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Under the dome: Air pollution and analyst forecast optimism☆

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ABSTRACT

In this study, we investigate whether unpleasant mood caused by air pollution leads to lower analyst forecast optimism. Using a sample of 103,768 observations from 2014 to 2021, we show that there is a negative association between air pollution and analyst forecast optimism. Furthermore, we find that analysts become more optimistic forecasters after moving to a city with lower level of air pollution. Our results hold through various robustness tests including alternative measures of air pollution, controlling for various fixed effects, 2SLS by instrumenting for air pollution using thermal inversions and a placebo test by randomizing the headquarter locations of brokerage firms in our sample. Our paper provides plausibly causal evidence that air pollution lowers analyst forecast optimism.

1. Introduction

Air pollution can not only increase risks of a large number of physical diseases (Gehring et al., 2013; Fischer et al., 2015), but also has been shown to affect one's individual mood and even damage mental health. Psychology literature finds that exposure to air pollution makes people feel depressed (Lim et al., 2012), anxious (Power et al., 2015), stressed (Mehta et al., 2015) and may increase the incidence of suicide attempts (Bakian et al., 2015). The air pollution-induced negative mood affects the individual decision-making and consequently brings a series of negative economic impacts. For example, a large body of studies suggest that the air pollution-induced negative mood leads to biased decisions by investors (Heyes et al., 2016; Li et al., 2017) and thus affects the stock returns (Levy and Yagil, 2011; Wu and Lu, 2020). In addition, higher levels of air pollution can also decrease worker productivity (Chang et al., 2019) and lead firms to apply more conservative accounting practices and utilize more conservative estimates in their reporting (Wu et al., 2022).

Analysts' earnings forecasts are an important channel for investors to obtain relevant financial information before firms' annual reports announcements. As a kind of forward-looking forecasting activity, the results of analyst forecasts are inevitably affected by analysts' individual subjective factors. Kong et al. (2018) and Li et al. (2020) note that air pollution reduces the timeliness and accuracy of analyst forecasts. A more recent and more closely related work documents a negative relation between air pollution during corporate site visits by investment analysts and subsequent earnings forecasts (Dong et al., 2021). Based on the negative impact of air

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pollution on individual mood (Lim et al., 2012; Bakian et al., 2015; Mehta et al., 2015; Power et al., 2015), we speculate that air pollution around analysts' offices during the writing of analyst forecasts will also affect analysts' individual mood, and consequently influence analyst forecast optimism. Specifically, analysts in a bad mood induced by air pollution during the writing of forecasts will be less optimistic, which will provide lower probabilities for positive events and higher probabilities for negative events (Johnson and Tversky, 1983; Wright and Bower, 1992), while people in a good mood caused by lighter air pollution will report higher probabilities for positive events and be more optimistic.

To estimate the effect of air pollution on analyst forecast optimism, we examine the relationship between the air quality index and the analyst forecast bias. Specifically, we use the air quality index around the brokerage firm's headquarters within a 2-km radius over a 15-day window preceding the earnings forecast issuance date as our measure of air pollution. Based on a sample of 103,768 observations from 2014 to 2021, we find a strong negative association between air pollution and analyst forecast optimism. Our results suggest that analysts' forecasts issued during polluted periods are less optimistic. To strengthen our identification, we conduct several robustness checks on our baseline results. First, we re-estimate our baseline regressions after controlling for city-fixed effects, analyst-fixed effects, brokerage firm-fixed effects and day-of-the-week fixed effects to avoid the impact of other unobservable characteristics that affect analyst forecast optimism. We also control for high-dimensional fixed effects to alleviate any omitted variable bias. Second, we employ alternative air pollution measures based on a city-level air quality index, constructing a de-seasonalized measure of air pollution and dividing AQI into 6 categories referring to the practice of the Ministry of Environmental Protection of China (MEPC). We also consider the effects of other weather dimensions on analyst forecast optimism. Third, we re-construct our air pollution measure based on alternative event windows of 10-days and 20-days preceding the earnings forecast issuance date, as well as alternative distance radii of 4-km, 6-km and 8-km around the brokerage firm headquarters. Fourth, we conduct additional analyses to identify the factors that may mitigate the effect of air pollution on analyst forecast optimism. We consider the impact of analysts' ability, educational level, gender, experience, pressure and the uncertainty of forecasts and discover the negative association between air pollution and analyst forecast optimism is stronger for analysts with longer experience, lower ability and pressure, as well as under higher levels of uncertainty. Fifth, we mitigate potential reverse endogeneity concerns by employing a 2SLS framework and conducting a placebo test. Specifically, we instrument for air pollution using thermal inversions and conduct a placebo test by randomizing the locations of brokerage firms' headquarters. We also conduct a difference-in-differences (DID) analysis using analysts' job-hopping as an exogenous shock to the air pollution in which analysts issue forecast reports, which aims to test whether analyst optimism changes if analysts move to other brokerage firms in different cities. Further, we compare the effect of air pollution on analyst forecast optimism between optimistic and pessimistic analysts, as well as before and after the COVID −19 pandemic. Finally, we further control for the 1-month stock return before the forecast, which is an important variable in our regression. Our baseline holds for the above tests.

We make several contributions to research and practice. First, we extend the research on geographic proximity in corporate finance. The issue of geographic proximity between economic agents has been investigated in various contexts, for example, previous literature has explored the diverse economic impacts that arise from the proximity of clients (Malloy, 2005; Choi et al., 2012; O'Brien and Tan, 2015; Dong et al., 2018), regulatory agencies (Kedia and Rajgopal, 2011; DeFond et al., 2015) and labor markets (Lee et al., 2021). On the other hand, fewer studies have examined the influence of air pollution proximity. By using the air quality monitoring station data, which is different from Dong et al.'s (2021) city-level daily air pollution data, our study fills this void and helps to better understand the role of air pollution proximity in analyst forecast behavior.

Second, we add to the literature investigating the impact of air pollution-induced negative mood on worker productivity (Chang et al., 2019), as well as literature investigating the effect of air pollution on individual decision-making by capital market participants (Levy and Yagil, 2011; Heyes et al., 2016; Li et al., 2017; Wu and Lu, 2020; Wu et al., 2022). In studying analyst workers, Li et al. (2020) document that analysts exposed to air pollution are less likely to issue timely forecasts or improve their forecast accuracy. Furthermore, Dong et al. (2021) find that air pollution in the city where the listed company is located during corporate site visits by investment analysts will reduce the subsequent earnings forecasts optimism. Because we use air quality monitoring station data around brokerage firms, rather than the firm city daily air pollution data, we extend Dong et al.'s (2021) research by finding that not only the air quality of the city where the listed company is located during corporate site visits, but also the air pollution around the brokerage firms where the analyst is located during the period prior to the forecast release date will have a negative relationship with analyst forecast optimism. Following this logic, our research also finds that analysts become more optimistic forecasters when they switch jobs to a city with lower levels of air pollution.

Finally, yet importantly, our study extends the literature investigating the factors affecting analyst forecast optimism. Because analysts' interests are subject to brokerage firms or customer companies (Easterwood and Nutt, 1999; Francis and Philbrick, 1993; Lim, 2001), prior literature finds that analysts tend to issue more optimistic forecasts for the sake of their own commission income (Cowen et al., 2006; Mola and Guidolin, 2009; Gu et al., 2013) and reputation (Scharfstein and Stein, 1990; Hong et al., 2000). We enrich the extant literature by confirming the negative impact of air pollution around analysts' workplace on analyst forecast optimism. Our findings suggest that the working environment of analysts, including air pollution, also plays an important role in influencing the optimism of analysts' forecasts.

