The impact of air pollution on analyst earnings forecasts: Evidence from analysts' corporate site visits in China

Rui Dong
School of Business
Renmin University of China
Beijing 100872, China
E-mail: dongrui@ruc.edu.cn

Yongxiang Wang
Marshall School of Business
University of Southern California
E-mail: Yongxiaw@marshall.usc.edu

Nianhang Xu
School of Business
Renmin University of China
Beijing 100872, China
E-mail: nhxu@ruc.edu.cn

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Abstract

This study examines the influence of air pollution on analyst earnings forecasts. Using a unique sample of analysts' corporate site visits in China and accounting for firm characteristics, analyst characteristics, and weather conditions, we document that air pollution has a negative effect on post-visit earnings forecasts. Specifically, one rank increase in air pollution level (a total of six levels) on the visit day, on average, leads to 7.9% decrease in post-visit earnings forecast. This effect can be attributed to the passive performance in the Q&A session of the visits. In addition, we find a negative relation between air pollution and analysts' regular earning forecast activities. We contribute to the psychology and economics literature by shedding light on the hitherto unexplored effect of air pollution on analyst earnings forecasts.

Key words: Air pollution; analyst earnings forecasts; corporate site visits

JEL Classification Codes: G14, G24

1. Introduction

Air pollution has adverse effects on human physically and psychologically. Medical studies suggest that air pollution is a major threat to human health because it deteriorates cardiopulmonary conditions and contributes to excess mortality (e.g., Dockery et al., 1993; Pope et al., 2009). In the context of psychology, studies find air pollution has a negative effect on brain, causing depressive moods, and passive behaviors[1] (e.g., Fonken et al., 2011; Yackerson, Zilberman, Todder and Kaplan, 2014; Perera et al., 2012).

In finance, several studies document that air pollution influences investor behavior as well. For example, researchers have found air pollution negatively affects investors trading performance and makes them more susceptible to behavioral biases (Huang, Xu, and Yu, 2017; Li, Massa, Zhang, and Zhang, 2017). The finance literature focuses much attention to individual investors, however. It is not clear how air pollution contributes to the behavior of another important participant of capital market – analysts.

The objective of this paper is to examine the impact of air pollution on sell-side analysts' activities. Specifically, we choose the analysts who have conducted site visits to listed firms and study the effect of air pollution during the visiting days on analysts' post-visit earnings forecast in China. Corporate site visit is one of the most important information sources to sell-side analysts (Cheng, Du, Wang and Wang, 2016; Han, Kong and Liu 2017). Visiting analysts gain a greater increase in forecast accuracy than analysts without site visits. The effect is attributed to the analysts' face to face communications with managers and close observations of a firm's operations, which facilitates analysts' information acquisition.

[1] For instance, Fonken et al (2011) report that long-term exposure to ambient air particles causes altered morphological characteristics in hippocampal neurons, leading to depression and anxiety like behaviors in mice. Yackerson, Zilberman, Todder and Kaplan (2014) find a significant correlation between the concentration of solid air-suspended particles and the number of suicide attempts and mental disorders. Perera et al. (2012) follow over 200 children in New York City from in utero to 6-7 years and find that high level exposure to air pollution is positively associated with symptoms of anxiety, depression, and attention problems in children.

In a parallel body of literature, analysts' moods influence their earnings forecasts. For example, Dehaan, Madsen, and Piotroski (2017) find that weather induced negative moods and hence, cause analyst pessimism following earnings announcements. Linking the pollution-investor mood and analyst mood-earnings forecasts literature together, we inference that air pollution during an analyst's corporate site visit affects analysts' moods and that moods have a negative effect on analyst earnings forecast optimism.

China provides a powerful setting for us to test our hypothesis. First, air pollution in China is severe. In 2013, a comprehensive environmental analysis published by Asian Development Bank states that fewer than 1% of the 500 largest cities in China meet the air quality standards recommended by the World Health Organization, and seven of these cities are ranked among the 10 most polluted cities in the world. In addition, air pollution conditions show a great variation across different regions and different time periods. According to China Meteorological Administration, most industrialized and urbanized cities suffer most from air pollution; also, hazy weather occurs more frequently during fall and winter seasons due to the heating operation via coal burning. These circumstances provide an excellent background for our study. Second, in the U.S. and Europe, records of analysts' corporate site visits are not publicly available. In contrast, the Shenzhen Stock Exchange (SZSE) has mandated listed firms to disclose the information related to investors' site visits to the market since 2009. After each visit, a firm needs to disclose the related information such as the visitor's name, the agency she belongs to, and the location where the visit takes place, which enables us to pin down the visiting analyst, the visit city, and the date of visit. Therefore, we combine analysts' site visit records and city-level daily air pollution data to examine the effect of air pollution on analysts' post-visit earnings forecast pessimism. In Appendix A, we present a map displaying the average air quality index (AQI) of the visit cities on visit days. From the map, we observe that there are plenty of cities which have been visited by analysts, and that the air quality shows great variations.

We conduct several analyses using combined data of daily AQI of Chinese cities, analysts' site visit records, and analyst earnings forecasts from 2009 to 2015. Our findings suggest that air pollution increases analysts' post-visit earnings forecast pessimism. This effect remains significant after we control for firm characteristics, analyst characteristics and weather conditions. Economically, analysts' post-visit forecast optimism drops about 7.9% relative to the sample mean when AQI increases 50 units (about 1 rank up as for the level of air pollution). The influence of air pollution varies across different groups of analysts. Specifically, non-star and less experienced analysts are more susceptible to the impact of air pollution, suggesting their professional judgment is not as strong as that of star and experienced analysts. We also find that the effect of air pollution on visiting analysts is short-term, however. If an analyst issues the earnings forecast after site-visit in more than five days, the impact of air pollution is not significant. However, in practice, most earnings forecasts are made in the first five days after a site-visit in China. Therefore, the impact of air pollution on visiting analysts' forecast activities is real.

Our several robustness checks support our findings. First, we use analysts' post-visit recommendations and recommendation revisions as alternative proxies of analysts' optimism and find that air pollution has a negative influence on analysts' stock ratings. Besides, when we take analysts' consensus forecasts into account and construct relative forecast optimism, our results are qualitatively the same. Second, we use different forms of AQI to measure air pollution, such as AQI rank, natural logarithm of AQI, and the scaled quartile rank score of AQI. We also consider the air pollution facing the analysts in their forecast process after the site visit and calculate the relative AQI. All forms of air pollution measures show significant and negative effect on analyst optimism. Next, after swapping the window of five business days to seven calendar days, the results are qualitatively the same. Finally, we further control for analyst fixed effect to account for analyst-level unobserved variables, the results remain robust.

Next, we use some tests to address potential endogeneity issues. First, by presenting numerous comparative statistics between air quality of visit days and the full sample, we clarify that it is highly unlikely for either the firm or the analyst to choose a haze-free day for the visit. Furthermore, when we add variables related to the timing of site visits following Cheng, Du, Wang, Wang (2017), our estimates are virtually unchanged in statistical significance and in economic scale. Next, we apply a quasi-experiment of "Huai-River policy" to further validate our results. Huai River, along with Mountain Qinling, splits China into the northern region and the southern region. Since the 1950s, the Chinese government has adopted a central heating policy which provides free winter heating of homes and offices as a basic right for and only for the urban regions located north of the Huai River. The heating is produced mainly by coal-fueled facilities, in which harmful gases and particulates are generated and released into the atmosphere. Therefore, Huai-River policy creates a discontinuity of air pollution across the Huai-River. We make use of this discontinuity and apply a regression discontinuity design to study the differences of air pollution and analysts' post-visit forecast optimism around the Huai River. We find that from south to north of the Huai River, the severity of air pollution rises drastically while the optimism of visiting analysts' shows a decreasing pattern. Finally, we construct a change model by selecting the analysts who pay multiple visits to the same firm within the same year and regressing the difference of earnings forecast on the differences of visiting AQI as well as other variables. We find that when suffering from higher levels of air pollution, analysts express higher tendency to make downward revisions of their prior earnings forecasts.

Then we explore the channel through which air pollution influences visiting analysts. By analyzing the records of Q&A sessions during corporate site visits, we find a negative effect of air pollution on the number of questions raised by analysts during the visits. This finding suggests that air pollution makes visiting analysts perform more passively in their information acquisition process and further increase their pessimism in the later forecast process.

In additional tests, we further study the influence of air pollution on analysts' regular earnings forecast activities. By regressing analysts' forecast optimism on average AQI of the cities where they work in certain time periods prior to the forecasts, we find a negative relation between air pollution and analysts' regular forecast optimism, which, similar as the effect of air pollution on post-visit earnings forecast optimism, is more salient among non-star analysts and less experienced analysts. Economically, the magnitude of negative effect caused by air pollution on analysts' regular earnings forecasts is smaller than that of post-visit earnings forecasts .

Our paper advances the literature on the relation between moods and investors' behaviors in several ways. First, prior studies find that moods can change individuals' attitude toward future. Although there are ample studies on the relation between air pollution and moods (e.g., Evans, Jacobs, Dooley and Catalano, 1987; Cohen, Evans, Stokols and Krantz, 1986), our paper is the first to link air pollution with analysts' moods (as reflected in their earnings forecasts), investigating how air pollution transmits signals to the capital market by affecting analysts' moods. Second, our findings enhance our understanding on how air pollution impacts individuals' day to day activities. We extend this body of literature from the effect of air pollution in the labor market (e.g., Chang, Zivin, Gross and Neidell, 2016), professional baseball umpires' performance on the field (e.g., Archsmith, Heyes and Sabrian, 2017), the purchase or cancel of health insurance (e.g., Chang, Huang and Wang, 2017), and investors' stock market trading performance (e.g., Huang, Xu, and Yu, 2017; Li, Massa, Zhang, and Zhang, 2017) to analyst behavior. Finally, this paper contributes to a growing literature of analysts' corporate site visit activities. Private interaction with management is valuable to sell-side analysts (Soltes, 2014). Recent studies show that analysts' site visit activities are crucial to analysts' earnings forecasts and to the aggregate capital market (Cheng, Du, Wang and Wang, 2016; Han, Kong and Liu, 2017; Cheng, Du, Wang and Wang, 2017). We contribute to this literature by documenting a material impact of an exogenous factor, air pollution, on analysts' site visit activities.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and develops hypothesis. Section 3 describes the data and sample. Section 4 presents the research design as well as the results and Section 5 concludes.

