respectively. Given that, positive fund inflows skewing the mean up from fund outflows. We report fund size in million, but we calculate log of fund size in time of running regression. Mean (2,338.11 CNY) of fund size is quite larger than median (950.61 CNY) that indicates the number of big size funds are more prevalent in our sample. Funds' operation period is at least 4 years on average in the sample. It occurs that 50 percent of our sample mutual funds have maximum 3.84 percent manager turnover daily.

We report turnover ratio, yearly data but assigned daily considering constant over the year, in percentage. It refers to how frequently mutual fund managers replace their holding of stocks. Mean and median of turnover ratio are 361.37% and 275.02%. Looking at these values, we can say that mutual fund managers in our sample are regularly changing their holding positions in a year. Expense ratio represents the management and operating fees for investors in a mutual fund. There is not much difference in mean and median of expense ratio in our sample data. Funds in our sample charge their investors as little as .25% and as high as 4.46%.

In our sample, management team refers to the number of fund managers designated to manage a mutual fund at a given month. We construct this monthly variable, construction method reported in the data collection section, to see how frequently more than one team member manage funds, which affects fund performance. Considering mean and median are close to each other, we can say that one manager on average manages funds, but we can observe maximum five management team members in a given month. However, the minimum value "0", which indicates very short period in manager turnover, is not strong enough to distort the result of mean and median.

In addition to managers' other characteristics, we present manager experience statistics to proxy for measuring cognitive abilities in months. In our sample, managers have at least three years of experience for 50% percent of our managers and they manage two funds on average. Eighty seven percent of the managers in our sample are male and the remaining managers are female. That might be a sign of gender discrimination in this profession or women do not have interest in the jobs of financial market, as men dominate the Chinese capital market. All the managers have bachelor's degree and 96 percent of them have master's degree in the sample. Only 14 percent of the managers go for higher academic study, PhD as per our sample. Very few managers in this sample, 7 percent have professional degree, CFA.

Additionally, we use market environment characteristics as risk indicator parameters for market and examine their impact on the tracking errors. This section reports the data summary statistics of these characteristics in Panel E. Mean and median of interest spread, which refers to inflationary growth, are .38 percent and .36 percent respectively. We observe daily volatile trading volumes of 5170.75 CNY in both Shenzhen and Shanghai stock exchange on average. Unemployment rate in China 4.10 percent and vary .13 percent annually per day on average. We cannot find anything out of ordinary to present in this data distribution for other variables.

Section 4 Methodology

4.1 Impact of Air Pollution on Tracking Errors

4.1.1 Baseline Analysis

As we have all categories of AQI variables, we would like to find an answer to our first research question(R_1). To test the impact of air pollution on tracking errors, we specify our model, used to generate our baseline result, as follows:

$$TE_{(i,j,t)} = \alpha_0 + \alpha_1 AQI_{(j,t-1)} + \epsilon_{(i,j,t)} -----------(5)$$

Where $TE_{(i,j,t)}$ refers to the tracking error of fund i in city j in day t, $AQI_{(j,t-1)}$ represents the 1 lag value of AQI assigned to fund i based on funds' firm city j in day $t-1$ after we merge city based AQI to each fund's operation centre. We add $Trend_y$ variable (Wooldridge, 2016, p. 329) to the above equation to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we use θ_t as a fund fixed-effect variable (Wooldridge, 2016) for equation (5) to capture the time-invariant unobserved fund characteristics and $\epsilon_{(i,j,t)}$ represents residuals of the tracking error for fund i in city j in day t.

In equation (5), we substitute AQI each time with our different AQI categories, such as base AQI, Log AQI, Abnormal AQI, Dummy AQI and Category AQI, to check the variation of our results. We use different models of several AQI to justify our findings and check whether they hold across all types of AQI models or not. Therefore, we run five regressions by substituting AQI categories each time in model (5). We report these results in Panel A of Table 2 and interpretation of them in empirical result sections.

4.1.2 Baseline Analysis per City

To have a further look on the results at the city level, we run similar baseline regression to show deeply the impact of air quality on tracking errors city by city. We follow model (5) and run similarly 45 regressions by substituting AQI categories each time for each city. We report the results citywide for each AQI category in Panel B of Table 2. We show the summarized interpretation of these results in a later section: empirical results.

4.2 Robustness Check for Air Pollution Impact

In this stage, we focus on building up models to check the validity of our results from baseline analysis. We add different fund, manager, and market environment characteristics as control variables. We run regressions of these models separately with each set of characteristics. Our intention is to check whether funds still have constant tracking errors in the event of poor air quality after controlling for three sets of control variables. We use a model that can fit our three analyses and work into three steps to explore the findings of the research question (R_1) and prove our second hypothesis. The model for these analyses is as follows:

$$TE_{(i,j,t)} = \beta_0 + \beta_1 AQI_{(j,t-1)} + \beta_2 CH_{(i,t-1)} + v_{(i,j,t)} --------(6)$$

Where $TE_{(i,j,t)}$ refers to the tracking error of fund i in city j in day t, $AQI_{(j,t-1)}$ represents the 1 lag value of AQI assigned to fund i based on funds' firm city j in day $t-1$ after we merge city based AQI to each fund's operation centre. $CH_{(i,t-1)}$ are all fund, manager and market environment characteristic variables used as control variables for fund i in day $t-1$. We add $Trend_y$ variable to the above equation to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we use θ_t as a fund fixed-effect variable for equation (6) to capture the time-invariant unobserved fund characteristics and $v_{(i,j,t)}$ represents residuals of the tracking error for fund i in city j in day t.

From model (6), we generate 15 models by substituting AQI each time with our different AQI categories and substituting each set of characteristics for each AQI model to check the variation of our results. We report and interpret the result of our different sets of AQI models with fund, manager and market environment characteristics separately in Table 3, Table 4 and Table 5 consecutively in later sections.

To clarify more about our steps, we present our methodology in three steps for the above model for the research question(R_1). In the first step, we use only fund characteristics as our control variables by fitting our sample data in model (6) to run regressions and we continue this process for all AQI category variables. In the second step, we work with only manager characteristics and follow the remaining process similarly to the first step to run regressions. In the third step, we take only market environment characteristics and follow the remaining procedure similar to the first step to run regressions with the help of model (6) as well. Our market environment characteristics are nationwide variables, so we assume that the data are same for all cities and all funds in terms of running regressions.

4.3 Factors Reducing Air Pollution Impact

If we establish the impact of air pollution on tracking errors because of managers' psychological biases, then we would like to investigate factors that help managers alleviate these biases. This analysis can help us then to understand how the factors consequently mitigate tracking errors of fund managers. Therefore, we develop a second research question to investigate how these three sets of dominant factors, reducing or stimulating managers' psychological biases, mitigate or aggravate the impact of poor air quality on tracking errors. To find the answer to our second research question(R_2), we come up with a model where we would like to see whether the tracking errors vary across fund, manager and market environment characteristics.

We believe managers will take their decision-making tasks by following a heuristic approach, considered as system 1 of a human being's brain (e.g. Kahneman, 2011), in average market conditions. Given that, we would like to capture the consequences of managers' activities in higher stressing market condition. Thus, we use abnormal value of all three sets of characteristics in this model in terms of interacting with AQI so that we can look beyond managers' average working conditions. Here, the average market condition refers to the average condition of the characteristics that dominate tracking errors.

Managers can either use their system 2 part of their brains to mitigate tracking errors or rely on the system 1 part of their brains to execute traditional investment decisions, which do not fulfil the demand of abnormal market conditions. Consequently, we can observe both scenarios like higher tracking errors as well as declining tracking errors in a certain abnormal market state along with the presence of poor air quality.

4.3.1 Factors Affecting Cognitive Abilities

In this stage, we use interaction term, AQI with abnormal value of characteristics, in our later model. We develop this model by following the studies of Graham and Rogers, (2002) as well as Li et al., (2017). That is why we calculate abnormal value of all three sets of characteristics, shown in the variable construction section. These factors can revamp or debilitate managers' cognitive abilities, thus reduce or intensify the impact of air pollution on tracking errors. Fund managers in high stress situations, abnormal movement in aforementioned characteristics, can depend on their system 1 part of their brain to make trading decisions. We, consequently, observe an upward trend in tracking errors, as managers do not think hard enough to tackle the abnormality in the market. They fail in taking proper management decisions, which are essential in the event of air pollution and abnormality in dominant characteristics, to prevent tracking errors. On one hand, managers can think hard enough in this kind of situation and utilize the system 2 part of their brains. Managers with high cognitive abilities have control over their system 1 and are able to take rational decisions using the system 2 part of their brain. Therefore, we hypothesize that managers with high cognitive abilities reduce tracking errors in the event of air pollution, even in a stress-generating environment around them but the others without higher cognitive abilities cannot produce the same result. We report the findings of this section in the empirical result section.

We follow three steps to get the findings from our research question (R_2) and use slightly different models in each step. We present and explain our methodology below:

$$TE_{(i,j,t)} = \beta_0 + \beta_1 AQI_{(j,t-1)} + \beta_2 AQI_{(j,t-1)} \times ACH_{(i,t-1)} + \beta_3 ACH_{(i,t-1)} + \omega_{(i,j,t)} --- (7)$$

Where $TE_{(i,j,t)}$ refers to the tracking error of fund i in city j in day t, $AQI_{(j,t-1)}$ represents the 1 lag value of AQI assigned to fund i based on funds' firm city j in day $t-1$ after we merge city based AQI to each fund's operation centre. $AQI_{(j,t-1)} \times ACH_{(i,t-1)}$ is the interaction-term (multiplication) value of AQI in city j in day $t-1$ and abnormal characteristics for fund i in day $t-1$. $ACH_{(i,t-1)}$ represents abnormal characteristics for fund i in day $t-1$. We add $Trend_y$ variable to the above equation to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we use θ_t as a fund fixed-effect variable for equation (7) to capture the time-invariant unobserved fund characteristics and $\omega_{(i,j,t)}$ represents residuals of the tracking error for fund i in city j in day t.

We first develop our following model by using interaction terms of AQI and demeaning of fund characteristics, which we get from the variable construction section. This model will provide us with the partial answer of our second research question(R_2). We run 35 regressions of the following model (7) by substituting AQI categories and plugging in abnormal fund characteristics each time of the operation. We tabulate the results in Table 6 and report the interpretation of the results in the empirical result section.

We develop our following model, plugging in abnormal manager characteristics, to obtain another fraction of the answer of our second research question(R_2). We go through 35 regressions by replacing each AQI category to obtain the results across all AQI models in model (7). We tabulate the results in Table 7 and report the interpretation of these results in the empirical results section.

In this stage, we construct our last model of interaction term analysis using abnormal market environment characteristics. We obtain the final piece of the answer to our second research question (R_2) here. We, similarly, run 35 regressions in the model (7) using a different category of AQI each time and plugging in abnormal market environment characteristics. We tabulate the results in Table 8 and report the interpretation of the results in the empirical results section.

Section 5 Empirical Results

5.1 Air Pollution Influences on Tracking Errors

5.1.1 Evidence from Baseline Model

Poor air quality does influence tracking errors of mutual fund managers, which we find from our baseline analysis. When poor air quality prevails, managers are highly unlikely to be capable of maintaining fund returns of their managed funds at par with the returns of benchmark funds. All AQI models in our baseline analysis consistently provide evidence that poor air quality increases the tracking errors of mutual funds. These findings concur with our first hypothesis that we develop in our hypothesis development section.

[Please insert Table 2 here]

We report the results of our findings in Table 2 from our first equation, which tests the baseline impact of AQI on tracking errors. We report the results in several columns for different AQI models. In table 2, we have Panel A for reporting results of all cities together and Panel B for reporting each city result.

We interpret the findings of the equation (5) here, which we report in Table 2 Panel A and answering the first research question(R_1). In Panel A, all the columns (1), (2), (3), (4) provide us with positive coefficients with highly statistically significant results after controlling for fund-fixed effects and yearly time trend. Trend variable is also positive and highly statistically significant for all columns indicating that the tracking errors follow an upward trend over time.

From our baseline results in Table 2 Panel A, we can decide that AQI explains the volatility of the active return of mutual funds. In column (1) and (3), rise of one unit in base AQI and Abnormal AQI induces .070 bps increase in the tracking error consecutively. It generally tells us that the tracking errors of mutual funds managed by managers tend to increase in the event of poor air quality or on hazy days. Column (2) also agrees with prior findings that one percentage increase of AQI surges up the tracking errors by around seven basis points. Our last two columns (4) and (5), built up on MEPC standard, show 6.18 basis points and 3.40 basis points increase in tracking errors, when AQI is greater than 100 and moves on its each category.[12] As the value of AQI 100

[12] The Marine Environment Protection Committee (MEPC) confirms the AQI standard range with an AQI category list, we present in Appendix A.

or less has little or no impact on managers' cognitive function, we see a drastically upward surge in the tracking errors in the event of poor air quality (AQI > 100). Thus, our findings give us strong evidence of positive association between the tracking errors of mutual fund managers and poor air quality, meaning that poor air quality affects managers' cognitive function. To shed light on the findings, we test more models to verify the results later. We are confident that managers experience several behavioural biases and mistakes in decision-making, which are undoubtedly the determinants for upward trending tracking errors on hazy days. Hence, our findings are in line with the prior findings of emerging literature that air pollution is adversely influencing investors' decision making (Heyes et al. 2016; Hirshleifer & Shumway 2003; Li et al., 2017; Huang et al., 2019), particularly in our case of study, professional investors.

5.1.1.1 Citywide Evidence

We also explore the results of our baseline analysis at city level. The majority of cities consistently provide a positive correlation between air pollution and tracking errors across all models of AQI, meaning that air pollution increases the magnitude of the tracking errors of mutual fund managers, residing in those cities. We find that the first hypothesis of this study also matches with these results at the city level.

In panel B, this study presents city level results aligning with our aforementioned baseline-analysis result on panel data. Five cities (Beijing, Chongqing, Guangzhou, Hangzhou and Shanghai) individually provide strong evidence of the impact of air pollution on the tracking errors across all AQI models. Their result represents the findings of 480 funds among 618 funds and strongly shows, when air pollution increases, the tracking errors of mutual funds increase as well. Nevertheless, Zhuhai and Tianjin do not capture the impact of air pollution on the tracking error in our dummy and log transformed AQI model sequentially. These results are statistically insignificant and only 9 funds out of 618 funds are managed in these two cities. We find weak evidence of the impact of air pollution on tracking errors across two of our AQI models in Shenzhen but the remaining three AQI models in Shenzhen provide highly statistically significant results, supporting the view that air pollution magnifies the tracking errors of mutual funds. As most of the cities with the sample funds answer the question of our first research question with a positive association between air pollution and tracking errors, we would like to examine the robustness of these results by controlling for dominant characteristics of tracking errors. We further discuss the results of the analysis in the following sections.

5.1.2 Air Pollution Impact Offsetting Control Variables

In this part, we report the findings of our further investigation on the robustness tests for the first research question(R_1). The study presenting the impact of air quality on the tracking errors remains robust even after considering the relationship of the tracking error with three sets of leading characteristics, such as fund, manager and market environment characteristics. Thus, if air pollution rises, the tracking errors of mutual funds tend to exist. We consistently find this significant positive impact of poor air quality across all AQI models in our analysis after controlling three sets of characteristics. The results from model (6) concur with our second hypothesis in this study. Our results consistently support the findings of the baseline analysis from Table 2.

The positive association between poor air quality and the tracking errors proves that air pollution affects mutual fund managers and hampers their cognitive function. As a result, mutual fund managers show more behavioural biases and mistakes in decision making in the event of poor air quality. Our findings complement the prior empirical findings of the positive correlation between poor air quality and decision-making mistakes from financial market participants like retail investors. However, our findings contribute to the literature on how air pollution also affects professional investors like mutual fund managers to exhibit decision-making mistakes. We observe the lowest impact of poor air quality over 100 AQI on the tracking errors, which represent the increase of 2.4 basis points tracking errors daily, when we control for market environment characteristics. Given that, we believe market environment characteristics contribute more to the tracking errors' volatility than fund and manager characteristics.

5.1.2.1 Fund Characteristics Vs Air Pollution

Table 3 presents highly statistically significant evidence that the rise in air pollution causes an upsurge in tracking errors. All AQI models in this analysis support that prior statement. We find nothing out of the ordinary to do with coefficients from the fund characteristic variables. For instance, managers' turnover, fund flow, fund size, funds' turnover ratio and management team have positive association with the tracking error. When they mount, the tracking errors seem to increase as well. On the other hand, funds' age and expense ratio reduce the tracking errors at the time of their rising, which implies that well-established funds are capable of reducing tracking errors.

[Please insert Table 3 here]

All the columns of Table 3 provide consistent results. If we look at column (4) of Dummy AQI estimate, we see that tracking error increases by 5.25 basis points. Whenever AQI is more than 100, which indicates hazardous signal for health, we observe the presence of higher tracking errors. This directs to the premise that mutual fund managers face many side effects, like cognitive dysfunction, neuroinflammation, lack of concentration and interpretation by inhaling hazardous air pollutants. As a result, they exhibit cognitive biases and behavioural mistakes in decision-making, and we observe increasing tracking errors in the event of air pollution.

In this analysis, our findings show that fund management institutions resource older funds well to reduce their tracking errors. Older funds can hire well-experienced managers, to attract more fund flows for their reputation and to take any necessary steps to survive and perform well for the long run. Similarly, the higher the expense ratio, the lower the tracking errors observed in our findings. The reason behind this is that high performing active mutual funds usually charge more for their services. Therefore, mutual fund managers in these funds are apt and confident enough to minimize tracking errors and to charge more fees as they provide consistent gains to their clients.

On the contrary, managers’ turnover in mutual funds magnify the tracking errors. Newly joined mutual fund managers can involve in frequent trade that is completely different from the tactics of old managers, or skilled old managers can quit the job for better career prospects. Either way, mutual funds experience difficult situations in the time of their managers’ turnover, which can result in deviation from their goals and increase in tracking errors. Likewise, higher fund flow and bigger fund size also increase tracking errors according to our estimation from the sample. Managers constantly rebalance their fund portfolio to tackle their fund flows. They feel pressure to perform better than others and trade more irrationally if they manage large size funds. Subsequently, managers engage in replacing their holdings to outperform the benchmark and these actions can be frequent. Thus, increase in the turnover ratio of mutual funds causes the presence of higher tracking errors.

We also spot higher tracking errors, whenever the number of management team members increases. Managers can face herding biases and conflicts in decision making in this situation. Having more members in a management team means more people with cognitive dysfunction or conflicts in decision making in the event of poor air quality. That can be a result of our findings where tracking errors increase with the increase of management team members.

5.1.2.2 Manager Characteristics Vs Air Pollution

In this stage, our findings in Table 4 concur with the previous analysis. In this estimate, we find that air pollution strongly explains the volatility of active return, the tracking error, even after looking at the explanation of the tracking errors from manager characteristics across all AQI models. Managers having higher experience along with higher education, except PhD qualification, tend to minimize the tracking errors of mutual funds. We, interestingly, find that the more the number of male members in a management team of a fund, the more presence of tracking errors. Female managers are more risk averse than male managers (Eckel & Grossman, 2008) and we believe that is why male managers experience more tracking errors as they continuously trade and look for new risky investment opportunities. Additionally, managers, who are managing more than one fund in a particular point of time, might experience stress and allocate less time to decision-making and the tracking error of those managers increases at the same point of time.

