Air Pollution and Analyst Information Production

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ABSTRACT

Recent studies investigate the impact of air pollution on labor productivity. We extend this literature by showing that air pollution negatively affects equity analysts in their role as information producers for capital markets. Compared to analysts experiencing clean air, analysts exposed to particulate matter (PM) pollution are less likely to issue timely/ bold (especially, negatively bold) forecasts or to improve their forecast accuracy. Both information supply and demand factors explain the variation in negative effects of PM pollution. Our results are robust to controlling for firm/analyst and time fixed effects, as well as additional specifications employing difference-in-difference designs and placebo tests.

Keywords: particulate matter (PM) pollution; air pollution; analysts; forecast timeliness; forecast boldness; work productivity

1. Introduction

Over 80% of urban residents around the world are exposed to dangerous outdoor particulate matter pollution (hereafter PM pollution), which has risen 8% in the past five years (Vidal 2016; Walsh 2016).[1] Consistent with anecdotal evidence that outdoor air pollution imposes large losses on the economy because of threats to health, Ebenstein et al. (2015) document that high air pollution level reduces life expectancy.[2] Recent economic studies find that outdoor pollution results in a reduction of worker productivity (Chang et al. 2014; Chang et al. 2016; Zivin and Neidell 2012). We extend this enquiry by investigating whether outdoor air pollution affects analyst information production for the capital market. Specifically, we examine two related questions: 1) Does PM pollution affect the timing/likelihood of analyst earnings forecast revisions in response to firm earnings announcements? and 2) Does PM pollution affect the properties of analyst forecast revisions? Answers to these two questions can advance our understanding of the effects of air pollution on the work productivity of highly skilled professionals, providing additional insights regarding hidden costs associated with pollution.

We conduct our empirical tests in China, where PM pollution is common and varies across time and by location. This allows us to detect changes in analyst information production relative to changes in PM pollution within the same firm/analyst. China's air pollution is representative of similar issues in other developing countries in the world (e.g., Brazil, India, Iran). For decades, China has been criticized for developing its economy at the expense of the environment (Christmann and Taylor 2001). Results from this setting may

1. Throughout the study, we interchangeably use air pollution level, particulate matter pollution, PM pollution and outdoor pollution.
2. Details at: http://www.worldbank.org/en/news/press-release/2016/09/08/air-pollution-deaths-cost-global-economy-225-billion.

shed light on indirect costs related to this strategy, with practical implications for many developing countries/regions worldwide that implement similar development strategies.

An emerging line of literature documents negative effects of air pollution on investors' decision making (Heyes et al. 2016; Hirshleifer and Shumway 2003; Li et al. 2017). The theoretical link between the air pollution and decision making in these studies is the negative mood induced by air pollution, which has been well established by related studies (Bakian et al. 2015; Calderón-Garcidueñas et al. 2015; Lim et al. 2012; Power et al. 2015; Szyszkowicz 2007).[3] Although not examining pollution, prior literature also establishes that negative mood triggered by bad weather results in analysts' sluggish responses to earnings announcements in revising their forecasts and pessimistic analyst forecasts (DeHaan et al. 2017) as well as pessimistic management forecasts (Chen et al. 2017).

In addition to fostering a negative mood, prior literature has documented that the air pollution worsens agents' performance due to physical impacts (Chang et al. 2014; Chang et al. 2016; Lavy et al. 2014; Suglia et al. 2007; Zivin and Neidell 2012). In the capital market, analysts have incentives to issue forecasts within a short-term window of earnings announcements (Gul and Lundholm 1995; Guttman 2010; Zhang 2008), which implies that, on average, analysts face a high workload immediately after firm earnings announcements. The negative effects of PM pollution (bad mood and physical effects), together with the workload demands on analysts following earnings announcements, may cause a delay in analysts' synthesis of new information into their earnings forecasts. This argument predicts that relative to analysts in cleaner environments, analysts experiencing PM pollution will issue less timely forecasts in response to earnings announcements.

3. See a review paper by Block et al. (2012).

This prediction is based upon the assumption that an analyst does not issue his forecast if he has not completed his synthesis of the new information contained in the earnings announcement. However, prior studies suggest that analysts do not necessarily issue their forecasts independently. Instead, they may simply mimic peer forecasts (i.e., issue herding forecasts), which makes it unnecessary for the analysts to rely on their own information acquisition and processing (Clement and Tse 2005; Hong et al. 2000). Further, analysts may prefer to issue early forecasts, although this may negatively impact forecast accuracy (Gul and Lundholm 1995; Guttman 2010). These studies imply that, in the presence of air pollution, analysts could still issue timely forecasts by herding. Accordingly, we predict that forecasts released by analysts exposed to air pollution immediately after earnings announcements are less likely to be bold (i.e., more likely to be the result of herding) than those issued by analysts operating in cleaner environments. Further, because positively bold forecasts benefit analysts (Beyer et al. 2010; Ke and Yu 2006; Michaely and Womack 1999; O'Brien et al. 2005; Ramnath et al. 2008), we expect the reduction in issuance of bold forecasts to predominantly affect analysts' tendency to issue negatively bold forecasts. The lower (higher) likelihood of being bold (herding) during the PM pollution period also leads to our final prediction that forecasts issued in the presence of air pollution are less likely to represent improvements in the analyst's forecast accuracy, since herding forecasts are less accurate (Clement and Tse 2005; Welch 2000).

To develop our sample, we manually collect the office landline phone numbers of more than 2,000 analysts from their analyst reports and extract the first three/four digits of an analyst's phone number to identify the analyst's location. We merge this location dataset with quarterly earnings announcement dates and the city-level daily air quality index to construct our main explanatory variable, air quality index (AQI). We estimate linear probability models by regressing the measures of timely forecasts, bold forecasts, negatively/positively bold forecasts and the improvement in forecast accuracy on AQI to examine our hypotheses.

Results of our analysis support our hypotheses. Analysts exposed to high PM pollution are less likely to revise their earnings forecasts within a two-day short-window of earnings announcements. In addition, earnings forecasts issued within the short-window by analysts located in high PM pollution cities are less likely to be bold than those issued by analysts located in low PM pollution cities. This second finding is primarily driven by analysts' reluctance to issue negatively bold forecasts. Finally, relative to their peers, forecasts issued by analysts experiencing high PM pollution are less likely to represent improvements in forecast accuracy. These findings are robust to inclusion of a battery of control variables at both the firm and analyst levels and firm/analyst/time fixed effects. We also conduct difference-in-difference designs by constructing treatment and control samples and two placebo tests by randomizing PM pollution within each analyst-firm combination and by randomizing cities to each analyst. All tests corroborate the main findings.

Further analyses indicate that factors related to both analyst supply of the forecasts as well as investor demand for forecasts contribute to the negative effects of air pollution on analyst information production. From the supply side, the negative association between air pollution level and earnings forecast properties is more pronounced in the subsample where analysts have a higher workload and where competition among analysts is weak. From the demand side, investors' high demand for information following annual earnings announcements relative to following other earnings announcements attenuates the negative effects of the PM pollution.

We contribute to three strands of literature. First, we extend research investigating the impact of air pollution on worker productivity (Archsmith et al. 2016; Chang et al. 2014;

Chang et al. 2016; Zivin and Neidell 2012) and research investigating how air pollution affects decisions made by capital market participants (Heyes et al. 2016; Li et al. 2017). Previous research focuses on output of physical goods, non-financial services or investor trading behaviors. To the best of our knowledge, our study is among the first to investigate how air pollution affects information production by analysts, who are highly skilled professionals. Our findings suggest that the air pollution generates negative effects on their production of information for the capital market.

Second, we contribute to the literature linking weather conditions to information production (more broadly, decision making) of market participants (Chen et al. 2017; DeHaan et al. 2017; Heyes et al. 2016; Li et al. 2017; Hirshleifer and Shumway 2003; Huang et al. 2018). Our study differs from this line of literature. Air pollution is fundamentally different from the more general notion of weather conditions. Specifically, unlike bad weather, air pollution can be influenced by policy makers, which implies that the costs of air pollution observed in our study might be controllable.[4] Further, our results hold after controlling for local weather conditions. Indeed, the effect of air pollution on analyst forecast timeliness is as large as that of weather conditions. Unlike poor weather, however, air pollution significantly affects analysts' likelihood to issue bold forecasts (particularly negatively bold forecasts) and their forecast accuracy. This indicates that relative to poor weather, air pollution has large incremental impacts on analyst information production. Finally, DeHaan et al. (2017) implicitly build on the assumption that analysts issue forecasts independently, which overlooks the widely documented interaction among analysts following the same firm (Clement and Tse 2005; Hong and Kubik 2003). Our study explicitly

4. Market participants can move to locations with better local weather to mitigate the negative effects of bad weather. However, their current location probably reflects the outcome of their cost/benefit trade-off and there are likely significant frictions associated with changing locations.

incorporates this possiblity and demonstrates that air pollution impedes analysts' release of bold (especially negatively bold) forecasts.

Finally, our study also adds to the literature on determinants of analyst forecast timeliness and properties of analyst forecasts (Clement and Tse 2005; Yezegel 2015; Zhang 2008). Our findings imply that the air pollution may negatively affect how the capital market functions. Given that air pollution is widespread and is a growing problem in the world, particularly in emerging countries/regions, our findings provide insights regarding an additional indirect cost of prioritizing economic development over environmental protection.

2. Particulate matter pollution in China

The Chinese government started to release the daily AQI in 2009. AQI calculation is based on three criteria air pollutants and follows an algorithm developed by the U.S. Environmental Protection Agency (EPA 2006). The pollutant that has the highest index determines the AQI on a specific day. In China, the primary form of air pollution is PM, measured as detrimental airborne particulate matter with a diameter smaller than 10μm (one seventh of the width of human hair) (PM10). Other systems track particles as small as 2.5μm (PM2.5).