2. Hypotheses development

Psychological literature has done extensive research about the relation between air pollution and moods. Studies show that air pollution can cause negative sentiments. For example, Cohen, Evans, Stokols and Krantz (1986) find that air pollution is a stressor whose effects can lead to behavioral and physical changes. Evans, Jacobs, Dooley and Catalano (1987) finds that exposure to acute levels of ambient air pollution leads to heightened levels of depression, anxiety, tension, helpless, and anger. Moods affect judgment and decision-making process. Morris (2000) finds that people in positive/negative moods tend to make more optimistic/pessimistic decisions, and changes in mood can affect the success of individuals' activities. A bad mood can lead to higher levels of risk aversion and impact the subjective assessment of the risk in future events (Constans and Mathews, 1993; Slovic and Peters, 2006). Evidence in capital market suggests air pollution affects investor sentiment. Levy and Yagil (2011) finds that levels of air pollution around American stock exchanges is negatively related to the stock returns and they attribute the evidence to bad air quality, mediated by mood, that leads to a collective change in the level of risk aversion, resulting in lower stock returns. Dehaan, Madsen, and Piotroski (2017) shows that bad weather induces moods affect analysts' forecast activities around earnings announcements.

Among the participants in the capital market, analysts, as professional institutional investors, engage in information production. Among many research output, earnings forecast is an important piece information to the market and provides guidance for other investors. Corporate site visits allow analysts to acquire information about the firms. According to a comprehensive survey to over 300 analysts conducted by Brown, Call, Clement, and Sharp (2015), private communication with management is even more useful to analysts than their own primary research using the firms' recent earnings performance, the recent 10-K, or 10-Q reports. During the site visits, analysts get the access of managers and a close observation of firms' operations. Visiting analysts gain a greater improvement in forecast accuracy compared to their counterparts (Cheng, Du, Wang and Wang, 2016; Han, Kong and Liu, 2017). A typical visit usually lasts for 3-4 hours, consisting of a manger's briefing, Q&A session, and a tour of a firm's facilities. Information from this process helps analysts get a more thorough understanding of the firms' conditions and improve their forecast models. As air pollution influences moods and moods affect visiting analysts' perspective of the firm, we infer that analysts' post-visit earnings forecasts are downward biased by the air pollution on the visit day.

Based on the analysis, we hypothesize that air pollution influences visiting analysts' moods and reduce their post-visit earnings forecast optimism. Our null hypothesis is that air pollution has no effect on visiting analysts' forecast optimism. It is because that analysts are professional and have more resources to conduct their research. Hence, their judgments of the firms are likely immunized from external factors like air pollution. Besides, if analysts' site visits are conducted in-door all along, and the visited firms install air cleaners to guarantee fresh air in the offices, then air pollution should have minimal effect on analysts. Finally, if visiting analysts simply listen to the narrative of the management without their own interpretation and judgment of the information, or analysts do not incorporate information acquired from the visits into their subsequent earnings forecasts, then air pollution during the visits may not influence post-visit forecast optimism. Our testable hypothesis, as presented in alternative form, is:

H: Air pollution during an analyst's corporate site visit adversely affects her earnings forecast optimism after corporate site visits.

3. Data and Summary Statistics

3.1 Analysts' site visits and forecasts

The records of analysts' corporate site visits are from the investor relationship activity forms released by SZSE listed firms. From 2009, the SZSE has mandated all listed firms to disclose details about investors' visits, including the visitors' names, dates of visit, their agencies, and the visiting places. We hand collect a sample of such visits of SZSE listed firms from 2009 to 2015. We keep the observations where the visitors' names are on the record and restrict the visitors to sell-side analysts from Chinese brokerages. Then, we combine the visit records with analysts' forecast data from the Chinese Stock Market and Accounting Research (CSMAR) database. To give the visiting analysts enough time to process the information and make sure the firm information is reflected in the earnings forecasts, we drop the earnings forecasts issued the same day as the visit and allow the visiting analyst five trading days to finish her report. Specifically, we choose the earnings forecast from the first report a visiting analyst release within trading days [1, 5] after a visit and calculate her forecast optimism. Following Jackson (2005), we define analysts' forecast optimism as follows,

$$Forecast\_optimism_{i,j,t} = (FEPS_{i,j,t} - AEPS_{i,j,t}) / P_{\mathrm{j}} \times 100$$

Where $FEPS_{i,j,t}$ is the analyst *i*'s forecasted earnings per share (EPS) for firm *j* of year *t*, $AEPS_{i,j,t}$ is the realized EPS of firm *j* in year *t*, and P_{j} is firm *j*'s stock price as of the day prior to the earnings forecast. Follow Huyghebaert and Xu (2016), we keep the EPS forecasts of all years in a report to explore analysts' forecast features across various forecast horizons.

Panel A of Table 1 presents the summary statistics of the main variables. The sample mean and standard deviation of analysts' forecast optimism is 1.953 and 3.498, respectively, which are consistent with prior literature that sell-side analysts' earnings forecasts of the firms are usually higher than the realized value (Francis and Philbrick, 1993; Sedor, 2002). There is a considerable variation of different analysts' levels of optimism.

3.2 Air quality and weather variables

We obtain daily AQI from the official website of the Ministry of Environmental Protection of China (MEPC) and use the data from the EPMAP website as a supplement where there are missing values. The EPMAP/Qingyue Open Environment Data Center (https://data.epmap.org) is an organization which compiles environment data from the government and offers them to the public in standard data formats. The AQI data from EPMAP are extracted from daily air quality report at province and city level environmental protection bureaus. Our data contain AQI and Air Pollution Index (API) of 367 major cities in China. Daily Air Quality Index are available from 2014, which is constructed based on the level of six atmospheric pollutants, namely sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates smaller than 10 μm in aerodynamic diameter (PM10), suspended particulates smaller than 2.5 μm in aerodynamic diameter (PM2.5), carbon monoxide (CO), and ozone (O_3). Before 2014, the Chinese government use API as an official criterion to measure air quality, which monitors SO_2, NO_2, and PM10. According to the standard of Ministry of Environment Protection of China, Air quality can be divided into six categories based on AQI (or API): I-excellent (AQI≤50), II-good (50<AQI≤100), III-lightly polluted (100<AQI≤150), IV-moderately polluted (150<AQI≤200), V-heavily polluted (200<AQI≤300) and VI-severely polluted (AQI>300). A bad pollution is indicated by a larger index and a higher rank. The mean and standard deviation of AQI presented in Panel A of Table1 is 89 and 50, respectively, indicating that air pollution levels of during the site visits have a large variation.

In Panel B of Table 1, we present grouping statistics of analysts' post-visit optimism based on six AQI categories and display them in a histogram in Figure 1. We notice that as the pollution worsens, a descending trend of optimism emerges. When we apply t- and Wilcoxon tests to examine the forecast optimism between the lowest and the highest AQI categories, the differences are significant. Prior literature suggests that certain weather factors can affect investors' moods and further influence their anticipations of the future. Therefore, we collect weather data and match it with analysts' site visit records. Daily weather data are obtained from all 194 international meteorological stations in China provided by China Integrated Meteorological Information Service System, including sunny hours, temperature, humidity, precipitation and wind speed. We match each city to a closest meteorological station based on geographic distance.

3.3 Firm characteristics and analyst characteristics

Following prior literature, we choose firm size, market to book ratio, intangible asset ratio, stock price volatility, stock turnover, stock return, and analyst attention as firm-level control variables (Lim, 2001; Das, Levine and Sivaramakrishnan,1998; Bonner, Beverly, Walther and Young, 2003). We use gender, the number of firms followed by the analyst, the number forecast made by the analyst, brokerage size, and forecast horizon as analyst-level control variables (Clement, 1999; Kang, O'Brien and Sivaramakrishnan, 1994). We obtain financial data from RESSET database and analyst data from CSMAR database.

4. Empirical Results

4.1 Baseline regressions

We use the following model to investigate the influence of air pollution on analysts' post-visit forecast optimism:

$$Forecast\_optimism_{i,j,t} = \alpha + \beta \times AQI_{j,t} + C \times M_{i,j,t} + \varepsilon_{i,j,t}$$

Where $Forecast\_optimism_{i,j,t}$ is analyst *i*'s earnings forecast optimism for firm *j* of year *t* from the first report released within trading days [1, 5] after a site visit; $AQI_{j,t}$ is the AQI of the visit city on the visit day, $M_{i,j,t}$ stacks a list of control variables, including firm characteristics, analyst characteristics and weather conditions. All continuous variables are winsorized at the1% and 99% level. Definitions of all the variables are listed in Appendix B. We control for industry fixed effect and year fixed effect in the model. Also, to account for potential issues raised from seasonality, we further control for season fixed effect. Standard errors are clustered at the firm level.

The results of the main regressions are presented in Table 2. Model (1) does not contain any control variables, while Models (2), (3) and (4) add firm characteristics, analyst characteristics and weather conditions progressively. Consistently in all four models, the coefficients of *AQI* are negative and significant at the 1% or 5% level. That is, there is a significant negative relationship between air pollution of the visit day and analysts' post-visit earnings forecast optimism. Economically, the influence of air pollution on post-visit earnings forecast optimism is significant. For instance, based on the result of Model (4) in Table and the descriptive statistics from Table 1, one level increase of

AQI induces 0.0031*50/1.953*100%≈7.9% decrease in post-visit earnings forecast optimism relative to the average level.

