Place attachment and affective bias: Evidence from Chinese analysts

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Abstract

We examine the consequences of affective place attachment for decision-making by Chinese financial analysts. Place attachment implies an emotional connection to a physical locale; hometowns often provide this sense of place. We show that high pollution in an analyst's hometown leads to more pessimistic earnings forecasts, a result that unaffected by the inclusion of hometown and even analyst fixed effects. Our results are driven by pessimistic forecasts for high-polluting firms, for which hometown pollution may be particularly salient, further bolstering our interpretation of affective hometown attachment as the explanation for our empirical results.

JEL classifications: D91; G41; Q5

Keywords: Pollution; Forecasting bias; Investment analysts; Place attachment

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1 Introduction

While place attachment has seen very extensive theoretical development and empirical application in sociology and psychology, the concept is largely unknown within economics and finance. Our paper aims to further expose place attachment to a wider audience of scholars, and to emphasize its relevance for influencing individual judgment and decision making. We do so via the analysis of how hometown conditions (specifically, pollution) impact the forecast bias of Chinese financial analysts.

Place attachment is, broadly speaking, the bond between an individual and her "meaningful" environments (Scannell and Gifford, 2010). This person-place connection may continue and indeed even intensify when an individual is no longer physically in a particular locale. Notably, migrants hold a connection to their hometown or home country precisely because they lack its immediate presence which thus creates a sense of nostalgia and longing, and this bond is not easily supplanted by ties to their new place of residence (e.g., Du, 2017; Barcus and Brunn, 2010). Such attachments can affect individuals' assessments of a physical space, for example leading them to hold a more optimistic view of a hometown or neighborhood (e.g., perceiving a lower level of crime or disorder than objective facts would indicate (Billig, 2006; Brown et al., 2003)). Attachment similarly creates a sense of obligation or stewardship; most relevant for our setting, place attachment may promote pro-environmental attitudes and behaviors toward a place (Halpenny, 2010; Xu and Han, 2019).[1]

As has been extensively discussed in the place attachment literature, new technologies have made it far easier for migrants to maintain their hometown attachments and remain informed on local goings-on, via email communication with friends and families, and access to internet news sites (Barcus and Brunn, 2010; Hiller and Franz, 2004). This has reinforced the already-powerful hometown attachments among Chinese who move away from their hometowns, which is the setting we study here.[2]

We study the forecasts of Chinese financial analysts. Our analysis is made possible by the detailed administrative data we have obtained from the Securities Association of China (henceforth SAC); these data include information on individual analysts' personal backgrounds, including their

[1] The conception of place attachment that we describe here is quite distinct from – though related to – the idea of hometown bias or hometown favoritism that will be more familiar to most economists. Hometown attachment emphasizes an affective connection between a person and a physical place, whereas hometown favoritism implies a sense of obligation or at least reciprocity toward individuals with a shared background. As we will also discuss below, place attachment as conceived as an emotional bond to a physical place rather than a group of individuals from that place is less apt to suffer from the challenge of distinguishing empirically between in-group favoritism (including hometown favoritism) versus better information about in-group members.

[2] As one indication of the strengths of these connections to home, as we discuss in the next section, a 2017 survey found that over 90 percent of Chinese adults reported talking to their parents at least once a month (nearly 70 percent at least weekly).

place of birth.[3]

We show that when pollution is more severe in an analyst's hometown, it leads to more pessimistic earnings forecasts for the companies she covers. Our estimates suggest a discernable and robust impact: in our preferred specification, a doubling of air pollution (as captured by the standard Air Quality Index) leads to a 3.6 percentage point increase in the probability of an analyst issuing a forecast that is below realized earnings. The effect size is extremely robust, and is relatively unaffected by the inclusion of firm, hometown, and even analyst fixed effects.

Importantly, because most of the companies covered (well over 90 percent) are not located in analysts' hometowns, we can reject the possibility that analysts' downward-biased forecasts are the result of direct exposure to pollution, as documented by, for example, Dong et al. (2020) and Chang et al. (2019). Rather, we interpret our finding as reflecting the influence that hometown conditions have on analysts' emotional states, which in turn may lead to affective bias in their evaluations of companies they cover. Intriguingly, we also observe that the relationship between hometown pollution and forecast pessimism is driven almost entirely by firms in government-designated high pollution industries, which may make pollution concerns more salient. This type of 'directed' affective bias is, to our knowledge, a new and quite intuitive result to the literature.

In studying the empirical relevance of place attachment, our focus on hometown pollution is useful for several reasons. First, one's "home place" (residence, neighborhood, or hometown, for example) is seen as the most common and most powerful source of place attachment (Gustafson, 2001), and hometowns serve as the focus of this home-based emotional bond in many settings.[4] Our results may thus have broader geographic and cultural applicability beyond China.

Second, the high and variable pollution across much of China provides a source of variation in analysts' hometown environments that is sufficiently large as to plausibly impact their emotional states. We thus may exploit time-varying shifts in threats to specific analysts' home places, allowing for a difference-in-differences methodology that is distinct from much prior work on place attachment.

Finally, analyst forecasts plausibly capture the real effects of affective bias, based on whether forecasts are on average too optimistic or pessimistic. Prior work has tended to rely on survey responses to capture the affective impact of place attachment (most prominently the impact of home place separation on well-being for migrants or college students).