The remainder of this study is structured into five sections. Section two contains our literature review and hypothesis development. Section three describes the sample and data we employ, and in section four, we present our empirical results and discuss our main findings. In section five, we provide our robustness tests. Section six concludes.

2. Literature review and hypothesis development

A longstanding literature documents that there is a systematic optimistic bias in analysts' earnings forecasts (O'brien, 1988), which weakens the role of analysts as information intermediaries to alleviate information asymmetry and decrease the efficiency of stock market pricing and information transmission (Scherbina, 2008). Based on the assumption that analysts are rational, previous literature argues that the optimistic bias is driven by the profit seeking motives of analysts, e.g., they forecast upward in order to cater the interest of clients (Lin and McNichols, 1998; Dechow et al., 2000; O'brien et al., 2005), become better compensated (Cowen et al., 2006) and maintain relationships with managers or gain private information from them (Lim, 2001). However, most literature focuses on the impact of rational factors on analyst forecast optimism, with less attention paid to the role of subjective emotional factors.

Although analysts are well-educated, well-trained, and well-motivated (Beyer et al., 2010), they are not fully rational. As a kind of forward-looking forecasting activity, the results of analyst forecasts are inevitably affected by analysts' individual subjective factors such as mood (Chang and Hsu, 2018), which has a significant influence on a wide variety of social judgements (Forgas and Moylan, 1987; Goetzmann et al., 2015). Immersed in more positive emotions, people tend to be more optimistic and prefer to assign higher probabilities for positive events and lower probabilities for negative events (Johnson and Tversky, 1983; Wright and Bower, 1992). Therefore, people in positive (negative) moods usually make more optimistic (pessimistic) decisions (Morris, 2000).

More importantly, individual mood is significantly affected by the surrounding environment and others. For example, prior studies find that investors' sentiment is positively correlated with analysts' mood and analysts become more optimistic when investor sentiment is high (Bhojraj et al., 2009; Qian, 2009; Hribar and McInnis, 2012). Based on the relationship between environment and mood, Dehaan et al. (2017) document that analysts experiencing unpleasant weather are slower or less likely to respond to an earnings announcement. Otherwise, the air pollution level is an important factor among the surrounding environmental factors. Based upon the negative effect of air pollution on mood (Lim et al., 2012; Bakian et al.,2015; Mehta et al., 2015; Power et al., 2015; Orru et al., 2016), an emerging body of studies investigate how the negative mood induced by air pollution affects worker productivity (Chang et al., 2019) and investor behavior in capital markets (Levy and Yagil, 2011; Wu and Lu, 2020; Wu et al., 2022).

In studying analyst behaviors, Kong et al. (2018) and Li et al. (2020) find compelling evidence that analysts exposed to air pollution are less likely to issue timely forecasts or improve their forecast accuracy due to the negative air pollution-induced mood. Further, Dong et al. (2021) document a negative relation between air pollution during corporate site visits by analysts and subsequent earnings forecast optimism. However, the air pollution level in the location of the listed company during site visits only affects analysts' private information acquisition, while the impact of air pollution on public information acquisition and information processing is ignored. Building upon the above literature, we argue that the air pollution during the forecast issuing period also affects analyst forecast optimism. Therefore, we formulate our testable hypothesis as follows:

Hypothesis 1. There is a negative association between air pollution and analyst forecast optimism.

3. Sample and data

3.1. Data source and sample selection

Our initial sample consists of all earnings forecasts in the China Stock Market Accounting Research (CSMAR) database. Following Huyghebaert and Xu (2016), we keep the EPS forecasts for all years in a forecast report. We then obtain analyst following information and firm financial data from CSMAR to construct our control variables. We keep all A-share firms listed on the Chinese main stock exchange boards and exclude the observations of financial firms and firm-year observations labeled with "ST" or "ST*".[1] The air quality index data is obtained from the CnOpenData database (www.cnopendata.com), which contains hourly air quality indices of more than 2000 air quality monitoring stations since May 13, 2014. These data are matched to analyst forecasts obtained from the CSMAR database.

Our final sample consists of 103,768 firm-year-analyst observations from 2014 to 2021. All continuous variables in our sample are winsorized at the 1 % and 99 % levels to reduce outliers and data noise.

3.2. Variable construction

3.2.1. Measuring analyst forecast optimism

Following Jackson (2005), Dong et al. (2021) and the vast literature in accounting on analyst forecast optimism, we measure analyst forecast optimism as follows:

$$Optimism_{i,j,t} = \frac{(FEPS_{i,j,t} - EPS_{j,t})}{P_j} * 100 \tag{1}$$

Where the subscript i denotes analyst i, j denotes firm j and t denotes year t. Specifically, $FEPS_{i,j,t}$ is the analyst i' s forecasted EPS of firm j for year t. $EPS_{j,t}$ is the actual EPS of firm j for year t. P_j is the stock price on the day prior to the earnings forecast of firm j. Higher values of *Optimism* mean analysts are issuing more optimistic forecasts.

[1] ST stands for special treatment, indicating that a firm has non-normal financial situations such as suffering losses in two consecutive years or the firm's net asset value per share is less than the book value of equity per share. ST* indicates that a firm suffered losses in three consecutive years and faced the possibility of being delisted.

3.2.2. Measuring air quality

Following prior literature, we measure the air quality of each analyst's workplace by using the information from the air quality monitoring stations within a 2-km radius of brokerage firm headquarters (e.g., Chen et al. 2017, Chhaochharia et al. 2019). The air quality data are obtained from the CnOpenData database (www.cnopendata.com), which contains hourly air quality indices of more than 2000 air quality monitoring stations in China since May 13, 2014. To identify air quality around brokerage firms, we first assign the latitude and longitude of the location of each brokerage firm's headquarters and each air quality monitoring station from CnOpenData and CSMAR, respectively. Following Vincenty (1975), we then calculate the distance between each air quality monitoring station and each brokerage firm in kilometers and identify the air quality monitoring stations within a 2-km radius of each brokerage firm's headquarters. We calculate our independent variable, the air quality index (*AQI*), as the average hourly air quality index over a 15-day window preceding the earnings forecast announcement date (i.e., *t-15* to *t-1*) for all the air quality monitoring stations within a 2-km radius of the brokerage firm's headquarters, scaled by 1000. We primarily choose a 15-day window as our air quality-induced mood priming period in our baseline regression. Considering this specific window is inherently arbitrary, we then use alternative windows (i.e., *t-20* to *t-1* and *t-10* to *t-1*) to help dispel the concern that our results are not simply a consequence of a specific mood priming period. Higher values of *AQI* correspond to higher levels of air pollution.

3.2.3. Control variables

We follow prior work by including several control variables to capture other determinants of analyst forecast optimism in our regression analysis. Our first set of controls capture several firm characteristics including: firm size (*Size*), the book-to-market ratio (*BM*), the stock turnover (*Turnover*), the stock return (*Revenue*), the intangible asset ratio (*IntAsset*), the percentage of institutional ownership (*Institution*), shareholding of top ten shareholders (*Larger*), the standard deviation of EPS of firm *j* in year *i* from *t-3* to *t-1* (*Volatility*), and the number of analysts following firm *j* in year *t* (*AnaAttention*).