[Please insert Table 4 here]

This part of the study attributes the increasing tracking errors to increasing air pollution with highly statistically significant evidence across all AQI models. In column (4), we observe an increase of 5.71 basis points in tracking errors when AQI is more than 100. This genuinely tells us the negative impact of air pollution on tracking errors. We detect similar significant results in other columns of Table 4. We find expected negative coefficients for managers' experience and education except for one case. We mention in our literature section that previous studies find fewer biases affiliated with experienced managers. Therefore, more highly experienced managers are able to minimize tracking errors.

Similarly, more highly educated managers might develop high intelligence and cognitive abilities that help them to mitigate behavioural biases and mistakes in decision-making. As a result, we spot declining tracking errors in the hands of educated managers. However, we get a positive coefficient for managers holding PhD. The reason behind this could be overconfidence for having the highest academic degree. We know from our literature study that overconfidence induces some behavioural biases that reduce mutual fund performance. Another reason might be less experience in the corporate field as PhD graduates spend a minimum three to five years for full-time study.

Male managers are overconfident and unlikely to be risk averse relative to female managers (Estes & Hosseini, 1988; Barber & Odean, 2001; Gysler, Kruse, & Schubert, 2002). According to Barber and Odean (2001), male investors generally execute 45 percent more trades than female investors, which minimizes their net returns by 2.7 percent. Probably, that is why increasing the percentage of male proportion in a management team of a fund causes rising tracking error in our estimation. On the contrary, we can say that 1 percent increase in female proportion in a management team of a fund mitigates the tracking errors by .87 basis points.

5.1.2.3 Market Environment Characteristics Vs Air Pollution

Our findings suggest that air pollution increases the tracking errors of mutual funds in this part of the analysis. All our tracking error estimations from all AQI models return statistically significant positive coefficients. However, the variation in tracking errors is much less than the prior analysis. We observe an increase in the tracking errors by 2.4 basis points as soon as AQI hits more than 100 value. Consistent estimations of the positive impact from air quality on tracking errors signify that air pollution explains the presence of tracking errors after considering the influence of market environment characteristics on tracking errors. Therefore, all columns of Table 5 indicate how strongly mutual fund managers' cognitive functions get affected and consequently produce behavioural biases as well as mistakes in decision-making.

[Please insert Table 5 here]

From our estimations, we find that all market risk factors like daily interest rate spread, market volatility, unemployment rate, and trading volume, magnify the tracking errors of mutual funds. However, we find conflicting evidence in economic indicators. For example, OLED leading indicator, consumer confidence index and business confidence index indicate good economy ahead when they start to rise. Thus, the tracking errors decline significantly except in the case of business confidence in our estimation. On the other hand, we find a negative association between tracking error and producer price index, which is the indicator of future inflation and interest rate rise. Additionally, inflation does not explain the tracking error in our study. Probably, the reason behind these situations can be the government's interest rate cut policy to control economy and the rise of inflation so that investors do not lose confidence, but instead, contribute to the economy's growth.

5.2 Air Pollution Impact Magnified across Factors

In this section, we report our investigation of the second research question(R_2). Our findings suggest that the factors - helping managers to improve (worsen) their cognitive abilities - strengthen (weaken) the tracking errors. Highly educated managers, having PhD, CFA and working for well-established funds in good market environments, have less exposure to the negative impact of air pollution, as the tracking errors of the funds that they manage reduce significantly. Therefore, we obtain the answer to our second research question that factors, helping managers to reduce their psychological biases, can mitigate the impact of poor air quality. Additionally, the findings from Table 6, 7 and 8 support our third hypothesis at a statistically significant level.

We report the interesting findings of model (7) in detail in this part of our study. For instance, managers, who work in poor air quality, can reduce tracking errors if they work in the funds with more than average operation age, higher fund inflow and expense ratio. That refers to managers' immunity to air pollution when they belong to well-established funds or a preferable investment environment. They can also reduce tracking errors if they think deeply about investment decisions and have at least a bachelor's degree even in a stressful market environment. We examine how managers of all mutual funds with the aforementioned characteristics behave in the event of hazardous air pollution by using interaction terms of AQI with those three sets of characteristics. We discuss specific findings of Table 6, 7 and 8 in the following section one by one.

5.2.1 Fund Characteristics' Effect on Cognitive Abilities

As our findings in all panels of Table 6 suggest that air pollution increases tracking error, we explore deeply into the situation where funds' distinct characteristics can minimize or strengthen this tracking error issue. Our findings complement our third hypothesis and suggest that the magnitude of the impact of air pollution depends on fund characteristics.

[Please insert Table 6 here]

We find very strong evidence that experienced funds with higher fund inflow and expense ratio than average funds minimize the tracking errors of mutual fund managers, but the result is completely opposite in terms of big size funds. Experienced funds, which run their operation for the long term, can introduce air purification to their managers' offices, increase the esteem of fund managers and arrange training programs to develop managers' cognitive abilities. Therefore, managers use the system 2 part of the brain in investment decisions, develop self-esteem in working for those funds and think deeply enough to perform well. Managers charging higher fees and getting more fund inflows put themselves in a position of high responsibility. So, they think hard to rebalance their investment and work on innovative measures to continue the momentum for their managing funds even if they are in contact with unsafe air pollutants. This situation tells us that managers with higher cognitive abilities can manage depression and anxiety. As a result, they are immune to some bad impacts of air pollution. Conversely, we observe weak evidence of increase in tracking errors with the increase of management team members. The more managers in a team, the more potential for victims of severe air pollution, so the tracking errors jump up.

5.2.2 Manager Characteristics' Effect on Cognitive Abilities

We obtain some fascinating findings in Table 7, which reports results in Panel A, B, C, D and E according to AQI category variables. Managers with more than average experience, number of managing funds, and education can reduce the magnitude of the tracking errors in their managing funds even if they are in contact with air pollutants. Typical reasons for this situation could be managers' learning from previous mistakes, applying effort to ponder cautiously as they have more funds to worry about and higher cognitive abilities, which help them to be immune to the effects of air pollution.

[Please insert Table 7 here]

We observe neither any relationship nor any significant result from Table 7 if there are more managers with master's degrees. Given the situation is surprising, it seems that bachelor's degree is good enough for managers to grow high cognitive abilities to fight off the air pollution effect from their system. Nevertheless, increase in the proportion of higher educated managers like PhD holders and professional degree CFA holders generally reduces the tracking errors of managers' managing funds as per our findings in all panels of Table 7. Thus, it is always good to have highly educated managers to take precaution against the negative effect of air pollution on the mutual funds.

On the other hand, our results interestingly suggest that air pollution affects a male manager more than a female manager because tracking errors increase as soon as the proportion of males in the management team increases. We consider this evidence weak as two of the AQI models cannot produce significant results in this case. Therefore, we cannot decide for sure whether female managers have better immune systems to protect their brain function from poor air quality or not.

5.2.3 Market Characteristics' Effect Cognitive Abilities

Our study also presents how managers in a particular market environment react to the impact of air pollution. We already observe in Table 5 that the tracking errors of the mutual funds in our sample exist in unsafe air conditions even after controlling the effect of market environment characteristics. In all panels of Table 8, we obtain the existence of variation in tracking errors when managers manage mutual funds at the time of heightened air pollution. Given the results' match to our hypothesis, we finally spot some characteristics in the market, that can help managers in contact with air pollution, fight off psychological biases to expand or lessen tracking errors in the capital market. The overall results from Table 8 support our third hypothesis as well.

[Please insert Table 8 here]

Our findings suggest that air pollution does not affect managers when the market environment is positive. For example, when interest rate spread, consumer confidence index, business confidence index, and producer price index except OLED leading indicator, rise abnormally, the tracking errors of mutual funds ease. It appears that air pollution does not affect managers' cognitive function in terms of decision making in a positive economic outlook. Air pollution does not stimulate as much depression and anxiety in fund managers in the presence of positive economic conditions as it does in negative economic conditions. Positive market outlook improves managers' cognitive abilities so that they minimize cognitive biases and mitigate tracking errors.

On the other hand, air pollution affects managers more by the rise of market risk. We can gauge that, by looking at the variation of the tracking error result. Market risk indicators, like abnormal market volatility and unemployment rate, magnify the tracking errors of fund managers with the hike of volatility. It appears that managers' cognitive function is in question on both stressful periods and hazy days. It is interesting to observe conflicting evidence in the market of high trading volume. Therefore, we cannot say for sure whether the risk interacted with poor air quality drives up the volatility of the active return. Nevertheless, most of the risk indicators direct us to the point where managers experience cognitive dysfunction in a stress period in the event of air pollution. As a result, we observe higher tracking errors of mutual funds managed by active fund managers during the aforementioned period.

Section 6 Endogeneity Test

In this part, we would like to check the robustness of our inferences from the above research models. We consider natural experiments to investigate omitted variable issues, reverse causality problems and any existent measurement errors in our research designs. We choose the event of 2008 Olympic Games held in Beijing (BOG08) in August because we want to employ the exogenous shock that tries to control AQI during the BOG08.[13] We, equally, follow the study of a natural experiment (He et al., 2016) to implement the idea in this study to establish causal effects of air pollution on the tracking errors of mutual funds. The Chinese Government introduced a sequence of essential pollution control regulations, starting from November 1, 2007 to July 20, 2008, to guarantee decent air quality during the BOG08.[14] Furthermore, we find in the British daily newspaper, The Guardian, that the initial regulations of pollution control implemented by the Chinese Government was not good enough to move the haze hanging over the city.[15] Therefore, the State Council of China announced a series of traffic control measures to ensure clean air during the BOG08. We present the brief description on these pollution control regulations in our Appendix B. However, the committee members of the BOG08 as well as the Ministry of Environmental Protection (MEP) in China (2008) report 60 percent decline in total vehicle exhaust emissions during this period.[16] Additionally, the Chinese government and the State Council of China halted major construction works, 56 powerhouses including coal-fired plants and over 100 industries in Beijing. These new measures spread over Beijing including nearby cities as well from July to September 2008 and we observe immediate improvement in air quality in these three months. Therefore, we develop our endogeneity tests by hypothesizing that the tracking errors of mutual funds will reduce during the BOG08. As air quality significantly improves in that time, mutual fund managers will mitigate the tracking errors, resultant of their less exposure to unsafe air pollutants during the event.

6.1 Event Study on Tracking Errors

Initially, we would like to observe the magnitude of the tracking errors during August, the month of Beijing Olympic Games 2008. Thus, we create a post dummy variable indicating “1” if our sample data is in post-period, August 2008 and “0” if it is in pre-period, August 2007. We expect

[13] According to the research conducted by the authors. (Chen et al., 2013, pp. 424–438).
[14] Please refer to the research conducted by the authors (He et al., 2016) to have detailed information about these pollution regulations.
[15] Please see https://www.theguardian.com/world/2008/aug/07/china.olympics2008, the British newspaper website for the news.
[16] Please see more at http://www.bj.xinhuanet.com/bjpd_2008/2008-09/22/content_14462703.htm.

the coefficient of this post dummy variable to be negative and significant. We choose these two months, as we would like to control for seasonality effect as well as to select a month before the regulation period (from November 2007 to September 2008). We pick mutual funds from only Beijing because fund managers in Beijing should benefit from the clean air environment and be able to minimize the tracking errors during this period. Our first model of the robustness tests is as follows:

$$TE_{(i,t)} = \beta_0 + \beta_1 Post\ Dummy_{(i)} + \beta_2 FCH_{(i,t-1)} + \mu_{(i,t)} - - - - - (8)$$

Where $TE_{(i,j,t)}$ refers to the tracking error of fund i in day t, $Post\ Dummy_{(i)}$ takes the value "1" if the tracking errors belong to August, 2008 and "0" if they belong to August, 2007 for fund i. $FCH_{(i,t-1)}$ represents fund characteristics for fund i in day $t-1$. We add θ_t as a fund fixed-effect variable to equation (8) to capture the time-invariant unobserved fund characteristics excluding fund expense ratio along with turnover ratio as their data report values yearly, and $\mu_{(i,j,t)}$ represents residuals of the tracking error for fund i in city j in day t. We tabulate the results from the equation (8) in Table 9 and interpret the results in the last part of this section.

6.2 Difference-in-differences in Tracking Errors

To check further the validity of our previous model, we expand our inspection period by adding two more months, July and September 2008. The reason for this is that the Chinese government with the State Council takes extra regulations to bring down poor air quality to World Health Organisation's standard safety level of 50 from July 20 to September 20, 2008. We follow both Fang, Tian & Tice (2014) and Brogaard et al. (2017) to build a treatment group and control group with the help of propensity score matching technique. In Figure 1, we present the air pollution distribution in pre, post and during the BOG08. We choose July, August and September of 2007 as our pre-match period and the same months of 2008 for post-match period to control for the seasonality effect. In the first step, we average the tracking errors and fund characteristics of all funds in our sample in monthly frequency for the three months in 2007. We then run pre-match regression by the following probit model:

$$Treatment_{(m)} = \beta_0 + \beta_1 FCH_{(i,m)} + \varepsilon_{(i,m)} - - - - - (9)$$

Where $Treatment_{(m)}$ equals to "1" if a fund belongs to Beijing or Tianjin, treatment group, in month m, and "0" if a fund belongs to other cities, control group, in month m. $FCH_{(i,m)}$ represents monthly average fund characteristics, excluding manager turnover ratio for some missing value issues, for fund i in month m, and $\varepsilon_{(i,m)}$ represents residuals of the treatment group for fund i in month m.

In the second step, we average the propensity scores of the three months for each fund. We match all of our treatment funds with other funds using propensity scores within a range of 0 to 2% gap. We report this distribution of this propensity scores in Panel B, Table 10. This process produces total treatment and control group of 34 funds. We construct a new post-match period sample with these 34 funds from July to September 2008 where we calculate the average of the tracking errors and fund characteristics of all funds in our sample in monthly frequency for the three months in 2008. We also continue the exact process to obtain a new matched sample from pre-match data. Afterwards, we run post-match regression by following the equation (9) to observe whether the significance of being a different group reduces or not.

In the final step, we run DID analysis (Brogaard et al., 2017) with funds from treatment and control group on both post-match and new matched sample from pre-match data in a regression framework as following:

$$TE_{(i,m)} = \beta_0 + \beta_1 Treatment_{(m)} * After_{(i)} + \beta_2 After_{(i)} + \beta_3 Treatment_{(m)} + \varepsilon_{(i,m)} (10)$$

Where $TE_{(i,m)}$ refers to the tracking errors of fund i in month m, $Treatment_{(m)}$ equals to "1" if a fund belongs to Beijing or Tianjin in month m, $After_{(i)}$ refers to "1" if fund i , in the months of 2008 otherwise "0". We control for monthly average fund characteristics, excluding manager turnover ratio for some missing value issues, in the equation (10) and $\varepsilon_{(i,m)}$ represents residuals of the tracking errors for fund i in month m. We tabulate the results from the equation (9) as well as (10) in Table 10 and interpret the results in the following section.

6.3 Causal Effect of Air Pollution on Tracking Errors

We consider regulations for BOG08 as exogenous shocks on air pollution, which help us to understand explicitly the causal effect of air pollution on tracking errors. The results from the above endogeneity tests strongly support our conclusion that the increase in air pollution causes tracking errors to rise. It also implies if we can get air quality under control to the safety limit of 50 AQI (as per World Health Organization), we can reduce the tracking errors of managers significantly. Both endogeneity tests show significant size of tracking errors reduced during Beijing Olympic Games 2008 when air pollution falls to a safety limit due to intense pollution control regulatory actions from the Chinese government. These findings suggest that managers are unlikely to exhibit cognitive dissonance in decent air quality. Therefore, both event study and differences-in-differences (DID) in tracking errors prove that the impairment of cognitive function comes from the impact of air quality comes.

[Please insert Table 9 here]

In Table 9, we observe the tracking errors reduce by 63.12 basis points in August, the month of BOG08 compared to the month of the previous year, 2007. We find this result statistically significant at less than 5% after controlling for fund characteristics and fund fixed effects. Our findings allow us to believe that improvement in air quality aids mutual fund managers to minimize their funds' tracking errors.

[Please insert Table 10 here]

Our DID analysis on the tracking errors also support the previous argument. Our first regression with probit model (9) returns us the results in the first column, which is not a matched sample. We find all results from explanatory variables insignificant except one in column 2 from Panel A of Table 10. However, the likelihood ratio is lower in the post-match model than the pre-match model. That implies that observable dissimilar characteristics do not exist between the treatment and control groups during the regulation period around BOG08. We obtain highly statistically significant negative coefficients across all columns in Panel C, Table 10. These results prove that the treatment funds in Beijing experience a larger drop in tracking errors during BOG08, pollution regulation period, relative to control groups. Our findings from DID analysis consistently point out that mutual fund managers can constrain tracking errors to their target level if they manage to work under safe air quality.

Section 7 Limitations of This Study

In this section, we identify some limitations arising from this study. We briefly present them as follows:

- We develop our endogeneity test around the Beijing Olympic Games 2008 event. Unfortunately, not many mutual funds started their operation during that period. As a result, our sample for the endogeneity test is small. However, we still perceive significant results from our present sample that support our hypothesis.
- Many previous studies address China's Huai River policy as a well-known factor for controlling air pollution in certain cities on the northern part of this river during winter.[17] We would like to use this policy as our robustness test, but with funds operating in only nine cities, this prevented us developing models around this policy. Future researchers can work in this area if more financial institutions expand their offices throughout the cities in China.
- We obtain names for each mutual fund's assigned benchmark only from Morningstar and Bloomberg. We do not get any daily benchmark or active return data, which challenges the collection from our resources. Nevertheless, we download each benchmark index manually from Bloomberg, assign a common benchmark in some cases when it is not available, and construct a benchmark from two to three indices based on their weights, a process which is very time consuming.

[17] Please see details regarding this policy in prior studies (Chen et al., 2013; Li et al., 2017; Ebenstein, Fan, Greenstone, He, & Zhou, 2017).

Section 8 Conclusions

We find in prior literature that air quality affects the cognitive dissonance of several market participants like analysts and retail investors, yet we fill the gap in the literature by examining the role of air pollution on professional investors like mutual fund managers. To our best knowledge, the influence of air pollution on tracking errors of mutual funds and the cognitive abilities of fund managers remains underexplored. We are confident that poor air quality can play a major part in increasing active mutual funds' tracking errors. Therefore, our objectives are to find firstly a link between air quality and tracking errors as well as to establish that association through robustness tests. Secondly, we would like to explore the factors that reduce or stimulate managers' psychological biases and eventually mitigate or magnify the impact of poor air quality on tracking errors. Finally, we develop endogeneity tests to capture the causal impact of air pollution on tracking errors.