We see our work as serving several important functions. First, we introduce a new concep-

[3] Public sources do not generally provide this information, except in the case of very high profile analysts.

[4] See Fisman et al. (2018) and references therein for a discussion of hometown ties in China in general, and Xu et al. (2015) for hometown ties as they specifically relate to place attachment. For studies of hometown attachments elsewhere see, for example, McAndrew (1998) for Americans and Smith (2002) for Hispanic Americans specifically; Scopelliti and Tiberio (2010) for Italy; Florek (2011) for Poland.

tualization of place attachment to the economics literature, one which is already well-established in other branches of the social sciences. In particular, we focus on the core element of affective consequences of place attachment that, to our knowledge, has never been considered by economists. In the few instances in which economists have invoked place attachment, it has been deployed as a source of hometown bias, which is already a well-established theme in economics and finance.[5] In particular Yonker (2017) invokes place attachment to argue that managers may be expected to favor hometown workers, while Jiang et al. (2019) uses place attachment as a way of explaining CEOs' preferences for acquisitions of companies based in their hometowns. These papers' findings, while important in the finance literature, invoke a very different conception of place attachment than the one we use here: in their settings, hometown attachment refers primarily to hometown favoritism, i.e., a sense of obligation or at least reciprocity toward individuals with a shared background.

Given researchers' interest in optimism bias across the social sciences, and the established role of emotions in mediating individuals' predictions of future outcomes, we hope our results will be of interest to a broad audience.[6] In a sense, we establish one underlying (and time-varying for a given individual) mechanism for affective bias, and show its effects in an empirically relevant setting.

2 Background and data

In the subsections that follow, we describe in greater detail the data sources and construction of the variables we use in our analysis. Before turning to the data description, we first provide some additional details on hometown attachment with particular reference to China, and why hometown conditions might be expected to impact financial analysts even after they have moved elsewhere.

2.1 Hometown attachment, pollution, and affective response

As we noted earlier, hometown connections are a common focus in the place attachment literature. Hometown attachment arises in standard survey scales on place attachment as a source of identity, ("I feel like [this place] is a part of me;" "[This place] is very special to me;" "I identify strongly with [this place];" see Williams and Roggenbuck (1989)), and is intimately linked to the notion of *rootedness* that is also a common theme in the place attachment literature. For example, McAndrew

[5]See, for example, Chu et al. (2020) and Fisman et al. (2018) on hometown bias in China. The literature on hometown bias more broadly is vast; several recent or prominent examples include Hong et al. (2008) on investor hometown bias; Fiva and Halse (2016) on hometown bias in a political context; and Kokkodis and Lappas (2019) for hometown bias in online reviews.

[6]See, e.g., Kahneman and Tversky (1977) for an early and classic example of optimism bias. For more recent work with a finance-relevant application, see Malmendier and Tate (2005) on overconfidence and CEO investment, and Hong and Kubik (2003) on the optimism bias of financial analysts.

(1998) measures college students' hometown rootedness via a questionnaire that inventories, among other things, students' feelings of homesickness, their desire to move back to their hometown, and whether they subscribe to a hometown newspaper. Migrants have similarly well-documented attachments to their home towns or regions, as described in qualitative studies (Morse and Mudgett, 2017) as well as more quantitative approaches (Du, 2017). The latter focuses on migrants in China, and observes that while individuals may feel connected both to hometowns and places of residence, "attachment/belonging ascribed by birth still has an advantage over the attachment/belonging acquired by residence."

It has become far easier in recent years for migrants to maintain their hometown attachments. As observed by Gustafson (2014), "computer-based communication – email, local news sites, image galleries, webcams, bulletin board systems, and chats – may perpetuate a sense of local belonging." The importance of these "virtual" connections are emphasized by Barcus and Brunn (2010) in their conception of "place elasticity" which emphasizes the declining role of physical proximity as a source of place attachment. In their study of place attachment in rural Appalachia, they find that a majority of migrants "have access to the local paper either by direct subscription, Internet access to the newspaper (which is not available for all local papers) or because another friend or family member routinely passed along each copy of the paper." They conclude that such mechanisms provide a means by which migrants can, "maintain a level of connectivity to people and events in that particular place." Thus, both through communication with hometown family and social networks as well as readily available local news, migrants may remain well-informed on hometown circumstances, even from a distance. While we know of no comparable study for China, a 2017 survey of nearly 20,000 Chinese adults across 32 provinces found that over 90 percent called their parents at least once a month, and nearly 70 percent at least weekly.[7]

Also central to our hypothesized link between hometown pollution and analyst forecasts, the place attachment literature also emphasizes individuals' affective responses to the endangerment of places to which they feel an attachment. Especially given prior work on place attachment and responses to environmental threats in particular (e.g., Wakefield et al., 2001; Cass and Walker, 2009), we conjecture a link from hometown pollution to analyst pessimism, resulting from an affective response to the threat such pollution poses to their hometown.

2.2 Analyst hometown data

At the end of 2017, we obtained access to a proprietary dataset, maintained by the Securities Association of China (henceforth SAC), which contains information on Chinese stock analysts that

[7]See `https://www.sohu.com/a/148590862_660031`. The results come from the "China Filial Piety Index" survey. See `http://jiaju.sina.com.cn/news/20170531/6275697089095991714.shtml`. Both links accessed May 7, 2020.

were active (see details below for the definition of "active") during 2017. This set of 2017-active analysts serves as our starting sample.