Detrimental effects of PM are pervasive as PM can easily penetrate buildings due to its small size (Vette et al. 2001). To curb the negative effects of PM pollution, most offices keep air filters operating during periods of high pollution. However, the usefulness of the filters is questionable. In a survey regarding the effectiveness of air filters, 72% of respondents did not believe that filters reduce indoor PM pollution. [5] Concerns about air filters include that the devices only have limited power in cleaning air in a fully closed laboratory, and that the

5. Details at: http://view.news.qq.com/original/intouchtoday/n2944.html

widely-used technology, which was developed in Western countries to filter larger pollutants (such as pollen and dust) may be useless in cleaning Chinese PM pollutants. Given the limited power of air filters, air pollution can affect workers even if they refrain from venturing outside of their offices.

Studies have documented a wide range of PM pollution impacts. Tie et al. (2016) investigate the effect of air pollution in China on wheat and rice yields and find that PM pollution significantly reduces outputs. Ebenstein et al. (2015) demonstrate that a 10-$\mu g/m^3$ increase in PM10 reduces life expectancy by 0.64 years. Chang et al. (2016) explore how the variation in daily AQI affects the office workers' productivity in two call centers of *Ctrip,* a Chinese travel agency, and document detrimental effects. Li et al. (2017) examine the extent to which daily air quality explains the trading behavior of a mutual fund in China and find that air pollution increases the disposition effect, in which traders tend to sell shares whose price has increased, but keep those that have dropped in value. In our study, we focus on highly skilled professionals and the market's information environment by examining whether and how PM pollution affects the activities of financial analysts.

3. Hypothesis development

A large body of literature provides evidence that PM pollution results in physical diseases, such as respiratory conditions and cognitive performance impairment (Calderón-Garcidueñas et al. 2015). Lavy et al. (2014) investigate the effects of fine PM on Israeli high school students' performance in tests, and find that students' test scores and the likelihood to enter college are negatively associated with exposure to PM pollution during exam days. Suglia et al. (2007) indicate that a high level of black carbon (a traffic pollutant) decreases intelligence and cognitive function.

PM pollution also has a negative impact on mood. Lim et al. (2012) find that increases in PM level are correlated with symptoms of depression. Szyszkowicz (2007) finds that, after controlling for weather conditions, PM pollution is positively associated with daily depression-related emergency visits. Power et al. (2015) find that exposure to PM2.5 pollution is associated with high symptoms of anxiety. Building upon the negative effects of PM pollution on mood, Bakian et al. (2015) document that exposure to PM pollution increases the likelihood of people attempting suicide.

The negative effects of PM pollution on physical health and mood motivate economic research examining the effects of air pollution on workers' marginal productivity. In a seminal study, Zivin and Neidell (2012) find that U.S. agricultural worker productivity is significantly harmed when there is an increase in ozone pollution levels. Chang et al. (2014) extend this enquiry by examining effects of PM pollution on indoor workers' productivity, focusing on workers at a U.S. pear-packing factory. Their results indicate a negative association between PM2.5 pollution and worker productivity. Chang et al. (2016) provide the first evidence that outdoor PM pollution also affects office workers' productivity. They compare the number of calls answered by call center workers in Shanghai and Nantong on high PM pollution versus low PM pollution days, and find that workers exposed to high PM pollution answer fewer calls. Further analysis shows that the reduction in workers' productivity is mainly driven by their reluctance to work during high pollution days. Archsmith et al. (2016) study professional baseball umpires—a setting with highly-skilled and quality-focused employees, who make complex decisions. They find that an increase in Carbon Monoxide/PM2.5 pollution increases the propensity of umpires to make incorrect calls.

An emerging body of studies investigates how the negative mood induced by PM pollution (or more broadly by bad weather conditions), affects investor behavior in the capital market. Hirshleifer and Shumway (2003) find strong evidence that sunshine is correlated with stock returns because of individuals' upbeat mood when the weather is sunny. Heyes et al. (2016) link the PM pollution level in Manhattan to stock price movements of S&P 500. They find that a one standard deviation increase in PM2.5 is associated with an 11.9% decrease in the same-day return. They argue that this result may be driven by decreased risk tolerance due to pollution-induced changes in mood or cognitive function. DeHaan et al. (2017) examine the extent to which bad weather-induced negative mood affects capital market participants' activities. They document that, relative to those exposed to good weather, analysts exposed to bad weather are less likely to revise their forecasts. These analysts also issue more pessimistic forecasts in response to earnings announcements. Earnings announced on bad weather days exhibit high post earnings announcement drift and low trading volume, implying that bad weather also reduces trading activities. Chen et al. (2017) investigate how local bad weather (cloud cover) affects management forecast properties. Consistent with the conjecture that negative mood induced by bad weather leads to pessimism in a complex task, management forecasts issued following bad weather are more pessimistic than those issued following good weather.

Building upon the above literature, we argue that the particulate matter pollution may negatively affect analyst ability to process information contained in earnings announcements to provide a forecast. Forecasting is a complex task, for which analysts consider not only firm-specific but also intra-/inter industry information (Ivković and Jegadeesh 2004; Jacob et al. 1999; Piotroski and Roulstone 2004). In addition to skill and knowledge, the analyst's physical health, proper cognitive performance, and mood can impact forecasting ability.

Theoretical literature suggests that, upon the arrival of earnings news, analysts have incentive to issue forecasts within a short-term window of earnings announcements so that they can lead peer forecasts and have the potential to induce more trading (Gul and

Lundholm 1995; Guttman 2010). Empirically, Zhang (2008) documents that, in the U.S. from 1996-2002, approximately 40% of analyst-firm-quarter forecasts are issued within a two-day window of earnings announcements. In combination, the complex nature of the forecasting task and analysts' incentive to update their forecasts immediately after earnings announcements, imply that analysts face a heavy workload after earnings announcements. If PM pollution negatively affects the analyst's health, cognitive performance, or mood, the analyst's ability to complete the complex forecasting task may be impaired.

Exposure to PM pollution can impact forecasting even if there is no direct effect on analysts' health condition, cognitive performance, or mood. Exposure can impact forecasts if it reduces analysts' willingness to work (Chang et al. 2016). With less time devoted to forecasting, along with the short-term window in which to develop forecast revisions, analysts may be unable to effectively process information and develop timely forecasts. Our first hypothesis is:

HYPOTHESIS 1 (H1). *There is a negative association between PM pollution and the likelihood of analysts issuing forecast revisions immediately after earnings announcements.*

Hypothesis H1 builds on the assumption that, upon completion of their synthesis of information contained in earnings announcements, anlaysts issue independent forecasts. However, this assumption may not hold. Gul and Lundholm (1995) and Guttman(2010) find that there is a trade-off between the timing and accuracy of analyst forecasts. In particular, an early forecast containing errors could be tolerated by investors, if the forecast leads other analysts' forecasts and is an attempt to provide a timely signal to investors. This allows analysts, who have not fully digested the information in earnings, to revise their forecasts immediately after earnings announcements.

Another line of literature documents that if forecasts are not accurate, deviation from the prevailing forecast consensus may damage analysts' career prospects. As a result, Clement and Tse (2005) and Hong and Kubik (2003) argue that if analysts are not confident about their own forecasts, they will be reluctant to deviate from the prevailing consensus forecast. This lack of confidence can result from either lack of ability or may be due to incomplete synthesis of information, such as we expect following analyst exposure to high PM levels.

Gleason and Lee (2003) provide evidence that deviation from the prevailing consensus by an individual analyst (i.e., issuing a bold forecast) is associated with a stronger market reaction than when the analyst merely mimics peer forecasts. This implies that high innovation/bold analyst forecasts, on average, contain more information. Further, Kadous et al. (2009) find that, when forecasts are bold, investors tend to attribute poor forecasting performance to analysts' low ability and effort. Together, these findings support the notion that analysts are more likely to be bold when they have better information. With an impaired ability to process information, we expect that analysts exposed to high PM levels are less likely to issue bold forecasts, but instead, will be more likely to mimic peer forecasts. This argument leads to our second hypothesis:

HYPOTHESIS 2 (H2). *PM pollution levels are negatively associated with the likelihood that analysts will issue bold forecasts immediately after earnings announcements.*

Prior studies find that analysts are likely to issue over-optimistic forecasts because of conflicts of interest and/or cognitive bias (Beyer et al. 2010; Ramnath et al. 2008). Analysts may want to appear optimistic to facilitate their access to management, to advance their career, or to win investment banking business (Hong and Kubik 2003; Ke and Yu 2006; Michaely and Womack 1999; O'Brien et al. 2005). In addition, cognitive bias can lead to over-optimism among analysts (Kadous et al. 2006; Sedor 2002).

The optimism literature implies that issuing positively bold forecasts may not be related to the amount of information processing, and thus may be less affected by the presence of air pollution. The same may not be true for negatively bold forecasts, however. Issuing negatively bold forecasts is arguably more costly for an analyst, since negative information is relatively penalized by market participants (e.g., no access to management).[6] Therefore, the analyst will issue negatively bold forecasts only if results of extensive information processing substantiate the decision. If high PM levels affect the analyst's ability to process information within the short-window of earnings announcements, the analyst is less likely to have processed information sufficiently to be comfortable issuing a negatively bold forecast. Our third hypothesis is:

HYPOTHESIS 3 (H3). *The negative association between the PM pollution and analysts' likelihood to issue negatively bold forecasts is stronger than the association between PM pollution and analysts' likelihood to issue positively bold forecasts.*

If analysts exposed to high PM pollution only have limited ability to digest the information embedded in earnings announcements, they may not be as effective in developing their earnings forecasts. Based on the above arguments, analysts exposed to high PM pollution are more likely to issue herding forecast revisions following earnings announcements. Since herding forecasts are less informative and less accurate than bold forecasts (Clement and Tse 2005; Welch 2000), we expect that, relative to the latest forecast just before earnings announcements, analysts experiencing high PM pollution are less likely to improve their forecast accuracy. Our hypothesis is:

6. See anecdotal evidence where an analyst who released negative recommendation for a firm while other analysts recommended purchase of the firm's shares, was required to leave the conference site by the CFO of the firm (http://cj.sina.com.cn/articles/view/2418201593/9022d3f9019001g6c).