We hypothesize that poor air quality positively associates with tracking errors and the result remains robust across fund, manager and market environment characteristics. We also hypothesize that factors, strengthening (weakening) cognitive abilities of fund managers can reduce (increase) tracking errors. In our baseline model, we find that air pollution positively associates with tracking errors. Our multivariate tests prove this positive association statistically significant, even after controlling these three sets of characteristics. Our channel analysis with factors, improving managers' cognitive abilities, additionally provides us an insight that managers can alleviate the impact of air pollution on their tracking errors. Lastly, we introduce event study and difference-in-differences in tracking errors to employ an exogenous shock from the air pollution control regulations implemented for Beijing Olympic Games 2008 event (BOG08). Our findings from these endogeneity tests show significant decline in tracking errors because air quality immediately and significantly improved in the regulated city, Beijing during the BOG08. To conclude, the impact of air quality comes from managers' impairment of cognitive abilities.

Our findings are in harmony with the notion that poor air quality can increase economic costs of society. Our results contribute to the literature of the empirical findings of the positive association between poor air quality and mistakes of decision making from financial market participants, particularly by examining the gap in the literature, the effect of air pollution on professional investors: mutual fund managers. Without this study, we are missing out significant information on the behaviour of professional capital market participants like active mutual fund managers and their abilities to process, investigate and act on information in the presence of poor air quality.

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Tables

Table 1: Summary Statistics

This table presents summary statistics of our sample data and variables in this table. It reports the fund return of our sample funds, AQI across all cities in our sample with number of days when AQI is over 100, and all dominant characteristics in Panel A, B, C, D, and E respectively. We present the description of these variables in Appendix B.

Panel A: Fund Return

	N Obs	Minimum	Mean	Std Dev	1st Pctl	Median	99th Pctl	Maximum
Fund Return	978,434	-2,039.37	2.41	160.60	-538.40	2.80	416.42	1,462.86
Active Return	978,434	-1,819.00	-0.11	93.00	-288.82	0.87	254.05	1,360.41
Tracking Error	977,820	5.73	80.86	46.35	26.07	67.81	255.44	788.08

Panel B: AQI

City	N Obs	Minimum	Mean	Std Dev	1st Pctl	Median	99th Pctl	Maximum	Days AQI > 100
Beijing	4,217	12.00	98.79	59.58	23.00	87.00	334.00	500.00	1354
Chongqing	4,217	11.00	82.58	33.71	28.00	77.00	196.00	340.00	865
Guangzhou	4,217	14.00	68.08	27.65	22.00	63.00	162.00	225.00	441
Hangzhou	4,217	15.00	80.66	32.32	29.00	75.00	183.00	365.00	823
Shanghai	4,217	12.00	72.55	35.72	24.00	65.00	192.00	500.00	620
Shenzhen	4,217	14.00	54.86	22.82	20.00	53.00	125.00	289.00	122
Tianjin	4,217	15.00	89.54	43.93	30.00	79.00	266.00	500.00	1042
Xiamen	4,217	12.00	55.10	21.92	18.00	54.00	105.00	500.00	58
Zhuhai	4,217	11.00	49.72	24.79	15.00	47.00	142.00	187.00	145
All Cities	37,953	11.00	72.60	38.91	20.00	65.00	205.00	500.00	5470

Panel C: Fund Characteristics

	N Obs	Minimum	Mean	Std Dev	1st Pctl	Median	99th Pctl	Maximum
Fund flow	946,773	-1.06	0.06	1.70	-0.57	-0.05	2.57	177.33
Fund Size (in million)	972,662	4.92	2338.11	3724.87	23.87	950.61	18012.16	48174.03
Turnover (%)	936,313	1.12	361.37	306.41	31.70	275.02	1470.71	3724.11
Expense ratio (%)	924,977	0.25	1.85	0.20	1.48	1.79	2.58	4.46
Management team	978,434	0.00	1.30	0.52	1.00	1.00	3.00	5.00
Fund Age (in month)	978,434	1.00	54.41	40.18	2.00	45.00	161.00	210.00
Manager Turnover (%)	972,799	0	3.86	17.79	0	0	100	300

Table 1 – Continues

Panel D: Managers' Characteristics

	N Obs	Minimum	Mean	Std Dev	1st Pctl	Median	99th Pctl	Maximum
Experience (in month)	73,080	1.00	39.42	32.67	1.00	31.00	145.00	225.00
Managing Funds	73,054	0.00	2.00	1.56	0.00	2.00	8.00	10.00
Gender	1,339	0.00	0.87	0.34	0.00	1.00	1.00	1.00
Bachelor	1,339	0.00	1.00	0.04	1.00	1.00	1.00	1.00
Master	1,339	0.00	0.96	0.19	0.00	1.00	1.00	1.00
PhD	1,339	0.00	0.14	0.34	0.00	0.00	1.00	1.00
CFA	1,339	0.00	0.07	0.25	0.00	0.00	1.00	1.00

Panel E: Market Environment Characteristics

Variable	N Obs	Minimum	Mean	Std Dev	1st Pctl	Median	99th Pctl	Maximum
Interest Rate Spread	4,217	-0.0013	0.0038	0.0019	-0.0002	0.0036	0.0088	0.0095
Market Volatility	4,217	54.90	153.24	66.05	61.69	134.10	355.38	416.52
Inflation Rate	4,217	-1.20	0.22	0.58	-1.10	0.10	1.60	2.60
OLED Indicator	4,217	-0.81	-0.01	0.22	-0.81	0.00	0.75	0.75
Consumer Confidence	4,217	-1.92	0.01	0.36	-1.82	0.03	0.88	1.55
Business Confidence	4,217	-1.72	-0.01	0.39	-1.45	-0.01	1.56	1.94
Producer Price	4,217	-4.41	0.00	0.93	-3.09	0.00	3.81	3.85
Trade Volume (in bill)	4,217	145.77	5170.75	5792.20	149.96	3682.94	31225.23	36755.89
Unemployment Rate	4,217	3.67	4.10	0.13	3.67	4.10	4.30	4.30

Table 2: Baseline Results

This table reports the result from running regression from equation (5). Our baseline analysis model presents results across all cities in Panel A. Following columns in Panel A refers to each AQI category model that mention in our empirical methodology section. We add $Trend_y$ variable to the equation (5) to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we employ fund fixed-effect variable for equation (5) to capture the time-invariant unobserved fund characteristics. Please refer to empirical methodology section for the details of the equation. We also follow this equation to produce city level result, which we present in Panel B. We parenthesize t-statistics under each coefficient below. In Panel A, $*$, $**$, and $***$ designate statistical significance at the 10%, 5%, and 1% level, respectively. In Panel B, we change font style of coefficients to bold to show their statistical significance at the 10% level or more.

Panel A: Baseline Analysis

	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)				
	(1)	(2)	(3)	(4)	(5)
Base AQI (1 lag)	0.070***				
	(65.83)				
Log AQI (1 lag)		6.999***			
		(72.37)			
Abnormal AQI (1 lag)			0.070***		
			(65.83)		
Dummy AQI (1 lag)				6.175***	
				(52.88)	
Category AQI (1 lag)					3.404***
					(63.70)
Trend	0.609***	0.577***	0.609***	0.615***	0.624***
	(38.09)	(36.05)	(38.09)	(38.38)	(39.06)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes
No. of Obs	927,084	927,084	927,084	927,084	927,084
R-Sqr	18.19%	18.27%	18.19%	18.06%	18.17%

Panel B: Baseline Analysis by City

Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)

	Beijing	Chongqing	Guangzhou	Hangzhou	Shanghai	Shenzhen	Tianjin	Xiamen	Zhuhai
Base AQI (1 lag)	**0.035**	**0.044**	**0.041**	**0.057**	**0.124**	**0.034**	**0.017**	0.052	**0.039**
	(24.18)	(4.54)	(6.48)	(5.49)	(70.90)	(8.49)	(1.79)	(1.50)	(2.61)
Trend	**-0.213**	**1.336**	**1.664**	**-2.117**	**0.379**	**1.158**	0.135	**-23.502**	**3.763**
	-(6.10)	(8.80)	(28.18)	-(10.22)	(14.91)	(40.08)	(.69)	-(38.80)	(5.72)
Log AQI (1 lag)	**3.453**	**4.535**	**2.969**	**4.987**	**11.567**	**3.614**	1.310	**4.759**	**3.016**
	(20.91)	(5.37)	(6.36)	(5.53)	(76.27)	(16.18)	(1.20)	(2.63)	(3.19)
Trend	**-0.207**	**1.328**	**1.661**	**-2.121**	**0.303**	**1.146**	0.155	**-23.500**	**3.677**
	-(5.92)	(8.74)	(28.10)	-(10.23)	(11.87)	(39.66)	(.79)	-(38.84)	(5.59)
Abnormal AQI (1 lag)	**0.035**	**0.044**	**0.041**	**0.057**	**0.124**	**0.034**	**0.017**	0.052	**0.039**
	(24.18)	(4.54)	(6.48)	(5.49)	(70.90)	(8.49)	(1.79)	(1.50)	(2.61)
Trend	**-0.213**	**1.336**	**1.664**	**-2.117**	**0.379**	**1.158**	0.135	**-23.502**	**3.763**
	-(6.10)	(8.80)	(28.18)	-(10.22)	(14.91)	(40.08)	(.69)	-(38.80)	(5.72)
Dummy AQI (1 lag)	**5.221**	**2.068**	**2.582**	**4.139**	**8.077**	0.621	**3.498**	-2.254	-0.619
	(27.14)	(2.44)	(4.78)	(5.01)	(48.19)	(1.24)	(3.36)	-(.33)	-(.40)
Trend	**-0.243**	**1.343**	**1.689**	**-2.106**	**0.460**	**1.163**	0.066	**-23.536**	**3.789**
	-(6.98)	(8.83)	(28.75)	-(10.16)	(18.05)	(40.24)	(.34)	-(38.86)	(5.74)
Category AQI (1 lag)	**2.069**	**2.144**	**0.763**	**2.159**	**5.858**	-0.074	**1.500**	0.914	**1.143**
	(25.06)	(4.68)	(2.79)	(4.49)	(70.06)	-(.47)	(2.86)	(.83)	(1.73)
Trend	**-0.220**	**1.355**	**1.705**	**-2.075**	**0.407**	**1.164**	0.100	**-23.508**	**3.779**
	-(6.30)	(8.93)	(29.05)	-(10.02)	(16.01)	(40.31)	(.51)	-(38.78)	(5.74)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	193,332	16,101	57,464	6,127	440,226	203,334	5,878	3,213	1,409
R-Sqr	17.89%	10.67%	19.25%	23.65%	17.80%	16.13%	23.60%	5.06%	7.44%
R-Sqr	17.84%	11.15%	20.35%	24.94%	18.03%	17.13%	23.58%	35.50%	9.76%
R-Sqr	17.91%	11.10%	20.35%	24.93%	17.89%	17.05%	23.61%	35.41%	9.55%
R-Sqr	17.97%	11.02%	20.33%	24.87%	17.38%	17.02%	23.71%	35.36%	9.12%
R-Sqr	17.93%	11.11%	20.31%	24.81%	17.86%	17.02%	23.67%	35.37%	9.30%

Table 3: Fund Characteristics Outweighed by Air Pollution Impact

This table reports the result from running regression 5 times from equation (6) across all cities. Following columns in this table refers to each AQI category model that mention in our methodology section. We add $Trend_y$ variable to the equation (6) to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we employ fund fixed-effect variable to capture the time-invariant unobserved fund characteristics in each model. Please refer to empirical methodology section for the details of the equation where we control for fund characteristics. We parenthesize t-statistics under each coefficient below. Here, $*$, $**$, and $***$ designate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)				
	Base AQI (1)	Natural Log of AQI (2)	Abnormal AQI (3)	Dummy AQI (4)	Category AQI (5)
AQI (1 lag)	0.058***				
	(54.29)				
Log AQI (1 lag)		5.797***			
		(59.42)			
Abnormal AQI (1 lag)			0.058***		
			(54.29)		
Dummy AQI (1 lag)				5.250***	
				(44.70)	
Category AQI (1 lag)					2.833***
					(52.77)
Fund Age (1 lag)	-0.487***	-0.481***	-0.487***	-0.492***	-0.483***
	-(39.25)	-(38.83)	-(39.25)	-(39.69)	-(38.92)
Manager Turnover (1 lag)	0.058***	0.058***	0.058***	0.058***	0.058***
	(22.28)	(22.23)	(22.28)	(22.42)	(22.32)
Fund flow (1 lag)	0.393***	0.388***	0.393***	0.401***	0.394***
	(14.82)	(14.63)	(14.82)	(15.12)	(14.87)
Log of Fund Size (1 lag)	0.997***	1.007***	0.997***	1.009***	1.001***
	(12.36)	(12.48)	(12.36)	(12.49)	(12.40)
Turnover (1 lag)	0.037***	0.037***	0.037***	0.037***	0.037***
	(176.35)	(175.93)	(176.35)	(176.94)	(176.49)
Expense Ratio (1 lag)	-12.63***	-12.726***	-12.63***	-12.55***	-12.67***
	-(24.42)	-(24.62)	-(24.42)	-(24.26)	-(24.49)
Management team (1 lag)	2.395***	2.394***	2.395***	2.424***	2.402***
	(23.02)	(23.02)	(23.02)	(23.28)	(23.08)
Trend	6.911***	6.821***	6.911***	6.984***	6.877***
	(46.44)	(45.84)	(46.44)	(46.91)	(46.21)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes
No. of Obs	846,904	846,904	846,904	846,904	846,904
R-Sqr	22.92%	22.97%	22.92%	22.83%	22.90%

Table 4: Manager Characteristics Outweighed by Air Pollution Impact

This table reports the result from running regression 5 times from equation (6) across all cities. Following columns in this table refers to each AQI category model that mention in our empirical methodology section. We add $Trend_y$ variable to the equation (6) to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we employ fund fixed-effect variable to capture the time-invariant unobserved fund characteristics in each model. Please refer to empirical methodology section for the details of the equation where we control for manager characteristics. We parenthesize t-statistics under each coefficient below. Here, $*$, $**$, and $***$ designate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)				
	Base AQI (1)	Natural Log of AQI (2)	Abnormal AQI (3)	Dummy AQI (4)	Category AQI (5)
AQI (1 lag)	0.064***				
	(58.19)				
Log AQI (1 lag)		6.360***			
		(63.08)			
Abnormal AQI (1 lag)			0.064***		
			(58.19)		
Dummy AQI (1 lag)				5.708***	
				(46.71)	
Category AQI (1 lag)					3.152***
					(56.44)
Experience (1 lag)	-0.204***	-0.204***	-0.204***	-0.205***	-0.204***
	-(83.14)	-(82.91)	-(83.14)	-(83.55)	-(83.23)
Managing Funds (1 lag)	0.872***	0.864***	0.872***	0.867***	0.876***
	(20.34)	(20.18)	(20.34)	(20.21)	(20.45)
Male Pct (1 lag)	0.081***	0.080***	0.081***	0.081***	0.081***
	(33.21)	(33.01)	(33.21)	(33.45)	(33.18)
Bachelor Pct (1 lag)	-0.532***	-0.534***	-0.532***	-0.535***	-0.532***
	-(25.09)	-(25.19)	-(25.09)	-(25.21)	-(25.08)
Master Pct (1 lag)	-0.008**	-0.007*	-0.008**	-0.008**	-0.008**
	-(2.10)	-(1.88)	-(2.10)	-(2.07)	-(2.09)
PhD Pct (1 lag)	0.011***	0.011***	0.011***	0.011***	0.011***
	(5.02)	(5.30)	(5.02)	(4.85)	(5.09)
CFA Pct (1 lag)	-0.034***	-0.034***	-0.034***	-0.034***	-0.034***
	-(11.90)	-(11.87)	-(11.90)	-(11.89)	-(11.91)
Trend	1.144***	1.118***	1.144***	1.153***	1.158***
	(57.24)	(55.89)	(57.24)	(57.62)	(57.93)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes
No. of Obs	805,137	805,137	805,137	805,137	805,137
R-Sqr	19.63%	19.69%	19.63%	19.51%	19.61%

Table 5: Market Characteristics Outweighed by Air Pollution Impact

This table reports the result from running regression 5 times from equation (6) across all cities. Following columns in this table refers to each AQI category model that mention in our empirical methodology section. We add $Trend_y$ variable to the equation (6) to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we employ fund fixed-effect variable to capture the time-invariant unobserved fund characteristics in each model. Please refer to methodology section for the details of the equation where we control for market environment characteristics. We parenthesize t-statistics under each coefficient below. Here, $*$, $**$, and $***$ designate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)				
	Base AQI (1)	Natural Log of AQI (2)	Abnormal AQI (3)	Dummy AQI (4)	Category AQI (5)
Base AQI (1 lag)	0.034***				
	(41.57)				
Log AQI (1 lag)		3.439***			
		(46.60)			
Abnormal AQI (1 lag)			0.034***		
			(41.57)		
Dummy AQI (1 lag)				2.402***	
				(27.11)	
Category AQI (1 lag)					1.710***
					(42.01)
Interest Rate Spread (1 lag)	2,686***	2,669***	2,686***	2,718***	2,689***
	(96.64)	(96.02)	(96.64)	(97.81)	(96.77)
Market Volatility (1 lag)	0.320***	0.320***	0.320***	0.319***	0.320***
	(492.72)	(492.88)	(492.72)	(491.68)	(492.64)
Inflation Rate (1 lag)	-0.001	0.036	-0.001	-0.024	-0.005
	-(.02)	(.51)	-(.02)	-(.35)	-(.07)
OLED Indicator (1 lag)	-18.97***	-18.779***	-18.97***	-19.33***	-18.95***
	-(66.50)	-(65.81)	-(66.50)	-(67.78)	-(66.41)
Consumer Confid. (1 lag)	-13.4***	-13.381***	-13.38***	-13.50***	-13.39***
	-(110.74)	-(110.77)	-(110.74)	-(111.70)	-(110.80)
Business Confid. (1 lag)	1.578***	1.419***	1.578***	1.663***	1.542***
	(10.85)	(9.75)	(10.85)	(11.43)	(10.60)
Producer Price (1 lag)	-2.268***	-2.259***	-2.268***	-2.260***	-2.260***
	-(54.23)	-(54.03)	-(54.23)	-(54.01)	-(54.04)
Log of Trade Vol. (1 lag)	12.99***	12.96***	12.99***	13.09***	13.03***
	(173.58)	(173.16)	(173.58)	(174.89)	(174.11)
Unemployment Rate (1 lag)	83.43***	83.24***	83.43***	84.29***	83.27***
	(161.28)	(160.97)	(161.28)	(163.03)	(160.87)
Trend	2.616***	2.606***	2.616***	2.620***	2.610***
	(97.26)	(96.91)	(97.26)	(97.32)	(97.04)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes
No. of Obs	927,084	927,084	927,084	927,084	978,434
R-Sqr	53.51%	53.53%	53.51%	53.46%	53.51%

Table 6: Fund Characteristics Magnifying Air Pollution Effect

In each panel, this table reports the result from running regression 7 times from equation (7) across all cities. Following columns in this table refers to coefficients of interaction term (multiplication) between each abnormal fund characteristic and AQI category for all panels. We add $Trend_y$ variable to the equation (7) to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we employ fund fixed-effect variable to capture the time-invariant unobserved fund characteristics in each model. Please refer to empirical methodology section for the details of the equation. We parenthesize t-statistics under each coefficient below. Here, $*$, $**$, and $***$ designate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund Characteristics (Abnormal) interacted with Base AQI