The SAC administers a qualifying exam and issues certifications that are required of all financial analysts. Until 2018, SAC regulations required an analyst to renew her certification annually by taking online training and also paying the renewal fee of 150 RMB (a little over US$20).[8] Failure to renew would lead to the revocation of the analyst's certificate, without which she could not practice as an analyst. The certificate application required the submission of detailed demographic information, including an applicant's Resident Identity Card number, which can be linked directly to an individual's province, city, and county of birth as well as birthdate.[9] We additionally obtain each analyst's gender from the SAC data.

These data are matched to analyst forecasts obtained from the Chinese Research Data Service (CNRDS) database, a database commonly employed by Chinese finance and economics scholars.[10] Each earnings report may include multiple forecasts, for different time horizons. We control for time horizon in all analyses that follow (see, e.g., Kumar, 2010; Lo and Wu, 2018), and maintain each forecast as a distinct (but non-independent) observation.

Following Jackson (2005) and the vast literature in accounting on earnings forecasts, we define analysts' forecast optimism as follows:

$$Optimism_{ijt} = 100 * (FEPS_{ijt} - AEPS_{ijt})/P_j$$

where $FEPS_{ijt}$ is analyst i's forecasted earnings per share (EPS) for firm j for year t, $AEPS_{ijt}$ is the realized EPS of firm j for year t, and P_j is firm j's stock price on the day prior to the earnings forecast.

[8] This requirement was repealed in September 2018

[9] See https://www.sac.net.cn/cyry/zgpt/zgcjwtjd/ for the procedure for obtaining stock analyst certification from the SAC, and also see https://baike.baidu.com/item/%E5%B1%85%E6%B0%91%E8%BA%AB%E4%BB%BD%E8%AF%81%E5%8F%B7%E7%A0%81/3400358 for the procedure to link Resident ID to birthplace. Both links accessed on May 6, 2020. The requirement of SAC certification extends to all professionals engaged in the securities business, as laid out in Article 2 of the Measures for the Administration of the Qualifications of Securities Practitioners, issued on Dec 16, 2002 by the China Securities Regulatory Commission. See http://www.csrc.gov.cn/zjhpublic/zjh/200804/t20080418_14493.htm for the rule's full text. Accessed on May 6, 2020.

[10] The database is maintained by the Shanghai Efindata Company, http://www.efindata.com/Home/Index. CNRDS data has slightly more comprehensive coverage of analyst reports than the Chinese Stock Market and Accounting Research (CSMAR) database.

2.3 Air quality

For each city in China, we obtain the daily air quality index (AQI) from the official website of the Ministry of Environmental Protection of China (MEPC).[11] These data are derived from daily air quality reports provided by province- and city-level environmental protection bureaus since 2014. The AQI is constructed based on the levels of six atmospheric pollutants: sulfur dioxide (SO2), nitrogen dioxide (NO2), suspended particulates smaller than 10 µm in aerodynamic diameter (PM10), suspended particulates smaller than 2.5 µm in aerodynamic diameter (PM2.5), carbon monoxide (CO), and ozone (O3). The MEPC distinguishes among six categories of AQI: I-excellent (AQI$\leq$50), II-good (50$<$AQI$\leq$100), III-lightly polluted (100$<$AQI$\leq$150), IV-moderately polluted (150$<$AQI$\leq$200), V-heavily polluted (200$<$AQI$\leq$300) and VI-severely polluted (AQI$>$300).

2.4 Firm and analyst characteristics

To generate the set of firms covered by analysts, we follow standard practice by including all publicly traded companies, except finance firms (Ali and Hirshleifer (2019); He et al. (2019)).[12]

We include in our analysis controls for basic firm attributes which we obtain from CNRDS. These include size as captured by the market value of the firm (where market value equals the number of outstanding shares times stock price), market to book ratio, and analyst attention (the number of analysts covering the firm). For each listed firm in our sample, we also create a dummy variable, $HighPollution$, indicating whether the firm operates in an industry that is officially classified as high-pollution by the MEPC.[13] We also collected data on time-varying analyst characteristics, including his/her tenure as a stock analyst, time interval (in days) between her current forecast and the last EPS forecast on the same firm, number of reports she released in a given year, the number of years the analyst has covered a firm, and the number of companies the analyst covered

[11]Dong et al. (2020) show that weather conditions (hours of sun, temperature, humidity, precipitation and wind speed) have no impact on Chinese stock analysts' earnings forecasts; we thus do not include these as extra control variables.

[12]In practice the inclusion/exclusion of finance firms, which represent only about 5 percent of all analyst forecasts, has no effect on our results.

[13]The MEPC issued the "Industrial Classification on Inspection and Verification of Environmental Protection of Listed Companies" ("Shang Shi Gong Si Huan Bao He Cha Hang Ye Fen Lei Guan Li Mu Lu" in Chinese Pinyin) on June 24, 2008, which specifies the industries officially deemed as high-pollution. See `http://www.gov.cn/gzdt/2008-07/07/content_1038083.htm` for full text (accessed on May 6, 2020). These high-pollution industries include 61 SIC-3 level industries that are in 14 SIC-2 level industries; these 14 SIC-2 industries are: thermal power generation, steel, cement, electrolytic aluminum, coal, metallurgy, construction material production, mining, chemical industries, petrochemical,textile, tannery, and BPF (brewing, papermaking and fermentation). Firms in these industries face a number of extra disclosure and regulatory requirements. In particular, listed firms in high-pollution sectors must provide annual environmental reports, periodically disclose pollution emissions, andobtain approval from local MEPC branches before seeking refinancing from the public markets.

in the year of a forecast. In our favored specification, we include analyst fixed effects, which absorb the effects of any time-invariant analyst attributes. We also control for the size of the analyst's brokerage house, measured by the number of analysts housed by the firm in the year of the forecast.