HYPOTHESIS 4 (H4). *There is a negative association between PM pollution and the likelihood of forecast revisions within a short window after earnings announcements representing accuracy improvements.*

4. Research design

Model specification

To test the timeliness of analyst forecasts, we follow several recent studies to apply a linear probability model to estimate the probability of analysts' issuance of earnings forecast reports in response to quarterly earnings announcements (DeHaan et al. 2017; Hanlon and Hoopes 2014; Hoberg et al. 2014).[7] In particular, model (1) is specified as follows:

$$TL = \alpha_0 + \alpha_1 LOG\_AQI + \delta X + \theta_j + \lambda_q + QTR_t + \varepsilon \quad (1)$$

where *TL* equals 1 if an analyst revises his forecasts within two days (i.e., day 0 and 1) of a quarterly earnings announcement of firm j, otherwise 0.[8] The earnings announcement date is denoted as day 0. *AQI* equals the average daily air quality index between the earnings announcement date and the analyst forecast revision date if an earnings forecast is issued within two days of the earnings announcement date. If the earnings forecast is not issued within this short window, we measure *AQI* over the two-day window. In our study, *AQI* is measured for each analyst, according to the air pollution level in his own location (city). Higher values of *AQI* correspond to higher levels of air pollution. To address heteroskedasticity associated with *AQI*, we use the logarithm of *AQI* in our analyses. θ_j and λ_q represent firm and year fixed effects respectively, which removes firm-invariant and time-

7. There are two advantages in our setting to use the linear probability model rather than the non-linear limited dependent variable model: (1) the linear probability model allows easier interpretation of the coefficient on our interested variable than the non-linear limited dependent variable model (Ai and Norton 2003); (2) our model incorporates fixed effects while the non-linear limited dependent variable model may yield biased estimates (Green 2004). In addition, the data fit the model well, with less than 5% predicted value of the dependent variable falling outside of [0,1].
8. We designate [0,2] as an alternative short-window to define our variables of interest. The results are qualitatively similar.

invariant characteristics affecting analysts' likelihood to issue timely forecasts. QTR_t denotes indicator variables for earnings announcement quarters. A negative coefficient on *LOG_AQI* is consistent with our prediction that PM pollution reduces the analyst information production, and would provide evidence supporting H1.

The vector *X* consists of a battery of both analyst- and firm-level control variables. All analyst-level control variables are defined in the year preceding the earnings announcement dates, unless stated otherwise. *N_FIRM* measures the number of firms one analyst follows. *N_IND* measures the number of unique industries one analyst follows. *SIZE_BROKER* measures the number of analysts employed by the analyst's brokerage. *EXP* is the number of quarters for an analyst between his first forecast report date recorded in the database and the current earnings announcement date. *N_FOLLOW* is the number of analysts who issued at least one report for the firm. *STAR* equals one if an analyst was awarded the title of star analyst by the *NEW FORTURE* magazine in the preceding calendar year, otherwise 0.

The remaining control levels are at the firm-level. *HOLDPERCT* is the percentage of shares held by funds. *LEV* is the total liabilities deflated by total assets. *SIZE* is the logarithm of total market capitalization on the day before the earnings announcement. *MB* equals total market capitalization plus the book value of total debt deflated by the book value of total assets. *SALES_GROWTH* is quarter-to-quarter sales revenue difference deflated by the sales revenue for the same quarter last year. *ROA* equals net profit divided by total assets. *LOSS* equals 1 if ROA is less than 0, otherwise 0. *SUE* is the quarter-to-quarter net profit difference deflated by the market capitalization on the day before the earnings announcement date.[9] *TRVOL* is the average trading volume over the [-1,+1] window of the three earnings announcement dates, scaled by the average trading volume in the non-earnings announcement

9. We follow the random walk assumption of earnings generation process (Ball and Brown 1968; Bernard and Thomas 1989).

days in the previous year. *RETVAR* is the standard deviation of daily stock returns over the [-1,+1] window of the three earnings announcement dates minus the standard deviation of daily stock returns over other non-earnings announcement days in the previous year. We cluster by firm to correct for firm-level auto-correlation.[10]

To test the effects of air pollution level on the propensity of analysts to issue bold forecasts and improve their forecasts accuracy during the high pollution period, we estimate the following linear probability model:

$$[BOLD, NEG\_BOLD, POS\_BOLD, ACCURACY] = \alpha_0+\alpha_1 LOG\_AQI+ \delta X +\theta_j+\lambda_q+QTR_t+FPI+\varepsilon \qquad (2)$$

Figure 1 depicts the timeline to construct the four dependent variables. Before revising earnings forecasts in response to earnings announcements, an analyst may have two reference estimates to start with: 1) his own latest forecast previously issued, and 2) the consensus forecasts issued by all peer analysts in the year preceding the analysts' forecast revision (constructed using all peer analysts' latest forecasts). To address the potential for stale information contained in the two reference estimates, we require that the prior analyst forecast and peer consensus forecast must be issued within one year preceding earnings announcements. Following Clement and Tse (2005), we define *BOLD* as 1 if an analyst revises his forecast below or above both reference estimates, otherwise 0. *NEG_BOLD* equals 1 if the analyst's revised earnings forecast is below his own prior forecast and peer consensus forecasts, otherwise 0. *POS_BOLD* equals 1 if the analyst's revised earnings forecast is above his own prior forecast and peer consensus forecasts, otherwise 0.

[Insert Figure 1 about here]

10. When we cluster by firm and analyst or firm and city-quarter, results remain qualitatively the same.

We construct *ACCURACY* to measure whether the analyst improves his own forecast accuracy surrounding earnings announcements. *ACCURACY* equals 1 if one analyst's revised earnings forecast accuracy is higher than his prior earnings forecast accuracy, otherwise 0.[11]

Given that prior research documents a strong association between forecast horizon and analysts' information production, in addition to all control variables in model (1), we include *DAYS* and the forecast period fixed effects (*FPI*). Specifically, *DAYS* is the number of days between the analyst forecast revision date and the forecast period end date. *FPI* denotes the accounting period for which an earnings forecast is made. For example, *FPI* equal to 0 (1) represents that the earnings revision is made for the current (next) accounting period.

Evidence consistent with H2 and H4, would be negative α_1s when the dependent variables are *BOLD* and *ACCURACY,* respectively. H3 predicts a more negative loading on *AQI* when *NEG_BOLD* is the dependent variable than when *POS_BOLD* is the dependent variable.

Data source

Analyst location

We first extract the list of analyst names recorded at the end of each reporting date by CSMAR for all brokers in China. We search each analyst name in the *HUIBO* terminal (http://www.hibor.com.cn) to find out all analyst reports issued by the analyst.[12] These reports include office landline phone numbers. The first three/four digits of landline phone numbers are area codes, which can be used to identify the analyst's location (city). Given that

11. This measure does not build on the assumption that an analyst accesses to peer estimates or he puts a weight on peer estimates. Earnings forecast accuracy is the distance between the forecasted earnings and actual realized earnings. If one earnings forecast shortens (prolongs) this distance compared with the prior forecast, we assign 1 (0) to the variable *ACCURACY.* This variable is only defined for forecasts issued on or one day after earnings announcement dates.
12. *HUIBO* terminal has archived a large volume of analyst reports (more than 1 million) and are widely used by investors in the Chinese market.

each analyst issues multiple forecast reports in a year, it is difficult for us to search each single analyst report. Instead, we assign the opening and closing dates for each analyst as the 1st of January and 31st December respectively. In each year, we search two reports, the one issued after, but closest to, 1st January (early report) and the one issued before, but closest to, 31st December (late report). We assign the early report to 1st January and the late report to 31st December in each year and collect the two office landline phone numbers appearing on the two reports. Furthermore, we require that, to be included in our analyses, the analyst-year observations cannot experience changes in the phone number's area code in a single year.[13]

Air quality index

We download the daily air quality index from the website of Ministry of Environmental Protection of the People's Republic China (http://www.mep.gov.cn/). On this website, the daily air quality index has been archived since 2010 for major cities in China. Hourly air quality data, similar to the data used in previous literature from other countries, is unavailable for China, so we employ daily air quality data in our study.

Sampling

We retrieve analyst forecast data from the CSMAR and merge it with quarterly earnings announcements. Based on the forecast revision date, each analyst-firm-year forecast is between the announcement date of quarter t and quarter $t+1$. This process leads to an initial sample of 592,706 analyst-firm-year observations. We first drop the forecasts for a year issued by one analyst after his first forecast for the same year in response to quarter t earnings announcement (124,091 observations). We delete observations without location information (149,036 observations) or observations without air quality index information (80,281

13. We drop those analysts from our sample is because it is very difficult to determine on which day they moved the location.

observations). The missing analyst and firm level control variables reduce the sample by 1,504 and 30,941 observations respectively. We also drop observations where an analyst did not cover a firm in the year preceding his earnings forecasts (99,826 observations). The resulting sample size comprises 107,207 analyst-firm-year forecasts, which corresponds to 43,195 analyst-firm reports and is used to estimate model (1).[14]

Due to missing accuracy improvement data for 14,626 observations, the sample size for estimating model (2) for accuracy improvement is 92,403 analyst-firm-year observations. These data represent 60,391 forecasts issued within the two-day window (i.e., 0 and 1) of earnings announcements and 32,012 forecasts issued after the two-day window. This sample includes 2,207 unique firms and 16,886 firm-quarter earnings announcements.

The lack of data for the boldness measures further reduces the accuracy improvement sample by 1,149 observations, resulting in 91,254 analyst-firm-year observations for examining our hypotheses concerning boldness. This sample includes 59,640 observations issued within the two-day window of earnings announcements and 31,614 observations issued after the two-day window. There are 2,207 unique firms, which generate 16,358 firm-quarter announcements. Table 1 summarizes the above sampling procedures.

[Insert Table 1 about here]

Panels A and B of Table 2 describe the distribution of analysts and air pollution across cities. Panel A indicates that analysts in our sample spread over 19 cities in China. Shanghai is the location for the largest number of analysts, accounting for 45.12% of our sample. Beijing, Shenzhen, Nanjing, Guangzhou and Wuhan also have a large number of analysts. Panel B summarizes variation in PM levels in the top 6 cites in China (i.e., Shanghai, Beijing,

14. Similar to in the US, analysts in China issue several period forecasts in one report. The examination of H1 is conducted at the analyst report level.