	Base AQI Model						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Base AQI Estimate (1 lag)	0.062***	0.058***	0.058***	0.058***	0.058***	0.058***	0.057***
	(57.46)	(54.29)	(54.31)	(54.52)	(54.48)	(54.56)	(52.92)
(Abnormal Fund Age * AQI) (1 lag)	-0.001***						
	-(26.93)						
(Abnormal Manager Turnover * AQI) (1 lag)		-0.00005					
		-(.92)					
(Abnormal Fund Flow * AQI) (1 lag)			-0.0027***				
			-(3.46)				
(Abnormal Fund Size * AQI) (1 lag)				0.023***			
				(15.62)			
(Abnormal Turnover * AQI) (1 lag)					-0.00002***		
					-(4.70)		
(Abnormal Expense Ratio * AQI) (1 lag)						-0.0465***	
						-(8.76)	
(Abnormal Management Team * AQI) (1 lag)							0.0016
							(.85)

Table 6 – Continues

Abnormal Fund Age (1 lag)	-0.428***	-0.487***	-0.487***	-0.489***	-0.486***	-0.487***	-0.487***
	-(34.04)	-(39.25)	-(39.24)	-(39.48)	-(39.24)	-(39.31)	-(39.26)
Abnormal Manager Turnover (1 lag)	0.058***	0.062***	0.058***	0.058***	0.058***	0.058***	0.058***
	(22.14)	(12.46)	(22.26)	(22.30)	(22.26)	(22.35)	(22.29)
Abnormal Fund flow (1 lag)	0.390***	0.393***	0.611***	0.388***	0.392***	0.392***	0.393***
	(14.72)	(14.81)	(8.92)	(14.63)	(14.80)	(14.79)	(14.81)
Abnormal Fund Size (1 lag)	1.016***	0.997***	0.996***	-0.721***	1.001***	0.999***	0.998***
	(12.59)	(12.36)	(12.34)	-(5.29)	(12.40)	(12.38)	(12.36)
Abnormal Turnover (1 lag)	0.037***	0.037***	0.037***	0.037***	0.039***	0.037***	0.037***
	(175.57)	(176.35)	(176.36)	(176.28)	(92.70)	(176.48)	(176.34)
Abnormal Expense Ratio (1 lag)	-12.518***	-12.627***	-12.646***	-12.441***	-12.612***	-9.021***	-12.627***
	-(24.21)	-(24.42)	-(24.45)	-(24.05)	-(24.39)	-(13.65)	-(24.42)
Abnormal Management Team (1 lag)	2.417***	2.395***	2.396***	2.402***	2.400***	2.384***	2.266***
	(23.24)	(23.02)	(23.03)	(23.09)	(23.07)	(22.92)	(12.29)
Trend	7.001***	6.910***	6.909***	6.933***	6.905***	6.917***	6.911***
	(47.06)	(46.44)	(46.43)	(46.60)	(46.40)	(46.48)	(46.44)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	846,904	846,904	846,904	846,904	846,904	846,904	846,904
R-Sqr	22.98%	22.92%	22.92%	22.94%	22.92%	22.92%	22.92%

Panel B: Fund Characteristics (Abnormal) interacted with Log AQI

	Natural Log of AQI Model						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log AQI Estimate (1 lag)	5.990***	5.797***	5.794***	5.786***	5.802***	5.793***	5.708***
	(61.28)	(59.42)	(59.39)	(59.32)	(59.47)	(59.38)	(57.21)
(Abnormal Fund Age * AQI) (1 lag)	-0.082***						
	-(28.43)						

Table 6 – Continues							
(Abnormal Manager Turnover * AQI) (1 lag)		0.003					
		(.54)					
(Abnormal Fund Flow * AQI) (1 lag)			-0.2230***				
			-(3.34)				
(Abnormal Fund Size * AQI) (1 lag)				2.355***			
				(18.17)			
(Abnormal Turnover * AQI) (1 lag)					-0.002***		
					-(4.33)		
(Abnormal Expense Ratio * AQI) (1 lag)						-4.5309***	
						-(9.30)	
(Abnormal Management Team * AQI) (1 lag)							0.7616***
							(4.24)
Abnormal Fund Age (1 lag)	-0.146***	-0.481***	-0.481***	-0.484***	-0.481***	-0.482***	-0.482***
	-(8.56)	-(38.83)	-(38.83)	-(39.05)	-(38.83)	-(38.91)	-(38.86)
Abnormal Manager Turnover (1 lag)	0.057***	0.046***	0.058***	0.058***	0.058***	0.058***	0.058***
	(22.06)	(2.14)	(22.22)	(22.24)	(22.20)	(22.30)	(22.28)
Abnormal Fund flow (1 lag)	0.385***	0.388***	1.349***	0.379***	0.387***	0.387***	0.387***
	(14.53)	(14.63)	(4.67)	(14.31)	(14.60)	(14.59)	(14.61)
Abnormal Fund Size (1 lag)	1.033***	1.007***	1.002***	-8.886***	1.011***	1.010***	1.009***
	(12.81)	(12.48)	(12.42)	-(16.15)	(12.54)	(12.52)	(12.50)
Abnormal Turnover (1 lag)	0.037***	0.037***	0.037***	0.037***	0.045***	0.037***	0.037***
	(175.14)	(175.93)	(175.91)	(175.87)	(24.99)	(176.08)	(175.90)
Abnormal Expense Ratio (1 lag)	-12.595***	-12.727***	-12.754***	-12.451***	-12.705***	6.426***	-12.719***
	-(24.37)	-(24.62)	-(24.67)	-(24.08)	-(24.57)	(3.03)	-(24.60)
Abnormal Management Team (1 lag)	2.414***	2.394***	2.395***	2.408***	2.399***	2.383***	-0.839
	(23.22)	(23.02)	(23.03)	(23.16)	(23.06)	(22.91)	-(1.09)
Trend	6.908***	6.821***	6.821***	6.839***	6.818***	6.830***	6.824***

Table 6 – Continues

	(46.44)	(45.84)	(45.85)	(45.97)	(45.82)	(45.91)	(45.86)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	846,904	846,904	846,904	846,904	846,904	846,904	846,904
R-Sqr	23.04%	22.97%	22.97%	23.00%	22.97%	22.98%	22.97%

Panel C: Fund Characteristics (Abnormal) interacted with Abnormal AQI

	Abnormal AQI Model						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abnormal AQI Estimate (1 lag)	0.061***	0.058***	0.058***	0.058***	0.058***	0.058***	0.057***
	(56.94)	(54.26)	(54.30)	(54.42)	(54.50)	(54.44)	(52.12)
(Abnormal Fund Age * AQI) (1 lag)	-0.001***						
	-(22.77)						
(Abnormal Manager Turnover * AQI) (1 lag)		0.0002***					
		(2.77)					
(Abnormal Fund Flow * AQI) (1 lag)			-0.0016***				
			-(1.94)				
(Abnormal Fund Size * AQI) (1 lag)				0.014***			
				(9.02)			
(Abnormal Turnover * AQI) (1 lag)					-0.00003***		
					-(5.18)		
(Abnormal Expense Ratio * AQI) (1 lag)						-0.0287***	
						-(5.31)	
(Abnormal Management Team * AQI) (1 lag)							0.0083***
							(4.13)
Abnormal Fund Age (1 lag)	-0.495***	-0.487***	-0.487***	-0.489***	-0.486***	-0.487***	-0.487***
	-(39.90)	-(39.26)	-(39.25)	-(39.41)	-(39.24)	-(39.29)	-(39.29)

Table 6 – Continues

Abnormal Manager Turnover (1 lag)	0.058***	0.057***	0.058***	0.058***	0.058***	0.058***	0.058***
	(22.22)	(21.95)	(22.27)	(22.29)	(22.27)	(22.31)	(22.28)
Abnormal Fund flow (1 lag)	0.389***	0.393***	0.408***	0.388***	0.392***	0.392***	0.392***
	(14.68)	(14.81)	(14.74)	(14.64)	(14.79)	(14.80)	(14.80)
Abnormal Fund Size (1 lag)	1.018***	0.998***	0.997***	0.958***	1.002***	1.000***	0.998***
	(12.61)	(12.36)	(12.35)	(11.86)	(12.41)	(12.39)	(12.37)
Abnormal Turnover (1 lag)	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***
	(176.19)	(176.36)	(176.35)	(176.34)	(175.48)	(176.41)	(176.35)
Abnormal Expense Ratio (1 lag)	-12.734***	-12.635***	-12.635***	-12.584***	-12.635***	-12.499***	-12.628***
	-(24.63)	-(24.43)	-(24.43)	-(24.33)	-(24.43)	-(24.14)	-(24.42)
Abnormal Management Team (1 lag)	2.398***	2.395***	2.396***	2.397***	2.396***	2.390***	2.364***
	(23.06)	(23.02)	(23.03)	(23.04)	(23.03)	(22.97)	(22.66)
Trend	7.003***	6.912***	6.910***	6.928***	6.906***	6.914***	6.916***
	(47.05)	(46.44)	(46.43)	(46.55)	(46.41)	(46.46)	(46.47)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	846,904	846,904	846,904	846,904	846,904	846,904	846,904
R-Sqr	22.96%	22.92%	22.92%	22.92%	22.92%	22.92%	22.92%

Panel D: Fund Characteristics (Abnormal) interacted with Dummy AQI

	Dummy AQI						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy AQI Estimate (1 lag)	6.087***	5.250***	5.250***	5.341***	5.250***	5.309***	5.197***
	(50.37)	(44.70)	(44.70)	(45.39)	(44.58)	(45.12)	(43.37)
(Abnormal Fund Age * AQI) (1 lag)	-0.114***						
	-(29.21)						
(Abnormal Manager Turnover * AQI) (1 lag)		-0.00876					
		-(1.36)					

Table 6 – Continues							
(Abnormal Fund Flow * AQI) (1 lag)			-0.1302*				
			-(1.83)				
(Abnormal Fund Size * AQI) (1 lag)				1.995***			
				(12.28)			
(Abnormal Turnover * AQI) (1 lag)					0.00001		
					(.01)		
(Abnormal Expense Ratio * AQI) (1 lag)						-4.8641***	
						-(8.32)	
(Abnormal Management Team * AQI) (1 lag)							0.4852**
							(2.21)
Abnormal Fund Age (1 lag)	-0.481***	-0.492***	-0.492***	-0.494***	-0.492***	-0.493***	-0.492***
	-(38.76)	-(39.69)	-(39.69)	-(39.81)	-(39.69)	-(39.73)	-(39.70)
Abnormal Manager Turnover (1 lag)	0.058***	0.060***	0.058***	0.058***	0.058***	0.059***	0.058***
	(22.24)	(20.84)	(22.42)	(22.46)	(22.42)	(22.48)	(22.46)
Abnormal Fund flow (1 lag)	0.400***	0.401***	0.422***	0.400***	0.401***	0.401***	0.401***
	(15.07)	(15.11)	(14.57)	(15.08)	(15.11)	(15.11)	(15.10)
Abnormal Fund Size (1 lag)	1.015***	1.009***	1.010***	0.639***	1.009***	1.012***	1.009***
	(12.57)	(12.49)	(12.51)	(7.41)	(12.49)	(12.53)	(12.50)
Abnormal Turnover (1 lag)	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***
	(176.10)	(176.94)	(176.95)	(176.87)	(158.07)	(177.02)	(176.92)
Abnormal Expense Ratio (1 lag)	-12.424***	-12.548***	-12.551***	-12.412***	-12.551***	-11.554***	-12.547***
	-(24.02)	-(24.25)	-(24.26)	-(23.98)	-(24.26)	-(21.76)	-(24.25)
Abnormal Management Team (1 lag)	2.438***	2.423***	2.424***	2.427***	2.424***	2.415***	2.319***
	(23.43)	(23.28)	(23.29)	(23.32)	(23.28)	(23.20)	(20.28)
Trend	7.055***	6.984***	6.985***	6.996***	6.984***	6.988***	6.985***
	(47.40)	(46.91)	(46.91)	(46.99)	(46.91)	(46.94)	(46.92)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6 – Continues							
No. of Obs	846,904	846,904	846,904	846,904	846,904	846,904	846,904
R-Sqr	22.91%	22.83%	22.83%	22.84%	22.83%	22.84%	22.83%
Panel E: Fund Characteristics (Abnormal) interacted with Category AQI							
	Category AQI						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Category AQI Estimate (1 lag)	3.084***	2.833***	2.832***	2.870***	2.854***	2.847***	2.815***
	(56.59)	(52.78)	(52.76)	(53.42)	(53.08)	(53.01)	(51.31)
(Abnormal Fund Age * AQI) (1 lag)	-0.045***						
	-(26.36)						
(Abnormal Manager Turnover * AQI) (1 lag)		-0.00464*					
		-(1.64)					
(Abnormal Fund Flow * AQI) (1 lag)			-0.100***				
			-(2.59)				
(Abnormal Fund Size * AQI) (1 lag)				1.258***			
				(17.17)			
(Abnormal Turnover * AQI) (1 lag)					-0.002***		
					-(7.17)		
(Abnormal Expense Ratio * AQI) (1 lag)						-2.162***	
						-(8.10)	
(Abnormal Management Team * AQI) (1 lag)							0.156
							(1.58)
Abnormal Fund Age (1 lag)	-0.404***	-0.483***	-0.483***	-0.485***	-0.483***	-0.483***	-0.483***
	-(31.70)	-(38.92)	-(38.92)	-(39.16)	-(38.92)	-(38.97)	-(38.93)
Abnormal Manager Turnover (1 lag)	0.058***	0.067***	0.058***	0.058***	0.058***	0.058***	0.058***
	(22.19)	(10.72)	(22.31)	(22.36)	(22.28)	(22.38)	(22.33)

Table 6 – Continues

Abnormal Fund flow (1 lag)	0.392***	0.394***	0.601***	0.389***	0.394***	0.394***	0.394***
	(14.79)	(14.86)	(7.15)	(14.67)	(14.86)	(14.85)	(14.86)
Abnormal Fund Size (1 lag)	1.024***	1.001***	1.000***	-1.500***	1.006***	1.002***	1.001***
	(12.70)	(12.40)	(12.39)	-(9.01)	(12.47)	(12.42)	(12.40)
Abnormal Turnover (1 lag)	0.037***	0.037***	0.037***	0.037***	0.041***	0.037***	0.037***
	(175.79)	(176.49)	(176.50)	(176.43)	(78.41)	(176.61)	(176.48)
Abnormal Expense Ratio (1 lag)	-12.561***	-12.663***	-12.680***	-12.439***	-12.635***	-8.272***	-12.665***
	-(24.30)	-(24.48)	-(24.52)	-(24.05)	-(24.43)	-(11.03)	-(24.49)
Abnormal Management Team (1 lag)	2.423***	2.401***	2.403***	2.410***	2.409***	2.393***	2.081***
	(23.29)	(23.08)	(23.09)	(23.17)	(23.16)	(23.00)	(9.10)
Trend	6.963***	6.877***	6.877***	6.898***	6.872***	6.882***	6.878***
	(46.79)	(46.20)	(46.20)	(46.35)	(46.17)	(46.24)	(46.21)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	846,904	846,904	846,904	846,904	846,904	846,904	846,904
R-Sqr	22.96%	22.90%	22.90%	22.93%	22.90%	22.91%	22.90%

Table 7: Manager Characteristics Strengthening Air Pollution Effect

In each panel, this table reports the result from running regression 7 times from equation (7) across all cities. Following columns in this table refers to coefficients of interaction term (multiplication) between each abnormal manager characteristic and AQI category for all panels. We add $Trend_y$ variable to the equation (7) to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we employ fund fixed-effect variable to capture the time-invariant unobserved fund characteristics in each model. Please refer to empirical methodology section for the details of the equation. We parenthesize t-statistics under each co-efficient below. Here, $*$, $**$, and $***$ designate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Manager Characteristics (Abnormal) interacted with base AQI

	Base AQI						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Base AQI Estimate (1 lag)	0.065***	0.065***	0.064***	0.064***	0.064***	0.064***	0.064***
	(58.64)	(58.46)	(58.20)	(58.27)	(58.22)	(58.24)	(58.21)
(Abnormal Experience * AQI) (1 lag)	-0.001***						
	-(22.25)						
(Abnormal Managing Funds * AQI) (1 lag)		-0.009***					
		-(10.07)					
(Abnormal Male Pct * AQI) (1 lag)			0.0001*				
			(1.87)				
(Abnormal Bachelor Pct * AQI) (1 lag)				-0.001***			
				-(3.59)			
(Abnormal Master Pct * AQI) (1 lag)					-0.00001		
					-(.13)		
(Abnormal PhD Pct * AQI) (1 lag)						-0.0002***	
						-(4.86)	
(Abnormal CFA Pct * AQI) (1 lag)							-0.0004***
							-(5.64)
Abnormal Experience (1 lag)	-0.122***	-0.204***	-0.204***	-0.204***	-0.204***	-0.204***	-0.204***
	-(27.40)	-(83.20)	-(83.11)	-(83.12)	-(83.10)	-(83.16)	-(82.81)
Abnormal Managing Funds (1 lag)	0.872***	1.559***	0.880***	0.880***	0.880***	0.877***	0.881***
	(20.36)	(19.52)	(20.53)	(20.53)	(20.53)	(20.47)	(20.55)
Abnormal Male Pct (1 lag)	0.075***	0.076***	0.069***	0.076***	0.076***	0.076***	0.076***

Table 7 – Continues							
	(30.90)	(31.10)	(14.84)	(31.13)	(31.15)	(31.14)	(31.24)
Abnormal Bachelor Pct (1 lag)	-0.535***	-0.533***	-0.530***	-0.419***	-0.530***	-0.530***	-0.531***
	-(25.23)	-(25.12)	-(25.03)	-(11.18)	-(25.02)	-(25.00)	-(25.03)
Abnormal Master Pct (1 lag)	-0.006*	-0.007*	-0.007*	-0.007*	-0.006	-0.007*	-0.007*
	-(1.67)	-(1.82)	-(1.84)	-(1.85)	-(.81)	-(1.84)	-(1.82)
Abnormal PhD Pct (1 lag)	0.006***	0.007***	0.007***	0.007***	0.007***	0.024***	0.007***
	(2.97)	(3.13)	(3.21)	(3.20)	(3.20)	(5.82)	(3.13)
Abnormal CFA Pct (1 lag)	-0.032***	-0.033***	-0.034***	-0.033***	-0.033***	-0.034***	-0.007
	-(11.17)	-(11.80)	-(11.88)	-(11.85)	-(11.85)	-(11.89)	-(1.27)
Trend	1.125***	1.133***	1.141***	1.141***	1.141***	1.142***	1.140***
	(56.25)	(56.64)	(57.10)	(57.07)	(57.07)	(57.12)	(57.01)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	805,063	805,063	805,063	805,063	805,063	805,063	805,063
R-Sqr	19.68%	19.64%	19.63%	19.64%	19.63%	19.64%	19.64%