4.2 The role of analyst characteristics

Analysts with stronger abilities may have more resistance to the behavioral bias induced by air pollution during the visits. Therefore, we conduct several sub-sample tests based on analyst characteristics. First, according to Clarke, Ferris, Jayaraman, and Lee (2006) and Xu, Chan, Jiang and Yi (2012), star analysts have a better understanding of firm-specific information and perform better in forecast activities. Hence, we divide the visiting analysts into two groups: star analysts and non-star ones and reexamine the main regression. As shown in columns (1) and (2) of Table 3, air pollution only significantly affects non-star analyst subsample. Second, we consider analysts' experiences to proxy for analyst ability and professionalism (Clement, 1999; Hong, Kubik and Solomon, 2000a), we divide analysts into two categories based on their experiences: highly experienced analysts whose experiences are above the sample median, and less experienced analysts otherwise. Analysts' experiences data are from CSMAR database, which is measured by the logarithm of the number of quarters from an analyst's first report to the end of the visit year. Columns (3) and (4) of Table 3 present the results. We notice that the negative effect of air pollution on visiting analysts is more salient than the less experienced ones, and the economic scale of effect is also larger.

4.3 Robustness tests

We conduct several robustness checks. First, we use other proxies to measure analysts' post-visit optimism. Considering that, apart from earnings forecast, an analyst's stock recommendation can also reflect her projection of the firm's future (Loh and Mian, 2006; Bandyopadhyay, Brown and Richardson, 1995). We use the first post-visit recommendation and recommendation revision within trading days [1, 5] as the dependent variables. Analysts' standardized recommendation data are from CSMAR database. We assign the numbers 1-5 to the ranks "strong sell", "sell", "hold", "buy", and "strong buy", respectively. The higher rank represents more optimistic of the analyst.

Recommendation revision data are also from CSMAR database, representing an analyst's recommendation change compared to her prior recommendation of the same firm. An upward/downward revision corresponds to the number 1/-1, while an unchanged record is assigned to 0. We use ordered probit regressions to estimate our models and tabulate the results in columns (1) and (2) of Panel A of Table 4. We notice that, in column (1), the effect of air pollution on visiting analysts' optimism can also be inferred from their post-visit ranking activities, though not as significant as the forecasts. When the air quality on the visit day is worse (in column (2)), the analyst is more likely to give a less appealing recommendation or downgrade their prior one.

Moreover, we take other visiting analysts' opinions into account and calculate analysts' relative optimism. Following Hong and Kubik (2003), we use the median forecast EPS of all visiting analysts within the same quarter as analysts' consensus forecast and define relative optimism as 1 if an analyst's forecast EPS is above the consensus, zero otherwise. We use a logit model to estimate the influence of air pollution on analysts' relative optimism. As shown in column (3) of Panel A, using consensus forecast, air pollution still has a significant and negative effect on analysts' relative optimism.

Next, we test the robustness of our results using different measures of AQI and tabulate the results in Panel B of Table 4. In column (1), we use AQI rank classified according to Ambient Air Quality Standard regulated by Ministry of Environmental Protection of China. AQI ranks are defined as follows: I-excellent (AQI≤50), II-good (50<AQI≤100), III-lightly polluted (100<AQI≤150), IV-moderately polluted (150<AQI≤200), V-heavily polluted (200<AQI≤300), and VI-severely polluted (AQI>300), we assign the numbers 1-6 to each category, respectively. Higher rank represents worse air quality. In column (2), we use the natural logarithm of AQI as the explanatory variable. In column (3), we use the scaled quartile rank score of AQI as the explanatory variable. Specifically, we divide our sample of AQI into quartiles and assign the numbers 0-3 to each quartile in descending order, then the quartile numbers are divided by 3 to get the quartile rank scores which always lie between [0,1]. We also take air quality during analysts' forecast process after the visit into consideration and construct a relative AQI. The explanatory variables of columns (4) and (5) are AQI of the visited city on the visit day scaled by AQI of the city where the analyst lives on the forecast day, and AQI of the visit city on the visit day scaled by AQI of the city where the analyst lives on the day before the forecast day respectively. All five estimates of different AQI measures are significant and negative, indicating strong robustness of the effect air pollution imposes on analysts' optimism.

Then we explore the duration of air pollution's effect on analysts' post-visit optimism. We choose a month, which is approximately 20 trading days, as our estimation window and divide it into sub-periods. The windows used in columns (1) to (5) of Panel C are trading days [1,5], [5,10], [1,10], [11,20], and [1,20], respectively. The results indicate that the influence of air pollution on visiting analysts lasts for ten trading days, while it mainly works through the former 5 trading days. However, from the sample size, we can see that the frequency of post-visit reports decreases with time, and the main proportion of earnings forecasts are released within the first 5 trading days, which is almost twice as many as the forecasts issued within the next 5 trading days. Therefore, we can conclude that the influence of air pollution on visiting analysts is short-term. However, it affects most of the post-visit forecasts.

Furthermore, in Panel D, we use calendar days [1, 7] as the estimation window and rerun our main regression. The result is also robust and shows a consistent coefficient of AQI as the main regression. Last, to control for unobserved variables of analyst level, we include analyst fixed effect in our main regression, the result shown in Panel E is also robust.

4.4 Endogeneity issues

Although our variable of interest – air pollution, is a highly exogenous variable, this paper is still faced with some potential endogenous issues. First, analysts may choose to visit firms in fine weather while the firms may also pick up haze-free days to invite analysts over. To address this concern, we interview an analyst about the timing of site visits, and her response is: "The decision maker is the company. Normally, an analyst makes an appointment with the firm one week ahead, then the firm will check their schedule and notify the analyst of the visit time. Normally, the host is the investor relation manager or the board secretary, so the visit date depends on their schedules." The official AQI forecast made by the MEPC is 72 hours ahead, so the air quality of the visit day is basically unpredictable when they make the appointment. Therefore, it is not likely either the analyst or the firm to manipulate the air quality of the visit day. To further clarify this issue, we compare the distribution of AQI on visit days and all sample dates, the results are shown in Table 5. Columns (1) to (3) of Panel A present the frequency distribution of the AQI rank in our sample period all over the country, the AQI of visit days weighted by the number of visitors and the AQI of visit days equally weighted respectively. We draw a histogram based on the statistics of Table 5 in Figure 2. From the results, we can infer that the distribution trends are similar in all three samples, there is no evidence of manipulation. Next, we present the summary statistics of the three groups in Panel B. As we can see, there is little gap between full sample AQI and visit AQI, if anything, the air quality is worse on visit days, not the other way around (which is probably because the visit cities are usually highly prosperous yet severely polluted, like Beijing and Shanghai). Therefore, we have no reason to believe the analysts or firms choose better air condition days to conduct site visits.

Nevertheless, even if firms cannot manipulate the air quality on the visit days, the visit timing can still be endogenous. Analysts may want to visit a firm when the information is abundant, such as days around major announcements, thus influencing analysts' post-visit forecasts. To address this concern, we follow Cheng, Du, Wang and Wang (2017) and add three variables related to the timing of site visits into our model. The first variable is *Adjacent*, which equals to 1 if a visit is accompanied by another one on the following day or on the prior day and zero if there is only a sole visit. The underlying mechanism is that if a firm is visited consecutively, there's high chance to be some firm-specific news. The second one is *Bigevent*, which is an indicator for visits that occur in the [-1,1] window of major events such as mergers and acquisitions, seasoned equity offerings, right offerings, related party transactions, law suits, regulatory violations, and dividends. The last control variable is the absolute abnormal returns of the trading day prior to the visit, *ABSAR(-1)*. We think that if analysts conduct news-driven visits, the information content should be captured by the abnormal return on day -1. We add the three variables into the regressions respectively in Models (1) to (3) and put them altogether in Model (4). From Table 6, our results stay robust to the timing of the visits, statistically and economically.

Our second endogeneity concern is that, due to environmental reasons, listed firms from polluted areas are faced with stronger environmental risks, such as operation suspensions and pollution fines imposed by the government. The visiting analysts may get aware of these factors which may affect the firms' fundamentals and express their conservativeness in earnings forecasts. We apply two methods: regression discontinuity design and change model to alleviate this issue.

4.4.1. Regression discontinuity design

The Huai River, along with Mountain Qinling, partitions China into two regions: the northern and the southern. From the 1950s, Chinese government has been performing the Huai-river policy, which provides the northern region and only the northern region free heating in winter. Heating operates via the provision and burning of free coal for boilers, in which process multiple air pollutants are produced and released into the atmosphere. Therefore, the Huai-river policy causes a discontinuity in terms of AQI across the river. RD studies based on the Huai-river policy have found that air pollution impacts people's life expectancy (Chen, Ebenstein, Greenstone, and Li, 2017). Following Li, Massa, Zhang and Zhang (2017), we apply a RD design to examine the Huai-river policy's impact on air quality and visiting analysts' optimism across the Huai River. The Huai River and Mountain Qinling stretch through the east of China while the scenarios in the west part are under discussion. The northwestern region are mainly Tibet Autonomous Region and the southwestern are mainly Xinjiang Autonomous Region, both of which are vast territories with sparse populations and economically underdeveloped. Not many listed firms are located there and the site visit records of these firms are limited due to the remote location and traffic inconvenience. Besides, from 2012, the Tibet Autonomous Region starts to provide winter heating in its province capital Lhasa and gradually generalize to other cities, which causes an inconsistency of status in our sample period 2009-2015. Due to the complexity of the western region and the limited visit records (which makes up only 3% of our sample), we drop the western observations.

