Air Pollution and Advertising Spending: Causal Evidence from an Emerging Market*

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This version: May 2022

Abstract

While air pollution has tremendous impacts on many aspects of the economy, little is known about how pollution affects marketing activities. We provide the first study on the causal impact of air pollution on advertising markets. Taking an instrumental variable approach by exploiting the meteorological phenomenon of thermal inversions and using monthly data from 24 mega-cities in China for 10 years (2008-2017), we find that air pollution has a significant negative effect on outdoor advertising spending. Specifically, a 10 $\mu g/m^3$ increase in the same month's average fine particulate matter ($PM_{2.5}$) concentration reduces monthly outdoor advertising spending by 2.5% or CNY 2.1 million per city. Consistent with the consumer exposure effect that air pollution reduces consumers' outdoor activities and consumption trips, the adverse effect of air pollution is more pronounced on advertising in residential and shopping areas than in work-related areas, such as industrial and government districts. Moreover, we do not find any significant effect of air pollution on newspaper advertising. Our study offers a novel perspective to understand the impact of environmental changes on the media landscape.

Keywords: advertising, air pollution, consumer attention

*We thank Jianmin Jia, Tony Ke, and Shanjun Li for helpful comments. Yizhi Lu and Mengyuan Xia provided excellent research assistance. Shi acknowledges financial support from the Research Grant Council of Hong Kong. Any errors are our own.

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1 Introduction

Environmental issues like air pollution have tremendous impacts on modern societies. A growing body of literature has documented the adverse effects of air pollution on not only health outcomes (e.g., Chen et al. 2013; Arceo et al. 2016), but also other important aspects of the economy, including productivity (Chang et al. 2016, 2019), stock returns (Heyes et al. 2016), trading performance (Huang et al. 2020), and financial forecasting (Dong et al. 2021). While many firms from oil companies to Internet giants have invested billions of dollars in green marketing to increase their environmental appeal,[1] little is known about whether and how pollution affects marketing activities in general. Aiming to fill this knowledge gap, we present the first study on the causal effect of air pollution on advertising. By linking monthly environmental and advertising information in geographic markets and employing a meteorology-based instrumental variable (IV) method, we show that even moderate changes in ambient air pollution can generate a market-wide impact on advertising spending.

As increasingly emphasized in the theoretical literature on advertising media, capturing consumer attention is key for effective advertising, especially in the age of information overload (e.g., Anderson and de Palma 2013; Athey et al. 2018). At the same time, a burgeoning literature shows that air pollution reduces peoples' outdoor activities (Neidell 2009), especially consumption-related trips (Barwick et al. 2019; Sun et al. 2019).[2] Inspired by the two separate bodies of research, we posit a consumer exposure effect of air pollution. We hypothesize that by reducing consumer exposure to the outdoors, air pollution renders out-of-home marketing less effective in catching attention, thereby causing a decline in related marketing spending. Moreover, air pollution should have a greater impact on advertising in consumption-related areas than in work-related areas, as individuals are more likely to reduced shopping trips and restaurant visits on polluted days (Barwick et al. 2019; Sun

1. See Newman (2020).
2. See, e.g., evidence of pollution avoidance behavior from England (Janke 2014) and South Korea (Yoo 2021), besides US and Chinese cities.

et al. 2019). Such an exposure effect is relevant not only for traditional outdoor advertising[3]—the context in which we test our hypotheses—but also for other important marketing activities, such as point-of-sale marketing and geo-targeted mobile advertising. In addition, air pollution can lead to low ambient visibility (Hyslop 2009) and impaired cognitive ability of consumers (e.g., Block and Calderón-Garcidueñas 2009; Fonken et al. 2011), which may also contribute to reduced effectiveness of advertising.[4]

To empirically explore the impact of air pollution on advertising, we examine China's outdoor advertising industry. Due to its broad presence and wide reach, outdoor advertising remains rapidly growing in the digital age (McKinsey 2015). China is the third-largest outdoor advertising market in the world and the largest among emerging economies (OAAA 2017). At the same time, China has also experienced severe air pollution problems in recent decades. During our sample period, the average monthly air pollution level—measured by fine particulate matter ($PM_{2.5}$)—is 8 times higher than the WHO standard. Air pollution is responsible for numerous problems in China, from health hazards to productivity loss.[5] Thus, China is a natural setting to study the relationship between air pollution and outdoor advertising. We obtain a unique dataset from a leading market research company, covering monthly city-level outdoor advertising spending for 24 major Chinese cities (accounting for 85% of outdoor spending in China) from 2008 to 2017. The advertising information is further broken down by location: functional area (e.g., shopping or industrial districts) and type of road (e.g., branch or main roads). We then link the advertising information with external meteorological and environmental data to examine the impact of air pollution on outdoor advertising.

The main empirical hurdle in establishing causal relationship is the endogeneity of air pollution caused by omitted variable bias. In our context, air pollution is typically correlated

3. Outdoor or out-of-home (OOH) advertising includes billboards, street furniture ads, and many in-building formats, such as elevator advertising. See OAAA's classification at https://bit.ly/3yzXf0i.

4. In the supplementary appendix, we build a simple model to illustrate the pollution effect as a firm's optimal response to reduced marketing efficiency caused by pollution. The theoretical results hold under different models of advertising (informative versus complementary advertising).