The remaining control levels are at the brokerage firm- and analyst- level. We control for the analyst experience (*Experience*), the brokerage firm size (*BroSize*), the number of firms followed by analyst *i* in year *t* (*ComNumber*) and the number of forecasts issued by analyst *i* in year *t* (*ForNumber*). Specifically, *Experience* is calculated as the natural logarithm of one plus the time interval in the years between analysts' current forecast issuance date and their first forecast date (Clement, 1999). *BroSize* is the logarithm of one plus the number of analysts working for the same firm as analyst *i* (Malloy, 2005). We also control for *Horizon*, which is calculated as the gap between the earnings forecast time and the announcement date of the actual earnings.

3.3. Summary statistics

Panel A of Table 1 shows the descriptive statistics of the sample of 103,768 firm-year-analyst observations. All continuous variables are winsorized at the top and bottom 1 % to mitigate the influence of extreme values. The sample mean and standard deviation of forecast optimism are 1.703 and 3.376, respectively, consistent with the prior literature. This result suggests that analysts issue optimistic forecasts, on average, which reinforces prior research implying that sell-side analysts' earnings forecasts are generally higher than the actual value of EPS (Cowen et al., 2006; Mola and Guidolin, 2009; Gu et al., 2013). Turning to the control variables, an average, firms in our sample have a log size of 22.960, BM ratio of 0.950, EPS volatility of 0.247, shareholding of top ten shareholders of 62.320 %, and percentage of institutional ownership of 51.110 %. The average time interval between the earnings forecast time and the announce date of the actual earnings in our sample is approximately 257 days (*Horizon* =5.556).[2] The average tenure of each analyst (or analyst teams) in the sample is 8 years (*Experience* =2.222) and they follow 17 companies (*ComNumber* =2.917) each year.[3]

Panel A of Table 1 reports descriptive statistics for variables in our sample. *Optimism* denotes the difference between the forecast and actual EPS, scaled by the stock price on the day prior to the earnings forecast of the firm, multiplied by 100. Panel B presents the means of *Optimism* by the median of *AQI*. Details for other variables are reported in Appendix A.

By grouping and calculating according to the air quality (*AQI*) of the analysts' locations, we compare the analyst forecast optimism in different air pollution environments. For earnings forecasts released for the same listed company in the same year, we first calculate the median value of *AQI*. If the observed *AQI* is greater than the median *AQI* for all samples of the same company in the same year, it is considered that the prediction was issued in a more severe polluted environment. On the contrary, if the observed *AQI* is equal to or less than the median, it means the forecast is issued in a less polluted environment. As reported in Panel B, Table 1, the mean value of analyst forecast optimism (*Optimism*) increases moving from observations with higher pollution to lower pollution, which preliminarily confirms our hypothesis. In addition, results from the two sample t-tests reveal that the analyst forecast optimistic of the higher and lower air pollution subsamples are significantly different.

4. Empirical results

4.1. The air quality and analyst forecast optimism

In this section, we report our baseline results for the relation between air quality around brokerage firms and analyst forecast

[2] $257 \approx (e^{5.556} - 1)$

[3] $8 \approx (e^{2.222} - 1); 17 \approx (e^{2.917} - 1)$

Table 1
Descriptive Statistics.

Panel A: Summary Statistics for the Main Variables

Variable	N	Mean	Std Dev	Min	P25	Median	P75	Max
Optimism	103,768	1.703	3.376	-7.010	0.030	0.900	2.570	18.750
AQI	103,768	0.082	0.031	0.031	0.059	0.076	0.100	0.175
Size	103,768	22.960	1.491	20.100	21.900	22.690	23.730	27.410
Revenue	103,768	0.271	0.559	-0.519	-0.130	0.137	0.544	2.464
BM	103,768	0.950	1.129	0.075	0.310	0.551	1.077	6.590
Volatility	103,768	0.247	0.283	0.010	0.082	0.155	0.300	1.765
Turnover	103,768	1.864	1.491	0.173	0.815	1.417	2.465	11.640
IntAsset	103,768	0.046	0.048	0.000	0.018	0.034	0.056	0.312
Institution	103,768	51.110	25.110	1.918	30.490	56.320	71.550	94.720
Larger	103,768	62.320	14.380	28.110	52.500	62.840	72.870	95.750
Horizon	103,768	5.556	0.386	3.497	5.252	5.561	5.900	6.273
AnaAttention	103,768	2.941	0.728	0.693	2.485	3.045	3.497	4.111
Experience	103,768	2.222	0.816	0.565	1.633	2.183	2.852	3.956
BroSize	103,768	3.780	0.669	1.946	3.135	4.060	4.277	4.635
ComNumber	103,768	2.917	0.754	0.693	2.485	2.944	3.401	4.543
ForNumber	103,768	3.680	0.893	1.099	3.135	3.784	4.317	5.455

Panel B: Mean of Forecast Optimism by Median of AQI

	Observations	***Optimism***
	(1)	(2)
Higher Pollution	45,713	1.654
Lower Pollution	58,055	1.742
Difference		-0.088***

optimism. To rigorously test the effect of air quality on analyst forecast optimism, we conduct the following baseline ordinary least squares (OLS) regression model at the firm-year-analyst level:

$$Optimism_{i,j,t} = \beta_0 + \beta_1 AQI_{i,t} + \beta_2 FirmVar_{j,t} + \beta_3 \text{Analyst}Var_{i,t} + Year + Quarter + Firm + \varepsilon \quad (2)$$

where the subscript *i* denotes analyst *i, j* denotes firm *j, t* denotes year *t*, and ε denotes the error term. Following Li et al. (2020), we include *Year*, *Quarter* and *Firm* in our baseline regressions, which denote year-fixed effects, quarter-fixed effects and firm-fixed effects, respectively.

Following Dong et al. (2021), we employ the air quality index to measure the level of air pollution around brokerage firms' headquarters. Higher values of *AQI* indicate analysts exposed to higher levels of air pollution when they were issuing the forecasts. Table 2 presents the results for estimating model (2) where we examine how air quality around the brokerage firms affects the optimism of analyst forecasts. Column (1) of Table 2 reports the baseline regression without any control variables. For this model, the coefficient on *Optimism* is −1.184 and highly significant (p<0.01). This model provides results consistent with the value of *AQI* being significantly negatively associated with analyst forecast optimism, which indicates that the analyst forecasts in high pollution weather are even more pessimistic. In Column (2), we include other firm characteristics correlated with analysts' forecast optimism, such as the firm size and revenue, book-to-market ratio, etc. In Column (3), we further control for other analyst- and brokerage firm- levels characteristics. The coefficients on *Optimism* in Columns (2) and (3) are −1.289 and −1.545, respectively. Both of the coefficients remain negative and significant at the 1 % level. The results in Table 2 suggest that air pollution is negatively associated with analyst forecast optimism. Consistent with the first hypothesis, we find that analyst forecasts issued during polluted periods are less optimistic.

Table 2
Air Pollution and Analyst Forecast Optimism.