Shenzhen, Nanjing, Guangzhou, and Wuhan) during our sample period of 2009-2016. There are 158 days with AQI index between 50 and 100 simultaneously in all six cities; 209 days have a high AQI in only one city. There are only 9 days with AQI index higher than 100 simultaneously in all six cities, but 701 days with such a high AQI in only one city. During our sample period, there are 435 (1,477), 899 (1,298), 68 (1,254), 697 (1,611), 258 (1,594), and 800 (1,482) days with AQI higher than 100 (higher than 50 but no higher than 100) in Shanghai, Beijing, Shenzhen, Nanjing, Guangzhou, and Wuhan respectively. These numbers suggest that there is significant variation in air pollution across the cities where analysts are located.

[Insert Table 2 about here]

5. Empirical findings

Summary statistics

Table 3, panel A tabulates summary statistics of all model variables. 55.37% of analyst forecasts are issued with the two-day window of earnings announcements in China, which is higher than the corresponding fraction (40.32%) in the U.S. market, as documented by Zhang (2008). On 49.52% occasions, analysts deviate from both their own prior forecasts and from other peer consensus forecasts, which is much lower than the ratio reported by Clement and Tse (2005). Most of those bold forecasts (0.3177/0.4952=64%) are negatively bold forecasts, in which analysts downwardly revise their forecasts. Mean *ACCURACY* suggests that 45.41% analyst forecasts reduce forecast errors relative to analysts' prior latest forecasts. Mean and median *AQI* are 73 and 64, which is highly comparable to those reported by Li et al. (2017), although they cover a slightly different period.[15]

15. Mean and median *AQI* in Li et al. (2017) are 80 and 70 respectively.

Regarding control variables, a representative Chinese analyst follows 12 firms and 3 industries, which is lower than his peers in the U.S. (Clement and Tse 2005). On average, a brokerage employs 42 analysts. Each firm-year observation has an average following of 20 analysts. Mean and median *EXP* are 18 and 17 quarters respectively. 25% forecasts are issued by star analysts. Mean *TRVOL* implies that trading volume is 18% higher in earnings announcement periods than on non-earnings announcement days. However, the stock return volatility (*RETVAR*) does not appear to be affected by earnings announcements. 18.49% of earnings announcements are related to annual earnings. The fraction of loss firms is only 2.49%, which is much lower than in the U.S.

Table 3, panel B presents the mean statistics for all four dependent variables across *AQI* quintiles, with quintile 0 (1) representing the lowest (highest) PM pollution periods. There is a generally monotonic declining trend for each of the four variables from the least to most polluted periods.[16] For instance, 62% of analyst forecasts are issued within the two-day window of earnings announcements in the least polluted period, whereas this percentage drops to only 48% in the most polluted period. Mean *BOLD* and *NEG_BOLD* are 54.54% (49.77%) and 35.32% (30.44%) in the lowest (highest) *AQI* quintile respectively. Compared with the lowest *AQI* quintile where 49.77% of analyst forecasts experience improvement in accuracy; this fraction in the highest *AQI* quintile is much lower (45.83%). The differences in all four variables between the lowest and highest quintiles are significant, not only statistically (with the lowest t-statistic being -7.64) but also in economic magnitude.[17] These results provide some preliminary evidence in support of our hypotheses.

16. The generally monotonic trend provides support for our linear model specification.
17. To assess the economic magnitude, we benchmark the difference against the unconditional mean of the variable in the top quintile. If the difference accounts for more than 5% of the benchmark, we treat the difference as economically significant. For example, the difference in *BOLD* between the bottom and top quintile is 0.0477, which is 9.58% of 0.4977.

[Insert Table 3 about here]

Multivariate results

Table 4 reports summary statistics for estimating equation (1) where we examine PM pollution and timeliness of analyst forecasts. In column (1), the base model without any control variables or fixed effects, the coefficient of *LOG_AQI* is -0.0976 with a t-statistic of -17.03. In column (2), where we include firm, year and quarter fixed effects, the coefficient of *LOG_AQI* changes slightly to -0.0901 with a t-statistic of -14.50. The model in column (3) includes additional control variables. The coefficient of *LOG_AQI* is -0.0872 with a t-statistic of -13.94. In all models, the level of PM pollution is significantly negatively associated with analysts' propensity to issue forecasts within the two-day window of earnings announcements. Turning to the control variables, broker size, the number of analysts following the firm, the number of firms followed by the analyst, firm profitability and firm size are positively associated with timely forecasts. Leverage, earnings surprise, and growth prospect are negatively associated with timely forecasts. Column (4) presents results where we remove the effects of analyst invariant characteristics (e.g., gender and education background). The coefficient of *LOG_AQI* remains negative. Furthermore, in column (5), where we control for weather, the coefficient of *LOG_AQI* remains negative. The coefficients of the two weather related variables suggest that bad weather is negatively related to analysts' likelihood to revise earnings forecasts immediately after earnings announcements, which is consistent with the findings in prior literature (DeHaan et al. 2017).

To explore the economic magnitude of the coefficient on *LOG_AQI,* we re-estimate the standardized coefficients of regression for column (5) Table 4. In un-tabulated results, the coefficients on *LOG_AQI, WIND* and *CLOUD_RAIN* are -0.1012, -0.0156 and -0.1109 respectively, implying that the effect of air pollution on analysts' tendency to release timely forecasts quite similar to that of *CLOUD_RAIN*. Compared to the unconditional mean of *TL*, a one standard deviation change in *LOG_AQI* leads to an 18.27% change in the sample mean. Overall, we find evidence supportive of H1, that high PM pollution reduces analysts' propensity to issue timely forecasts. More importantly, this effect is different from the previously documented weather effect.

[Insert Table 4 about here]

Panel A, Table 5 presents results of estimating equation (2) when the dependent variable is *BOLD*. Column (3) indicates that after including control variables and fixed effects, there is a negative coefficient of *LOG_AQI,* providing evidence supportive of H2. Further results indicate that analysts with wide coverage are less likely to issue bold forecasts. Analyst experience, analyst following, and early forecasts (relative to the forecast period end) are positively associated with the presence of bold forecasts. Firm size, earnings surprise, growth prospect, and institutional shareholdings all exhibit negative association with the presence of bold forecasts. These results are robust to inclusion of analyst fixed effects and weather-related control variables.

To provide evidence regarding H3, we estimate equation (2) by using *NEG_BOLD* and *POS_BOLD* as dependent variables. Panel B and panel C of Table 5 present the results. Column (3) in panel B, Table 5 report a negative coefficient of *LOG_AQI* (-0.0227 with a t-statistic of -3.41), whereas column (3) in panel C reports a positive but insignificant coefficient of *LOG_AQI* (0.0057 with a t-statistic of 1.04). The difference in two coefficients provides evidence that the negative effect of PM pollution on analysts' tendency to issue bold forecasts manifests in the effect of PM pollution on negatively bold forecasts. This association is robust to inclusion of analyst fixed effects and weather-related variables. Therefore, we find evidence in support of H3.

Panel D of Table 5 documents evidence consistent with H4, that analysts are less likely to improve their forecast accuracy in periods with high PM pollution. In particular, column (3) reports a negative coefficient of *LOG_AQI* (-0.0204 with a t-statistic of -3.06). Analyst coverage, firm size, earning surprise, and firm growth prospect are negatively associated with analyst tendency to improve their forecast accuracy. Analyst experience, analyst following, and early forecasts are positively associated with the presence of improvement in forecast accuracy. These results are robust to analyst fixed effects and weather-related variables.

[Insert Table 5 about here]

Difference-in-difference designs

To strengthen our model identification, we conduct difference-in-difference (hereafter, diff-in-diff) empirical designs. We first identify analyst-firm-announcement quarter observations, for which there were drastic differences in air quality during the short-window forecasting periods between two adjacent quarters (the treatment sample). To be included in this sample, the change in AQI of two adjacent quarter analyst-firm forecasts must be at least 40 (one standard deviation of our full sample AQI). Conceptually, within this sample, an analyst-firm forecast potentially receives two types of treatment, one experiencing an increase in AQI (pollution) and the other one experiencing a decrease in AQI (clean). Once we identify treatment observations, the change in the timeliness and properties of analyst forecasts between the two earnings announcements should partially reflect the effect of the air quality change.

Given that the timeliness and earnings forecasts properties in our study also change in relation to other analyst-/firm-level characteristics (e.g., analyst experience), we need to construct a control sample to evaluate the effects of these characteristics on the observed changes in dependent variable. For each observation in the treatment sample, we choose one observation from the remaining observations that did not experience drastic changes in AQI. The observation chosen must have forecasts issued by an analyst from a different city, but following the same firm. For treatment sample observations with multiple control observations, we first drop those observations with fundamentally different AQI (the difference in AQI must be less than 30) in the preceding earnings announcement quarter. If there is still more than one control observation left, we choose the observation with the closest AQI. This process ensures that all changes between the prior and current quarter timeliness and forecast properties of the control sample should result from changes in analyst-/firm-level characteristics other than changes in AQI.

To assess the effect of PM pollution on our dependent variables, we compare differences in changes in forecasts of the treatment sample and changes in forecasts of the control sample between the prior and current quarter earnings announcements. For pollution (clean) observations, we should witness a decrease (an increase) in timeliness, boldness, negative boldness, and accuracy improvement of forecasts. The diff-in-diff model is specified as follows:

$$[TL, BOLD, NEG\_BOLD, ACCURACY] = \alpha_0+\alpha_1 POLLUTION+ \alpha_2 CLEAN+ \alpha_3 POST+ \alpha_4 POLLUTION* POST+ \alpha_5\ CLEAN * POST+ X\delta+\theta_j+\lambda_q+\varepsilon \qquad (3)$$

where *POLLUTION* (*CLEAN*) equals 1 if an analyst-firm observation experiences an (a) increase (decrease) in AQI from the previous quarter forecast, otherwise 0. *POST* equals 1(0) for the current (previous) quarter forecast. To be consistent with our hypotheses, there should be negative α_4s and/or positive α_5s.