Panel B: Manager Characteristics (Abnormal) interacted with Log AQI

	Natural Log of AQI						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log AQI Estimate (1 lag)	6.395***	6.373***	6.362***	6.372***	6.363***	6.362***	6.370***
	(63.45)	(63.21)	(63.10)	(63.18)	(63.10)	(63.10)	(63.18)
(Abnormal Experience * AQI) (1 lag)	-0.115***						
	-(26.37)						
(Abnormal Managing Funds * AQI) (1 lag)		-0.842***					
		-(10.68)					
(Abnormal Male Pct * AQI) (1 lag)			0.0140***				
			(3.03)				
(Abnormal Bachelor Pct * AQI) (1 lag)				-0.152***			
				-(4.43)			
(Abnormal Master Pct * AQI) (1 lag)					0.007		

Table 7 – Continues

					(.91)		
(Abnormal PhD Pct * AQI) (1 lag)						-0.0241***	
						-(5.65)	
(Abnormal CFA Pct * AQI) (1 lag)							-0.0328***
							-(5.90)
Abnormal Experience (1 lag)	0.279***	-0.204***	-0.203***	-0.204***	-0.204***	-0.204***	-0.203***
	(15.11)	-(82.95)	-(82.86)	-(82.89)	-(82.89)	-(82.94)	-(82.55)
Abnormal Managing Funds (1 lag)	0.865***	4.423***	0.872***	0.873***	0.872***	0.870***	0.874***
	(20.21)	(13.20)	(20.37)	(20.37)	(20.36)	(20.30)	(20.39)
Abnormal Male Pct (1 lag)	0.074***	0.075***	0.016	0.075***	0.075***	0.075***	0.076***
	(30.55)	(30.90)	(.84)	(30.93)	(30.96)	(30.91)	(31.07)
Abnormal Bachelor Pct (1 lag)	-0.537***	-0.534***	-0.532***	0.129	-0.533***	-0.532***	-0.532***
	-(25.34)	-(25.22)	-(25.13)	(.85)	-(25.14)	-(25.09)	-(25.13)
Abnormal Master Pct (1 lag)	-0.005	-0.006	-0.006	-0.006	-0.035	-0.006	-0.006
	-(1.41)	-(1.60)	-(1.61)	-(1.63)	-(1.09)	-(1.60)	-(1.59)
Abnormal PhD Pct (1 lag)	0.007***	0.007***	0.008***	0.008***	0.008***	0.108***	0.007***
	(3.18)	(3.42)	(3.52)	(3.49)	(3.49)	(6.03)	(3.43)
Abnormal CFA Pct (1 lag)	-0.031***	-0.033***	-0.034***	-0.033***	-0.033***	-0.033***	0.103***
	-(10.87)	-(11.75)	-(11.88)	-(11.82)	-(11.82)	-(11.85)	(4.43)
Trend	1.096***	1.106***	1.115***	1.114***	1.115***	1.116***	1.113***
	(54.79)	(55.23)	(55.76)	(55.71)	(55.74)	(55.77)	(55.66)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	805,063	805,063	805,063	805,063	805,063	805,063	805,063
R-Sqr	19.76%	19.70%	19.69%	19.69%	19.69%	19.70%	19.70%

Panel C: Manager Characteristics (Abnormal) interacted with Abnormal AQI

	Abnormal AQI
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)

Table 7 – Continues

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abnormal AQI Estimate (1 lag)	0.065***	0.065***	0.064***	0.064***	0.064***	0.064***	0.064***
	(58.49)	(58.41)	(58.21)	(58.30)	(58.22)	(58.23)	(58.22)
(Abnormal Experience * AQI) (1 lag)	-0.001***						
	-(13.86)						
(Abnormal Managing Funds * AQI) (1 lag)		-0.007***					
		-(7.44)					
(Abnormal Male Pct * AQI) (1 lag)			0.0001				
			(1.02)				
(Abnormal Bachelor Pct * AQI) (1 lag)				-0.002***			
				-(5.32)			
(Abnormal Master Pct * AQI) (1 lag)					0.0001		
					(.65)		
(Abnormal PhD Pct * AQI) (1 lag)						-0.0002***	
						-(3.38)	
(Abnormal CFA Pct * AQI) (1 lag)							-0.0001
							-(1.41)
Abnormal Experience (1 lag)	-0.203***	-0.204***	-0.204***	-0.204***	-0.204***	-0.204***	-0.204***
	-(82.59)	-(83.08)	-(83.11)	-(83.13)	-(83.12)	-(83.11)	-(83.09)
Abnormal Managing Funds (1 lag)	0.882***	0.895***	0.880***	0.880***	0.880***	0.879***	0.880***
	(20.59)	(20.86)	(20.53)	(20.54)	(20.53)	(20.51)	(20.53)
Abnormal Male Pct (1 lag)	0.076***	0.076***	0.076***	0.076***	0.076***	0.076***	0.076***
	(31.08)	(31.15)	(31.13)	(31.16)	(31.15)	(31.14)	(31.15)
Abnormal Bachelor Pct (1 lag)	-0.532***	-0.531***	-0.530***	-0.534***	-0.531***	-0.530***	-0.530***
	-(25.10)	-(25.03)	-(25.03)	-(25.18)	-(25.03)	-(25.03)	-(25.03)
Abnormal Master Pct (1 lag)	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*
	-(1.75)	-(1.84)	-(1.85)	-(1.79)	-(1.84)	-(1.87)	-(1.84)

Table 7 – Continues							
Abnormal PhD Pct (1 lag)	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(3.21)	(3.18)	(3.20)	(3.20)	(3.20)	(3.24)	(3.20)
Abnormal CFA Pct (1 lag)	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***
	-(11.70)	-(11.84)	-(11.85)	-(11.85)	-(11.85)	-(11.84)	-(11.84)
Trend	1.135***	1.137***	1.141***	1.141***	1.141***	1.141***	1.141***
	(56.79)	(56.87)	(57.08)	(57.08)	(57.09)	(57.09)	(57.09)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	805,063	805,063	805,063	805,063	805,063	805,063	805,063
R-Sqr	19.65%	19.64%	19.63%	19.64%	19.63%	19.64%	19.63%
Panel D: Manager Characteristics (Abnormal) interacted with Dummy AQI							
				Dummy AQI			
			Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy AQI Estimate (1 lag)	5.885***	5.827***	5.711***	5.725***	5.713***	5.710***	5.701***
	(48.08)	(47.54)	(46.72)	(46.82)	(46.74)	(46.70)	(46.63)
(Abnormal Experience * AQI) (1 lag)	-0.129***						
	-(23.42)						
(Abnormal Managing Funds * AQI) (1 lag)		-1.193***					
		-(12.12)					
(Abnormal Male Pct * AQI) (1 lag)			0.0159***				
			(2.75)				
(Abnormal Bachelor Pct * AQI) (1 lag)				-0.143***			
				-(3.63)			
(Abnormal Master Pct * AQI) (1 lag)					0.00567		
					(.60)		
(Abnormal PhD Pct * AQI) (1 lag)						-0.0041	
						-(.73)	

Table 7 – Continues							
(Abnormal CFA Pct * AQI) (1 lag)							-0.0353***
							-(4.87)
Abnormal Experience (1 lag)	-0.180***	-0.205***	-0.205***	-0.205***	-0.205***	-0.205***	-0.205***
	-(67.26)	-(83.62)	-(83.53)	-(83.53)	-(83.53)	-(83.53)	-(83.31)
Abnormal Managing Funds (1 lag)	0.870***	1.117***	0.875***	0.875***	0.875***	0.874***	0.875***
	(20.29)	(23.61)	(20.40)	(20.40)	(20.40)	(20.39)	(20.41)
Abnormal Male Pct (1 lag)	0.076***	0.076***	0.073***	0.076***	0.077***	0.076***	0.077***
	(31.20)	(31.32)	(27.40)	(31.36)	(31.38)	(31.38)	(31.45)
Abnormal Bachelor Pct (1 lag)	-0.536***	-0.535***	-0.533***	-0.495***	-0.534***	-0.533***	-0.533***
	-(25.26)	-(25.22)	-(25.13)	-(20.84)	-(25.15)	-(25.14)	-(25.15)
Abnormal Master Pct (1 lag)	-0.006*	-0.007*	-0.007*	-0.007*	-0.008*	-0.007*	-0.007*
	-(1.64)	-(1.79)	-(1.81)	-(1.81)	-(1.91)	-(1.81)	-(1.79)
Abnormal PhD Pct (1 lag)	0.006***	0.006***	0.007***	0.007***	0.007***	0.007***	0.006***
	(2.79)	(2.95)	(3.03)	(3.02)	(3.02)	(3.07)	(2.97)
Abnormal CFA Pct (1 lag)	-0.032***	-0.033***	-0.034***	-0.033***	-0.033***	-0.033***	-0.028***
	-(11.26)	-(11.80)	-(11.88)	-(11.84)	-(11.84)	-(11.85)	-(9.01)
Trend	1.132***	1.140***	1.150***	1.150***	1.150***	1.150***	1.149***
	(56.57)	(56.94)	(57.49)	(57.45)	(57.47)	(57.47)	(57.42)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	805,063	805,063	805,063	805,063	805,063	805,063	805,063
R-Sqr	19.57%	19.53%	19.51%	19.52%	19.51%	19.51%	19.52%

Panel E: Manager Characteristics (Abnormal) interacted with Category AQI

	Category AQI						
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Category AQI Estimate (1 lag)	3.205***	3.179***	3.154***	3.158***	3.154***	3.153***	3.152***
	(57.34)	(56.85)	(56.46)	(56.52)	(56.46)	(56.45)	(56.43)

Table 7 – Continues							
(Abnormal Experience * AQI) (1 lag)	-0.056***						
	-(22.90)						
(Abnormal Managing Funds * AQI) (1 lag)		-0.420***					
		-(9.59)					
(Abnormal Male Pct * AQI) (1 lag)			0.004				
			(1.44)				
(Abnormal Bachelor Pct * AQI) (1 lag)				-0.066***			
				-(3.59)			
(Abnormal Master Pct * AQI) (1 lag)					0.003		
					(.63)		
(Abnormal PhD Pct * AQI) (1 lag)						-0.013***	
						-(5.45)	
(Abnormal CFA Pct * AQI) (1 lag)							-0.015***
							-(4.66)
Abnormal Experience (1 lag)	-0.092***	-0.205***	-0.204***	-0.204***	-0.204***	-0.204***	-0.204***
	-(16.74)	-(83.28)	-(83.19)	-(83.21)	-(83.20)	-(83.25)	-(82.93)
Abnormal Managing Funds (1 lag)	0.877***	1.726***	0.884***	0.884***	0.884***	0.882***	0.885***
	(20.46)	(17.66)	(20.63)	(20.63)	(20.63)	(20.58)	(20.65)
Abnormal Male Pct (1 lag)	0.075***	0.076***	0.068***	0.076***	0.076***	0.076***	0.076***
	(30.83)	(31.08)	(11.78)	(31.11)	(31.13)	(31.11)	(31.20)
Abnormal Bachelor Pct (1 lag)	-0.534***	-0.532***	-0.530***	-0.381***	-0.531***	-0.530***	-0.530***
	-(25.21)	-(25.09)	-(25.01)	-(8.20)	-(25.02)	-(24.98)	-(25.02)
Abnormal Master Pct (1 lag)	-0.006	-0.007*	-0.007*	-0.007*	-0.012	-0.007*	-0.007*
	-(1.61)	-(1.81)	-(1.83)	-(1.83)	-(1.31)	-(1.83)	-(1.80)
Abnormal PhD Pct (1 lag)	0.007***	0.007***	0.007***	0.007***	0.007***	0.033***	0.007***
	(3.02)	(3.22)	(3.28)	(3.27)	(3.27)	(6.32)	(3.21)
Abnormal CFA Pct (1 lag)	-0.031***	-0.033***	-0.034***	-0.034***	-0.034***	-0.034***	-0.004

Table 7 – Continues

	-(11.12)	-(11.80)	-(11.89)	-(11.87)	-(11.87)	-(11.91)	-(.62)
Trend	1.137***	1.147***	1.154***	1.154***	1.154***	1.155***	1.153***
	(56.88)	(57.35)	(57.79)	(57.76)	(57.78)	(57.80)	(57.73)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	805,063	805,063	805,063	805,063	805,063	805,063	805,063
R-Sqr	19.67%	19.62%	19.61%	19.62%	19.61%	19.62%	19.62%

Table 8: Market Characteristics Strengthening Air Pollution Effect

In each panel, this table reports the result from running regression 7 times from equation (7) across all cities. Following columns in this table refers to coefficients of interaction term (multiplication) between each abnormal market environment characteristic and AQI category for all panels. We add $Trend_y$ variable to the equation (7) to represent the time trend variable to capture time-varying unobserved characteristics in year y. Additionally, we employ fund fixed-effect variable to capture the time-invariant unobserved fund characteristics in each model. Please refer to empirical methodology section for the details of the equation. We parenthesize t-statistics under each coefficient below. Here, $*$, $**$, and $***$ designate statistical significance at the 10%, 5%, and 1% level, respectively. In addition, we change font style of coefficients for control variables to bold to show their statistical significance at the 10% level or more.

Panel A: Market Environment Characteristics interacted with Base AQI

	Base AQI								
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Base AQI Estimate (1 lag)	0.041***	0.040***	0.034***	0.035***	0.034***	0.033***	0.034***	0.034***	0.052***
	(47.10)	(48.85)	(41.71)	(42.90)	(42.01)	(40.83)	(42.28)	(40.73)	(55.48)
(Interest Rate Spread * AQI) (1 lag)	-10.99***								
	-(22.46)								
(Market Volatility * AQI) (1 lag)		0.001***							
		(42.26)							
(Inflation Rate* AQI) (1 lag)			0.005***						
			(3.34)						
(OLED Leading Indicator * AQI) (1 lag)				0.093***					
				(15.43)					
(Consumer Confidence * AQI) (1 lag)					-0.02***				
					-(7.73)				
(Business Confidence * AQI) (1 lag)						-0.05***			
						-(13.74)			
(Producer Price * AQI) (1 lag)							-0.01***		
							-(8.46)		
(Trade Volume * AQI) (1 lag)								0.0001	

Table 8 – Continues

								-(.08)	
(Unemployment Rate * AQI) (1 lag)									0.251***
									(38.76)
Abnormal Interest Rate Spread (1 lag)	**3471.222**	**2728.226**	**2686.74**	**2707.318**	**2681.385**	**2675.087**	**2671.812**	**2685.773**	**2717.669**
	(77.74)	(98.19)	(96.67)	(97.30)	(96.46)	(96.22)	(95.96)	(96.20)	(97.82)
Abnormal Market Volatility (1 lag)	**0.319**	**0.284**	**0.320**	**0.320**	**0.320**	**0.320**	**0.320**	**0.320**	**0.319**
	(492.38)	(265.36)	(492.72)	(492.89)	(492.51)	(492.92)	(492.63)	(492.53)	(492.73)
Abnormal Inflation Rate (1 lag)	-0.068	-0.059	**-0.386**	0.007	0.014	-0.069	-0.016	-0.001	**-0.152**
	-(.96)	-(.84)	-(2.85)	(.10)	(.20)	-(.97)	-(.23)	-(.02)	-(2.15)
Abnormal OLED Indicator (1 lag)	**-18.934**	**-19.075**	**-18.981**	**-24.811**	**-19.016**	**-19.154**	**-18.853**	**-18.971**	**-18.330**
	-(66.39)	-(66.93)	-(66.54)	-(52.35)	-(66.65)	-(67.08)	-(66.01)	-(66.50)	-(64.20)
Abnormal Consumer Confidence (1 lag)	**-13.397**	**-13.448**	**-13.398**	**-13.417**	**-11.758**	**-13.385**	**-13.383**	**-13.382**	**-13.432**
	-(110.88)	-(111.37)	-(110.8)	-(111.01)	-(48.47)	-(110.77)	-(110.74)	-(110.63)	-(111.22)
Abnormal Business Confidence (1 lag)	**1.513**	**1.442**	**1.602**	**1.613**	**1.562**	**4.585**	**1.553**	**1.577**	**1.503**
	(10.40)	(9.92)	(11.00)	(11.09)	(10.74)	(17.45)	(10.68)	(10.84)	(10.34)
Abnormal Producer Price (1 lag)	**-2.264**	**-2.176**	**-2.266**	**-2.321**	**-2.267**	**-2.221**	**-1.700**	**-2.268**	**-2.248**
	-(54.14)	-(52.00)	-(54.16)	-(55.31)	-(54.20)	-(52.91)	-(21.46)	-(54.23)	-(53.79)
Abnormal Trade Volume (1 lag)	**12.902**	**12.869**	**12.994**	**12.995**	**13.012**	**12.956**	**12.971**	**13.001**	**12.980**
	(172.12)	(171.92)	(173.55)	(173.60)	(173.73)	(172.94)	(173.15)	(118.81)	(173.51)
Abnormal Unemployment Rate (1 lag)	**83.084**	**83.041**	**83.364**	**83.408**	**83.469**	**83.400**	**83.256**	**83.432**	**64.783**
	(160.57)	(160.65)	(161.01)	(161.25)	(161.34)	(161.23)	(160.81)	(161.23)	(91.74)
Trend	**2.609**	**2.588**	**2.614**	**2.612**	**2.614**	**2.622**	**2.619**	**2.616**	**2.579**
	(97.03)	(96.29)	(97.21)	(97.15)	(97.18)	(97.51)	(97.38)	(97.23)	(95.92)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	978,434	978,434	978,434	978,434	978,434	978,434	978,434	978,434	978,434
R-Sqr	53.54%	53.60%	53.51%	53.52%	53.51%	53.52%	53.51%	53.51%	53.59%

Table 8 – Continues									
Panel B: Market Environment Characteristics interacted with Log AQI									
	Natural Log of AQI								
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log AQI Estimate (1 lag)	3.905***	3.853***	3.432***	3.516***	3.564***	3.380***	3.434***	3.432***	5.230***
	(50.83)	(51.81)	(46.48)	(47.47)	(47.93)	(45.75)	(46.45)	(46.44)	(62.31)
(Interest Rate Spread * AQI) (1 lag)	-877.4***								
	-(21.78)								
(Market Volatility * AQI) (1 lag)		0.041***							
		(42.57)							
(Inflation Rate* AQI) (1 lag)			-0.60***						
			-(4.14)						
(OLED Leading Indicator * AQI) (1 lag)				5.480***					
				(12.45)					
(Consumer Confidence * AQI) (1 lag)					-3.30***				
					-(13.71)				
(Business Confidence * AQI) (1 lag)						-4.17***			
						-(16.38)			
(Producer Price * AQI) (1 lag)							0.105		
							(1.34)		
(Trade Volume * AQI) (1 lag)								0.180**	
								(2.00)	
(Unemployment Rate * AQI) (1 lag)									24.23***
									(44.63)
Abnormal Interest Rate Spread (1 lag)	**6317.062**	**2721.768**	**2667.75**	**2686.533**	**2659.861**	**2653.804**	**2671.725**	**2674.627**	**2705.069**
	(37.21)	(97.91)	(95.96)	(96.53)	(95.67)	(95.43)	(95.90)	(95.77)	(97.37)
Abnormal Market Volatility (1 lag)	**0.319**	**0.148**	**0.320**	**0.320**	**0.320**	**0.320**	**0.320**	**0.320**	**0.319**