We calculate the latitude degree north of the Huai River line for each city as the forcing variable *North* and use local linear regression models to regress AQI and post-visit optimism on *North*. For each model, we use bandwidth 1.5, 2,…,5, respectively. The reason to start with 1.5 is that 1.5 is the narrowest bandwidth to meet the sample requirement for the RD regression. Besides, from a geographic point of view, the Huai-River line is not technically a "line", but rather a "band", using wider bandwidths can mitigate the imprecise mapping of the Huai-River line. The results are reported in Table 7.

The dependent variables in Panel A and B of Table 7 are the daily AQI of cities around the Huai River line while the dependent variables in Panel C and D are the forecast optimism of analysts who conduct corporate site visits in these cities. There are no covariates included in Panel A and Panel C while city level covariates such as GDP, population, the number of domestic firms and government income are added in the models of Panels B and D. We can see that, from south to north across the Huai River, there is an upward jump in AQI and a downward jump in post-visit optimism. Basically, our results stay robust through all the bandwidths, with or without the covariates. In Figure 3, we plot distributions of AQI and forecast optimism around the Huai River with the bandwidth of 3. We can observe a clear discontinuity in both figures with the orientations as expected. In Figure 4, we plot the RD estimators and their 95% confidence intervals over the spectrum of bandwidths. From Figure 4, we observe that the RD estimates of AQI/optimism are always positive/negative and stable, suggesting strong robustness of our results.

4.4.2. Change model

To further control for multiple fixed effects, we apply a change model to examine how air pollution affect the difference in post-visit forecasts when an analyst visits the same firm on different dates. Specifically, we choose analysts who pay multiple visits to the same firm within the same year, and calculate the difference between the post-visit forecasts of two consecutive visits. According to Cheng, Du, Wang, and Wang (2016), analysts do not visit firms frequently, our sample indicates the same: the records of multiple visits are rare, and the time interval between two visits are usually long (our sample mean of the visit interval is 124 days). Analysts who conduct site visits of extreme frequency (consecutive visits within 60 days) only make up less than 1/4 of our sample while most of these analysts do not update their forecast after the second visit. Our conjecture is that analysts frequently visit firms not for information to make better forecasts but for contacts with management, cooperative projects or other incentives, so we drop these observations from our sample.

For consecutive visits, we construct *Forecast_revision* to capture the change in analysts' optimism. Specifically, we define *Forecast_revision*=1/0/-1 when an analyst upgrades/makes no revision/downgrades her prior forecast EPS. We also calculate the change of the explanatory variables in the model. Since we limit the visits to be conducted in the same year, we don't need to calculate the differences of control variables of firm level and analyst level as they basically don't change. The only discrepancies are in date-specific variables such as AQI and weather conditions, so we only calculate the changes for these variables. Similarly, industry fixed effect and year fixed effect are unnecessary. To control for the time span, we add the variable *delta_visit* which is measured as the time interval between the two visits. We use ordered probit regression to estimate this model and present the result in Column (1) of Table 8. We can see that, when AQI of the second visit is worse, analysts are more likely to downgrade their prior forecasts. In Column (2), we replace the forecast EPS with forecast optimism and construct *Delta_optimism* in the same manner, the results are still robust.

4.5 Mechanism tests

From the analysis above, we can infer that air pollution negatively affects visiting analysts' future earnings forecasts. In this section, we further explore the channel through which these analysts are influenced. Specifically, we look into the information acquisition process during the visits, that is, the number of questions raised during the Q&A sessions. When an analyst is more active and effective during a site visit, she may make better communication with the management by asking more questions.

We hand collect the Q&A records of all site visits during our sample period and regress the number of questions on AQI. Due to the fact that firms usually receive multiple visitors in one visit and there is no record on who raises the questions during the visits in the dataset, we do not control analyst characteristics in this regression. From the results shown in Column (1) of Table 9, we can see a negative correlation between the number of questions raised and the level of air pollution during a site visit. As the questions raised during the Q&A sessions are related to the number of visitors, we further add the variable *Visitors* to control for the number of analysts participating in the visit into the regression. As shown in Column (2) , the negative relationship between air pollution and the number of questions raised by analysts during the visits still holds. This finding suggests that air pollution makes visiting analysts perform more passively in their information acquisition process and further increase their pessimism in the later forecast process.

4.6 Additional tests

In prior sections, we study the influence of air pollution on post-visit forecast optimism. However, is it possible that air pollution can also affect analysts' regular forecast activities? In this section, we focus on this issue. We calculate average AQI of the city where the analyst lives within 5 trading days prior each earnings forecast in our sample as the explanatory variable and regress the forecast optimism on it, along with firm characteristics, analyst characteristics and average weather conditions like we do in prior sections. Industry fixed effect, year fixed effect and quarter fixed effect are included with standard errors clustered at the firm level. The results are shown in Panel A of Table 10. We find that air pollution has a significant and negative influence on analysts' regular forecasts. A 50 pollution level increases in AQI leads to 1.7% decrease in earnings forecast optimism relative to our sample mean 2.003. Economically, the effect of air pollution on analysts' regular earnings forecasts is smaller than that of post-visit earnings forecasts, which indicates that analysts' corporate site visits are more informative and cognitive demanding than their regular information acquisition activities. Moods may play a more important role in site visits because subjective information processing and judgments are more intensive in regular forecasts.

Next, we study the differences of air pollution effect among different groups of analysts on regular forecasts. Like prior analyses, we divide analysts into subsamples based on their experiences and whether they are star analysts then rerun our main regressions respectively. From the results tabulated in Panel A of Table 10, we notice that, similar to the results of the visiting analysts, air pollution significantly influences non-star analysts and less experienced analysts.

Finally, we explore the duration of air pollution's negative effect on analysts' regular forecasts. Specifically, we replace the windows to trading days [-6,0], [-9,0], [-11,0], and [-15,0] prior to the forecasts and rerun the main regression. From the results in Panel B of Table 10, we can see that, though economically smaller, the effect of air pollution on analysts' regular forecasts lasts longer than that of post-visit forecasts. On the one hand, air conditions do not change drastically, so the results may be attributed to the correlation of AQI across different windows. On the other hand, the results indicate that air pollution has a long-term and cumulative effect on analysts' regular forecast activities.

5. Conclusions

In this paper, we examine the relation between air pollution and analysts' earnings forecast optimism. Using a sample of analysts' corporate site visits to firms listed in Shenzhen Stock Exchange of China from 2009 to 2015, we find that air pollution has a negative influence on analysts' post-visit forecast optimism. One rank increase of AQI leads to 7.9% decrease in analysts' optimism. The effect stays robust after we control for firm characteristics, analyst characteristics and weather conditions. Air pollution's negative effect is more significant and larger in magnitude among non-star analysts and less experienced analysts, suggesting better ability analysts can mitigate the impact of air pollution.

This effect is short-term, which last about 5 trading days. This effect is probably due to the passive performance in the Q&A session during the visits. In addition, we also find a negative effect of air pollution on analysts' regular forecast optimism, which is smaller than the effect on post-visit optimism yet lasts longer.

This paper studies the hitherto unexplored effect of air pollution on professional investors and contributes to the literature of air pollution and capital market. In the meantime, the evidence implicates pollution induced moods has a negative influence on analysts' forecast activities and it can reduce analyst optimism. Overall, this study helps to understand the hazard of the air pollution and the importance of pollution abatement.

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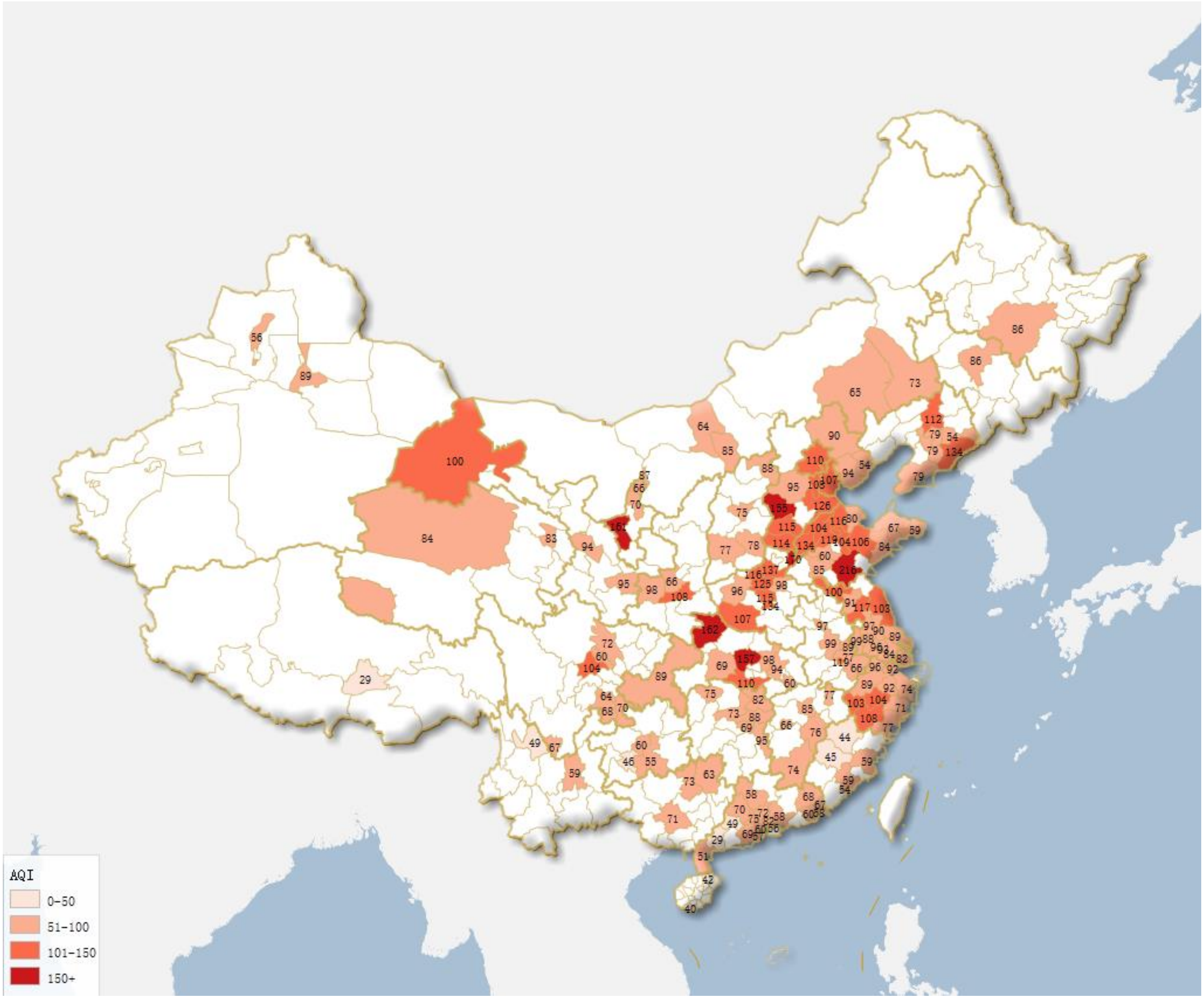
Appendix A: Average visit AQI Map