	Optimism (1)	Optimism (2)	Optimism (3)
AQI	-1.184***	-1.289***	-1.545***
	(-2.973)	(-3.274)	(-3.652)
Size		1.101***	1.077***
		(19.801)	(19.311)
Revenue		-0.132***	-0.148***
		(-4.938)	(-5.562)
BM		0.596***	0.617***
		(14.311)	(14.568)
Volatility		1.229***	1.230***
		(14.261)	(14.347)
Turnover		-0.169***	-0.171***
		(-12.221)	(-12.377)
IntAsset		-1.612***	-1.525***
		(-3.019)	(-2.856)
Institution		0.024***	0.022***
		(10.929)	(10.147)
Larger		-0.037***	-0.036***
		(-12.136)	(-11.738)
Horizon			0.375***
			(4.710)
AnaAttention			0.135***
			(3.786)
Experience			-0.046***
			(-3.605)
BroSize			0.024
			(1.494)
ComNumber			0.108***
			(3.139)
ForNumber			-0.035
			(-1.224)
_cons	2.149***	-21.537***	-23.740***
	(29.596)	(-17.086)	(-17.828)
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	103,768	103,768	103,768
Adj.R2	0.264	0.281	0.282

This table reports the results of regressions of air pollution (*AQI*) on analyst forecast optimism (*Optimism*). The sample period is between 2014 and 2021. We control for year-fixed, season-fixed and firm-fixed effects to capture unobserved heterogeneity in time and across firms. *T*-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

5. Robustness tests

5.1. Baseline regression with different sets of fixed effects

Although we control for a set of firm-, analyst-, and brokerage firm characteristics in our baseline regressions, there could be other unobservable characteristics that affect analyst forecast optimism. As an initial robust test, we further include different sets of fixed effects in this section to control for potential omitted variables in our baseline regression and report the results in Table 3. As reported in Columns (1) and (2) in Panel A of Table 3, the inclusion of city and analyst fixed effects reduces the coefficients on *AQI* by about 22 %. Though we further add brokerage-firm fixed effects (Column (3)) and day-of-the-week fixed effects (Column (4)), the coefficients on *AQI* remain negative, taking on values of −1.199 and −1.229, respectively. Across all specifications, the coefficients on *AQI* are significant at the 1 % level, which are consistent with those reported in Table 2 without controlling for any fixed effects.

In addition, we also set high-dimensional fixed effects to re-estimate our baseline regressions in Panel B of Table 3, which is considered the most effective way to alleviate omitted variable bias for high-dimensional data. Specifically, in Column (1), we control for firm-year fixed effects to control for the omitted firm-year level variables. On this basis, we further add the individual analyst fixed effects in Column (2). The relevant analyst characteristics are also included. After controlling for the high- dimensional fixed effects, the coefficients on *AQI* are still negative and significant at the 1 % level, which further supports our results.

5.2. Varying measures of air pollution

In this section, we examine whether our main results are robust to alternative definitions of air pollution. We first calculate the

Table 3
Regressions with Additional Fixed Effects.

Panel A

	Optimism (1)	Optimism (2)	Optimism (3)	Optimism (4)
AQI	-1.205***	-1.204***	-1.199***	-1.229***
	(-2.705)	(-2.621)	(-2.608)	(-2.672)
Size	1.080***	1.122***	1.122***	1.123***
	(19.351)	(19.328)	(19.322)	(19.335)
Revenue	-0.147***	-0.100***	-0.101***	-0.101***
	(-5.508)	(-3.598)	(-3.616)	(-3.628)
BM	0.621***	0.686***	0.686***	0.685***
	(14.648)	(15.325)	(15.327)	(15.291)
Volatility	1.223***	1.193***	1.193***	1.195***
	(14.262)	(13.365)	(13.360)	(13.381)
Turnover	-0.170***	-0.140***	-0.140***	-0.139***
	(-12.320)	(-9.557)	(-9.521)	(-9.497)
IntAsset	-1.526***	-2.164***	-2.162***	-2.181***
	(-2.857)	(-3.934)	(-3.929)	(-3.962)
Institution	0.022***	0.021***	0.021***	0.021***
	(10.024)	(9.174)	(9.172)	(9.158)
Larger	-0.036***	-0.027***	-0.027***	-0.027***
	(-11.777)	(-8.381)	(-8.387)	(-8.363)
Horizon	0.386***	0.427***	0.426***	0.427***
	(4.854)	(5.333)	(5.323)	(5.340)
AnaAttention	0.134***	0.129***	0.129***	0.127***
	(3.753)	(3.472)	(3.486)	(3.431)
Experience	-0.050***	-0.154***	-0.157***	-0.157***
	(-3.854)	(-2.881)	(-2.935)	(-2.936)
BroSize	0.096***	0.472***	0.459***	0.459***
	(3.882)	(5.165)	(4.947)	(4.948)
ComNumber	0.110***	0.166**	0.162**	0.164**
	(3.113)	(2.568)	(2.497)	(2.531)
ForNumber	-0.048*	-0.084*	-0.081*	-0.083*
	(-1.648)	(-1.771)	(-1.707)	(-1.741)
_cons	-23.887***	-26.130***	-27.085***	-27.179***
	(-17.904)	(-18.168)	(-18.902)	(-18.954)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	Yes	Yes
Brokers FE	No	No	Yes	Yes
Day-of-the-Week FE	No	No	No	Yes
Observations	103,762	103,743	103,743	103,743
Adj.R2	0.284	0.312	0.312	0.312

Panel B

	Optimism (1)	Optimism (2)
AQI	-2.416***	-2.208***
	(-6.711)	(-5.588)
Horizon	-0.137***	-0.139***
	(-5.536)	(-4.959)
Experience	0.003	-0.042
	(0.234)	(-0.778)
BroSize	0.064***	0.218**
	(4.066)	(2.463)
ComNumber	-0.003	-0.052
	(-0.088)	(-0.736)
ForNumber	0.021	0.071
	(0.729)	(1.404)
_cons	2.347***	1.815***
	(15.889)	(4.766)
Year×Firm FE	Yes	Yes
Analyst FE	No	Yes
Observations	103,768	10,3724
Adj.R2	0.455	0.454

Panel A reports the results of regressions of air pollution (*AQI*) on analyst forecast optimism (*Optimism*) with more fixed effects. In Columns (1) to (4), we re-estimate our baseline regression after including city-fixed, analyst-fixed, brokerage firm-fixed, and day-of-the-week fixed effects. Panel B reports the results of regressions of air pollution (*AQI*) on analyst forecast optimism (*Optimism*) with high-dimensional fixed effects. The sample period is between 2014 and 2021. *T*-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

average hourly air quality index over a 15-day window preceding the earnings forecast announcement date (i.e., *t-15* to *t-1*) for all the air quality monitoring stations within a 2-km radius of the brokerage firm's headquarters. Then, we construct several dummy variables corresponding to Chinese air pollution categories. The Ministry of Environmental Protection of China (MEPC) divides AQI into 6 categories. In order of pollution degree from light to heavy, they are: I-excellent (0<AQI≤50), II-good (50<AQI≤100), III-light pollution (100<AQI≤150), IV-moderate pollution (150<AQI≤200), V-serious pollution (200<AQI≤300) and VI-heavy pollution (AQI>300). In Panel A of Table 4, we replace our measure of air pollution with a dummy variable for each of the MEPC' s six categories of air pollution. These dummy variables will be coded one if the average hourly air quality index over a 15-day window preceding the earnings forecast announcement date falls within the corresponding range,[4] and zero otherwise.

In Panel A of Table 4, the dependent variable is the analyst forecast optimism (*Optimism*) and the independent variables in Columns (1) to (4) are the dummy variables *AQI0-50*, *AQI51-100*, *AQI101-150* and *AQI151-200* corresponding to I-excellent (0<AQI≤50), II-good (50<AQI≤100), III-light pollution (100<AQI≤150) and IV-moderate pollution (150<AQI≤200), respectively. The coefficients on *AQI0-50* and *AQI51–100* are 0.142 and 0.010, respectively, which indicate that analysts tend to issue more optimistic forecasts when the air quality is excellent (0<AQI≤50) or good (50<AQI≤100). On the contrary, both the coefficients on *AQI101-150* and *AQI151-200* are negative, which reveal that air pollution makes analysts more pessimistic forecasters.