Our main analysis sample is comprised of 120,405 earnings forecasts issued between 2014 to 2018.[14]

2.5 Data overview

We begin by presenting some basic patterns on analysts' hometowns and their pollution, to provide the reader with a better sense of our identifying variation.

Figure 1 provides, for the full sample of forecast dates, the distribution of the 30-day average AQI, demeaned by hometown. The distribution has a long right tail, reflecting a small number of very high pollution episodes. To reduce the influence of these extreme cases, we will generally use the log of 30-day AQI as our independent variable. Also note that there are substantial within-city swings in pollution. The interquartile range has a width of just over 25, while the gap between the 10th and 90th percentiles is 53, or more than the width of a MEPC pollution category. We will also use the highest AQI in the prior 30 day period as an alternative measure, as these extreme pollution days may have particular salience. Finally, we may use hometown AQI in the month *following* a forecast as a placebo pollution measure, to examine whether the relationship we document is specific to the period immediately preceding a forecast.

This variation comes from a total of 232 distinct prefectures that are the hometowns of 1249 individual analysts. There are 53 cities that are the hometowns of only a single analyst in our dataset . These tend to be smaller cities (e.g., Shaoguan and Luohe, each with populations under 3 million); the cities with the most analysts are Shanghai (78), Beijing (57), and Wuhan (34); half of the analysts in our sample comes from cities that have produced 9 or more analysts each.

We present summary statistics at the forecast-level in Table 1a. The sample mean and standard deviation of forecast optimism are 0.70 and 1.98, respectively, consistent with the prior literature which finds that sell-side analysts' earnings forecasts are generally higher than the realized values (e.g., Francis and Philbrick, 1993; Lim, 2001; Sedor, 2002). There is also considerable variation in analysts' excess optimism, and we limit the influence of extreme errors by winsorizing the top and bottom 1 percent of observations. (The highest and lowest errors are 325 and -44 percent; after

[14]The CNRDS data include 220,919 EPS forecasts during 2014-2018. 10,830 of these are forecasts on financial firms, which we drop; 2,855 forecasts are further dropped as some information is missing on one or more control variables. For 58,168 forecasts, we do not have hometown information for the analyst, because they were not practicing in 2017, the year we obtained our master list of financial analysts. Finally, we drop 28,661 observations for which we do not have city-level pollution information. These are almost exclusively observations from 2014, since some cities only began reporting AQI figures in 2015.

winsorizing, the extreme values are 10.4 percent and -5.6. Our results are entirely insensitive to our choice of cutoff – if we use more conservative thresholds of 0.5 percent or 0.25 percent (or drop outliers completely) the coefficient of interest is always significant at least at the 5 percent level and generally larger than that which we report in our main results.) We similarly winsorize continuous variables that have extreme right tails, including forecast horizon, experience, time at firm, and time since last forecast.

Table 1b shows summary statistics for the firm-year variables.

3 Results

Our main regression specification is as follows:

$$Optimism_{ijt} = \beta \times log(AQI30_{h(i)jt}) + \gamma \times X_{ijt} + \gamma_i + \delta_j + \upsilon_{y(t)} + \omega_{q(t)} + \epsilon_{ijt} \tag{1}$$

for analyst i making forecast for firm f at date t. We include analyst-year and firm-year controls, which are captured in the vector X_{ijt}; we also include fixed effects for the analyst (γ_i), firm (δ_j), and year and quarter of the forecast ($\upsilon_{y(t)}$ and $\omega_{q(t)}$ respectively). Standard errors are clustered at the hometown level (i.e., 232 clusters) throughout. The coefficient of interest, β, reflects the extent to which average pollution in the analyst's hometown $h(i)$ in the 30 days prior to a forecast, $log(AQI30_{h(i)jt})$, affects the analyst's forecast optimism. We emphasize that our results are insensitive to our particular choice of pollution: our $[-30, -1]$ window is meant to capture the extent to which potentially salient high pollution was observed at a time in which he/she was in contact with her hometown; as we show below, we obtain near-identical results with one and two week windows rather than a full month, and also a measure based on the highest AQI recorded in the prior month.

We present the results of specification (1) in Table 2. For brevity, we suppress the coefficients on control variables; the full regression output may be seen in Appendix Table A1. We begin in column (1) with only controls for year and quarter, as well as firm, forecast, and analyst covariates. The coefficient on hometown pollution of -0.11 (significant at the 5 percent level) indicates that higher pollution leads to lower optimism. We add hometown and firm fixed effects in column (2) and also analyst fixed effects in column (3). In the latter specification, hometown fixed effects are absorbed by the analyst effects, and the relationship between pollution and optimism is identified entirely from within-analyst variation in hometown pollution between different forecast dates. The coefficient is largely unchanged (though slightly larger) relative to our original estimate (-0.151 and -0.137 respectively) and significant at least at the 1 percent level in both cases.