Appendix B: Variable definitions

Variable	Definition	Source
Dependent variables		
Forecast_optimism	Annual EPS forecast issued within trading days [1, 5] after the site visit less actual EPS, scaled by price as of the trading day prior to the forecast, multiplied by 100.	CSMAR
Standard_rank	Stock recommendation made within trading days [1, 5] after the site visit, with a value of 5 for 'Strong Buy', 4 for 'Buy', 3 for 'Hold', 2 for 'Sell', and 1 for 'Strong Sell'.	CSMAR
Rank_revision	A trinary variable equals to one if the analyst upgrades the previous recommendation within days [1, 5] after the site visit, zero if there is no change, and negative one for downgrades.	CSMAR
Relative_optimism	A dummy variable equals to one if the analyst's forecast is greater than the consensus, which is the median of the forecasts submitted by all the analysts that visit the same firm within the same quarter, and zero otherwise.	CSMAR
Air pollution variables		
AQI	Air quality index of the visit city on the visit day.	MEPC\EPMAP
AQI_rank	Air quality rank of the visit city on the visit day.	MEPC\EPMAP
Ln_AQI	The natural logarithm of AQI.	
AQI_quartile	The scaled quartile rank score of AQI.	MEPC\EPMAP
Relative_AQI_0	AQI of the visit city on the visit day scaled by AQI of the city where the analyst works on the forecast day.	MEPC\EPMAP
Relative_AQI_-1	AQI of the visit city on the visit day scaled by AQI of the city where the analyst lives on the day before the forecast day.	MEPC\EPMAP
Firm characteristics		
Size	Natural logarithm of total assets at the beginning of the visit year.	RESSET
Market_to_book	The ratio of market value of equity to book value of equity at the beginning of the visit year.	RESSET
Intangible_asset	The ratio of intangible assets to total assets at the beginning of the visit year.	RESSET
Volatility	Daily volatility of stock return of the year prior to the visit year.	RESSET
Turnover	Daily turnover rate of the visit year.	RESSET
Return	Annual stock return of the year prior to the visit year.	RESSET
Analyst_attention	Natural logarithm of total analysts (groups) following the firm within the visit year.	CSMAR
Analyst characteristics		
Analyst_gender	A dummy variable equals to one if the analyst is male and zero otherwise.	CSMAR
Follow_co_number	Natural logarithm of the number of companies the analyst follows up to the end of the visit year.	CSMAR
Forecast_number	Natural logarithm of the number of reports issued by the analyst up to the end of the visit year.	CSMAR
Broker_size	Natural logarithm of the number of analysts working for the brokerage at the end of the visit year.	CSMAR
Forecast_horizon	The days between the forecast date and the corresponding date of the actual earnings announcement.	CSMAR
Star_analyst	A dummy variable equals to one if the analyst is ranked by the New Fortune magazine as a star analyst in the year preceding the site visit and zero otherwise.	CSMAR
Analyst_experience	Natural logarithm of the number of quarters since the analyst make his/her first forecast up to the end of the visit year.	CSMAR
Weather conditions		
Sunny_hours	Sunny hours of the visit city on the visit day (0.1h).	CIMISS

Temperature	Average temperature of the visit city on the visit day (0.1℃).	CIMISS
Humidity	Average humidity of the visit city on the visit day (1%).	CIMISS
Precipitation	Average precipitation of the visit city on the visit day (0.1mm).	CIMISS
Wind_speed	Average wind speed of the visit city on the visit day (0.1m/s).	CIMISS
Timing variables		
Adjacent	A dummy variable equals to 1 if a visit is accompanied by another one on the following day or on the prior day and zero otherwise.	SZSE
Bigevent	An indicator for visits that occur in the [-1,1] window of major events such as mergers and acquisitions, seasoned equity offerings, right offerings, related party transactions, law suits, regulatory violations, and dividends.	CSMAR
ABSAR(-1)	The absolute value of size-adjusted abnormal returns of the trading day prior to the visit.	CSMAR
RDD variables		
North	Latitude degree north of the Huai River.	NBSC
GDP	Natural logarithm of gross domestic product of the year in billions of RMB.	CSMAR
Population	Natural logarithm of total population of the city.	CSMAR
Dom_firm	Natural logarithm of the number of domestic firms.	CSMAR
Gov_inc	Natural logarithm of government revenue of the year on billions of RMB.	CSMAR
Change model variables		
Forecast_revision	A trinary variable equals to one if the analyst upgrades the previous EPS forecast after the second visit within the same year, zero if there is no change, and negative one for downgrades.	CSMAR
Delta_optimism	A trinary variable equals to one if the analyst's forecast optimism after the second visit within the same year is higher than the first visit, zero if there is no change, and negative one for lower optimism.	CSMAR
Delta_AQI	The difference of AQI between two sequential visits.	MEPC\EPMAP
Delta_visit	The time interval between two sequential visits.	CNINF
Delta_sunny_hours	The difference of sunny hours between two sequential visits.	CIMISS
Delta_temperature	The difference of temperature between two sequential visits.	CIMISS
Delta_humidity	The difference of humidity between two sequential visits.	CIMISS
Delta_precipitation	The difference of precipitation between two sequential visits.	CIMISS
Delta_wind_speed	The difference of wind speed between two sequential visits.	CIMISS
Mechanism test		
Questions	Natural logarithm of the number of questions raised during the visit.	CIMISS
Visitors	Natural logarithm of the number of visitors participating during the visit.	CIMISS
Additional tests		
AQI_avg	Average AQI of the city where the analyst works within the estimation window.	CIMISS
Sunny_hours_avg	Average sunny hours of the city where the analyst works within the estimation window (0.1h).	CIMISS
Temperature_avg	Average temperature of the city where the analyst works within the estimation window (0.1℃).	CIMISS
Humidity_avg	Average humidity of the city where the analyst works within the estimation window (1%).	CIMISS
Precipitation_avg	Average precipitation of the city where the analyst works within the estimation window (0.1mm).	CIMISS
Wind_speed_avg	Average wind speed of the city where the analyst works within the estimation window (0.1m/s).	CIMISS

Table 1. Summary statistics

This table describes the statistical properties of the main variables. Panel A presents the distribution of the variables in the sample period from 2009 to 2015. Panel B shows the average levels of forecast optimism across different AQI categories. All variables are defined in Appendix B.

Panel A: Descriptive statistics					
	Mean	STD	Q1	Median	Q3
Forecast_optimism	1.953	3.498	0.150	1.190	2.930
Standard_rank	4.390	0.535	4.000	4.000	5.000
Rank_revision	0.072	0.291	0.000	0.000	0.000
Relative_optimism	0.429	0.495	0.000	0.000	1.000
AQI	89.495	50.504	56.000	76.000	110.000
Size	21.790	1.099	21.024	21.586	22.317
Market_to_book	3.156	1.687	2.094	2.660	3.916
Intangible_asset	0.044	0.047	0.018	0.033	0.057
Volatility	0.027	0.007	0.022	0.026	0.030
Turnover	2.491	2.006	1.108	2.008	3.157
Return	0.180	0.545	-0.181	0.073	0.440
Analyst_attention	2.689	0.771	2.197	2.833	3.296
Analyst_gender	0.737	0.440	0.000	1.000	1.000
Follow_co_number	2.343	0.862	1.792	2.485	2.944
Forecast_number	2.894	1.138	2.197	3.045	3.714
Broker_size	4.004	0.805	3.584	4.060	4.522
Forecast_horizon	479.639	291.306	238.000	436.000	697.000
Analyst_experience	1.999	0.771	1.437	1.964	2.533
Star_analyst	0.121	0.327	0.000	0.000	0.000
Sunny_hours	48.703	41.447	0.000	53.000	86.000
Temperature	177.775	89.732	115.000	195.000	249.000
Humidity	69.408	17.057	59.000	71.000	83.000
Precipitation	42.221	124.936	0.000	0.000	14.000
Wind_speed	21.643	9.255	15.000	20.000	27.000

Panel B: Forecast optimism across different AQI ranks			
Air Quality	AQI	AQI Rank	Forecast_optimism
Excellent	0-50	1	1.916
Good	51-100	2	2.003
Lightly Polluted	101-150	3	1.877
Moderately Polluted	151-200	4	1.746
Heavily Polluted	201-300	5	1.627
Severely Polluted	300+	6	0.486
t-test	R1-R6=1.354	t=1.818	p=0.070
Wilcoxon test		z=2.215	p=0.027