In addition, we follow Dong et al. (2021) allowing for greater flexibility in the relation between air pollution and forecast optimism by replacing the linear form on the right-hand side of Eq. (2) with a dummy variable for each of the Chinese government's categories of air pollution (category I, *AQI0-50*, is the omitted category) and report the results in the Column (5). The results indicate that the linear specification fits the data well, and the coefficients are monotonically decreasing in pollution severity, which is consistent with Dong et al. (2021).

Following Chen et al. (2017), Li et al. (2020) and Dong et al. (2021), we further employ three more proxies for our main test variables to validate our findings. First, rather than the average hourly air quality index over the 15-day period preceding the analyst forecast release, we construct a de-seasonalized pre-forecast air quality index. Specifically, for each air quality monitoring station, we calculate the average hourly air quality index (*AQI*) for each analyst forecast release month and then deduct this average, or normal, air quality index from the actual mean air quality index. We then calculate the average de-seasonalized air quality index in the 15-day window preceding the issuance of the analyst forecasts (*ΔAQI*) as our independent variable. As reported in Column (1) of Panel B in Table 4, the coefficient on *ΔAQI* is −2.387 and statistically significant at the 1 % level, consistent with a negative association between air pollution and analyst forecast optimism.

Second, rather than using the air quality index information based on the air quality information driven from the air quality monitoring stations within 2-km radius of brokerage firms, we use the air quality information at the city-level where the brokerage headquarters is located as our measure of air pollution. Consistent with prior analysis, we calculate the average daily air quality index over the 15-day window preceding the forecast release (*AQI_City*) based on the city-level air quality index information. The corresponding results based on city-level air quality data are reported in Column (2) of Panel B. The coefficient on *AQI_City* is −1.458 and significant at the 1 % level, which continues to support our main result.

Considering the potential impact of weather on analyst forecast optimism (Dong et al., 2021), we re-estimate our baseline regression after controlling for other weather dimensions obtained from CnOpenData database to exclude the possibility that the air pollution variable (*AQI*) is merely picking up the effect of aggregate weather conditions on analyst forecast optimism. Specifically, we control for rainfall (*Precipitation*), sunshine exposure (*Sunishine*), temperature (*Temperature*), wind speed (*WindSpeed*) and humidity (*Humidity*). As reported in Column (3) of Panel B, the coefficient on *AQI* is −0.977 and statistically significant at the 5 % level. We therefore show that we obtain consistent results when we control for other weather dimensions.

5.3. Varying Time Windows and Distance Radii

In this section, we use alternative time windows and distance radii over which we capture the degree of air pollution in the pre-forecast period. We do not know exactly when analysts issue their earnings forecasts, or the precise time window over which air pollution occurs. In order to exclude the possibility that our results are driven by the choice of pre-forecast time window, we employ the two following alternative event windows as robustness checks: [*t-10*, *t-1*] and [*t-20*, *t-1*]. As shown in Columns (1) and (2) of Table 5, the coefficients on *AQI* are −0.856 and −1.921, respectively. The coefficients on *AQI* are both negative and significant at the 5 % or higher levels.

In our baseline regressions, we use the air quality information within a 2-km radius of the brokerage firm headquarters to construct our measurement of air pollution (*AQI*). To verify that our results are not driven by the choice of distance radii, we use the three alternative distance radii to construct *AQI*. Specifically, we calculate the degree of pollution (*AQI*) as the average hourly air quality index over a 15-day window preceding the earnings forecast announcement date for the air quality monitoring stations within a 4-km, 6-km and 8-km radius of the brokerage firms' headquarters. As reported in Columns (3) to (5) of Table 5, the coefficients on *AQI* remain negative and significant at the 1 % level, consistent with those reported in Table 2. Overall, these results reported in Table 5 imply that the choice of time windows and distance radii are not responsible for our results.

[4] After being winsorized at the 1 % and 99 % levels, the value of *AQI* in our sample has a maximum value of 0.175 (We construct the *AQI* by dividing the initial air quality index by 1000 in our analysis). So, the categories V and VI, i.e., serious pollution and heavy pollution, are omitted.

Table 4
Alternative Measures of Air Pollution.

Panel A: Different AQI Categories					
	Optimism	**Optimism**	**Optimism**	**Optimism**	**Optimism**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
AQI0–50	0.142***				
	(4.635)				
AQI51–100		0.010			-0.122***
		(0.522)			(-3.878)
AQI101–150			-0.037		-0.127***
			(-1.526)		(-3.143)
AQI151–200				-0.354***	-0.350***
				(-6.327)	(-5.269)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	103,768	103,768	103,768	103,768	103,768
Adj.R2	0.282	0.282	0.282	0.282	0.284

Panel B: Additional Tests			
	Optimism	**Optimism**	**Optimism**
	(1)	**(2)**	**(3)**
ΔAQI	-2.387***		
	(-3.427)		
AQI_City		-1.458***	
		(-7.428)	
AQI			-0.977**
			(-2.174)
Precipitation			-0.011**
			(-2.464)
Sunshine			-0.025**
			(-2.382)
Temperature			0.016***
			(6.853)
WindSpeed			0.112***
			(4.119)
Humidity			-0.004**
			(-2.226)
_cons	-23.924***	-24.123***	-24.053***
	(-17.985)	(-37.638)	(-17.697)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	103,768	422,115	102,804
Adj.R2	0.284	0.270	0.284

Panel A reports the effect of different *AQI* categories on analyst forecast optimism. Specifically, we divide the air quality index into 6 categories referring to the practice of The Ministry of Environmental Protection of China (MEPC). We construct four indicator variables: *AQI0-50*, *AQI51-100*, *AQI101-150* and *AQI151-200*, which are coded one if the air quality index meets the corresponding range of values. Panel B reports the results of alternative measures of air pollution. In Column (1), we deduct the average hourly air quality index (*AQI*) for each analyst forecast release month from the actual *AQI* to construct the measure of air pollution (*ΔAQI*). In Column (2), we re-calculate the *AQI* based on the city-level air quality index data. In Column (3), we re-estimate our baseline-regression after controlling for other weather dimensions. All regressions include year-fixed, quarter-fixed and firm-fixed effects to capture unobserved heterogeneity in time and across firms. The sample period is between 2014 and 2021. T-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

5.4. Conditional on analyst characteristics and forecast uncertainty

In this section, we examine individual analyst attributes and forecast uncertainty that could plausibly mitigate the effects of air pollution on analyst forecast optimism. First, we consider whether the role of ability moderates the effect. Following Dong et al. (2021), we rely on analysts' all star status as a comprehensive measure to quantify their ability (*Star*). Specifically, *Star* is an indicator variable that takes a value of 1 if the analyst is ranked as a star analyst by the New Fortune Magazine at the beginning of the year. As reported in Column (1) of Table 6, the coefficient on the interaction term *Star*AQI* is positive and statistically significant at the 1 % level, revealing that air pollution will have a weaker impact on analyst forecast optimism when analysts are more capable.

Second, we obtain the educational background of analysts from CSMAR and divide education level into five degrees (*Degree*) that take values from one to five (one = technical secondary school degree, two = associate degree, three = bachelor' s degree, four = master' s degree, five = doctoral degree). However, the coefficient on *Degree*AQI* is insignificant, indicating that there is no evidence that the effect of air pollution on analyst forecast optimism is mitigated by the educational level of analysts.

Table 5
Varying Time Windows and Distance Radii.