To emphasize the special nature of the hometown link, we include the 30 day average AQI for the city where the analyst works in column (4). Somewhat surprisingly, given prior work on pollution and affective bias, we find that this variable is uncorrelated with forecast optimism, while its inclusion has no effect on the hometown variable's coefficient.

Column (5) looks what we see as a placebo, based the average AQI in the 30 day window *following* the forecast (i.e., $[+1, +30]$). This post-forecast measure of pollution is uncorrelated with forecast optimism, and its inclusion has very little effect on our measure of pre-forecast hometown pollution. (Serial correlation in pollution is a concern for the preceding specification. To alleviate this issue, we also ran a specification with $[-15, -1]$ and $[16, 30]$ average AQIs. In that specification, the difference between pre- and post-forecast pollution is even more striking: pre-event hometown pollution is highly correlated with forecast optimism, while the coefficient on the post-forecast variable is a precisely estimated zero. These results appear in our Appendix Table A2, which provides our collection of robustness checks.)

Finally, in column (6) we employ the same specification as in (4), but use an indicator variable, $I(Optimism \geq 0)$, which denotes whether the earnings forecast is above or below the realized value. This specification has the advantage of offering a straightforward interpretation, and also is insensitive to outlier forecasts. The point estimate on $log(AQI30_{h(i)jt})$ is 0.036, indicating that a doubling of the average pollution index is associated with a 3.6 percentage point increase in the likelihood of an upward-biased forecast.

We explore whether there exist non-linearities in the data in Figure 2, in which $log(AQI30_{h(i)jt})$ is replaced with its quintiles within each hometown in our data. The pattern, using our preferred specification in column (4) with analyst and firm fixed effects, shows a roughly linear decline in optimism as pollution worsens.

In Appendix Table A2, we present specifications that include a range of alternative measures and transformations of hometown AQI. Columns (1) and (2) provide shorter 15 and 7 day windows of average AQI prior to the forecast date. The point estimate in both cases is significant at least at the 1 percent level. (Column (3) adds the 15-day lead of AQI as a covariate as referenced above as an extra placebo check.) Column (4) uses the highest AQI in the month preceding a forecast rather than the average, while column (5) uses AQI rather than its log transformation – again, we observe a robust relationship with forecast optimism. Finally, column (6) uses forecast accuracy – the absolute value of forecast optimism – as the dependent variable. Interestingly, accuracy is positively correlated with hometown pollution (though significant only at the 10 percent level), a result that stems directly from the fact that analysts are, on average, overly optimistic, which is counteracted by the downward bias from hometown pollution.

3.1 Heterogeneity in the hometown pollution–optimism relationship

In this section we explore a number of dimensions of heterogeneity, with the aim of better understanding the mechanism by which hometown pollution affects analyst forecasts, and the attributes that may attenuate or amplify the relationship we documented in the preceding section. We begin by examining the relationship between hometown pollution and forecast bias as a function of firm attributes. Our main interest is comparing high- versus low-pollution firms, motivated by the idea that pollution may be made more salient for an analyst evaluating, say, a company that runs coal-burning power plants as compared to a software services firm. We thus add to our specification the interaction of hometown AQI and an indicator variable, $HighPollution$, which as discussed in Section 2.4 denotes firms operating in industries classified by the Chinese environment ministry (MEPC) as high pollution.

This result appears in column (1) of Table 3. We observe that the relationship between hometown pollution and forecast bias is driven entirely by the set of firms (just under a third of the full sample) in high pollution industries: the direct effect of hometown AQI is very close to zero, while the interaction term is negative and significant at the 1 percent level. To our knowledge, this type of "place salience" result has not yet been documented previously. Furthermore, we see it as valuable as helping to validate pollution as the particular hometown attribute that influences analyst forecasts. To emphasize the distinct role of firm pollution, we include the interaction of hometown AQI and two other basic firm attributes, $log(MarketValue)$ and market-to-book (MB), in column (2). Neither of these interaction terms is significant, nor does their inclusion affect the estimated coefficient on the high pollution interaction. (Their point estimates and significance are similar if they are included separately, rather than together.)

We now turn to analyst attributes. One natural dimension to consider is expertise, which we aim to capture via experience and a proxy for ability. For experience, we use the period elapsed since the analyst first made a forecast ($Experience$), and for the latter we use $Star$, an indicator variable denoting that the analyst is ranked as a star by the New Fortune Magazine at the beginning of the year that the forecast was made. These results, in columns (3) and (4), indicate that neither experience nor skill attenuates the relationship between hometown pollution and bias.

Finally, in column (5) we include the interaction of hometown AQI and an indicator variable denoting that the analyst is female. This final test is motivated by earlier work, which finds stronger place attachment in males than females.[15] We do not, however, find any significant difference in the relationship between hometown pollution and forecast bias for male versus female analysts.

[15] see, e.g., Dallago et al. (2009), Albanesi et al. (2007), among others.

4 Conclusion

Building on insights from the place attachment literature in other branches of the social sciences, we posit a relationship between hometown pollution and analyst forecast bias. We document a negative monotonic relationship hometown pollution and forecast optimism, a result that is robust to an array of controls and fixed effects. We conjecture that this relationship is driven by analysts' affective response to hometown pollution. This interpretation is bolstered by our finding that the pollution-bias effect comes almost entirely from high-polluting firms, which may make pollution more salient for an analyst in her assessment of a company.