Table 2. The effect of air pollution on analysts' earnings forecast optimism

This table presents the results of the following multivariate specification, with industry, year, quarter fixed effects controlled for and standard errors clustered at the firm level:

$$Forecast\_optimism_{i,j,t} = \alpha + \beta \times AQI_{j,t} + C \times M_{i,j,t} + \varepsilon_{i,j,t}$$

Where $Forecast\_optimism_{i,j,t}$ refers to analyst *i*'s forecast optimism of her first earnings forecast for firm *j* of year *t* issued within 5 trading days after the analyst's site visit. $AQI_{j,t}$ refers to the air quality index of the visit city on the visit day. $M_{i,j,t}$ stacks a list of control variables, including firm characteristics, analyst characteristics and weather conditions. Model (1) does not include any control variables, Model (2) controls for firm characteristics, Model (3) further controls for analyst characteristics and Model (4) adds weather controls into the regression. The sample covers the period from 2009 to 2015. All variables are defined in Appendix B. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Dep. Var=Forecast_optimism	(1)	(2)	(3)	(4)
AQI	-0.0019**	-0.0024**	-0.0024**	-0.0031***
	(-2.02)	(-2.21)	(-2.15)	(-2.70)
Size		0.2152	0.1547	0.1597
		(1.42)	(0.94)	(0.99)
Market_to_book		0.0218	-0.0017	-0.0116
		(0.39)	(-0.03)	(-0.19)
Intangible_asset		-0.4192	-0.0545	-0.0188
		(-0.25)	(-0.03)	(-0.01)
Volatility		20.4776	20.3980	21.2613
		(1.42)	(1.25)	(1.29)
Turnover		-0.0473	-0.0351	-0.0366
		(-1.32)	(-0.91)	(-0.95)
Return		-0.3407*	-0.3393	-0.3362
		(-1.78)	(-1.59)	(-1.59)
Analyst_attention		-0.1503	-0.1428	-0.1428
		(-1.19)	(-1.11)	(-1.13)
Analyst_gender			0.3252***	0.3414***
			(2.65)	(2.80)
Follow_co_number			-0.1993	-0.2358
			(-0.95)	(-1.11)
Forecast_number			0.2844*	0.3215**
			(1.90)	(2.13)
Broker_size			0.0079	0.0096
			(0.11)	(0.14)
Forecast_horizon			0.0050***	0.0050***
			(19.04)	(19.02)
Sunny_hours				0.0024
				(1.33)
Temperature				-0.0035***
				(-2.71)
Humidity				0.0061
				(1.42)
Precipitation				-0.0003
				(-0.49)
Wind_speed				0.0006
				(0.07)
Constant	3.0720***	-1.7964	-4.3196	-4.5227
	(3.92)	(-0.46)	(-1.08)	(-1.16)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Obs	4,293	3,743	2,743	2,729
Adj Rsq	0.102	0.108	0.348	0.352

Table 3. The effect of analyst characteristics on the influence of air pollution

This table presents the results of some subsample tests. In models (1) and (2), the tests are conducted on the subsamples of star analysts and non-star analysts. In models (3) and (4), we divide analysts into two categories based on their experiences: highly experienced analysts whose experiences are above the sample median, and less experienced analysts otherwise. The sample covers the period from 2009 to 2015. All regressions control for industry, year and quarter fixed effects and cluster standard errors at the firm level. The superscripts ***, **, and * refer to the 1%, 5%, and 10% levels of statistical significance, respectively.

Dep. Var=forecast_optimism	*Star*	*Non-star*	*High exp*	*Low exp*
	(1)	(2)	(3)	(4)
AQI	0.0006	-0.0032***	-0.0020	-0.0036**
	(0.17)	(-2.67)	(-1.31)	(-2.50)
Control Variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Obs	331	2,398	1,365	1,364
Adj Rsq	0.359	0.356	0.373	0.341

Table 4. Robustness tests

This table presents the results of several robustness tests.Panel A links AQI to alternative proxies of forecast optimism. Model (1) and Model (2) use post-visit recommendation and recommendation revision as dependent variables respectively. Model (3) use relative optimism regarding analysts' consensus forecast as dependent variable. In Model (1) and Model (2), the coefficients are estimated using ordered probit regressions. Model (3) uses a logistic regression. In Panel B we rerun the main regression using alternative specifications of AQI. Model (1) uses AQI rank which takes the value 1-6 for 6 AQI categories: AQI≤50, 50<AQI≤100, 100<AQI≤150, 150<AQI≤200, 200<AQI≤300, and AQI>300. Model (2) uses the natural logarithm of AQI. Model (3) uses the scaled quartile rank score of AQI. Model (4) and Model (5) take the AQI of the city where the analyst works into account and calculate relative AQI. In Model (4), *Relative_AQI_0* denotes AQI of the visit city on the visit day scaled by AQI of the city where the analyst works on the forecast day. In Model (5) *Relative_AQI_-1* denotes AQI of the visit city on the visit day scaled by AQI of the city where the analyst lives on the day before the forecast day. Panel C tests the persistence of air pollution influence on analysts by altering the window from the site visits to the release of the forecasts. Models (1) – (5) use trading days [1, 5], [5, 10], [1, 10], [11, 20], [1, 20] as estimation windows respectively. Panel D provides a robustness check using natural day windows in place of trading day windows. Specifically, the model use the first earnings forecast made within natural days [1, 7] after an analyst's visit to the firm and rerun the main regression. Panel E adds analyst fixed effect into the model. The sample covers the period from 2009 to 2015. All variables are defined in Appendix B. All regressions control for industry, year and quarter fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Panel A: Alternative dependent variables

Dep.Var=	*Standard_rank*	*Rank_revision*	*Relative_optimism*
	(1)	(2)	(3)
AQI	-0.0013	-0.0031*	-0.0030**
	(-1.48)	(-1.90)	(-1.99)
Control Variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes
Obs	1,220	834	729
Pseudo Rsq	0.085	0.105	0.033

Panel B: Alternative specifications of AQI

Dep. Var=forecast_optimism	*AQI_rank*	*Ln_aqi*	*AQI_quartile*	*Relative_AQI_0*	*Relative_AQI_-1*
	(1)	(2)	(3)	(4)	(5)
AQI	-0.1584***	-0.2433**	-0.3143**	-0.1837***	-0.2030***
	(-2.75)	(-2.02)	(-2.03)	(-3.42)	(-3.65)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Obs	2,729	2,729	2,729	2,038	2,045
Adj Rsq	0.352	0.351	0.351	0.377	0.379

Panel C: The persistence of air pollution influence					
Dep. Var=forecast_optimism	*[1,5]* (1)	*[5,10]* (2)	*[1,10]* (3)	*[11,20]* (4)	*[1,20]* (5)
AQI	-0.0031***	-0.0007	-0.0021**	0.0011	-0.0010
	(-2.70)	(-0.47)	(-2.16)	(0.59)	(-1.20)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Obs	2,729	1,379	4,108	1,448	5,729
Adj Rsq	0.352	0.415	0.368	0.349	0.362

Panel D: Calendar day windows	
Dep. Var=forecast_optimism	*[1,7]* (1)
AQI	-0.0028**
	(-2.53)
Control Variables	Yes
Year fixed effects	Yes
Industry fixed effects	Yes
Quarter fixed effects	Yes
Obs	2,925
Adj Rsq	0.349

Panel E: Controlling for analyst fixed effects	
Dep. Var=forecast_optimism	(1)
AQI	-0.0034**
	(-2.26)
Control Variables	Yes
Year fixed effects	Yes
Industry fixed effects	Yes
Quarter fixed effects	Yes
Analyst fixed effects	Yes
Obs	2,729
Adj Rsq	0.467

Table 5. Comparison of AQI on full sample and visit days

This table compares AQI of all the cities in our AQI dataset in the sample period to AQI of the visit cities on the visit days. Panel A shows the frequency distributions of AQI rank among three different samples. Full sample represents daily AQI rank of every city in the sample period; Visitor weighted represents visit AQI weighted by the number of visitors in the visit city on the visit day; Equal weighted represents AQI of the visit city on the visit day equally weighted. Panel B presents summary statistics of AQI among these three samples.