	[t-10, t-1] (1)	[t-20, t-1] (2)	4-km (3)	6-km (4)	8-km (5)
AQI	-0.856**	-1.921***	-1.230***	-1.598***	-1.502***
	(-2.304)	(-4.322)	(-5.400)	(-7.819)	(-7.511)
Size	1.079***	1.077***	1.140***	1.109***	1.105***
	(19.345)	(19.311)	(36.608)	(39.042)	(40.135)
Revenue	-0.147***	-0.148***	-0.047***	-0.046***	-0.047***
	(-5.508)	(-5.580)	(-3.108)	(-3.305)	(-3.469)
BM	0.620***	0.617***	0.700***	0.677***	0.669***
	(14.624)	(14.565)	(29.780)	(32.487)	(33.061)
Volatility	1.230***	1.230***	1.317***	1.282***	1.313***
	(14.341)	(14.344)	(26.713)	(28.743)	(30.208)
Turnover	-0.170***	-0.171***	-0.166***	-0.174***	-0.175***
	(-12.343)	(-12.400)	(-21.800)	(-24.755)	(-25.723)
IntAsset	-1.524***	-1.525***	-1.438***	-1.399***	-1.412***
	(-2.854)	(-2.856)	(-4.639)	(-4.943)	(-5.160)
Institution	0.022***	0.022***	0.018***	0.018***	0.019***
	(10.106)	(10.165)	(14.746)	(16.157)	(16.792)
Larger	-0.036***	-0.036***	-0.030***	-0.031***	-0.031***
	(-11.711)	(-11.762)	(-17.169)	(-19.854)	(-20.388)
Horizon	0.371***	0.379***	0.313***	0.361***	0.352***
	(4.672)	(4.765)	(6.742)	(8.438)	(8.460)
AnaAttention	0.137***	0.134***	0.208***	0.250***	0.237***
	(3.829)	(3.766)	(10.485)	(13.696)	(13.325)
Experience	-0.045***	-0.047***	-0.020***	-0.024***	-0.025***
	(-3.511)	(-3.636)	(-2.756)	(-3.579)	(-3.874)
BroSize	0.014	0.030*	0.001	0.032***	0.035***
	(0.868)	(1.839)	(0.145)	(3.779)	(4.233)
ComNumber	0.106***	0.109***	0.014	0.008	0.006
	(3.090)	(3.165)	(0.766)	(0.447)	(0.347)
ForNumber	-0.034	-0.036	-0.001	-0.000	-0.001
	(-1.166)	(-1.255)	(-0.092)	(-0.003)	(-0.105)
_cons	-23.828***	-23.726***	-25.215***	-24.861***	-24.713***
	(-17.904)	(-17.826)	(-33.795)	(-36.553)	(-37.510)
Year FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	103,761	103,772	303,454	364,977	385,217
Adj.R2	0.284	0.284	0.270	0.269	0.269

This table reports the alternative distances and time windows for calculating *AQI*. In Columns (1) and (2), we employ the two following alternative event windows: [*t-10*, *t-1*] and [*t-20*, *t-1*], respectively. In Columns (3) to (5), we re-calculate *AQI* based on the air quality index of air quality monitoring stations within a radius of 4-km, 6-km and 8-km, respectively. All regressions include year-fixed, quarter-fixed and firm-fixed effects to capture unobserved heterogeneity in time and across firms. The sample period is between 2014 and 2021. T-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Third, we take the effect of pressure on analysts into account. Prior literature finds that analysts facing greater analyst labor market competition are more motivated to perform well. If stronger analyst labor market competition leads analysts to work harder regardless of the environmental situation, we may observe that the labor market competition mitigates the effect of air pollution on analyst forecast optimism. Following Li et al. (2020), we use the number of analysts following the firm (*AnaAttention*) to measure the analyst labor market competition. As Column (3) shows, the coefficient on the interaction term *AnaAttention***AQI* is 2.334 and significant at the 1 % level. The results suggests that air pollution has a weaker effect on the forecast optimism of analysts who are facing greater analyst labor market competition.

Fourth, we are motivated to look at heterogeneity by forecast uncertainty based on earlier research in earnings forecasts, which finds that the underlying volatility of firm's earnings amplifies the level of uncertainty and ambiguity involved in earnings forecasts (Chen et al., 2017). Psychologists believe that mood is a particularly important factor in making decisions under risk and uncertainty. Based on this, we expect the effect of air pollution on analyst forecast optimism to be more pronounced for forecasts issued for firms with higher uncertainty, proxied by higher earnings volatility (*Volatility*). As reported in Column (4), the coefficient on *Volatility***AQI* is -3.898 and significantly at the 5 % level, which states that the level of uncertainty amplifies the effect of air pollution on analyst forecast optimism.

Next, we consider the role of analyst work experience (*Experience*), as captured by the natural logarithm of the time interval in the years between analysts' current forecast issuance date and their first forecast date. In Column (5) of Table 6, we include the interaction of *Experience* and *AQI* in our model. The coefficient on *Experience***AQI* is -1.531 and statistically significant at the 1 % level, implying that analysts with longer work experience, usually older analysts, are more cautious about environmental hazards (Currie, 2011; Zhang et al., 2023) and may be more susceptible to negative mood induced by air pollution. Finally, we investigate the impact of

Table 6
Effect of Analyst Characteristics and Forecast Uncertainty.

	Optimism (1)	Optimism (2)	Optimism (3)	Optimism (4)	Optimism (5)	Optimism (6)
AQI	-2.303***	-0.710	-8.266***	-0.641	-1.611***	-1.336***
	(-5.142)	(-0.178)	(-5.539)	(-1.259)	(-3.801)	(-2.763)
Star*AQI	3.467***					
	(4.296)					
Degree*AQI		-0.209				
		(-0.212)				
AnaAttention *AQI			2.334***			
			(4.828)			
Volatility*AQI				-3.898**		
				(-2.341)		
Experience*AQI					-1.531***	
					(-4.112)	
Gender*AQI						-0.879
						(-1.170)
Star	-0.220***					
	(-3.011)					
Degree		-0.044				
		(-0.515)				
AnaAttention			-0.052			
			(-0.943)			
Volatility				1.529***		
				(9.993)		
Experience					-0.050***	
					(-3.902)	
Gender						-0.023
						(-0.353)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103,768	103,768	103,768	103,573	103,768	103,768
Adj.R2	0.284	0.284	0.284	0.285	0.284	0.284

This table reports the results of cross-sectional tests by analysts' ability, education level, pressure, gender, work experience and forecast uncertainty. All regressions include year-fixed, quarter-fixed and firm-fixed effects to capture unobserved heterogeneity in time and across firms. The sample period is between 2014 and 2021. T-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

analysts' gender (*Gender*) on the effect of air pollution on analyst forecast optimism, which receives the value of one for female or analyst teams with at least one female, and zero otherwise. We add *Gender* and the interaction of *Gender* and *AQI* to Eq. (2), but the interaction term (*Gender*AQI*) is insignificant, indicating that analyst gender does not impact the association between air pollution and analyst forecast optimism. Our findings are consistent with Dong et al. (2021), which may be due to the fact that female analysts are a special group of competitive and less risk-averse females who choose to pursue a career in a male-dominated industry (Kumar, 2010).

5.5. Endogeneity

In this section, we conduct several additional tests to mitigate potential reverse endogeneity concerns. Following Arceo et al. (2016), we first perform a two-stage-least-square (2SLS) analysis by employing the existence of thermal inversions as our instrumental variable. The appearance of temperature is not conducive to the rising movement of air, causing pollutants to stay in place for a long time and leading to worse air pollution. Specifically, we construct *Inversion* by using the number of inversions in the pre-forecasting window (15-days preceding the earnings forecast announcement date) to instrument for pollution level. We add one to *Inversion* to avoid losing observations with a value of zero and raise the number to the natural logarithm to reduce skewness.