Our results may serve to bridge several literatures: as we noted at the outset, to our knowledge researchers in finance and economics have only invoked place attachment as a way of rationalizing hometown favoritism; by contrast, we emphasize here its influence on individual utility and beliefs. The large corpus of work on this topic in sociology and psychology suggests that place attachment may have substantial effects, and we hope that by introducing this idea to scholars in our field, it will gain further visibility and see additional application. The most obvious connections are to judgment and decision-making, and we see our findings as illustrative of the many implications place attachment may have for a range of areas in our discipline.

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Figure 1: The distribution of 30 day average AQI, deviation from city-level mean

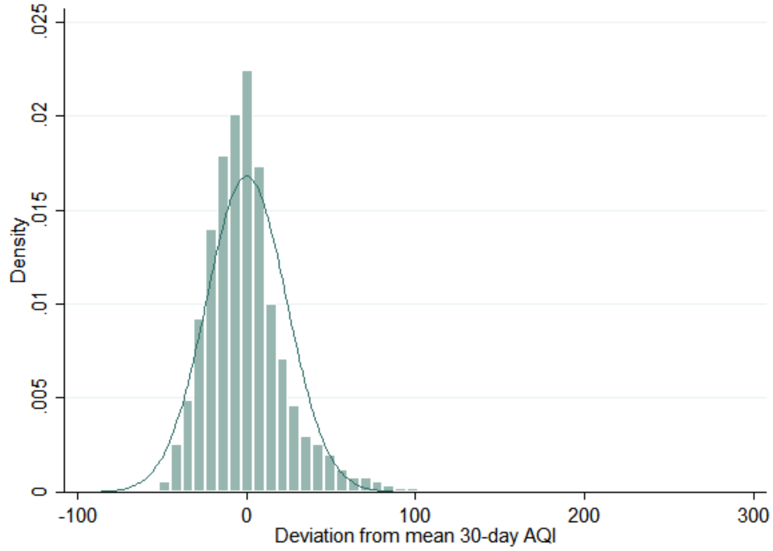
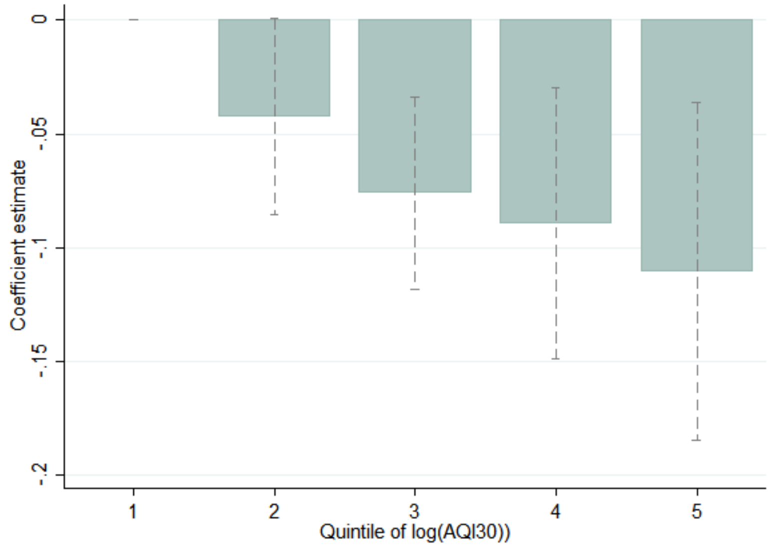


Figure 2: The relationship between pollution and forecast optimism, by lnAQI30 quintile



This figure provides the point estimates from a regression using the specification from Table 2, column 3, replacing lnAQI30 with indicator variables for each quintile of pollution. The lowest-pollution quintile is the omitted category.

Table 1: Summary statistics

Optimism is the difference between annual EPS forecast and realized EPS, scaled by price as of the trading day prior to the forecast, multiplied by 100. $log(AQI30)$ is the log of the analyst's hometown's Air Quality Index over the [-30,-1] window prior to the forecast. $log(BrokerSize)$ is the logarithm number of active analysts of the brokerage firm where the focal analyst works. *Experience* is the value of the date on which the analyst issued his forecast minus the date on which the analyst first issued his or her forecast, scaled by 365. *FirmExperience* is the analyst's experience in covering the firm (the date on which the analyst issued his forecast minus the date on which the analyst first issued a forecast for the firm, scaled by 365). $log(ForecastFrequency)$ is the log of the the number of forecasts made by an analyst during the fiscal year. $log(Companies)$ is the the log of the number of companies the analyst followed during the fiscal year. $log(Industries)$ is the the log value of the number of industries the analyst followed during the fiscal year. *DaysElapsed* is the interval between this forecast and the analyst's most recent prior forecast, scaled by 365. *Horizon* is the number of days from the forecast date to the corresponding earnings announcement date, scaled by 365. *MB* is the ratio of market value of equity to book value of equity at the end of the fiscal year. $log(MarketValue)$ is the the log of the market value of the listed firm at the end of the fiscal year. $log(Coverage)$ is the the log of the number of analysts following of firm during fiscal year. *Optimism*, *Experience*, *FirmExperience*, *DaysElapsed*, *Horizon*, *MB* are winsorized at 1% . Panel A provides summary statistics based on the main sample of forecast observations. Panel B provides summary statistics collapsed to the firm-year level.