Table 6 documents summary statistics for our main variables and the results of estimating equation (3). Panel A shows changes in both AQI and *TL* across firms between the preceding and current quarter announcements. There are 2,762, 910 and 1,852 analyst-firm observations in the control, clean, and pollution samples respectively. There is only a marginal increase in *TL* of the control sample from the preceding earnings announcement. In contrast, there is a decrease of 12.09% and an increase of 3.46% in *TL* in the clean and pollution samples respectively, consistent with the changes in AQI of these two samples.

Table 6, panel B reports changes in forecast property measures across samples. There are 1,316, 421 and 881 observations in the control, clean, and pollution samples respectively. In the clean (pollution) sample, *BOLD* increases (decreases) by 6.07% (3.41%) from the preceding to the current quarter, consistent with the drop in *AQI*. *NEG_BOLD* and *ACCURACY* also show similar patterns with respect to changes in air pollution level. The summary statistics in the diff-in-diff design samples provide preliminary evidence in support of our hypotheses.

Table 6, panel C tabulates the regression results controlling for both firm and analyst level variables as well as time and firm fixed effects. In column (1), the coefficients of *POLLUTION* POST* and *CLEAN* POST* are consistent with H1: an (a) increase (decrease) in AQI leads to less (more) timely earnings forecasts relative to control observations without any change in AQI. The remaining three columns document similar findings for *BOLD*, *NEG_BOLD,* and *ACCURACY.* Overall, the diff-in-diff design results corroborate our previous findings.

[Insert Table 6 about here]

Placebo test

We conduct two placebo tests and report the results in Table 7. Panel A reports the results where we randomize the PM pollution measure within an analyst-firm level. For example, take an analyst who follows a firm for 3 years and issues 12 forecasts in response to the 12 earnings announcements. Given a specific forecast issued after a quarter, we randomly find an *AQI* measure from other 11 quarters. After this randomization process, we re-estimate equations (1) and (2). We repeat this placebo tests 150 times. Panel A documents the distribution of coefficients. Column (1) reports a mean coefficient of *LOG_AQI*, when *TL* is the dependent variable, of -0.0015; only 1.7% of the actual coefficient reported in Table 3 column (3). Indeed, the actual coefficient and the three coefficients for the other three dependent variables are below the minimum values of the distribution.

Table 7, panel B documents results where we randomize the location information for one analyst. For example, for an analyst located in Beijing, we randomly assign the analyst to another city in China and recalculate the AQI measure using this randomized location. Then we re-estimate the prior equations and repeat this process 150 times. We expect that this randomized city AQI should not result in our findings. However, due to the large scale of air pollution in China, on a given day, there is a probably strong positive correlation in the PM pollution level between two cities. This strong positive correlation implies that we may still obtain associations between the randomized *AQI* measure and our dependent variables. Column (1) indicates that the average coefficients linking randomized *AQI* to *TL* is -0.0357, which is 41% of the actual coefficient. However, the percentile of the actual coefficient in the distribution of those false coefficients is 0. Regarding the position of actual coefficients of the other three dependent variables, the percentile is at least lower than 5%. Overall, the results from the above two placebo tests provide support for our findings.

[Insert Table 7 about here]

Underlying mechanisms

Table 8 reports the results where we partition our sample based upon variables which may capture mechanisms underlying our results. For example, we conjecture that analysts located in high pollution cities are reluctant to work. If this conjecture holds, we should observe that there are stronger associations between our dependent variables for analysts with an expected high workload than for those with lower workload. We measure the workload of an analyst by counting the number of contemporaneous earnings announcements made by firms followed by the analyst in the prior quarter within a three-day window surrounding an analyst-firm-quarter earnings announcement. Table 8, panel A provides results of this analysis. Columns (1) and (2) indicate that analysts with low workload are affected by the PM pollution to a lesser extent than are other analysts. In addition, our findings related to the association between PM pollution and improvement in forecast accuracy, bold forecasts, and negative bold forecasts are mainly driven by analysts with high workload.

We further partition the sample based on the number of analysts following a firm. If this measure reflects the labor market competition for an analyst which motivates the analyst to work hard (Stickel 1989; Zhang 2008), we should observe that competition mitigates the negative effects of air pollution. Panel B documents some evidence in this regard. Although competition does not attenuate the negative association between air pollution and analysts' likelihood to issue timely forecasts, we obtain expected results for *ACCURACY*, *BOLD,* and *NEG_BOLD*.

Prior literature postulates that, compared to interim announcements, annual earnings announcements trigger higher trading volume (Griffin 2003). High trading volume may reflect high information demand from investors, which could mitigate the negative effects of PM pollution on analyst information production. Table 8, panel C indicates that the effect of PM pollution on timely forecasts is less pronounced in annual earnings announcements than in interim earnings announcements. We also document consistent findings when *BOLD* and *NEG_BOLD* are the dependent variables.

[Insert Table 8 about here]

Trading volume

We further examine to what extent investors perceive the informativeness of analyst forecasts issued during air pollution period and change their trading behavior in the capital market. We construct abnormal trading volume within [0,1] of analyst forecast date (day 0 is the forecast date) to investigate investors' trading behavior. Abnormal trading volume is daily trading volume adjusted by the average trading volume over the 60 trading days before the analyst forecast date.

Table 9 presents the results where we control a number of analyst and firm level variables as well as firm and year fixed effects. The coefficient of *LOG_AQI* is negative and significant (-0.0474 with a t-statistic of -2.18), suggesting that investors may understand the deficiency of forecasts issued during the PM pollution period and be less likely to trade in the market. We note that while investors can come from all over China and are not necessarily impacted themselves by the pollution experienced by the analyst.

[Insert Table 9 about here]

6. Conclusion

Many countries are increasingly experiencing episodes of severe air pollution, especially PM pollution. Prior studies provide evidence that air pollution reduces human capital formation and decreases workers' marginal productivity. Our study extends the literature by investigating the extent to which PM pollution affects financial analysts' forecast behaviors immediately after firms' earnings announcements.

We find that PM pollution is negatively associated with analysts' propensity to issue forecasts within a short-term window of earnings announcements. Even when they issue forecasts within the short-term window, analysts' forecasts are less likely to be bold, (especially, less likely to be negatively bold) and are less likely to represent improvements in forecast accuracy. These findings are consistent with the notion that air pollution triggers health problems, diminishes brain function, and induces negative moods. Furthermore, we find that in the subsample of analysts who follow a large number of firms or compete with a low number of analysts, the association is more pronounced. High information demand during annual earnings announcement periods mitigates the negative effects of air pollution to a certain extent.

Our study suggests several directions for future research. First, a more direct test could be conducted to examine how air pollution affects the work pattern of analysts. For instance, how do they allocate time to work and leisure during pollution days. Second, financial analysts are only one of the agents producing information for the capital market. Further studies can investigate how air pollution changes the behavior of other market participants.

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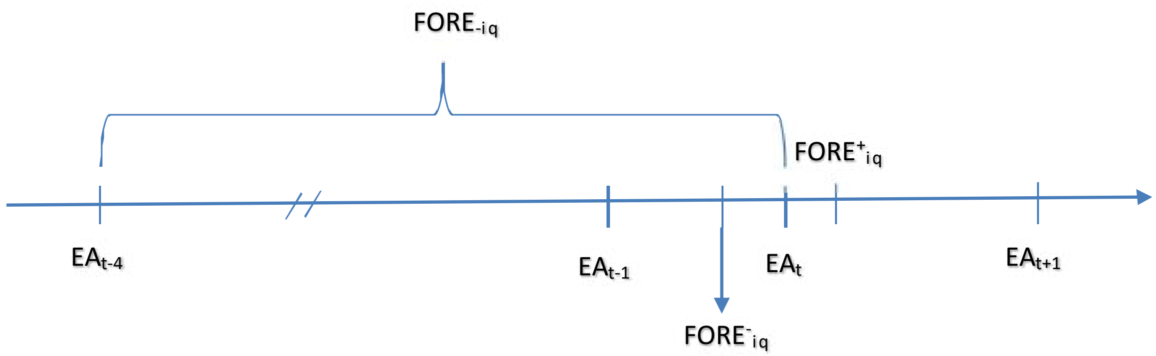
Figure 1 Timeline for the research design



Notes: This figure presents the timeliness for research design. EAs represent the earnings announcement dates for quarterly earnings. $FORE^{+}_{iq}$ denotes the analyst *i*'s forecast for year *q* in response to the earnings announcement of quarter *t*. $FORE^{-}_{iq}$ denotes analyst *i*'s latest forecast for year *q* before the earnings announcement of quarter *t*. $FORE^{-}_{iq}$ is the consensus forecast for year *q* before the earning announcement of quarter t by all analysts except analyst *i*. To calculate this consensus forecast, we keep all forecasts for year *q* issued between the earnings announcement of quarter *t*-4 and that of quarter *t*. If one analyst issues multiple forecasts during this period for year *q*, only the latest forecast is retained.