As shown in Column (1) of Table 7, Panel A, the first-stage results show that the coefficient on *Inversion* is 0.014, which is positive and significant at the 1 % level, indicating the positive relationship between the existence of thermal inversions and air pollution. Based on the results of the second-stage regression reported in Column (2), we find that the coefficient on *AQI* remains negative and statistically significant at the 5 % level. These results are consistent with our prior analysis. The weak-identification test F statistics of $1.5*10^4$ (Kleibergen-Paap Wald F-statistics) exceed the 10 % critical value of 16.38 (Stock and Yogo, 2005), meaning that we can reject the null hypothesis that the instruments are weak.

Second, we conduct a placebo test to test that the results of our baseline regression are not due to chance. Following Chen et al. (2017) and Li et al. (2020), we randomize the headquarter locations of brokerage firms in our sample, reconstruct a pseudo-air pollution variable (*AQI*) based on the randomized location 150 times, and re-estimate 150 times. We then average the coefficient, as well as the T-statistics on the pseudo-air pollution variable (*AQI*) and report these in Column (3) of Table 7. The result indicates that the average coefficient linking *AQI* to *Optimism* is −0.484 and statistically insignificant. The result of our placebo test provides

Table 7
Endogeneity.

Panel A: Two-Stage-Least-Square (2SLS) Analysis and Placebo Test			
	AQI	**Optimism**	**Optimism**
	(1)	**(2)**	**(3)**
AQI		-2.954**	-0.484
		(-2.305)	(-1.355)
Inversion	0.014***		
	(123.861)		
Size	-0.000	1.082***	
	(-0.070)	(19.317)	
Revenue	-0.001***	-0.150***	
	(-5.785)	(-5.584)	
BM	-0.000**	0.617***	
	(-2.112)	(14.542)	
Volatility	-0.000	1.233***	
	(-0.399)	(14.281)	
Turnover	-0.000**	-0.174***	
	(-2.138)	(-12.488)	
IntAsset	-0.005	-1.586***	
	(-1.279)	(-2.961)	
Institution	0.000***	0.022***	
	(2.947)	(10.206)	
Larger	-0.000*	-0.036***	
	(-1.927)	(-11.791)	
Horizon	0.004***	0.372***	
	(5.671)	(4.647)	
AnaAttention	-0.000	0.134***	
	(-1.452)	(3.725)	
Experience	-0.000***	-0.047***	
	(-4.190)	(-3.651)	
BroSize	0.007***	0.044*	
	(53.841)	(1.839)	
ComNumber	-0.001***	0.108***	
	(-3.053)	(3.137)	
ForNumber	0.000**	-0.036	
	(2.078)	(-1.249)	
_cons	0.046***		
	(4.964)		
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	103,393	103,384	
Adj.R2	0.581	0.003	

Panel B: DID Approach		
	(1)	**(2)**
	Optimism	**Optimism**
Lower×Post	0.059**	
	(2.391)	
Higher×Post		-0.021
		(-0.674)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	414,091	414,091
Adj.R2	0.270	0.270

Panel A reports the results of 2SLS and placebo tests. In the first stage (Column (1)), the dependent variable is our measure of the air pollution (*AQI*), and the instrumental variable is the number of days when temperature inversion occurs in the pre-forecasting window (15-days preceding the earnings forecast announcement date). In the second stage (Column (2)), the dependent variable is our measure of analyst forecast optimism (*Optimism*). Column (3) reports the results of our placebo test. Panel B reports the results of DID analysis using analysts' job-hopping as an exogenous shock. *Higher* (*Lower*) will be coded one if analysts move to a brokerage firm located in a city with worse (better) air quality, and zero otherwise. The post-job-hopping dummy (*Post*) equals one for the post-job-hopping years, and zero for the pre-job-hopping years. All regressions include year-fixed, quarter-fixed and firm-fixed effects to capture unobserved heterogeneity in time and across firms. The sample period is between 2014 and 2021. T-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

confidence that our findings are not the result of some unobservable analyst-location-time invariant characteristics.

Third, we employ a difference-in-differences (DID) design using analysts' job-hopping as an exogenous shock to the air pollution in which analysts issue forecast reports, which aims to test whether analyst optimism changes if analysts move to other brokerage firms in different cities. We first compare the city' s annual PM2.5 concentration before and after the job-hopping. If the annual PM2.5 concentration is higher after the job-hopping, we treat the event as a pollution-increasing event (*Higher* = 1), which means the analyst moved to a brokerage firm located in a city with worse air quality. On the contrary, if the analyst moved to a brokerage firm with better air quality, the annual PM2.5 concentration will become lower after the job-hopping, and we treat the event as a pollution-decreasing event (*Lower* = 1). The post job hopping dummy (*Post*) equals one for the post job hopping years, and zero for the pre-job-hopping years. In our analysis, we keep in our sample only analysts that have one job-hopping event. As shown in Panel B of Table 7, the coefficient on *Lower*×*Post* is positive and statistically significant at the 5% level, indicating that analysts issue more optimistic forecasts after moving to a city with better air quality. The coefficient on *Higher*×*Post* is negative, indicating that analysts become less optimistic forecasters after moving to a city with more severe pollution. Overall, these results further support our main conclusion that more severe air pollution makes analysts more pessimistic forecasters.

5.6. Optimistic analysts and pessimistic analysts

In our baseline regressions, we confirm the negative relationship between air pollution and analyst forecast optimism. An outstanding issue is that our results fail to identify the mechanism via which air pollution affects analyst earnings predictions. Specifically, does air pollution make optimistic analysts more cautious or make pessimistic analysts even more pessimistic? In order to further test the impact of air pollution on analyst earnings predictions, we group the dependent variable according to whether it is greater than 0. A positive value of *Optimism* means that this is the forecast made by an optimistic analyst. On the contrary, a negative value of *Optimism* means that analysts are relatively pessimistic forecasters.

As reported in Table 8, the coefficients on *AQI* are negative in both optimistic and pessimistic analyst groups. However, only the coefficient of the optimistic analyst group is significant at the 5 % level, which indicates that our result is mainly due to the air pollution making optimistic analysts more cautious or pessimistic.

Considering that the COVID-19 pandemic may decrease analysts' optimism[5] (Cuculiza et al., 2021) and make them more pessimistic forecasters, we re-estimate the effect of air pollution on analyst forecast optimism before and after the pandemic, respectively. As reported in Panel B of Table 8, both the coefficients on *AQI* are negative, while the effect of air pollution on analyst forecast optimism is only significant before the COVID-19 pandemic. It may be that the mood of analysts during the epidemic is more likely to be influenced by the fluctuations of the COVID-19 pandemic, and thus the effect of air pollution on analyst mood is relatively weakened during that period. In addition, since the pandemic makes analysts more pessimistic forecasters, these results reported in Panel B further emphasizes that the negative relationship between air pollution and analyst forecast optimism is mainly due to air pollution making optimistic analysts more cautious or pessimistic.

5.7. Controlling for stock returns

Considering that the 1-month stock return before the forecast should also be an important variable in the regression, which also affects analyst mood or forecast optimism, we further control for the 1-month stock return before forecasts (*Lreturn*) and re-estimate our baseline regression. As reported in Table 9, after controlling for the 1-month stock returns before the forecast, the coefficient on *AQI* remains negative and significant at the 1 % level, which still supports the negative relationship between air pollution and analyst forecast optimism.