Panel A: Frequency distributions of AQI rank

AQI rank	(1) Full sample	(2) Visitor weighted	(3) Equal weighted
1	0.21	0.21	0.20
2	0.59	0.53	0.56
3	0.13	0.17	0.16
4	0.03	0.06	0.05
5	0.02	0.03	0.02
6	0.01	0.01	0.01
N	384895	57118	12699

Panel B: Summary statistics of AQI

	Mean	STD	Q1	Median	Q3
Full sample	79.322	46.229	53.000	68.000	93.000
Visitor weighted	86.023	52.063	54.000	73.000	102.000
Equal weighted	84.432	48.917	54.000	72.000	100.000

Table 6. Controlling for the timing of site visits

This table presents the results of the regressions after controlling for the variables which may affect the timing of the visits. *Adjacent* equals to 1 for visits conducted in consecutive days and zero otherwise. *Bigevent* is a dummy variable that equals to 1 if the visit is conducted in the three-day event window [-1,1] of the following events: mergers and acquisitions, seasoned equity offerings, right offerings, related party transactions, law suits, regulatory violations, and dividends. *ABSAR(-1)* stands for absolute value of the size-adjusted abnormal returns on the day before the visit. Model (1)-(3) control for *adjacent*, *bigevent*, *ABSAR(-1)* respectively and Column (4) control all three of them altogether. The sample covers the period from 2009 to 2015. All variables are defined in Appendix B. All regressions control for industry, year and quarter fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Dep. Var=forecast_optimism	(1)	(2)	(3)	(4)
AQI	-0.0032***	-0.0031***	-0.0031***	-0.0031***
	(-2.74)	(-2.69)	(-2.67)	(-2.69)
Adjacent	-0.4180*			-0.3961*
	(-1.80)			(-1.71)
Bigevent		-0.3160		-0.3179
		(-1.42)		(-1.48)
ABSAR(-1)			-8.5156***	-8.1319***
			(-3.49)	(-3.30)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Obs	2,729	2,729	2,729	2,729
Adj Rsq	0.353	0.352	0.352	0.355

Table 7. Regression discontinuity design

This table presents discontinuity tests for the effect of Huai River Policy on the AQI and analysts' earnings forecast optimism. The results are estimated based on local linear regression models using bandwidth from 1.5 to 5 degrees of the Huai River. In Panel A and B, the dependent variables are daily AQI of cities located around the Huai River. In Panel C and D, the dependent variables are forecast optimism of the analysts who pay visits to these cities. In Panel A and C, the regression models doesn't include control variables. In Panel B and D, we include city-level control variables including GDP, total population, the number of domestic firms and local government revenue. The sample covers the period from 2009 to 2015. All variables are defined in Appendix B. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Panel A: RD regression of AQI without covariates

Bandwidth	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*	*4.5*	*5*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AQI	15.4856***	8.7841***	4.5562***	5.5738***	4.5685***	3.0901***	2.3536***	2.3953***
	(8.92)	(6.95)	(4.39)	(6.43)	(6.36)	(5.00)	(4.23)	(4.63)
Covariates	No	No	No	No	No	No	No	No
Obs	331,363	331,363	331,363	331,363	331,363	331,363	331,363	331,363

Panel B: RD regression of AQI with covariates

Bandwidth	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*	*4.5*	*5*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AQI	14.5946***	3.6412***	2.7012**	5.4588***	6.0624***	5.9202***	6.0007***	6.3643***
	(8.30)	(2.85)	(2.56)	(6.12)	(8.19)	(9.25)	(10.27)	(11.62)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	331,363	331,363	331,363	331,363	331,363	331,363	331,363	331,363

Panel C: RD regression of forecast optimism without covariates

Bandwidth	*1.5*	*2*	*2.5*	*3*	*3.5*	*4*	*4.5*	*5*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forecast_optimism	-3.1617**	-1.8813**	-1.7279***	-1.5720***	-1.5633***	-1.2551***	-0.8987***	-0.6951**
	(-2.07)	(-2.42)	(-2.90)	(-3.24)	(-3.53)	(-3.41)	(-2.78)	(-2.29)
Covariates	No	No	No	No	No	No	No	No
Obs	4,585	4,585	4,585	4,585	4,585	4,585	4,585	4,585

Panel D: RD regression of forecast optimism with covariates

Bandwidth	1.5	2	2.5	3	3.5	4	4.5	5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forecast_optimism	-2.4289	-1.4542*	-1.5783**	-1.3262***	-1.4069***	-1.1826***	-0.7998**	-0.6224*
	(-1.32)	(-1.73)	(-2.57)	(-2.60)	(-2.97)	(-2.91)	(-2.17)	(-1.76)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	4,585	4,585	4,585	4,585	4,585	4,585	4,585	4,585

Table 8. A change model

This table shows the results of a change model. We select the analysts who pay multiple visits to the same firm within the same year and compare the earnings forecasts they made after consecutive visits. We drop the observations where analysts visit the company too frequently (the interval between two visits is less than 60 days). *Forecast_revision* takes the value of 1/0/-1 if an analyst upgrades/doesn't alter/downgrades his/her forecast after the latter visit. *Delta_optimism* is constructed in a similar way. We calculate the difference of the variables between these visits to construct variables on the right hand of the regression model. The coefficients are estimated using ordered probit models. The sample covers the period from 2009 to 2015. All variables are defined in Appendix B. Standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Dep. Var=forecast_optimism	*Forecast_revision*	*Delta_optimism*
	(1)	(2)
Delta_AQI	-0.0043**	-0.0049**
	(-2.28)	(-2.17)
Delta_visit	-0.0043***	-0.0068***
	(-2.70)	(-3.08)
Delta_sunny_hours	0.0014	0.0063
	(0.36)	(1.21)
Delta_temperature	-0.0024*	-0.0034**
	(-1.82)	(-2.20)
Delta_humidity	0.0110	-0.0037
	(1.31)	(-0.36)
Delta_precipitation	-0.0022	0.0000
	(-1.20)	(0.02)
Delta_wind_speed	0.0201	-0.0034
	(1.20)	(-0.27)
Constant_cut1	-0.4786	-0.3205
	(-1.62)	(-0.96)
Constant_cut2	0.1403	-0.2395
	(0.51)	(-0.80)
Obs	127	127
Pesudo Rsq	0.08	0.12

Table 9. Mechanism tests

This table presents the result of mechanism tests. The dependent variables are natural logarithm of the number of questions raised during a site visit, the control variable *Visitors* added in Column (2) is the natural logarithm of the number of visitors participating in the site visit. We don't control analyst characteristics in either of the regressions and the other controls variables are the same as the main regression. The sample covers the period from 2009 to 2015. All variables are defined in Appendix B. Standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Dep. Var=Questions	(1)	(2)
AQI	-0.0005**	-0.0005***
	(-2.51)	(-2.76)
Visitors		0.1207***
		(12.11)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Obs	12,582	12,454
Adj Rsq	0.0540	0.0954

Table 10. Additional tests

This table presents the results of additional tests on the influence of air pollution on analysts' regular earnings forecasts. Model (1) of Panel A presents the results of the following multivariate specification:

$$Forecast\_optimism_{i,j,t} = \alpha + \beta \times AQI\_avg_{j,t} + C \times M_{i,j,t} + \varepsilon_{i,j,t}$$

Where $Forecast\_optimism_{i,j,t}$ refers to analyst *i*'s forecast optimism of her earnings forecast for firm *j* of year *t*. $AQI\_avg_{j,t}$ refers to the average air quality index of the city where the analyst works within trading days [-4,0] before the issuance of the earnings forecast. $M_{i,j,t}$ stacks a list of control variables, including firm characteristics, analyst characteristics and average weather conditions. In Models (2) and (3), the tests are conducted on the subsamples of star analysts and non-star analysts. In models (4) and (5), the tests are conducted on the subsamples of highly experienced analysts and less experienced analysts. Panel B alters the estimation windows. Models (1) – (5) use trading days [-6, 0], [-9, 0], [-11, 0], [-15, 0] as estimation windows respectively. The sample covers the period from 2009 to 2015. All variables are defined in the Appendix B. All regressions control for industry, year and quarter fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Panel A: The effect of local air pollution on analysts' forecast optimism					
Dep. Var=forecast_optimism	*Full_sample*	*Star*	*Non-star*	*High exp*	*Low exp*
	(1)	(2)	(3)	(4)	(5)
AQI_avg	-0.0007**	0.0015	-0.0010**	-0.0006	-0.0008*
	(-2.03)	(1.63)	(-2.56)	(-1.13)	(-1.86)
Size	0.2297***	0.3242***	0.2048***	0.2382***	0.2201***
	(4.18)	(4.19)	(3.94)	(4.01)	(4.05)
Market_to_book	-0.0448*	-0.0357	-0.0416*	-0.0546**	-0.0324
	(-1.86)	(-1.11)	(-1.74)	(-2.12)	(-1.34)
Intangible_asset	-0.7569	-1.6480	-0.5959	-0.6160	-0.9566
	(-0.95)	(-1.29)	(-0.77)	(-0.66)	(-1.31)
Volatility	38.8012***	8.2831	46.4600***	38.9695***	38.0812***
	(4.38)	(0.67)	(5.21)	(3.95)	(4.27)
Turnover	0.0284	0.0074	0.0319	0.0250	0.0316
	(1.32)	(0.22)	(1.50)	(0.99)	(1.52)
Return	-0.1853***	-0.1217	-0.1945***	-0.2009***	-0.1659***
	(-3.05)	(-1.37)	(-3.12)	(-2.82)	(-2.67)
Analyst_attention	-0.3594***	-0.5367***	-0.3108***	-0.3745***	-0.3437***
	(-5.59)	(-4.70)	(-5.09)	(-5.12)	(-5.47)
Analyst_gender	0.1223***	0.3724***	0.0762**	0.0133	0.2500***
	(3.50)	(4.81)	(2.08)	(0.28)	(5.42)
Follow_co_number	0.1635***	0.1131	0.1254*	0.1440*	0.2103***
	(2.68)	(0.90)	(1.96)	(1.74)	(3.03)
Forecast_number	-0.0653	-0.0245	-0.0654	-0.0532	-0.0939*
	(-1.43)	(-0.25)	(-1.30)	(-0.84)	(-1.77)
Broker_size	0.0729***	-0.2638***	0.0784***	0.0386	0.1113***
	(3.79)	(-2.86)	(4.09)	(1.33)	(4.47)
Forecast_horizon	1.6459***	1.8318***	1.6118***	1.6447***	1.6475***
	(44.16)	(33.43)	(44.23)	(40.92)	(43.20)
Sunny_hours_avg	-0.0002	-0.0006	-0.0003	-0.0016**	0.0012*
	(-0.41)	(-0.50)	(-0.51)	(-2.26)	(1.78)
Temperature_avg	-0.0019***	-0.0025***	-0.0017***	-0.0016***	-0.0022***
	(-7.66)	(-4.79)	(-6.73)	(-5.00)	(-7.60)
Humidity_avg	0.0019	-0.0011	0.0014	-0.0012	0.0051***
	(1.58)	(-0.33)	(1.06)	(-0.75)	(3.19)
Precipitation_avg	-0.0001	0.0004	-0.0001	0.0002	-0.0004*
	(-0.47)	(0.93)	(-0.62)	(0.84)	(-1.73)
Wind_speed_avg	0.0007	0.0129***	-0.0026	-0.0008	0.0024
	(0.40)	(3.21)	(-1.48)	(-0.33)	(1.13)
Constant	-13.6743***	-13.7620***	-13.1767***	-13.3269***	-14.0105***
	(-9.49)	(-6.50)	(-9.45)	(-8.59)	(-9.62)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Obs	222,114	35,786	186,328	114,223	107,891

Adj Rsq	0.230	0.253	0.228	0.223	0.240

Panel B: alternative windows				
Dep. Var=forecast_optimism	*[-6,0]*	*[-9,0]*	*[-11,0]*	*[-15,0]*
	(2)	(3)	(4)	(5)
AQI_avg	-0.0009**	-0.0012***	-0.0012***	-0.0015***
	(-2.42)	(-2.73)	(-2.60)	(-3.09)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Obs	221,066	221,191	221,215	221,262
Adj Rsq	0.235	0.235	0.235	0.235

Figure 1. Forecast optimism across different AQI categories

The figure plots average forecast optimism grouped by AQI ranks.