Appendix

Variable specifications

Variable name		Definition
TL	=	An indicator variable that equals 1 if an analyst revises his forecasts within two days (i.e. day 0 and 1) of a quarterly earnings announcement of a focal firm, otherwise 0.
BOLD	=	An indicator variable that equals 1 if an analyst revises his forecasts below or above both his own prior forecast and peer consensus forecasts, otherwise 0.
NEG_BOLD	=	An indicator variable that equals 1 if the analyst's revised earnings forecasts are below his own prior forecast and peer consensus forecasts, otherwise 0.
POS_BOLD	=	An indicator variable that equals 1 if the analyst's revised earnings forecasts are above his own prior forecast and peer consensus forecasts, otherwise 0.
ACCURACY	=	An indicator variable that equals 1 if one analyst's revised earnings forecast is more accurate than his prior earnings forecast, otherwise 0.
AQI	=	The average daily air quality index between the earning announcement date and the analyst forecast revision date if an earnings forecast is issued within two days of the earnings announcement date. If the earnings forecast is not issued within the above short window, we measure AQI over the two-day window. In our study, AQI is measured for each analyst according to the air pollution level in his own location (city).
N_FIRM	=	The number of firms one analyst follows.
N_IND	=	The number of unique industries one analyst follows.
SIZE_BROKER	=	The number of analysts employed by a broker。
EXP	=	The number of quarters for an analyst between his first forecast report date recorded in the database and the current earnings announcement date.
N_FOLLOW	=	The number of analysts who issued at least one report for the firm.
STAR	=	An indicator variable that equals 1 if one analyst was awarded the title of star analyst by the *NEW FORTURE* magazine in the preceding calendar year, otherwise 0.
DAYS	=	The number of days between the analyst forecast revision date and the forecast period end date.
HOLDPERCT	=	The percentage of shares held by funds.
ROA	=	Net profit divided by total assets.
LEV	=	The total liabilities deflated by total assets.
SALES_GROWTH	=	Quarter-to-quarter sales revenue difference deflated by the sales revenue for the same quarter last year
TRVOL	=	The average trading volume over the [-1, +1] window of the three earnings announcement dates, scaled by the average trading volume in the non-earnings announcement days in the previous year.
RETVAR	=	The standard deviation of daily stock returns over the [-1, +1] window of the three earnings announcement dates minus the standard deviation of daily stock returns over other non-earnings announcement days in the previous year.
MB	=	Total market capitalization plus the book value of total debt deflated by the book value of total assets
SUE	=	The quarter-to-quarter net profit difference deflated by the market capitalization on the day before the earnings announcement date.
SIZE	=	The logarithm of total market capitalization on the day before the earnings announcement dates.

ANNUAL	=	An indicator variable that equals 1 if an earnings announcement is made for annual earnings, otherwise 0.
INTERIM	=	An indicator variable that equals 1 if an earnings announcement is made for interim earnings, otherwise 0.
LOSS	=	An indicator variable that equals 1 if the ROA is less than 0, otherwise 0.
WIND	=	The average wind speed in a calendar day.
CLOUD_RAIN	=	An indicator variable that equals 1 if the weather in a calendar day is cloudy/rainy, otherwise 0.
VOLUME_0_REV	=	Abnormal trading volume within [0,1] of analyst forecast date (day 0 is the forecast date), where abnormal trading volume is daily trading volume adjusted by the average trading volume over the 60 trading days before the analyst forecast date.
TO_END_DAYS	=	The number of days between an analyst forecast revision date and the forecasts period end.

Notes: This table descripts the definitions of all variables employed in the study.

TABLE 1

Sample development

	Boldness sample	Accuracy improvement sample
Analyst forecasts merged with the quarterly earnings announcement dates (forecast period end between 31/12/2009-31/12/2016)	592,706	
Less: forecasts issued after one analyst's first revision in response to earnings announcement	124,091	
Less: observations without location information	149,036	
Less: observations without air quality information	80,281	
Less: observations without analyst level control variables	1,504	
Less: observations without firm level control variables	30,941	
Less: observations without preceding forecasts	99,826	
	107,207	
Less: observations without accuracy improvement	14,626	
Sample for accuracy improvement	*92,403*	
Less: observations without boldness measure	1,149	
Observations for boldness sample	*91,254*	
Forecasts issued within 2 days of earnings announcement dates	59,640	60,391
Forecasts issued 2 days of earnings announcement dates	31,614	32,012
Analyst quarter observations	11,519	11,557
Firm observations	2,207	2,207
Firm quarter announcements	16,538	16,886

TABLE 2
Statistics of the variation in analysts and AQI across locations

Panel A: Location distribution of analysts in our sample

City	No. of observations	% of observations	City	No. of observations	% of observations
Beijing	496	29.07	Shanghai	770	45.13
Changsha	11	0.64	Shenzhen	262	15.36
Dalian	2	0.12	Suzhou	6	0.35
Dongguan	8	0.47	Taiyuan	8	0.47
Guangzhou	24	1.41	Tianjin	12	0.70
Hangzhou	5	0.29	Wuxi	13	0.76
Hefei	4	0.23	Wuhan	15	0.88
Jinan	2	0.12	Xian	3	0.18
Nanjing	51	2.99	Chongqing	13	0.76
Nanning	1	0.06	Total	1,706	100

Panel B: Statistics of extreme event days with high AQI across top 6 cities in terms of the number of analysts during the period of 2009-2016 in China

	$50 < AQI <= 100$	$AQI > 100$
# Days in 6 cities	158	9
# Days in 5 cities	393	57
# Days in 4 cities	659	123
# Days in 3 cities	649	271
# Days in 2 cities	459	394
# Days in 1 city	209	701
# Days in Shanghai	1,477	435
# Days in Beijing	1,298	899
# Days in Shenzhen	1,254	68
# Days in Nanjing	1,611	697
# Days in Guangzhou	1,594	258
# Days in Wuhan	1,482	800

Notes: Panel A of this table displays the location distribution of analysts in our sample observations. Panel B presents the numbers of extreme event days with high AQI during our sample period of 2009-2016 across top 6 cities in terms of the number of analysts in China.

TABLE 3

Summary statistics

Panel A: Descriptive statistics for all variables

Variables	Mean	Std	P25	P50	P75
TL	0.5537	0.4971	0	1	1
BOLD	0.4952	0.5	0	0	1
NEG_BOLD	0.3177	0.4656	0	0	1
POS_BOLD	0.1775	0.3821	0	0	0
ACCURACY	0.4541	0.4979	0	0	1
AQI	72.6492	39.6294	51	64	84
N_FIRM	12.1423	11.2739	5	9	15
N_IND	2.7501	1.957	1	2	4
SIZE_BROKER	42.3377	20.831	28	40	54
EXP	18.3364	10.1303	11	17	26
N_FOLLOW	20.406	11.3844	12	19	27
STAR	0.2486	0.4322	0	0	0
DAYS	6.0846	0.6185	5.5053	6.25	6.5944
HOLDPERCT	0.0713	0.0804	0.0088	0.0425	0.1072
ROA	0.0463	0.0404	0.0166	0.0362	0.0654
LEV	0.4593	0.2264	0.2803	0.4551	0.6271
SALES_GROWTH	0.2835	0.4299	0.0709	0.2069	0.3851
TRVOL	1.1806	0.329	0.9513	1.1365	1.3604
RETVAR	0.0016	0.0086	-0.0037	0.001	0.0068
MB	2.6878	1.8259	1.3654	2.1262	3.3789
SUE	0.0047	0.0177	0.0003	0.0037	0.0096
SIZE	16.3861	1.1757	15.55	16.1729	17.0451
ANNUAL	0.1849	0.3882	0	0	0
LOSS	0.0249	0.1558	0	0	0

Panel B: Forecast timeliness, boldness and accuracy improvement across AQI quintiles

AQI quintile	*Mean_AQI*	*TL*	*BOLD*	*NEG_BOLD*	*ACCURACY*
0	35	0.62	0.5454	0.3532	0.4977
1	54	0.56	0.5299	0.3344	0.4812
2	66	0.58	0.4903	0.3017	0.4517
3	81	0.53	0.4955	0.3078	0.4523
4	137	0.48	0.4977	0.3044	0.4583
Q4-Q0		-0.14***	-0.0477***	-0.0488***	-0.0394***
t-statistic		-18.70	-9.18	-9.98	-7.64

Notes: Panel A of this table presents summary statistics of all variables used in the paper. Panel B presents the means of all four dependent variables across AQI quintiles, with quintile 0 (1) representing the lowest (highest) PM pollution observations. ***, **, * represent statistical significance at the 1%, 5%, 10% level (two-tailed), respectively. See the appendix for variable definitions.

TABLE 4

AQI and timeliness of analyst forecasts

	(1)	(2)	(3)	(4)	(5)
VARIABLES	TL	TL	TL	TL	TL
LOG_AQI	-0.0976***	-0.0901***	-0.0872***	-0.0969***	-0.1095***
	(-17.03)	(-14.50)	(-13.94)	(-14.70)	(-15.07)
LOG_N_FIRM			0.0472***	0.0608***	0.0528***
			(8.86)	(8.27)	(6.55)
LOG_N_IND			-0.0081	0.0128	0.0121
			(-0.86)	(1.04)	(0.90)
LOG_SIZE_BROKER			0.0339***	0.0274**	-0.0111
			(6.41)	(2.03)	(-0.76)
LOG_EXP			-0.0056	0.0509***	0.0388**
			(-1.31)	(2.80)	(2.01)
LOG_N_FOLLOW			0.0275***	0.0288***	0.0277***
			(2.94)	(4.45)	(4.20)
STAR			-0.0062	-0.0338***	-0.0409***
			(-0.93)	(-2.66)	(-2.95)
HOLDPERCT			0.0444	0.0475	-0.0098
			(0.61)	(0.89)	(-0.17)
ROA			0.3558**	0.2512**	0.1746
			(2.13)	(2.10)	(1.37)
LEV			-0.1342***	-0.0395*	-0.0387*
			(-3.15)	(-1.86)	(-1.81)
SALES_GROWTH			0.0013	0.0110*	0.0156**
			(0.16)	(1.82)	(2.41)
LOSS			0.0075	-0.0208	-0.0260
			(0.36)	(-1.25)	(-1.51)
SUE			-0.6489***	-0.3859**	-0.5018**
			(-3.24)	(-2.08)	(-2.38)
SIZE			0.0708***	-0.0029	-0.0014
			(5.56)	(-0.62)	(-0.30)
MB			-0.0220***	-0.0031	-0.0033
			(-5.33)	(-1.32)	(-1.37)
TRVOL			0.0162	0.0025	-0.0039
			(1.44)	(0.25)	(-0.37)
RETVAR			-0.1420	-0.0173	0.3830
			(-0.35)	(-0.05)	(1.06)
WIND					-0.0038*
					(-1.81)
CLOUD_RAIN					-0.1123***
					(-19.22)
Observations	43,195	42,973	42,973	42,504	37,658
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.008	0.137	0.145	0.216	0.235
Firm FE	NO	YES	YES	NO	NO
Year FE	NO	YES	YES	YES	YES
Quarter FE	NO	YES	YES	YES	YES

Analyst FE				YES	YES

Notes: This table presents OLS regression results using *TL* as the dependent variable. In all regression models, we log transform AQI, and all continuous analyst level control variables. In column (1), we do not control any variables or fixed effects. In column (2), we add firm, year and quarter fixed effects to the model. Column (3) presents the full model where we further control both analyst and firm level control variables. In column (4), we replace firm fixed effects with analyst fixed effects. In column (5), we further control for local weather conditions. All standard errors are corrected for firm level correlation. The sample period spans from 2010-2016. ***, **, * represent statistical significance at the 1%, 5%, 10% level (two-tailed), respectively. See the appendix for variable definitions.