6. Conclusions

In this paper, we examine whether analyst forecast optimism is affected by air pollution. Unlike previous studies focusing on how analyst forecasts are affected by the characteristics of analysts, we investigate the effect of the air pollution around the brokerage firms on analyst forecast optimism. We provide strong evidence that exposure to heavy air pollution will reduce analyst forecast optimism, consistent with the negative effects of air pollution on individual mood. Furthermore, using analysts' job-hopping as an exogenous shock to the air pollution in which analysts issue forecast reports, our DID analysis reveals that analysts become more optimistic forecasters after moving to a city with lower levels of air pollution. We show that this effect of air pollution is lower for analysts with higher ability, greater pressure, shorter working years or less uncertainty. Our results hold for a battery of other sensitivity checks, including reconstructing our air pollution measure based on the city-level air quality index, altering the time windows and distance radii, dividing AQI into 6 categories, controlling for other weather dimensions and controlling for various fixed effects. While our results are still robust to various tests including 2SLS by instrumenting for air pollution using thermal inversions and placebo tests by randomizing the headquarter locations of brokerage firms in our sample, our study documents association and not causation. Collectively, these findings extend the prior literature on analyst forecast optimism and negative effects of air pollution.

CRediT authorship contribution statement

Ying Wang: Conceptualization, Data curation, Writing – original draft, Writing – review & editing. **Zisen Liu:** Methodology,

[5] Our un-tabulated results show that analyst forecast optimism is significantly higher before the COVID −19 pandemic.

Table 8
Optimistic analysts and pessimistic analysts.

Panel A: The Effect of Air Pollution between Optimistic and Pessimistic Analysts		
	(1)	**(2)**
	Optimistic Analysts	**Pessimistic Analysts**
AQI	-0.949**	-0.515
	(-2.116)	(-1.304)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	78,749	25,019
Adj.R2	0.347	0.441
Panel B: The Effect of Air Pollution Before and After the COVID-19 Pandemic		
	(1)	**(2)**
	Before the Pandemic	**After the Pandemic**
AQI	-1.469***	-0.590
	(-3.375)	(-0.399)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	92,829	10,939
Adj.R2	0.275	0.588

Panel A reports the results of regressions of air pollution (*AQI*) on analyst forecast optimism (*Optimism*) based on the sub-samples of optimistic and pessimistic analysts. Panel B reports the effect of air pollution (*AQI*) on analyst forecast optimism (*Optimism*) before and after the COVID-19 pandemic. The sample period is between 2014 and 2021. T-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 9
Controlling for Stock Return.

	(1)
	Optimism
AQI	-1.355***
	(-3.121)
Lreturn	-0.543***
	(-7.191)
Controls	Yes
Year FE	Yes
Firm FE	Yes
Quarter FE	Yes
Observations	100,934
Adj.R2	0.287

This table reports the effect of air pollution (*AQI*) on analyst forecast optimism (*Optimism*) after controlling for the 1-month stock return before forecast. The sample period is between 2014 and 2021. T-statistics are reported in parentheses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Resources, Software, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix A. Variable definitions

Variable	Definition
Optimism	The difference between forecasted EPS and actual EPS scaled by the stock price on the day prior to the earnings forecast date, multiplied by 100. (*Source*: CSMAR)
AQI	The average hourly air quality index over a 15-day window preceding the earnings forecast announcement date (i.e., *t-15* to *t-1*) for all the air quality monitoring stations within a 2-km radius of the brokerage firm's headquarters, scaled by 1000. (*Source*: www.cnopendata.com)
Size	The natural logarithm of the total assets of a firm. (*Source*: CSMAR)
Revenue	The annual stock returns of the year prior to the earnings forecast date. (*Source*: CSMAR)
BM	The book-to-market ratio. (*Source*: CSMAR)
Volatility	The standard deviation of earning per share from *t*-1 to *t*-3. (*Source*: CSMAR)
Turnover	The average daily turnover rate of the earnings forecast year. (*Source*: CSMAR)
IntAsset	The intangible asset ratio. (*Source*: CSMAR)
Institution	The percentage of institutional ownership. (*Source*: CSMAR)
Larger	The shareholding of top ten shareholders. (*Source*: CSMAR)
Horizon	The natural logarithm of one plus the forecast age in days between the forecast issuance date and earnings announcement date. (*Source*: CSMAR)
AnaAttention	The natural logarithm of one plus the number of analysts following a firm. (*Source*: CSMAR)
Experience	The natural logarithm of one plus the time interval in the years between analysts' current forecast issuance date and their first forecast date. (Source: CSMAR)
BroSize	The natural logarithm of one plus the number of analysts in a brokerage firm in a year. (Source: CSMAR)
ComNumber	The natural logarithm of one plus the number of firms followed by analyst in a year. (*Source*: CSMAR)
ForNumber	The natural logarithm of one plus the number of forecasts issued by analyst in a year. (*Source*: CSMAR)
ΔAQI	The average de-seasonalized air quality index in the 15-day window preceding the issuance of the issuance of the analyst forecasts. (*Source*: www.cnopendata.com)
AQI_City	The average daily air quality index over the 15-day window preceding the forecast release, which is based on the air pollution level in the city of brokerage firm headquarters. (*Source*: www.cnopendata.com)
Precipitation	The average daily liquid precipitation in millimetres over the 15-day window preceding the forecast release where the brokerage firm headquarter is located. (*Source*: www.cnopendata.com)
Sunshine	The average hours of sun of the city over the 15-day window preceding the forecast release where the brokerage firm headquarter is located. (*Source*: www.cnopendata.com)
Temperature	The average temperature of sun of the city (℃) over the 15-day window preceding the forecast release where the brokerage firm headquarter is located. (*Source*: www.cnopendata.com)
WindSpeed	The average wind speed of the city (m/s) over the 15-day window preceding the forecast release where the brokerage firm headquarter is located. (*Source*: www.cnopendata.com)
Humidity	The average humidity of the city (%) over the 15-day window preceding the forecast release where the brokerage firm headquarter is located. (*Source*: www.cnopendata.com)
Star	An indicator variable that takes a value of one if the analyst is ranked as a star analyst by the New Fortune Magazine at the beginning of the year, and 0 otherwise. (*Source*: CSMAR)
Degree	Take value from one to five (one = technical secondary school degree, two = associate degree, three = bachelor' s degree, four = master' s degree, five = doctoral degree). (*Source*: CSMAR)
Inversion	The natural logarithm of one plus the number of inversions in the pre-forecasting window (15-day preceding the earnings forecast announcement date). (*Source*: NASA)
AQI0–50 (AQI51–100, AQI101–150, AQI151–200)	These dummy variables will be coded one if average hourly air quality index over a 15-day window preceding the earnings forecast announcement date falls within the corresponding range, and zero otherwise (*Source*: www.cnopendata.com).
Lower	An indicator variable that takes a value of one if the annual PM2.5 concentration become lower after the job-hopping, and zero otherwise.
Higher	An indicator variable that takes a value of one if the annual PM2.5 concentration become higher after the job-hopping, and zero otherwise.
Post	An indicator variable equals one for the post-job-hopping years, and zero for the pre-job-hopping years.
Gender	An indicator variable that takes a value of 1 for female or analyst teams with at least one female, and zero otherwise. (*Source*: CSMAR)
Lreturn	The 1-month stock return before forecast. (*Source*: CSMAR)

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