Panel A: Sample for main analysis

Variable Name	Mean	StdDev	Min	Max	Observations
Optimism	0.703	1.976	-5.631	10.436	120405
$log(AQI30)$	4.339	0.346	2.791	5.969	120405
$log(BrokerSize)$	4.063	0.566	0.000	5.056	120405
Experience	5.770	2.978	0.405	13.107	120405
FirmExperience	2.248	2.438	0.000	10.148	120405
$log(ForecastFrequency)$	4.815	1.007	0.000	7.432	120405
$log(Companies)$	3.604	0.736	0.000	5.513	120405
$log(Industries)$	2.103	0.675	0.000	3.850	120405
DaysElapsed	0.047	0.088	0.003	0.595	120405
Horizon	0.782	0.270	0.255	1.279	120405
MB	2.838	2.155	0.402	12.256	120405
$log(MarketValue)$	4.827	1.098	1.072	9.770	120405
$log(Coverage)$	3.278	0.710	0.000	4.710	120405

Panel B: Firm-year aggregates

Variable Name	Mean	StdDev	Min	Max	Observations
$Optimism$	0.932	2.007	-5.631	10.436	7939
$log(AQI30)$	4.359	0.223	3.253	5.630	7939
$log(BrokerSize)$	4.037	0.384	0.693	5.056	7939
$Experience$	5.667	2.077	0.405	13.107	7939
$FirmExperience$	1.710	1.716	0.000	10.148	7939
$log(ForecastFrequency)$	4.693	0.692	0.000	7.369	7939
$log(Companies)$	3.615	0.527	0.000	5.513	7939
$log(Industries)$	2.151	0.486	0.000	3.850	7939
$DaysElapsed$	0.129	0.151	0.003	0.595	7939
$Horizon$	0.778	0.188	0.255	1.279	7939
MB	2.643	2.169	0.402	12.256	7939
$log(MarketValue)$	4.322	0.995	1.072	9.770	7939
$log(Coverage)$	2.478	1.004	0.000	4.710	7939

Table 2: Hometown attachment and analyst forecast optimism
Numbers in parentheses are standard errors clustered by analyst hometown. The sample covers the period from 2014 to 2018. The dependent variable in columns 1-5 is *Optimism*, which is the difference between annual EPS forecast and realized EPS, scaled by price as of the trading day prior to the forecast, multiplied by 100. The dependent variable in column 6 is *Optimism_pos*, a dummy variable which is that the forecast has positive bias. $log(AQI30)$ is the log of hometown's Air Quality Index over over the [-30,-1] window preceding the forecast. $log(AQI30\_workplace)$ is the log of the Air Quality Index where the analyst works over the [-30,-1] window preceding the forecast. $log(AQI\_f30)$ is the log of hometown's Air Quality Index over the [1,30] window following the forecast. Controls include $log(BrokerSize)$, $Experience$, $FirmExperience$, $log(ForecastFrequency)$, $log(Companies)$, $log(Industries)$, $DaysElapsed$, $Horizon$, MB, $log(Marketvalue)$, $log(Coverage)$, with output suppressed to conserve space. See the notes to Table 1 for detailed definitions of the control variables. Note that Appendix A shows the results including point estimates for all control variables. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			*Optimism*			*Optimism_pos*
$log(AQI30)$	-0.113**	-0.151***	-0.137***	-0.138***	-0.118***	-0.036***
	(0.055)	(0.046)	(0.049)	(0.053)	(0.044)	(0.010)
$log(AQI30\_workplace)$				0.016		
				(0.038)		
$log(AQI\_f30)$					-0.047	
					(0.043)	
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
City FEs		Yes				
Analyst FEs			Yes	Yes	Yes	Yes
Firm FEs			Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120405	120265	120196	119419	120196	120196
R-Squared	0.059	0.295	0.321	0.322	0.321	0.234

Table 3: Heterogeneity analysis

Numbers in parentheses are standard errors clustered by analyst hometown. $Optimism$ is the difference between annual EPS forecast and realized EPS, scaled by price as of the trading day prior to the forecast, multiplied by 100. $log(AQI30)$ is the log of the analyst's hometown's Air Quality Index over the [-30,-1] window prior to the forecast. $HighPollution$ is an indicator variable denoting that the firm is in a high pollution industry as classified by China's environment ministry. MB is the ratio of market value of equity to book value of equity at the end of the fiscal year. $log(MarketValue)$ is the the log of the market value of the listed firm at the end of the fiscal year. $Experience$ is the value of the date on which the analyst issued his forecast minus the date on which the analyst first issued his or her forecast, scaled by 365. $Star$ is an indicator variable dnoting that the analyst was selected as a star analyst by New Fortune magazine in the forecast year. $Female$ is an indicator variable for the analyst's gender. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable			$Optimism$		
$log(AQI30)$	-0.039	0.092	-0.091*	0.168*	-0.144**
	(0.053)	(0.103)	(0.051)	(0.092)	(0.056)
$HighPollution * log(AQI30)$	-0.281***	-0.278***			
	(0.079)	(0.080)			
$log(Marketvalue) * log(AQI30)$		-0.037			
		(0.023)			
$MB * log(AQI30)$		0.017			
		(0.013)			
$Star * log(AQI30)$			-0.007		
			(0.017)		
$Experience * log(AQI30)$				-0.051***	
				(0.013)	
$Female * log(AQI30)$					0.029
					(0.089)
Year FEs	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes
Analyst FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	120196	120196	102490	120196	120196
R-Squared	0.322	0.322	0.356	0.322	0.321