Table 8 – Continues

	(492.32)	(36.42)	(492.90)	(492.96)	(492.64)	(493.14)	(492.88)	(492.81)	(492.68)
Abnormal Inflation Rate (1 lag)	-0.025	-0.041	**2.553**	0.052	0.067	-0.046	0.039	0.038	**-0.119**
	-(.36)	-(.58)	(4.17)	(.73)	(.94)	-(.65)	(.55)	(.54)	-(1.69)
Abnormal OLED Indicator (1 lag)	**-18.807**	**-19.002**	**-18.762**	**-40.855**	**-18.881**	**-19.063**	**-18.800**	**-18.774**	**-17.902**
	-(65.93)	-(66.65)	-(65.75)	-(22.76)	-(66.15)	-(66.69)	-(65.79)	-(65.79)	-(62.66)
Abnormal Consumer Confidence (1 lag)	**-13.382**	**-13.420**	**-13.356**	**-13.396**	**0.610**	**-13.395**	**-13.380**	**-13.390**	**-13.375**
	-(110.81)	-(111.20)	-(110.43)	-(110.90)	(.59)	-(110.90)	-(110.76)	-(110.77)	-(110.84)
Abnormal Business Confidence (1 lag)	**1.306**	**1.261**	**1.383**	**1.447**	**1.372**	**18.499**	**1.422**	**1.434**	**1.217**
	(8.97)	(8.67)	(9.49)	(9.95)	(9.43)	(17.57)	(9.77)	(9.84)	(8.37)
Abnormal Producer Price (1 lag)	**-2.257**	**-2.161**	**-2.263**	**-2.304**	**-2.257**	**-2.198**	**-2.702**	**-2.259**	**-2.242**
	-(53.98)	-(51.65)	-(54.10)	-(54.90)	-(53.98)	-(52.35)	-(8.10)	-(54.02)	-(53.67)
Abnormal Trade Volume (1 lag)	**12.876**	**12.870**	**12.962**	**12.970**	**12.988**	**12.912**	**12.968**	**12.204**	**12.958**
	(171.79)	(172.00)	(173.14)	(173.25)	(173.46)	(172.34)	(173.06)	(31.51)	(173.28)
Abnormal Unemployment Rate (1 lag)	**83.070**	**82.787**	**83.331**	**83.245**	**83.277**	**83.222**	**83.273**	**83.257**	**-18.170**
	(160.65)	(160.21)	(161.00)	(160.98)	(161.05)	(160.95)	(160.87)	(160.98)	-(7.80)
Trend	**2.602**	**2.567**	**2.608**	**2.604**	**2.602**	**2.613**	**2.605**	**2.607**	**2.559**
	(96.81)	(95.49)	(96.98)	(96.84)	(96.77)	(97.17)	(96.87)	(96.93)	(95.19)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	978,434	978,434	978,434	978,434	978,434	978,434	978,434	978,434	978,434
R-Sqr	53.56%	53.62%	53.53%	53.54%	53.54%	53.55%	53.53%	53.53%	53.63%

Panel C: Market Environment Characteristics interacted with Abnormal AQI

	Abnormal AQI								
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Abnormal AQI Estimate (1 lag)	0.040***	0.039***	0.034***	0.035***	0.034***	0.033***	0.034***	0.033***	0.049***
	(44.84)	(47.93)	(41.71)	(43.59)	(42.26)	(40.90)	(42.10)	(40.42)	(52.27)
(Interest Rate Spread * AQI) (1 lag)	-8.581***								

Table 8 – Continues									
	-(16.88)								
(Market Volatility * AQI) (1 lag)		0.0004***							
		(35.80)							
(Inflation Rate* AQI) (1 lag)			0.006***						
			(3.56)						
(OLED Leading Indicator * AQI) (1 lag)				0.130***					
				(19.65)					
(Consumer Confidence * AQI) (1 lag)					-0.03***				
					-(9.43)				
(Business Confidence * AQI) (1 lag)						-0.04***			
						-(9.98)			
(Producer Price * AQI) (1 lag)							-0.01***		
							-(7.11)		
(Trade Volume * AQI) (1 lag)								0.002*	
								(1.68)	
(Unemployment Rate * AQI) (1 lag)									0.217***
									(32.12)
Abnormal Interest Rate Spread (1 lag)	**2667.627**	**2723.403**	**2686.965**	**2707.353**	**2680.204**	**2678.327**	**2675.059**	**2690.801**	**2707.756**
	(95.92)	(97.99)	(96.67)	(97.36)	(96.41)	(96.33)	(96.10)	(96.30)	(97.45)
Abnormal Market Volatility (1 lag)	**0.319**	**0.318**	**0.320**	**0.320**	**0.320**	**0.320**	**0.320**	**0.320**	**0.319**
	(492.45)	(490.22)	(492.73)	(493.00)	(492.51)	(492.85)	(492.63)	(492.48)	(492.56)
Abnormal Inflation Rate (1 lag)	-0.053	-0.047	-0.012	0.005	0.020	-0.050	-0.013	0.000	**-0.130**
	-(.75)	-(.67)	-(.17)	(.07)	(.28)	-(.71)	-(.18)	(.00)	-(1.84)
Abnormal OLED Indicator (1 lag)	**-18.905**	**-18.987**	**-18.982**	**-17.724**	**-19.019**	**-19.104**	**-18.870**	**-18.973**	**-18.513**
	-(66.28)	-(66.61)	-(66.54)	-(60.66)	-(66.67)	-(66.90)	-(66.07)	-(66.51)	-(64.85)
Abnormal Consumer Confidence (1 lag)	**-13.397**	**-13.461**	**-13.401**	**-13.413**	**-13.316**	**-13.382**	**-13.382**	**-13.392**	**-13.414**
	-(110.87)	-(111.44)	-(110.79)	-(111.00)	-(110.00)	-(110.74)	-(110.73)	-(110.70)	-(111.06)

Table 8 – Continues									
Abnormal Business Confidence (1 lag)	**1.520**	**1.446**	**1.604**	**1.623**	**1.562**	**1.382**	**1.555**	**1.587**	**1.528**
	(10.45)	(9.94)	(11.01)	(11.16)	(10.74)	(9.42)	(10.69)	(10.90)	(10.51)
Abnormal Producer Price (1 lag)	**-2.261**	**-2.187**	**-2.266**	**-2.331**	**-2.265**	**-2.235**	**-2.246**	**-2.268**	**-2.245**
	-(54.05)	-(52.24)	-(54.16)	-(55.57)	-(54.16)	-(53.27)	-(53.53)	-(54.22)	-(53.68)
Abnormal Trade Volume (1 lag)	**12.925**	**12.868**	**12.992**	**13.000**	**13.014**	**12.964**	**12.976**	**12.989**	**13.000**
	(172.40)	(171.81)	(173.53)	(173.68)	(173.77)	(173.03)	(173.22)	(173.26)	(173.74)
Abnormal Unemployment Rate (1 lag)	**83.196**	**83.152**	**83.366**	**83.380**	**83.462**	**83.395**	**83.259**	**83.451**	**83.431**
	(160.78)	(160.82)	(161.04)	(161.20)	(161.34)	(161.21)	(160.76)	(161.28)	(161.36)
Trend	**2.613**	**2.600**	**2.615**	**2.611**	**2.613**	**2.621**	**2.617**	**2.616**	**2.588**
	(97.19)	(96.75)	(97.23)	(97.10)	(97.19)	(97.44)	(97.33)	(97.28)	(96.24)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	978,434	978,434	978,434	978,434	927,084	927,084	927,084	927,084	927,084
R-Sqr	53.52%	53.57%	53.51%	53.53%	53.51%	53.51%	53.51%	53.51%	53.56%
Panel D: Market Environment Characteristics interacted with Dummy AQI									
	Dummy AQI								
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dummy AQI Estimate (1 lag)	3.214***	3.037***	2.393***	2.536***	2.487***	2.412***	2.492***	2.116***	4.770***
	(32.34)	(33.82)	(26.90)	(28.39)	(27.83)	(27.23)	(28.09)	(23.15)	(43.64)
(Interest Rate Spread * AQI) (1 lag)	-965.7***								
	-(18.02)								
(Market Volatility * AQI) (1 lag)		0.048***							
		(41.72)							
(Inflation Rate* AQI) (1 lag)			-0.191						
			-(1.04)						
(OLED Leading Indicator * AQI) (1 lag)				8.445***					
				(11.53)					

Table 8 – Continues									
(Consumer Confidence * AQI) (1 lag)					-2.05***				
					-(7.24)				
(Business Confidence * AQI) (1 lag)						-5.31***			
						-(13.55)			
(Producer Price * AQI) (1 lag)							-1.58***		
							-(16.40)		
(Trade Volume * AQI) (1 lag)								1.488***	
								(12.60)	
(Unemployment Rate * AQI) (1 lag)									25.86***
									(36.93)
Abnormal Interest Rate Spread (1 lag)	**2869.355**	**2743.624**	**2718.248**	**2737.966**	**2713.889**	**2707.155**	**2700.598**	**2741.226**	**2744.860**
	(98.87)	(98.79)	(97.81)	(98.34)	(97.63)	(97.37)	(97.11)	(98.43)	(98.81)
Abnormal Market Volatility (1 lag)	**0.319**	**0.308**	**0.319**	**0.319**	**0.319**	**0.319**	**0.319**	**0.319**	**0.319**
	(491.25)	(443.46)	(491.66)	(491.80)	(491.29)	(491.70)	(491.26)	(490.64)	(491.42)
Abnormal Inflation Rate (1 lag)	-0.070	-0.095	0.008	-0.008	-0.016	-0.073	-0.067	-0.017	**-0.130**
	-(.99)	-(1.34)	(.10)	-(.11)	-(.22)	-(1.03)	-(.95)	-(.24)	-(1.83)
Abnormal OLED Indicator (1 lag)	**-19.328**	**-19.468**	**-19.333**	**-20.021**	**-19.341**	**-19.456**	**-19.183**	**-19.353**	**-18.711**
	-(67.78)	-(68.32)	-(67.79)	-(68.71)	-(67.82)	-(68.19)	-(67.24)	-(67.86)	-(65.54)
Abnormal Consumer Confidence (1 lag)	**-13.551**	**-13.603**	**-13.497**	**-13.562**	**-13.113**	**-13.497**	**-13.517**	**-13.564**	**-13.666**
	-(112.11)	-(112.63)	-(111.62)	-(112.11)	-(99.24)	-(111.68)	-(111.85)	-(112.13)	-(113.07)
Abnormal Business Confidence (1 lag)	**1.660**	**1.632**	**1.659**	**1.686**	**1.648**	**2.225**	**1.656**	**1.692**	**1.633**
	(11.41)	(11.22)	(11.40)	(11.59)	(11.32)	(14.71)	(11.38)	(11.63)	(11.23)
Abnormal Producer Price (1 lag)	**-2.253**	**-2.173**	**-2.262**	**-2.302**	**-2.262**	**-2.210**	**-1.954**	**-2.262**	**-2.254**
	-(53.84)	-(51.90)	-(54.01)	-(54.81)	-(54.05)	-(52.62)	-(42.63)	-(54.04)	-(53.90)
Abnormal Trade Volume (1 lag)	**13.042**	**13.023**	**13.090**	**13.080**	**13.108**	**13.066**	**13.058**	**12.821**	**13.050**
	(174.17)	(174.12)	(174.89)	(174.76)	(175.04)	(174.54)	(174.43)	(164.72)	(174.47)
Abnormal Unemployment Rate (1 lag)	**83.821**	**83.508**	**84.309**	**84.236**	**84.308**	**84.264**	**84.130**	**84.432**	**79.222**

Table 8 – Continues									
	(161.96)	(161.57)	(162.91)	(162.94)	(163.07)	(163.00)	(162.72)	(163.28)	(148.22)
Trend	**2.604**	**2.574**	**2.621**	**2.618**	**2.616**	**2.626**	**2.627**	**2.628**	**2.580**
	(96.71)	(95.62)	(97.32)	(97.24)	(97.19)	(97.55)	(97.58)	(97.60)	(95.83)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	927,084	927,084	927,084	927,084	927,084	927,084	927,084	927,084	927,084
R-Sqr	53.48%	53.55%	53.46%	53.47%	53.46%	53.47%	53.47%	53.47%	53.53%
Panel E: Market Environment Characteristics interacted with Category AQI									
	Category AQI								
	Dependent Variable: $TE_{(i,j,t)}$ (Tracking Errors)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Category AQI Estimate (1 lag)	2.086***	1.907***	1.717***	1.756***	1.784***	1.684***	1.727***	1.722***	2.714***
	(46.94)	(46.46)	(42.15)	(42.87)	(43.51)	(41.35)	(42.29)	(41.51)	(55.72)
(Interest Rate Spread * AQI) (1 lag)	-507.2***								
	-(21.07)								
(Market Volatility * AQI) (1 lag)		0.019***							
		(36.35)							
(Inflation Rate* AQI) (1 lag)			0.341***						
			(4.25)						
(OLED Leading Indicator * AQI) (1 lag)				2.992***					
				(10.18)					
(Consumer Confidence * AQI) (1 lag)					-1.91***				
					-(14.90)				
(Business Confidence * AQI) (1 lag)						-2.98***			
						-(18.12)			
(Abnormal Producer Price * AQI) (1 lag)							-0.24***		
							-(5.30)		
(Abnormal Trade Volume * AQI) (1 lag)								-0.08	

Table 8 – Continues

								-(1.55)	
(Unemployment Rate * AQI) (1 lag)									12.06***
									(37.47)
Abnormal Interest Rate Spread (1 lag)	**3657.232**	**2725.239**	**2690.280**	**2700.792**	**2678.969**	**2673.946**	**2680.598**	**2684.974**	**2706.802**
	(68.10)	(98.08)	(96.81)	(97.12)	(96.39)	(96.20)	(96.31)	(96.19)	(97.47)
Abnormal Market Volatility (1 lag)	**0.319**	**0.281**	**0.320**	**0.320**	**0.319**	**0.320**	**0.320**	**0.320**	**0.319**
	(492.28)	(227.00)	(492.63)	(492.69)	(492.41)	(492.97)	(492.58)	(492.55)	(492.53)
Abnormal Inflation Rate (1 lag)	-0.058	-0.050	-0.683	0.007	0.028	-0.093	-0.017	-0.006	**-0.124**
	-(.82)	-(.70)	-(3.91)	(.09)	(.39)	-(1.31)	-(.23)	-(.08)	-(1.75)
Abnormal OLED Indicator (1 lag)	**-18.880**	**-19.076**	**-18.955**	**-24.142**	**-18.978**	**-19.178**	**-18.865**	**-18.941**	**-18.276**
	-(66.19)	-(66.91)	-(66.44)	-(41.28)	-(66.53)	-(67.17)	-(66.04)	-(66.39)	-(63.99)
Abnormal Consumer Confidence (1 lag)	**-13.411**	**-13.506**	**-13.412**	**-13.405**	**-9.589**	**-13.400**	**-13.392**	**-13.381**	**-13.398**
	-(111.00)	-(111.81)	-(110.87)	-(110.92)	-(33.99)	-(110.91)	-(110.82)	-(110.62)	-(110.95)
Abnormal Business Confidence (1 lag)	**1.458**	**1.443**	**1.571**	**1.549**	**1.502**	**7.013**	**1.531**	**1.532**	**1.421**
	(10.03)	(9.93)	(10.79)	(10.65)	(10.33)	(20.93)	(10.52)	(10.52)	(9.77)
Abnormal Producer Price (1 lag)	**-2.254**	**-2.188**	**-2.257**	**-2.296**	**-2.259**	**-2.195**	**-1.773**	**-2.261**	**-2.237**
	-(53.91)	-(52.30)	-(53.94)	-(54.70)	-(54.01)	-(52.29)	-(17.56)	-(54.05)	-(53.53)
Abnormal Trade Volume (1 lag)	**12.953**	**12.960**	**13.027**	**13.031**	**13.061**	**12.971**	**13.013**	**13.192**	**13.038**
	(172.95)	(173.26)	(174.09)	(174.15)	(174.49)	(173.22)	(173.77)	(101.96)	(174.37)
Abnormal Unemployment Rate (1 lag)	**82.954**	**82.977**	**83.191**	**83.282**	**83.208**	**83.182**	**83.144**	**83.247**	**59.508**
	(160.23)	(160.40)	(160.61)	(160.90)	(160.76)	(160.72)	(160.46)	(160.76)	(72.72)
Trend	**2.601**	**2.583**	**2.608**	**2.609**	**2.603**	**2.618**	**2.612**	**2.609**	**2.566**
	(96.73)	(96.09)	(96.98)	(97.00)	(96.78)	(97.34)	(97.11)	(96.96)	(95.38)
Fund Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	927,084	927,084	927,084	927,084	927,084	927,084	927,084	927,084	927,084
R-Sqr	53.53%	53.58%	53.51%	53.52%	53.52%	53.53%	53.51%	53.51%	53.58%

Table 9: Results from Event Study

This table presents the result from equation (8) by running the regression twice. We only pick mutual funds from Beijing for this test because fund managers in Beijing should benefit from the clean air environment and be able to minimize the tracking errors during this period. Additionally, we employ fund fixed-effect variable to capture the time-invariant unobserved fund characteristics in each model. Please refer to endogeneity test section for the details of the equation. We parenthesize t-statistics under each coefficient below. Here, *, **, and *** designate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: Tracking Error	
	(1)	(2)
Post Dummy	-4.214***	-63.132***
	-(2.72)	-(2.01)
Fund Age (1 lag)		8.839***
		(3.41)
Manager Turnover (1 lag)		-0.017
		-(.40)
Fund flow (1 lag)		14.232***
		(4.64)
Natural Log of Fund Size (1 lag)		27.459***
		(6.38)
Management team (1 lag)		-1.014
		-(.64)
Fund Fixed Effect	Yes	Yes
No. of Obs	714	663
R-Sqr	22.42%	43.88%

Table 10: Difference-in-differences in the Effect of Air Quality on Tracking Errors

This table presents a difference-in-differences analysis of air quality on the tracking errors of mutual funds surrounding Beijing Olympic Games 2008 event. In Panel A, we report the result of this probit model depending on pre-matched funds in the treatment and control groups by following equation (9). The dependent variable of the probit model equals to "1" if the fund fits to the treatment group and "0" if the fund belongs to the control group. We use fund characteristics as control variables in this regression. In Panel A, we report the results of the same probit model depending on the post-matched funds in the treatment and control groups. We report statistical distribution of the propensity scores of the funds in both treatment and control groups along with their differences. We run difference-in-differences regression based on the matched sample by following equation (10). We report this result in Panel C. Please see the endogeneity test section in this study or variable description section in Appendix C for more details. We parenthesize t-statistics under each coefficient below. Here, ∗, ∗∗, and ∗∗∗ designate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Probit Regressions with pre-matched and post matched samples

Variables (Monthly Average)	Pre-match	Post-match
	(1)	(2)
Fund Age	0.006	-0.007
	(.97)	(.82)
Fund flow	-0.213*	-2.319
	(2.93)	(.40)
Log of Fund Size	0.331**	-0.541
	(3.71)	(1.40)
Fund Turnover	0.004***	-0.001
	(12.66)	(.28)
Expense Ratio	11.242**	-114.800*
	(5.37)	(3.26)
Management team	0.370**	0.014
	(4.12)	(.00)
No. of Obs	228	96
p-value of Chi-square	0.0026	0.0026

Panel B: Propensity Scores Distribution

Group	No. of Obs	Mean	Min.	Median	Max.	Std Dev
Treatment	17	0.251	0.014	0.260	0.460	0.141
Control	17	0.252	0.002	0.269	0.472	0.144
Difference	17	0.009	0.000	0.009	0.020	0.006

Table 10 – Continues

Panel C: Difference-in-differences Regression

Variables (Monthly Average)	Dependent Variable: Tracking Error			
	(1)	(2)	(3)	(4)
After*Treatment	-82.76***	-15.67***	-19.20***	-16.33***
	-(8.51)	-(2.50)	-(3.57)	-(2.94)
After	80.40***	17.62***	15.89***	23.53***
	(14.52)	(3.51)	(4.23)	(2.72)
Treatment	74.99***	8.78*	81.71***	9.90
	(13.00)	(1.90)	(8.29)	(1.16)
Fund Age		0.109		-1.080
		(1.26)		-(.66)
Fund flow		5.07***		0.555
		(3.66)		(.31)
Log of Fund Size		-4.28*		-10.58***
		-(1.90)		-(2.50)
Fund Turnover		0.031*		-0.062
		(1.91)		-(1.57)
Expense Ratio		53.24***		41.24***
		(4.06)		(2.62)
Management team		-1.936		-3.148
		-(.66)		-(.76)
Fund Fixed Effect	No	No	Yes	Yes
No. of Obs	199	182	199	182
R-Sqr	73.79%	92.92%	44.63%	50.33%

Figures

Figure 1: Air Pollution Distribution for Pre, Post and During BOG08

We present monthly average AQI of treated city, in this case only Beijing due to fund availability, and other control cities. We calculate the average of AQI of all other cities together. From this chart, we clearly observe treated city's AQI dives in during the BOG08 event, when Chinese government implemented a lot of additional pollution control regulations. However, we do not see any significant change in control cities' AQI before and during the BOG08 as the government did not enforce these regulations in these cities.