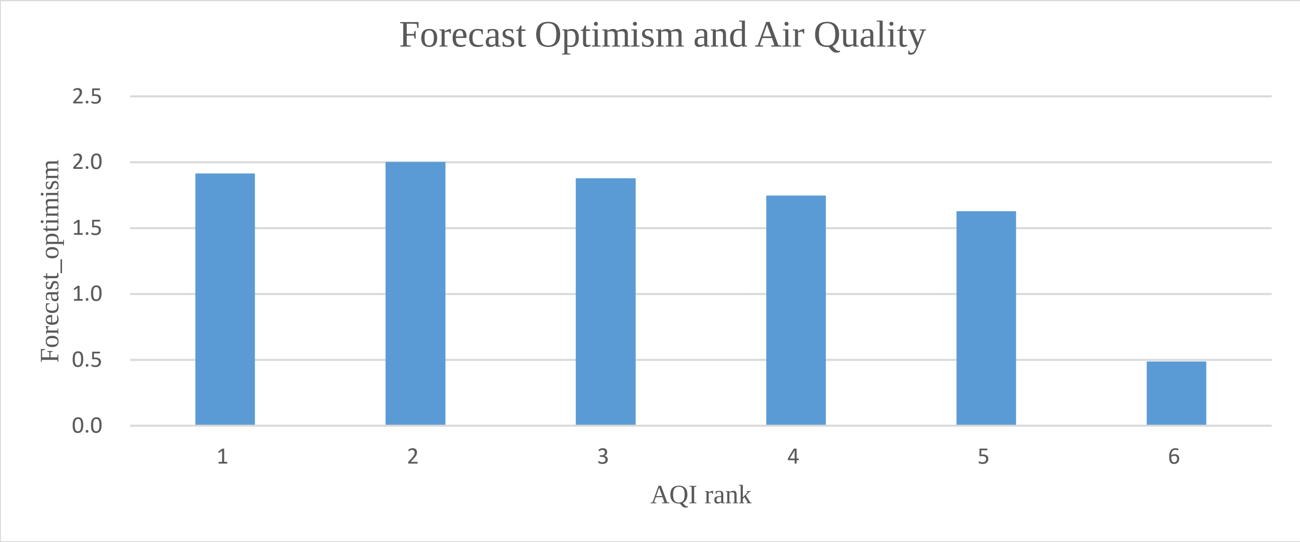


Figure 2. Histogram of AQI rank

This figure shows a histogram of AQI rank among three different samples. Full sample represents daily AQI rank of every city in the sample period; Visitor weighted group represents visit AQI weighted by the number of visitors in the visit city on the visit day; Equal weighted group represents AQI of the visit city on the visit day equally weighted.

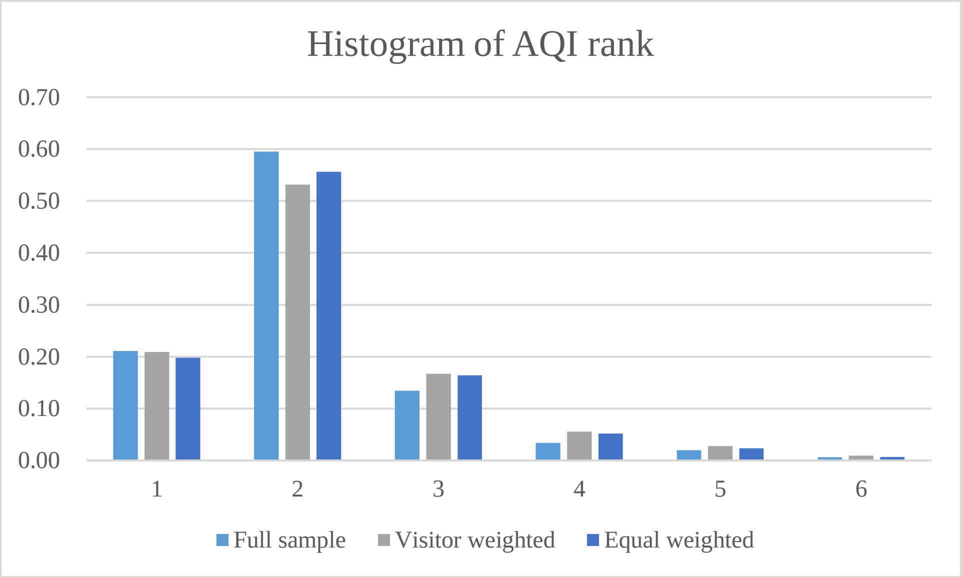
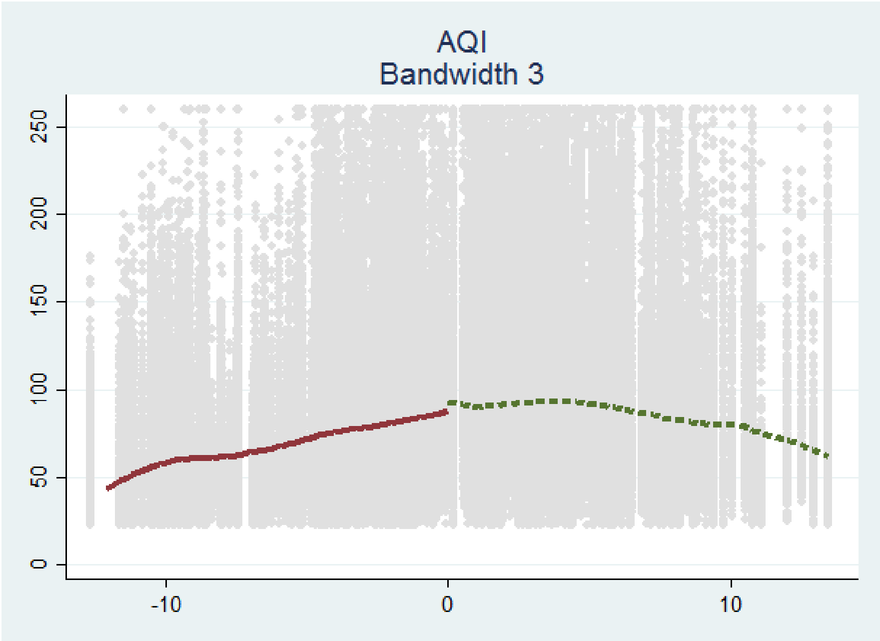


Figure 3. RD plots of AQI and forecast optimism across the Huai River line

The figure plots RD graphs of cities' AQI and analysts' forecast optimism after site visits against its degrees north of the Huai River line.



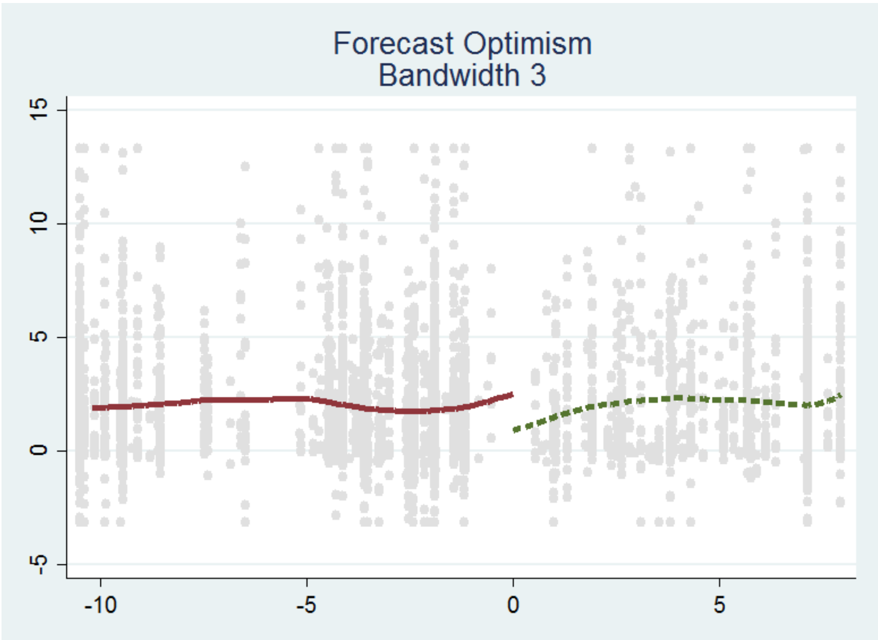


Figure 4. RD bandwidths

This figure plots the RD estimates with different bandwidths using the local linear regression models. The x axis represents the bandwidth from 1.5 to 5. The y axis represents the coefficient estimates and their upper/lower 95% confident limits.