Appendix A1: Hometown attachment and analyst forecast optimism

Numbers in parentheses are standard errors clustered by analyst hometown. The sample covers the period from 2014 to 2018. The dependent variable in columns 1-5 is *Optimism*, which is the difference between annual EPS forecast and realized EPS, scaled by price as of the trading day prior to the forecast, multiplied by 100. The dependent variable in column 6 is *Optimism_pos*, a dummy variable which is that the forecast has positive bias. $log(AQI30)$ is the log of hometown's Air Quality Index over over the [-30,-1] window preceding the forecast. $log(AQI30\_workplace)$ is the log of the Air Quality Index where the analyst works over the [-30,-1] window preceding the forecast. $log(AQI\_f30)$ is the log of hometown's Air Quality Index over the [1,30] window following the forecast. Controls include $log(BrokerSize)$, *Experience*, *FirmExperience*, $log(ForecastFrequency)$, $log(Companies)$, $log(Industries)$, *DaysElapsed*, *Horizon*, *MB*, $log(Marketvalue)$, $log(Coverage)$. See the notes to Table 1 for detailed definitions of the control variables. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			*Optimism*			*Optimism_pos*
$log(AQI30)$	-0.113**	-0.151***	-0.137***	-0.138***	-0.118***	-0.036***
	(0.055)	(0.046)	(0.049)	(0.053)	(0.044)	(0.010)
$log(AQI30\_workplace)$				0.016		
				(0.038)		
$log(AQI\_f30)$					-0.047	
					(0.043)	
$log(BrokerSize)$	-0.047	-0.082**	-0.040	-0.037	-0.041	-0.013
	(0.034)	(0.032)	(0.059)	(0.060)	(0.059)	(0.012)
Experience	-0.010*	-0.006	0.788***	0.796***	0.789***	0.084***
	(0.006)	(0.006)	(0.240)	(0.241)	(0.240)	(0.032)
FirmExperience	0.015	-0.003	0.002	0.002	0.002	0.001
	(0.013)	(0.010)	(0.009)	(0.009)	(0.009)	(0.001)
$log(ForecastFrequency)$	-0.031	-0.001	-0.040	-0.039	-0.040	0.001
	(0.054)	(0.048)	(0.084)	(0.084)	(0.084)	(0.017)
$log(Companies)$	-0.045	-0.078	-0.083	-0.084	-0.083	-0.030
	(0.075)	(0.073)	(0.122)	(0.122)	(0.122)	(0.023)
$log(Industries)$	0.050	0.075	0.133	0.131	0.133	0.032**
	(0.050)	(0.057)	(0.086)	(0.087)	(0.086)	(0.013)
DaysElapsed	-0.569***	-0.380***	-0.369***	-0.365***	-0.370***	-0.071***
	(0.103)	(0.102)	(0.104)	(0.104)	(0.105)	(0.017)
Horizon	1.912***	1.430***	2.064***	2.074***	2.070***	0.207***
	(0.130)	(0.134)	(0.232)	(0.229)	(0.232)	(0.038)
MB	-0.039***	0.046***	0.067***	0.068***	0.067***	-0.005*
	(0.008)	(0.015)	(0.012)	(0.012)	(0.012)	(0.003)
$log(MarketValue)$	-0.030*	-0.567***	-0.655***	-0.663***	-0.655***	-0.041***
	(0.016)	(0.082)	(0.057)	(0.058)	(0.057)	(0.010)
$log(Coverage)$	-0.348***	-0.318***	-0.300***	-0.301***	-0.301***	0.008
	(0.029)	(0.039)	(0.034)	(0.035)	(0.034)	(0.007)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
City FEs		Yes				
Analyst FEs			Yes	Yes	Yes	Yes
Firm FEs			Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120405	120265	120196	119419	120196	120196
R-Squared	0.059	0.295	0.321	0.322	0.321	0.234

Appendix A2: Hometown attachment and analyst forecast optimism

Numbers in parentheses are standard errors clustered by analyst hometown. $log(AQI30)$ is the log of the analyst's hometown's Air Quality Index over the [-30,-1] window prior to the forecast. $log(AQI15)$ is the log of hometown's Air Quality Index over the [-15,-1] window preceding the forecast. $log(AQI\_f15)$ is the log of hometown's Air Quality Index over the [16,30] window following the forecast. $log(AQI7)$ is the log of hometown's Air Quality Index over the [-7,-1] window preceding the forecast. $log(AQImax)$ is the maximum of the log of hometown's Air Quality Index over the [-30,-1] window preceding the forecast. $AQI30$ is the average hometown's Air Quality Index over the [-30,-1] window preceding the forecast. *Accuracy* is the absolute value of the value of optimism, multiplied by -1. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			*Optimism*			*Accuracy*
$log(AQI15)$	-0.110***	-0.108***				
	(0.034)	(0.033)				
$log(AQI\_f15)$		-0.015				
		(0.045)				
$log(AQI7)$			-0.069***			
			(0.026)			
$log(AQImax)$				-0.076***		
				(0.028)		
$AQI30$					-0.001**	
					(0.001)	
$log(AQI30)$						0.058*
						(0.032)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120196	119980	120196	120196	120196	120196
R-Squared	0.321	0.321	0.321	0.321	0.321	0.441