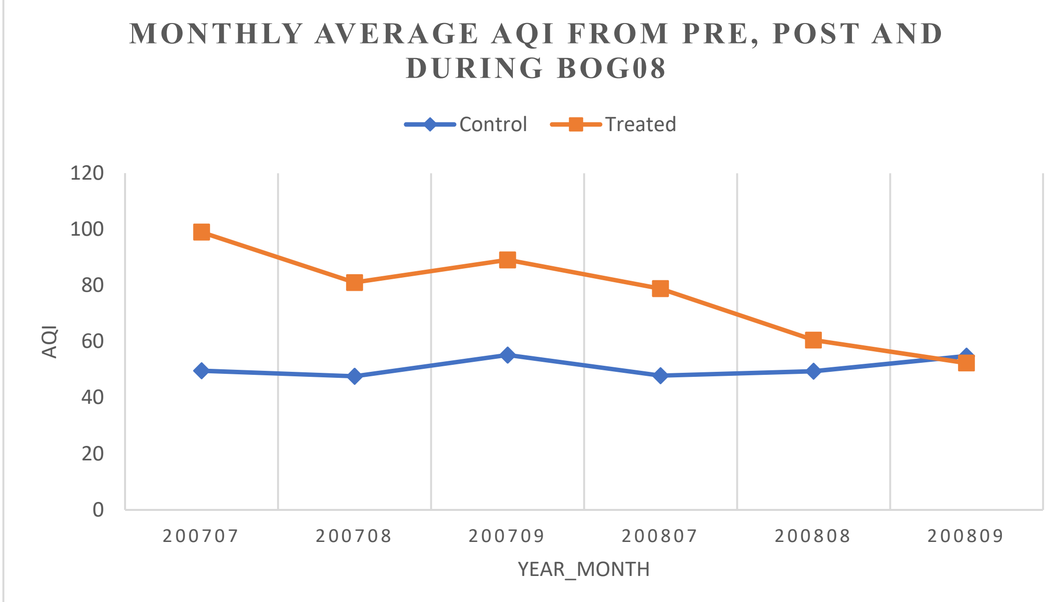


Figure 2: Beijing's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that some months in 2013 AQI data are missing, which we acknowledge in the footnotes beforehand.

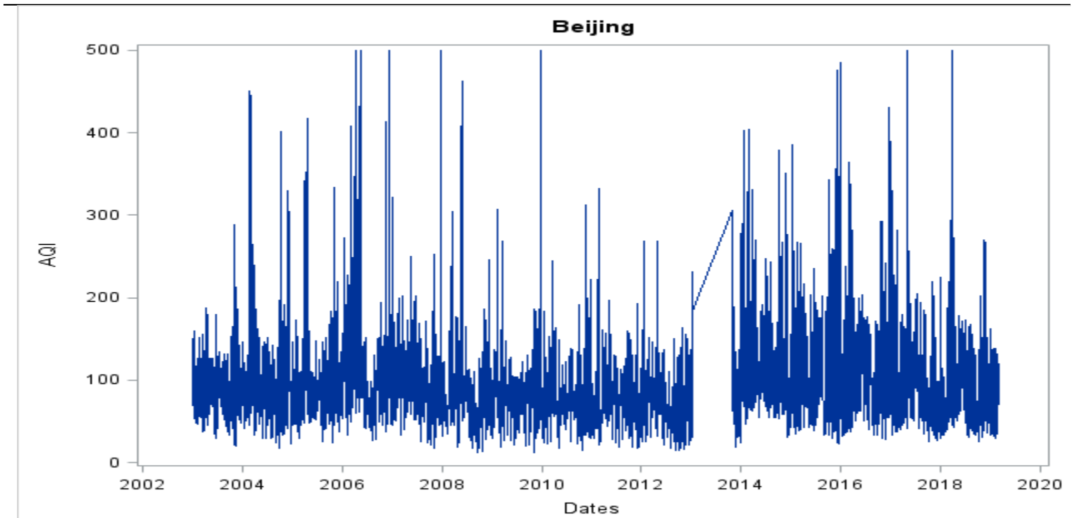


Figure 3: Chongqing's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that some months in 2013 AQI data are missing, which we acknowledge in the footnotes beforehand. From this figure, we can observe that the AQI volatile over the sample period in Chongqing.

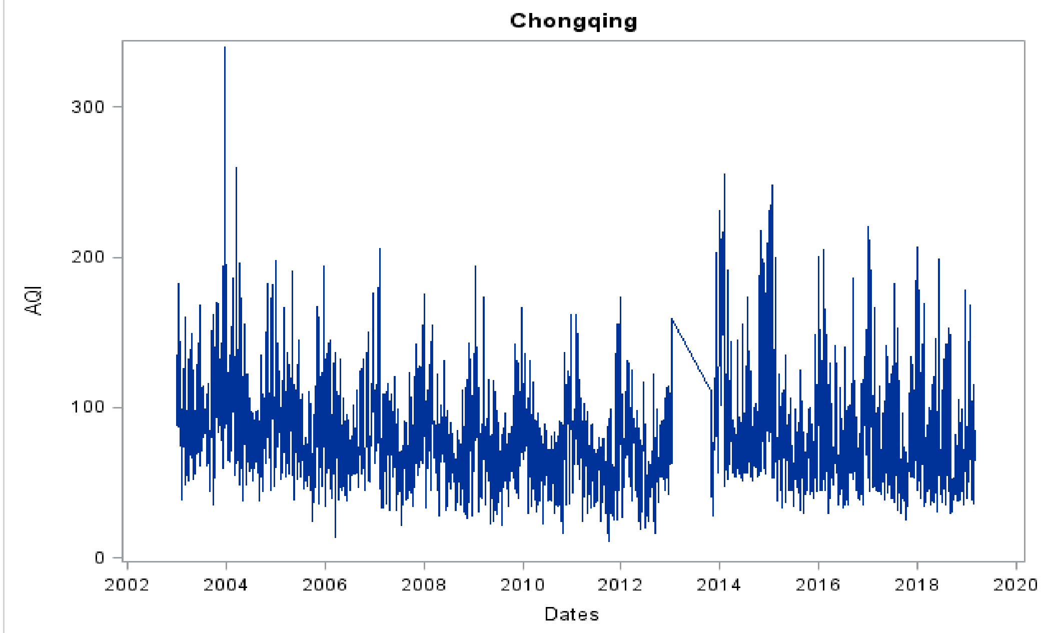


Figure 4: Guangzhou's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that some months in 2013 AQI data are missing, which we acknowledge in the footnotes beforehand. It seems that 200 AQI is quite regular after 2014 in Guangzhou.

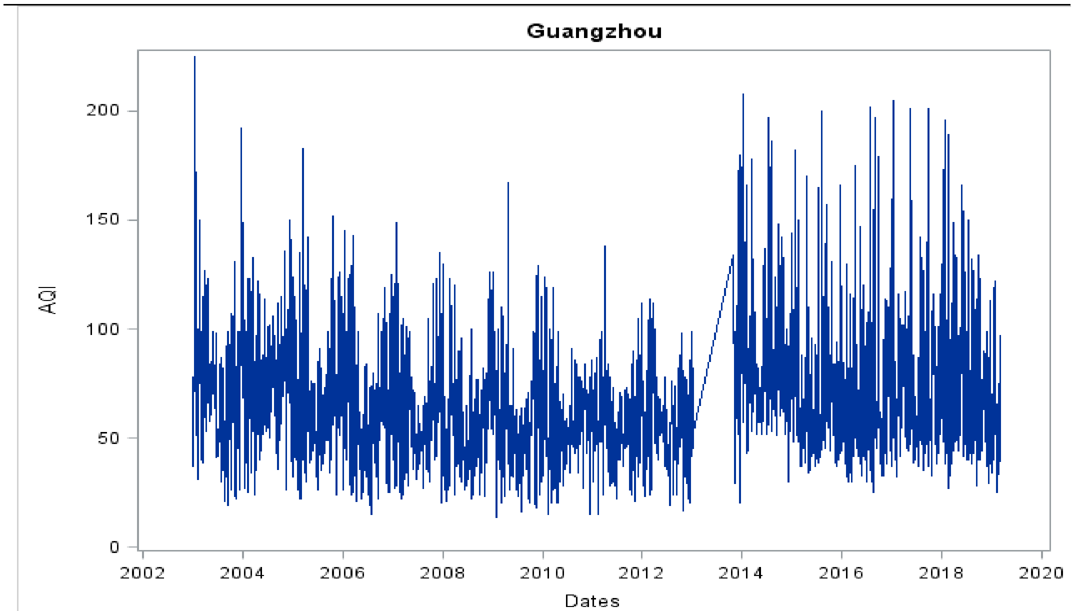


Figure 5: Hangzhou's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that no AQI data are missing in Hangzhou, which we acknowledge in the footnotes beforehand.

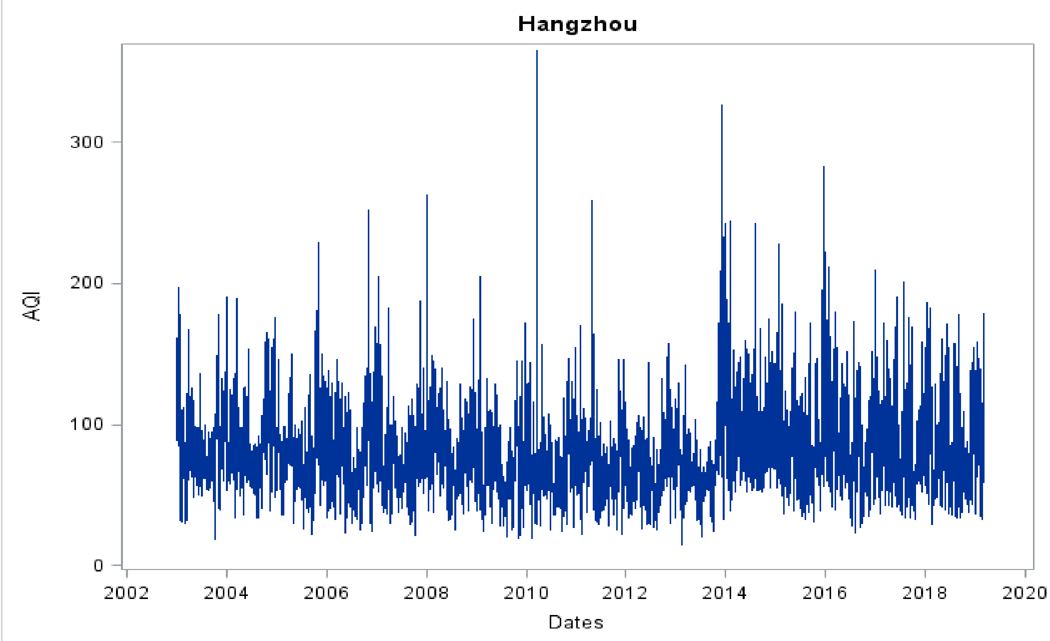


Figure 6: Shanghai's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that no AQI data are missing, which we acknowledge in the footnotes beforehand.

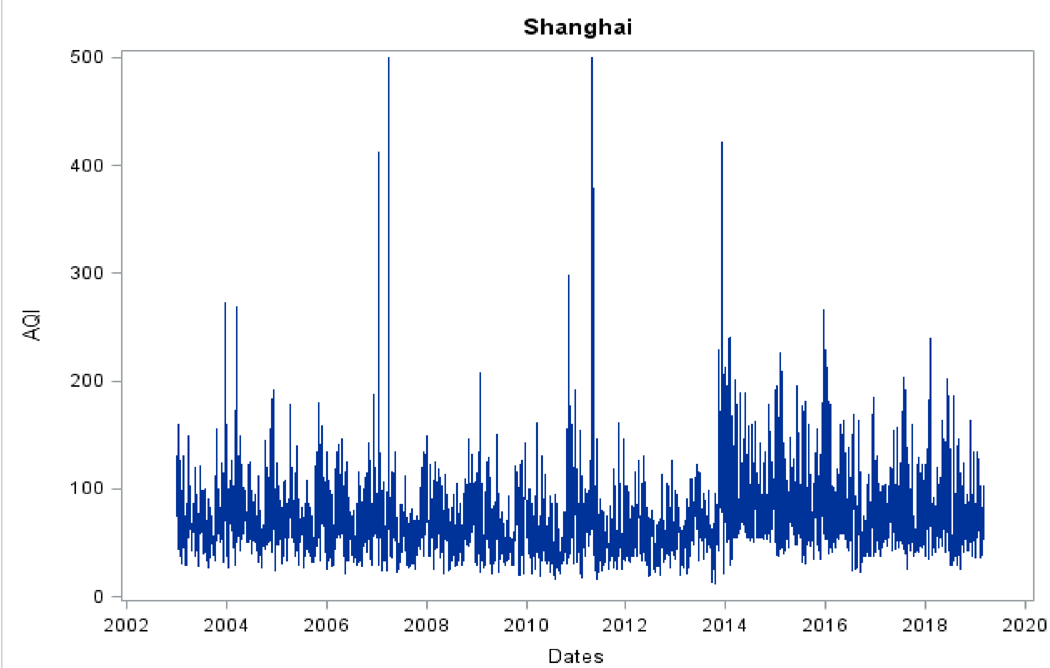


Figure 7: Shenzhen's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that some months in 2013 AQI data are missing in Shenzhen, which we acknowledge in the footnotes beforehand.

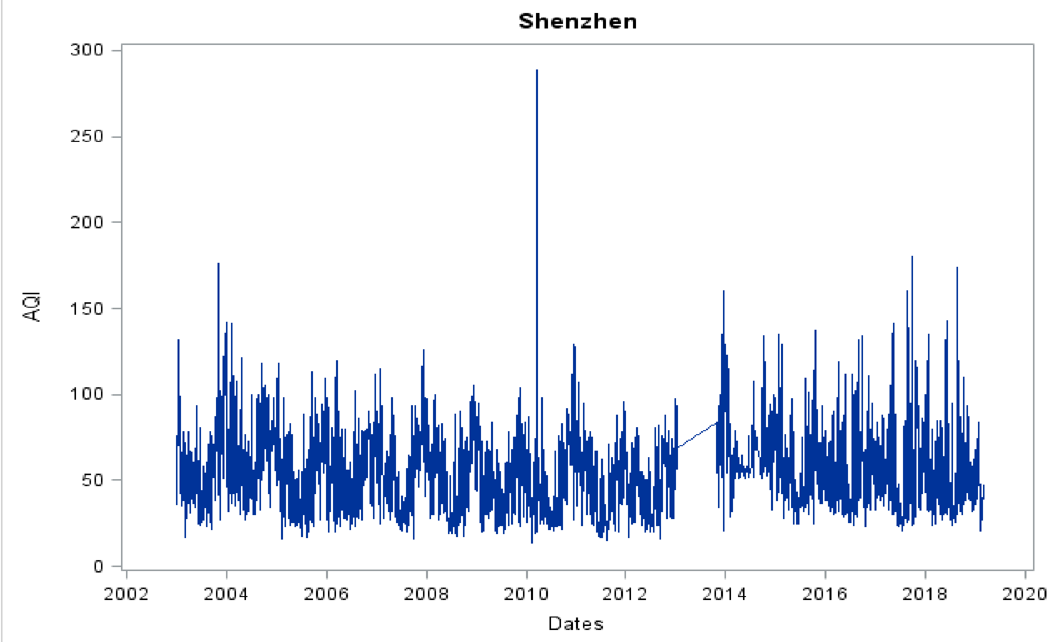


Figure 8: Tianjin's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that some months in 2013 AQI data are missing, which we acknowledge in the footnotes beforehand. We can observe higher AQI from 2014 in Tianjin.

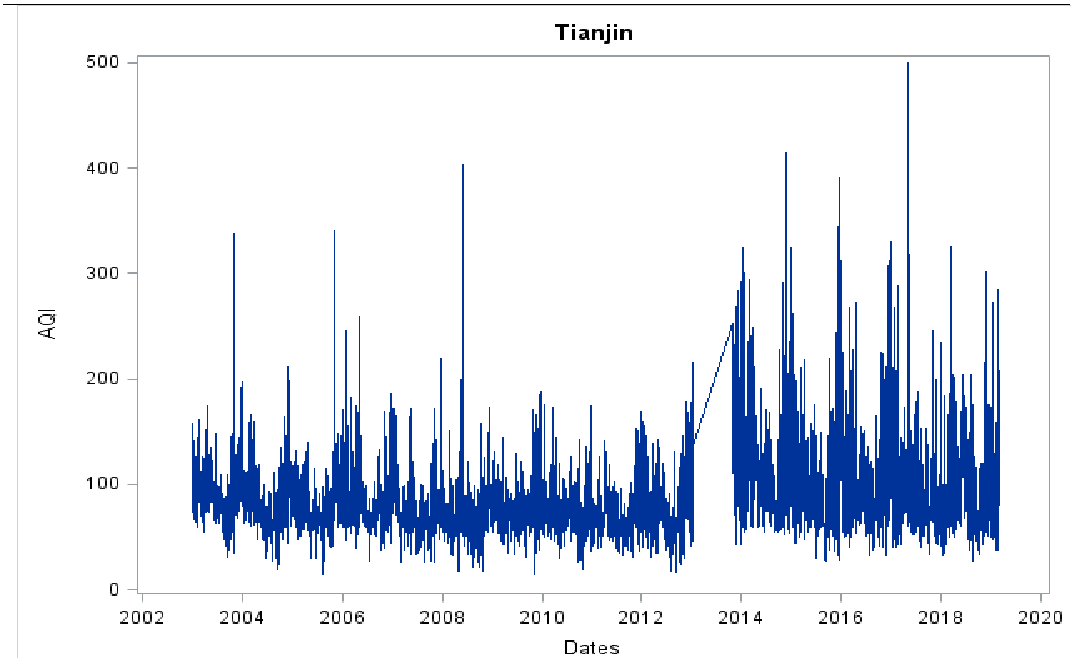


Figure 9: Xiamen's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that some months in 2013 AQI data are missing, which we acknowledge in the footnotes beforehand. Xiamen seems less polluted in our sample except in 2010, which indicates 500 AQI value in one day.