TABLE 5

Forecast properties and *AQI*

Panel A: Forecast boldness and *AQI*

	(1)	(2)	(3)	(4)	(5)
VARIABLES	BOLD	BOLD	BOLD	BOLD	BOLD
LOG_AQI	-0.0382***	-0.0154**	-0.0170**	-0.0151**	-0.0184**
	(-5.92)	(-2.23)	(-2.50)	(-1.99)	(-2.21)
LOG_N_FIRM			-0.0168***	-0.0488***	-0.0544***
			(-2.88)	(-5.43)	(-5.50)
LOG_N_IND			-0.0080	0.0046	0.0086
			(-0.77)	(0.31)	(0.51)
LOG_SIZE_BROKER			-0.0031	-0.0199	-0.0315*
			(-0.50)	(-1.24)	(-1.83)
LOG_EXP			0.0094**	0.0511**	0.0503**
			(2.05)	(2.51)	(2.11)
LOG_N_FOLLOW			0.0704***	0.0386***	0.0341***
			(6.06)	(5.17)	(4.27)
STAR			-0.0058	-0.0180	-0.0331*
			(-0.79)	(-1.21)	(-1.96)
LOG_DAYS			0.4656***	0.5044***	0.5380***
			(5.98)	(6.16)	(5.98)
HOLDPERCT			-0.1688**	-0.1495**	-0.1329*
			(-2.38)	(-2.25)	(-1.81)
ROA			0.1902	0.2725**	0.1407
			(1.04)	(1.97)	(0.94)
LEV			-0.0727	-0.0420*	-0.0501**
			(-1.44)	(-1.82)	(-2.10)
SALES_GROWTH			0.0019	0.0079	0.0023
			(0.18)	(1.01)	(0.26)
LOSS			0.0183	0.0215	0.0132
			(0.72)	(1.07)	(0.64)
SUE			-2.0507***	-2.3665***	-2.7064***
			(-8.00)	(-10.22)	(-10.64)
SIZE			-0.0482***	-0.0032	-0.0010
			(-3.18)	(-0.68)	(-0.21)
MB			-0.0147***	-0.0153***	-0.0148***
			(-2.58)	(-4.86)	(-4.46)
TRVOL			0.0061	0.0069	0.0053
			(0.49)	(0.65)	(0.46)
RETVAR			0.2582	0.3424	0.2333
			(0.54)	(0.82)	(0.53)
WIND					-0.0011
					(-0.41)
CLOUD_RAIN					0.0041
					(0.63)
Observations	59,640	59,497	59,497	59,452	51,969
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.001	0.125	0.133	0.174	0.183

Firm FE	NO	YES	YES	NO	NO
Year FE	NO	YES	YES	YES	YES
Quarter FE	NO	YES	YES	YES	YES
FPI FE	NO	YES	YES	YES	YES
Analyst FE				YES	YES

Panel B: Negative boldness and *AQI*

VARIABLES	(1) *NEG_BOLD*	(2) *NEG_BOLD*	(3) *NEG_BOLD*	(4) *NEG_BOLD*	(5) *NEG_BOLD*
LOG_AQI	-0.0351***	-0.0207***	-0.0227***	-0.0202***	-0.0285***
	(-4.91)	(-2.94)	(-3.41)	(-2.74)	(-3.46)
CONTROLS	NO	NO	YES	YES	YES
Observations	59,640	59,497	59,497	59,452	51,969
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.001	0.159	0.203	0.219	0.229
Firm FE	NO	YES	YES	NO	NO
Year FE	NO	YES	YES	YES	YES
Quarter FE	NO	YES	YES	YES	YES
FPI FE	NO	YES	YES	YES	YES
Analyst FE				YES	YES

Panel C: Positive boldness and *AQI*

VARIABLES	(1) *POS_BOLD*	(2) *POS_BOLD*	(3) *POS_BOLD*	(4) *POS_BOLD*	(5) *POS_BOLD*
LOG_AQI	-0.0031	0.0053	0.0057	0.0051	0.0102
	(-0.55)	(0.96)	(1.04)	(0.83)	(1.58)
CONTROLS	NO	NO	YES	YES	YES
Observations	59,640	59,497	59,497	59,452	51,969
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.000	0.141	0.165	0.190	0.174
Firm FE	NO	YES	YES	NO	NO
Year FE	NO	YES	YES	YES	YES
Quarter FE	NO	YES	YES	YES	YES
FPI FE	NO	YES	YES	YES	YES
Analyst FE				YES	YES

Panel D: Forecast accuracy improvement and *AQI*

VARIABLES	(1) *ACCURACY*	(2) *ACCURACY*	(3) *ACCURACY*	(4) *ACCURACY*	(5) *ACCURACY*
LOG_AQI	-0.0328***	-0.0201***	-0.0204***	-0.0166**	-0.0238***
	(-5.29)	(-3.01)	(-3.06)	(-2.20)	(-2.86)
LOG_N_FIRM			-0.0099*	-0.0312***	-0.0333***
			(-1.79)	(-3.52)	(-3.45)

	(1)	(2)	(3)	(4)	(5)
LOG_N_IND			-0.0090	-0.0039	-0.0020
			(-0.93)	(-0.26)	(-0.13)
LOG_SIZE_BROKER			0.0002	-0.0230	-0.0334**
			(0.03)	(-1.46)	(-1.99)
LOG_EXP			0.0122***	0.0447**	0.0557**
			(2.68)	(2.10)	(2.23)
LOG_N_FOLLOW			0.0550***	0.0159**	0.0140*
			(4.99)	(2.27)	(1.86)
STAR			0.0021	-0.0269*	-0.0328*
			(0.32)	(-1.80)	(-1.93)
LOG_DAYS			0.3395***	0.4096***	0.5093***
			(3.59)	(4.22)	(4.90)
HOLDPERCT			-0.1198	-0.2030***	-0.2070***
			(-1.64)	(-3.66)	(-3.37)
ROA			-0.0752	-0.0520	-0.0051
			(-0.39)	(-0.38)	(-0.03)
LEV			0.0218	0.0013	-0.0038
			(0.44)	(0.06)	(-0.15)
SALES_GROWTH			-0.0313***	-0.0248***	-0.0306***
			(-3.16)	(-3.20)	(-3.50)
LOSS			-0.0776***	-0.0339	-0.0345
			(-2.78)	(-1.60)	(-1.59)
SUE			-2.4201***	-2.7049***	-2.9685***
			(-8.76)	(-11.13)	(-11.24)
SIZE			-0.0547***	-0.0047	-0.0058
			(-3.49)	(-1.10)	(-1.27)
MB			-0.0205***	-0.0123***	-0.0116***
			(-3.37)	(-4.26)	(-3.76)
TRVOL			0.0060	0.0064	0.0173
			(0.44)	(0.54)	(1.39)
RETVAR			0.4888	0.1571	-0.1370
			(1.01)	(0.39)	(-0.32)
WIND					-0.0008
					(-0.30)
CLOUD_RAIN					0.0037
					(0.55)
Observations	60,391	60,246	60,246	60,203	52,649
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.001	0.115	0.127	0.150	0.158
Firm FE	NO	YES	YES	NO	NO
Year FE	NO	YES	YES	YES	YES
Quarter FE	NO	YES	YES	YES	YES
FPI FE	NO	YES	YES	YES	YES
Analyst FE				YES	YES

Notes: Panel A, Panel B, Panel C, and Panel D presents OLS regression results using *BOLD*, *NEG_BOLD*, *POS_BOLD*, and *ACCURACY* as the dependent variable, respectively. In all regression models, we log transform AQI, and all continuous analyst level control variables. In column (1), we do not control any variables or fixed effects. In column (2), we add firm, year, quarter, and the forecast period fixed effects to the model. Column (3) presents the full model where we further control both analyst and firm level control variables. In column (4), we replace firm fixed effects with analyst fixed effects. In column (5), we further control for local weather conditions. All standard errors are corrected for firm level correlation. The sample period spans from 2010-2016. ***, **, * represent statistical significance at the 1%, 5%, 10% level (two-tailed), respectively. See the appendix for variable definitions.

TABLE 6

Difference-in-difference designs

Panel A: Summary statistics for change in AQI and forecast timeliness

AQI			
	Control	Clean	Pollution
#observations	2,762	910	1,852
Post=0	66.2730	94.7146	56.9514
post=1	66.8125	41.0637	131.0400
Diff	-0.5395	53.6528***	-74.0886***

TL			
	Control	Clean	Pollution
#observations	2,762	910	1,852
Post=0	0.5807	0.5473	0.6026
post=1	0.5873	0.6681	0.5680
Diff	-0.0065	-0.1209***	0.0346*

Panel B: Summary statistics for change in AQI and forecast properties

AQI			
	Control	Clean	Pollution
#observations	1,316	421	881
Post=0	65.0501	92.7391	55.1044
post=1	65.2207	39.1814	126.5870
Diff	-0.1706	53.5577***	-71.4826***

BOLD			
	Control	Clean	Pollution
#observations	1,315	421	878
Post=0	0.4970	0.4457	0.5737
post=1	0.5449	0.5063	0.5395
Diff	-0.0479**	-0.0607	0.0341

NEG_BOLD			
	Control	Clean	Pollution
#observations	1,315	421	878
Post=0	0.2979	0.2011	0.3638
post=1	0.3379	0.3080	0.3488
Diff	-0.0400*	-0.1069***	0.0150

ACCURACY

	Control	Clean	Pollution
#observations	1,315	421	879
Post=0	0.5502	0.4076	0.4967
post=1	0.5053	0.5274	0.5116
Diff	0.0448*	-0.1198***	-0.0150

Panel C: Multivariate analyses for change in AQI and analyst forecasts

VARIABLES	(1) *TL*	(2) *BOLD*	(3) *NEG_BOLD*	(4) *ACCURACY*
POST	0.0281	0.0779**	0.0482	-0.0230
	(1.43)	(2.07)	(1.60)	(-0.63)
*POLLUTION*POST*	-0.0463*	-0.1229**	-0.0885**	0.0520
	(-1.68)	(-2.47)	(-2.18)	(1.01)
*CLEAN*POST*	0.1090***	0.0358	0.0747	0.1573**
	(3.05)	(0.64)	(1.61)	(2.37)
Observations	5,524	2,613	2,613	2,615
Year	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.193	0.269	0.367	0.248
Firm FE	YES	YES	YES	YES

Notes: This table presents the results of conducting difference-in-difference designs. We first identify treatment sample consisting of analyst-firm-quarter forecasts experiencing drastic changes (a difference of 40) in AQI between two adjacent quarters. Each pair of treatment observations represent the same analyst-firm forecasts with different AQIs. *POLLUTION* (*CLEAN*) equals 1 if there is an increase (a decrease) in AQI from the preceding to current quarter. For each treatment observation, we match one control observation where an analyst from a different city follows the same firm in the same periods. There should not be drastic changes in AQI of control observations between the two quarters. *POST* equals 1 (0) for the current (preceding) quarter. All standard errors are corrected for firm level correlation. ***, **, * represent statistical significance at the 1%, 5%, 10% level (two-tailed), respectively. See the appendix for variable definitions..

TABLE 7

Placebo tests

Panel A: Randomly assign *AQI* to an analyst-firm-announcement

Coefficient on *LOG_AQI*	(1) *TL*	(2) *BOLD*	(3) *NEG_BOLD*	(4) *ACCURACY*
Mean	-0.0015	-0.0069	-0.0063	-0.0039
Standard deviation	0.0043	0.0036	0.0019	0.0038
Minimum	-0.0114	-0.0158	-0.0150	-0.0153
P1	-0.0114	-0.0156	-0.0141	-0.0127
P5	-0.0080	-0.0138	-0.0120	-0.0096
P10	-0.0071	-0.0123	-0.0108	-0.0089
Max	0.0134	0.0036	0.0019	0.0075
Percentile of coefficient	**0.00**	**0.00**	**0.00**	**0.00**
Sample times	150	150	150	150
Avg Observations	42,806	59,299	59,299	60,046
Year	2010-2016	2010-2016	2010-2016	2010-2016
Avg R-squared	0.140	0.133	0.203	0.126
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
FPI FE		YES	YES	YES

Panel B: Randomly assign city to an individual analyst

Coefficient on *LOG_AQI*	(1) *TL*	(2) *BOLD*	(3) *NEG_BOLD*	(4) *ACCURACY*
Mean	-0.0357	-0.0021	-0.0030	-0.0043
Standard deviation	0.0075	0.0085	0.0079	0.0079
Minimum	-0.05460	-0.0209	-0.0224	-0.0260
P1	-0.05310	-0.0205	-0.0185	-0.0261
P5	-0.04830	-0.0170	-0.0158	-0.0180
P10	-0.0444	-0.0129	-0.0140	-0.0143
Max	-0.0174	0.0240	0.0202	0.0210
Percentile of coefficient	**0.00**	**<0.05**	**0.00**	**<0.05**
Sample times	150	150	150	150
Avg Observations	39,270	54,648	54,648	55,333
Year	2010-2016	2010-2016	2010-2016	2010-2016
Avg R-squared	0.144	0.136	0.207	0.129
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
FPI FE		YES	YES	YES

Notes: This table presents summary statistics for the coefficient of *AQI* and the fit statistics of models in two placebo tests. Panel A shows the results where we randomize the PM pollution measure within an analyst-firm level. The purpose of this placebo test is to indicate that the observed negative association between high air pollution and low likelihood to issue timely forecasts only relates to the current combination of analyst-firm-announcement *AQI*. Panel B shows results where we randomize the location information for one analyst. The purpose of this placebo test is to ensure that the observed association is not driven by other cities' *AQI*. See the appendix for variable definitions.

TABLE 8

Additional tests for the underlying mechanisms

Panel A: The effects of information supply-High vs low workload

The work load is constructed in this way: given one particular analyst-firm-quarter announcement, we count the number of concurrent earnings announcements made by other firms followed by the analyst in the prior quarter. For more than half of analyst-firm-quarter announcements, there is no or only one concurrent earnings announcement. Accordingly, we define *LOW_LOAD* as those observations with no or one concurrent earnings announcement, with remaining observations as *HIGH_LOAD*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*TL*	*TL*	*ACCURACY*	*ACCURACY*	*BOLD*	*BOLD*	*NEG_BOLD*	*NEG_BOLD*
	LOW_LOAD	*HIGH_LOAD*	*LOW_LOAD*	*HIGH_LOAD*	*LOW_LOAD*	*HIGH_LOAD*	*LOW_LOAD*	*HIGH_LOAD*
LOG_AQI	-0.0586***	-0.1185***	-0.0122	-0.0357***	0.0021	-0.0387***	-0.0050	-0.0425***
	(-7.05)	(-12.34)	(-1.41)	(-3.24)	(0.24)	(-3.38)	(-0.58)	(-3.98)
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
Observations	23,457	19,125	34,287	25,755	33,871	25,426	33,871	25,426
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.176	0.182	0.156	0.175	0.157	0.183	0.236	0.256
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
FPI FE			YES	YES	YES	YES	YES	YES

Panel B: The effects of information supply-High vs low labor market competition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*TL*	*TL*	*ACCURACY*	*ACCURACY*	*BOLD*	*BOLD*	*NEG_BOLD*	*NEG_BOLD*
	High	Low	High	Low	High	Low	High	Low
LOG_AQI	-0.0892***	-0.0841***	-0.0100	-0.0311***	-0.0129	-0.0184*	-0.0139	-0.0293***
	(-9.88)	(-9.51)	(-1.09)	(-3.24)	(-1.37)	(-1.83)	(-1.52)	(-3.16)

CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
Observations	22,016	20,894	31,400	28,816	31,369	28,098	31,369	28,098
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.134	0.192	0.115	0.185	0.124	0.186	0.218	0.246
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
FPI FE			YES	YES	YES	YES	YES	YES

Panel C: The effects of information demand-Annual vs interim earnings announcements

VARIABLES	(1) *TL* ANNUAL	(2) *TL* INTERIM	(3) *ACCURACY* ANNUAL	(4) *ACCURACY* INTERIM	(5) *BOLD* ANNUAL	(6) *BOLD* INTERIM	(7) *NEG_BOLD* ANNUAL	(8) *NEG_BOLD* INTERIM
LOG_AQI	-0.0356**	-0.0992***	-0.0219	-0.0156**	0.0136	-0.0238***	0.0027	-0.0255***
	(-2.48)	(-14.40)	(-1.37)	(-2.08)	(0.88)	(-3.08)	(0.17)	(-3.47)
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,668	34,891	10,994	49,099	10,835	48,514	10,835	48,514
Year	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016	2010-2016
R-squared	0.219	0.148	0.204	0.135	0.198	0.140	0.347	0.218
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
FPI FE			YES	YES	YES	YES	YES	YES

Notes: This table presents OLS regression results where we partition our sample based upon variables which may capture the underlying channels leading to our main findings. The partitioning variable in Panel A, Panel B, and Panel C is the number of firms followed by one analyst in the previous one year, the number of analysts following a firm in the previous one year, and a dummy variable indicating whether an earnings announcement is an annual one or an interim one, respectively. In all regression models, we log transform AQI, and all continuous analyst level control variables, and add firm, year and quarter fixed effects. We further add the forecast period fixed effects (FPI) when taking *BOLD*, *NEG_BOLD*, or *ACCURACY* as the dependent variable. All standard errors are corrected for firm level correlation. The sample period spans from 2010-2016. ***, **, * represent statistical significance at the 1%, 5%, 10% level (two-tailed), respectively. See the appendix for variable definitions.

TABLE 9

Market reaction test

VARIABLES	(1) *VOLUME_0_REV*
LOG_AQI	-0.0474**
	(-2.18)
REV	-0.0007
	(-0.00)
LOG_N_FIRM	-0.0549***
	(-3.45)
LOG_N_IND	0.0439
	(1.54)
LOG_SIZE_BROKER	0.0057
	(0.42)
LOG_EXP	0.0221*
	(1.94)
LOG_N_FOLLOW	0.0048
	(0.12)
STAR	-0.0094
	(-0.57)
TO_END_DAYS	1.0232***
	(5.82)
HOLDPERCT	-0.2198
	(-0.76)
ROA	0.8918
	(1.21)
LEV	-0.0725
	(-0.40)
SALES_GROWTH	0.0514
	(1.56)
LOSS	-0.0589
	(-0.76)
SUE	3.7930***
	(3.99)
SIZE	-0.1462***
	(-2.86)
MB	0.0264
	(1.50)
TRVOL	-0.2115***
	(-4.44)
RETVAR	4.2886**
	(2.44)
Observations	27,297
Year	2010-2016
R-squared	0.205
Firm FE	YES
Year FE	YES
Quarter FE	YES

Notes: This table presents the results by regressing abnormal trading volume on AQI. we construct abnormal trading volume within [0,1] of analyst forecast date (day 0 is the forecast date) to depict investors' trading behavior. Abnormal trading volume, *VOLUME_0_REV*, is daily trading volume adjusted by the average trading volume over the 60 trading days before the analyst forecast date. In the regression model, we log transform AQI, and all continuous analyst level control variables, and add firm, year and quarter fixed effects. All standard errors are corrected for firm level correlation. The sample period spans from 2010-2016. ***, **, * represent statistical significance at the 1%, 5%, 10% level (two-tailed), respectively. See the appendix for variable definitions.