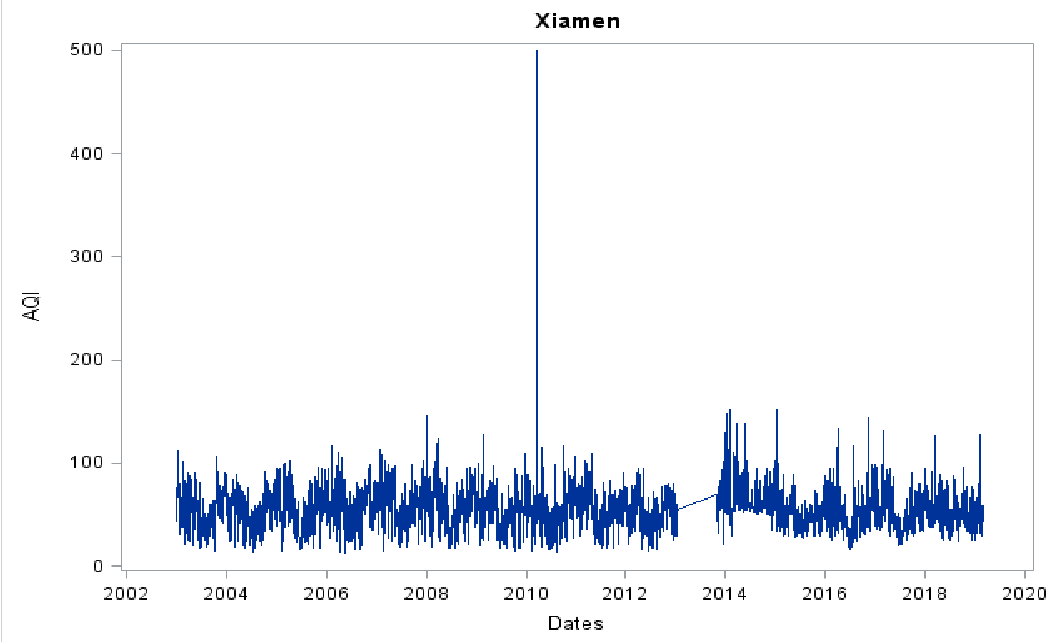
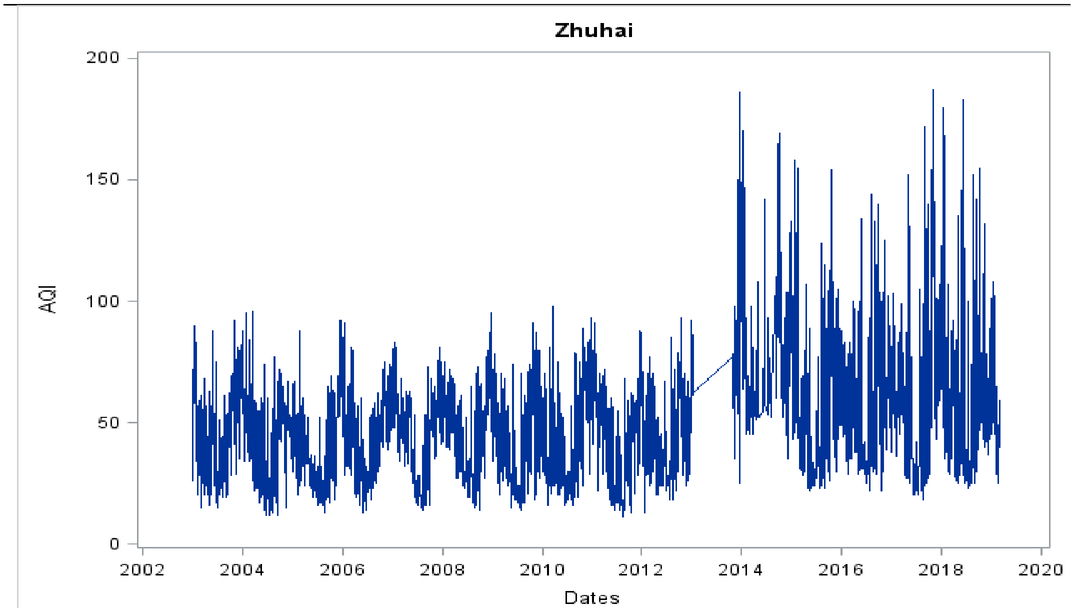


Figure 10: Zhuhai's Daily AQI Distribution

This presents daily AQI over the period in our sample. We can observe here that some months in 2013 AQI data are missing, which we acknowledge in the footnotes beforehand. It seems air pollution increases significantly in Zhuhai from 2014.



Appendices

Appendix A: List of Health Issues AQI Producing

To show the severity of poor air quality, Chinese Ministry of Environmental Protection classifies AQI into six groups. Under 100 value indicate no or little health risk, however people consider over 300 value as the most hazardous risk. People consider days with AQI more than 100 as hazy days and less than 100 as blue-sky days.

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 to all people
From 300 to the highest value	Most hazardous	Severe health problems to all people

Appendix B: Pollution Control Regulations for the BOG08 Event

Regulations in Pre-Olympic around Beijing (From November 1, 2007 to July 20, 2008)	Regulations during BOG08 around Beijing (From July 20 to September 20, 2008)
1. All the energy industries with coal-fired system must install denitrification services and system of removing dust and desulfurization. 2. Government sectors must swap all heavy-emission automobiles with low ones. 3. All gas stations, tankers and oil storage facilities must place oil and gas assembly as well as recovery system units. 4. The government shut down all the chemical plants along with other factories, specially polluted ones. 5. They increase the gas price double from November 2007 to June 2008. 6. They also make Capital Steel Company to reposition their production operation to reduce their productions.	1. The government bans automobiles that cannot meet the exhaustion standard from European No. 1. 2. They permit only automobiles, having licence plates even-numbered (odd-numbered), on even-numbered (odd-numbered) days. 3. They also set a rule of reducing emissions by 30 percent for power and chemical production plants. 4. The government shut down well above 140 concrete mixing plants, 100 lime production plants along with 20 cement factories entirely during the BOG08. 5. They also stop the government construction projects during this time. 6. Finally, they enforce similar regulations to all neighbouring cities as air can translocate hazardous air pollutants.

Appendix C: Variable Definition

Variables	Description
TE (Tracking Errors)	Refers to daily estimated volatility (using GARCH model) of the active return, difference between daily funds' return and their benchmark return.
Base AQI	Refers to original value of daily observation data of Air Quality Index (AQI), which contains the average of hourly AQI values over a day for each day value.
Log AQI	Refers to natural logarithm of base AQI.
Abnormal AQI	Refers to subtracting mean of base AQI from daily observations of AQI for each city.
Dummy AQI	If AQI is less than 101 then Dummy AQI value is "0" and if AQI is more than 100 then Dummy AQI value is "1".
Category AQI	Each category consecutively starting from 1. AQI (1-50) is categorized as 1, AQI (51-100) as 2, AQI (101–150) as 3, AQI (151–200) as 4, AQI (201–300) as 5, and AQI (300+) as 6 and no value means "0".
Trend	Refers to capturing time-varying unobserved characteristics in year y. If it is the 1st year of the sample, the value is 1 and then it increases by ascending order for each year.
Fund Age	Refers to funds' operation duration in monthly basis.
Manager Turnover	Refers to computing the percentage change of the members in the management team monthly and then using absolute function to get final variable of manager turnover in percent.
Fund flow	Refers to multiplying daily change in fund size by (1 + fund return) to obtain daily fund flow.
Log of Fund Size	Natural logarithm of fund size, money that funds manage.
Turnover	Turnover ratio represents a percentage of a fund's replacement of all its holdings over a year.
Expense Ratio	Refers to management expenses or fund operating costs as a percentage of average value of invested fund assets in a fund.
Management team	Refers to the number of members in a fund's management team in a certain day of a month in a year.
Experience	Refers to how long a manager runs his operation over his/ her career. This variable represents average of daily experience per fund across all fund managers on that day.

Appendix C – Continues	
Variables	**Description**
Managing Funds	Refers to managers' monthly average managing funds.
Male Pct	Refers to monthly proportion of male members in a management team in percentage.
Bachelor Pct	Refers to the proportion of bachelor's degree holders in a management team in percentage.
Master Pct	Refers to the proportion of master's degree holders in a management team in percentage.
PhD Pct	Refers to the proportion of PhD degree holders in a management team in percentage.
CFA Pct	Refers to the proportion of CFA degree holders in a management team in percentage.
Interest Rate Spread	Refers to the difference between 6-month interbank deposit rate and 10-year Treasury bond yield.
Market Volatility	Refers to the volatility of daily return of CSI 300.
Inflation Rate	Refers to monthly percentage change of consumer price index.
OLED Leading Indicator	Consists of economic variables that give a sense of the future state of an economy in monthly basis.
Consumer Confidence	Refers to the consumers' optimism through their spending and savings, in monthly basis.
Business Confidence	Refers to future growth, in monthly basis.
Producer Price	Refers to domestic producers' selling prices of goods and services.
Natural Log of Trade Volume	Refers to the sum of monthly market value traded data of both Shanghai Stock Exchange and Shenzhen Stock Exchange.
Unemployment Rate	Refers to quarterly unemployment rate in percentage.
Abnormal Characteristics	Refers to deducting the average of each dominant characteristic from its daily observed characteristic.
Post Dummy	Refers to the value "1" if the tracking errors belong to August 2008 and "0" if they belong to August 2007.
After	Refers to "1" if funds are in the months of 2008 otherwise "0".
Treatment	Equals to "1" if a fund belongs to Beijing or Tianjin.
After*Treatment	Refers to interaction between these two and capture the difference of the tracking errors in treatment group relative to control group.

Appendix D: AQI Trend across Cities

This appendix presents the results of AQI trend across cities in our sample over the whole period. We run simple regression (Wooldridge, 2016, p. 329) where dependent variable is AQI and independent variable is Trend. Trend variable assigns value one for the first year of our AQI sample and then increase the value in ascending order for each post year. We parenthesize t-statistics under each coefficient below. Here, ∗, ∗∗, and ∗∗∗ designate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: Air Quality Index
Cities	(1)
Beijing	0.00162**
	(2.12)
Chongqing	-0.00285***
	(-6.62)
Guangzhou	0.00142***
	(4.02)
Hangzhou	0.000836**
	(2.03)
Shanghai	0.0035***
	(7.73)
Shenzhen	-0.00053*
	(-1.81)
Tianjin	0.00697***
	(12.62)
Xiamen	-0.00092***
	(-3.27)
Zhuhai	0.00611***
	(20.08)

Appendix E: Analyses' Coding Description

We briefly present some important coding work that we do for our analysis in this section. We do not report the coding for cleaning the data and constructing most of the variables. However, we discuss the whole process of cleaning and constructing variables in data and variable section. In the following step, we first run equation (3) of our models to obtain estimated daily tracking errors. Please find the coding of that work below:

```
/*Reg with Garch Model*/

Proc Sort Data = Stat.Project;
By FundID Dates City;
Run;

Proc autoreg data = Stat.Project Outest = Stat.Test Covout Plots = None
Noprint;
By FundID;
      model Actret = Lagact/ garch = ( q=1, p=1);
        nloptions maxiter=500 maxfunc=5000;
        output out = Stat.Proj_gr ht = Wht;
   run ;
   quit;

Data Stat.Proj_gr1;
Set Stat.Proj_gr;
Res = sqrt(Wht);
Run;
```

Afterwards, we run our baseline analysis by following equation (5) on panel data. We run regressions 5 times with a substitute AQI category each time. Please find the example of first regression coding below and we execute rest of the regressions by plugging in other AQI category variables. "Res" refers to tracking errors for all of the following codings from here.

```
*Running a baseline regression on panel data with trend and Fund fixed
effect;

Proc sort Data = Stat.Proj_ gr1;
By FundID Dates City;
Run;

Proc glm Data = Stat.Proj_test;
Absorb FundID;
ods output
ParameterEstimates = Stat.Params
FitStatistics = Stat.fit
Nobs = Stat.Obs;
model Res = Lagcat Trend / noint solution;
Run;
Quit;
```

In the next step, we follow the same equation to run baseline analysis per city. Similarly, we run 5 regressions for each city with a substitute AQI category each time. To execute this analysis, we first sort our data by city in this time and then by other variable as follows. Please find the example of first regression coding in the next page.

Appendix E – Continues

```
*Running a baseline regression by city with trend and Fund effect;

Proc sort Data = Stat.Proj_gr1;
By City FundID Dates;
Run;

Proc glm Data = Stat.Proj_test;
By City;
Absorb FundID;
ods output
ParameterEstimates = Stat.Params
FitStatistics = Stat.fit
Nobs = Stat.Obs;
model Res = Lagcat Trend / noint solution;
Run;
Quit;
```

Before running the next regrssions, we want to calculate funds' manager characteristics. From each manager attributes, we calculate average and proportion depending on the management team in each day of fund operation. Managers' experience and managing fund variables are just the daily average across all managers. Other proportion variables are calculated as follows:

```
Proc sort data = Stat.Fundmngr;
By FundID Year_month;
Run;

Data Stat.Fundmngr;
Set Stat.Fundmngr;
Summ = Sum(Gender, Gender1, Gender2, Gender3, Gender4, Gender5, Gender6,
Gender7, Gender8, Gender9, Gender10, Gender11);
Sumba = Sum(Bachelor, Bachelor1, Bachelor2, Bachelor3, Bachelor4,
Bachelor5, Bachelor6, Bachelor7, Bachelor8, Bachelor9, Bachelor10,
Bachelor11);
Summa = Sum(Master, Master1, Master2, Master3, Master4, Master5, Master6,
Master7, Master8, Master9, Master10, Master11);
Sumph = Sum(PhD, PhD1, PhD2, PhD3, PhD4, PhD5, PhD6, PhD7, PhD8, PhD9,
PhD10, PhD11);
Sumcf = Sum(CFA, CFA1, CFA2, CFA3, CFA4, CFA5, CFA6, CFA7, CFA8, CFA9,
CFA10, CFA11);
Run;

Data Stat.Fundmngr;
Set Stat.Fundmngr;
Malepor = (Summ/Mngteam);
Femalepor = (1 - Malepor);
Bachelorpor = (Sumba/Mngteam);
Masterpor = (Summa/Mngteam);
Phdpor = (Sumph/Mngteam);
Cfapor = (Sumcf/Mngteam);
Run;
```

In this step, we control for all determinant characteristics of tracking errors to see whether our baseline result remains robust. We follow equation (6) and run 5 regression each time of fund, manager and market characteristics. Please find an example of our first regression with fund characteristics below. Remaining codings follow the process of substituting AQI each time by controlling different sets of characteristics. We just plug in the variables as follows:

Appendix E – Continues

```
*Running reg with fund characteristics and AQI; with Trend and Fund
Effects;

Proc sort Data = Stat.Proj_gr1;
By FundID Dates City;
Run;

Proc glm Data = Stat.Proj_test;
Absorb FundID;
ods output
ParameterEstimates = Stat.Params
FitStatistics = Stat.fit
Nobs = Stat.Obs;
model Res = Lagcat Lagfdflow Laglgsize Lagturn Lagexp Lagmngteam Trend/
noint solution;
Run;
Quit;
```

Next, we run our following codings for equation (7). As we are employing interaction term analysis for each set of tracking errors' determinant characteristics, we need to run 35 regressions for each step. We present the example of following coding work, where we substitute AQI, calculated abnormal characteristics and their interaction term in each regression.

```
*Running reg with fund characteristics interaction; We follow similar step
for others;

Proc glm Data = Stat.Proj_gr1;
Absorb FundID;
ods output
ParameterEstimates = Stat.Params
FitStatistics = Stat.fit
Nobs = Stat.Obs;
model Res = Lagcat Lagcat*Dmnmngteam Dmnfndage Dmnmngrturn Dmnflow Dmnsize
Dmnturn Dmnexpen Dmnmngteam Trend/ noint solution;
Run;
Quit;
```

We present final coding of equation (8) without showing cleaning data in this part. "Post" refers to a dummy variable, which we explain in details in endogeneity test section. Please find the codings of this regression as follows:

```
*Running event study with fund fixed effect;

Proc glm Data = Endo.maintest1;
Class FundID;
ods output
ParameterEstimates = Endo.Params
FitStatistics = Endo.fit
Nobs = Endo.Obs;
model Res = Post FundID Lagfndage Lagmngrturn Lagfdflow Laglgsize
Lagmngteam   / noint solution;
Run;
Quit;
```

Here, we show the prior codings for equation (9) and (10). As we need use monthly average of all variables that we use in the equation, we present the codings of that calculation below:

Appendix E – Continues

```
Proc sql;
Create table Endo.Premavg3 as
Select distinct FundID, Year_month, Y as Y, City as City, Mean(Res) as TE,
mean(fndage) as Fndage,
mean(mngrturn) as Mngrturn, mean(fdflow) as Fndflow, mean(lgsize) as
Fndsize, mean(turn) as Fundturn, mean(expen) as Expense, mean(mngteam) as
Mngteam from Endo.Prematch group by FundID, Year_month;
Run;
```

In this step, we run our pre-match regression to get propensity scores of funds. Please find the following codings for the equation (9) where, “Y” referes to Treatment dummy variable.

```
Proc logistic data = Endo.Premavg3 descending;
Model Y = Fndage Fndflow Fndsize Fundturn Expense Mngteam
 / link = probit;
output out = Endo.Pred_final3 Predicted = Phat;
Run;
```

Afterwards, we run post-match regression on a dataset, which comes from matching funds similar traits according to propensity scores. The codes are below:

```
Proc logistic data = Endo.Posteq3m descending;
Model Y = Fndage Fndflow Fndsize Fundturn Expense Mngteam / link = probit;
output out = Endo.Prod3m Predicted = Phat;
Run;
```

Finally, we run our last model (10) to run difference-in-differences analysis. We use our treated and control funds in this dataset. We present explanation of this part comprehensively in the endogeneity test section. “TE” refers to tracking errors and please refer to above section for others. Please find the following codings for the final test:

```
Proc glm Data = Endo.Diff3m;
ods output
ParameterEstimates = Endo.Params
FitStatistics = Endo.fit
Nobs = Endo.Obs;
model TE = After*Y Y After Fndage Fndflow Fndsize Fundturn Expense Mngteam
/ noint solution;
Run;
Quit;
```