5. For a review, see Greenstone et al. (2021).

with local economic conditions, which also determine advertising spending in geographic markets. To overcome this issue, we take a state-of-the-art IV approach by using the meteorological phenomenon of thermal inversions. Thermal inversions occur when the temperature in the upper atmospheric layer is higher than the ground temperature, thereby trapping air pollutants near the ground. As a high-atmosphere phenomenon, the occurrence of a thermal inversion is generally independent of economic activity, which makes it a valid and widely used instrument for air pollution in environmental research (see Section 3). In addition, we control for a rich set of weather variables and include detailed fixed effects at the city-year and month-year levels.

Using a two-stage least squares (2SLS) estimator, we find a significant negative effect of air pollution on advertising spending. Specifically, a 10 $\mu g/m^3$ (30% of one standard deviation) increase in the current-month's average $PM_{2.5}$ concentration reduces outdoor advertising spending by 2.5%, or CNY 2.1 million (USD 0.3 million) per city. This decrease in outdoor advertising spending is more than 20% of China's total spending on magazine advertising in 2008. In Section 4, we discuss the economic significance of our estimates in more detail. In reality, advertisers pay ad space sellers in advance and can negotiate ex-post for payment adjustments. Consistent with such contractual arrangements, we find that the previous month's average $PM_{2.5}$ also significantly affects the current month's advertising spending; however, advertising spending is not affected by $PM_{2.5}$ concentrations beyond the one-month window.

To provide further evidence for the consumer exposure effect, we examine the heterogeneity in the pollution effect by location. Leveraging location-specific advertising data, we find that air pollution significantly reduces advertising spending in shopping and residential areas but has no significant impact on work-related areas, such as industrial and government districts, consistent with existing evidence that consumers' outdoor leisure-related activities are sensitive to air pollution, but not work-related activities (Barwick et al. 2019; Sun et al. 2019). Moreover, air pollution significantly reduces advertising spending in near-building

branch roads with lower speed limits, but there is no effect on main roads and boulevards, which is consistent with people switching to using vehicles when pollution increases (Fan et al. 2021).

Lastly, in a supplementary analysis, we use additional data to examine whether $PM_{2.5}$ affects city newspaper advertising. Our results indicate no significant effect of pollution on newspaper advertising, which supports the key role of the consumer exposure effect in driving our main results. The findings also suggest a lack of substitution between the two media formats, implying that some of the commercial value of consumer attention lost from outdoor markets is not (re)captured by print media.

Overall, this paper provides a novel angle to understand the relationship between environmental changes and marketing activities. Existing research mostly focuses on marketing opportunities in face of environmental challenges, including the literature on green marketing (e.g., Laufer 2003; Delmas and Burbano 2011; Barrage et al. 2020).[6] Our examination builds on the idea of consumer attention as scarcity, which is at the heart of theoretical analyses of media markets (e.g., Anderson and de Palma 2013; Athey et al. 2018) and motivates empirical research on the relationship between Internet advertising and other media (e.g., Goldfarb and Tucker 2011; Chandra and Kaiser 2014). For instance, Goldfarb and Tucker (2011) show that the Internet reduces the effectiveness of government regulations on outdoor advertising, suggesting substitutability between the two media. We enrich this literature by investigating how ambient conditions can influence advertising activities by affecting the allocation of consumer attention in an underexplored market setting. Our study has implications for investigating the effect of air pollution in other marketing contexts, such as point-of-sale marketing and geo-targeted mobile advertising, and the influences of other environmental risks, such as extreme temperatures.

Our work also adds to the large literature examining the economic consequences of pol-

6. Very few studies in marketing examine how environmental conditions influence the effectiveness of marketing activities; one exception is Li et al. (2017), which studies how weather affects mobile promotions using field experiments.

lution, discussed at the outset. In addition, previous research finds that air pollution has negative effects on firm productivity (Chang et al. 2016, 2019; Fu et al. 2021). However, the role of marketing activities in generating revenue and complementing production is overlooked in this research. Our findings suggest a novel channel through which air pollution can hurt firm performance.

2 Background and Data

2.1 Outdoor Advertising in China

The setting for our main analysis is China's outdoor advertising market. The global outdoor advertising market has grown rapidly at an annual rate of 5%, with the emergence of new digital display technologies; its market size reached USD 30 billion in 2017, almost the same size as that of the newspaper market (McKinsey 2015; OAAA 2017). With an estimated market size of CNY 33 billion (USD 5.2 billion), China's outdoor advertising market is the third largest in the world, after the US and Japan (OAAA 2017). China also has the largest share (66%) in the global market for elevator ads.[7] Domestically, outdoor advertising has constantly been a top-three media in China, in terms of ad revenues (see Figure 1).

[Figure 1 about here.]

Market research often attributes the growth of outdoor advertising in China to the economic boom and urbanization in big cities (CODC 2018). The impact of air pollution has not been formally investigated in this context to date; however, anecdotes suggest that industry practitioners in China are aware of the issue. For instance, a quick online keyword search shows a few posts and articles discussing the adverse effects of smog on outdoor advertising (see Figure A.2).

7. See the MarketWatch report, https://on.mktw.net/38QzXbv.

In practice, advertisers pay agencies or ad space owners in advance to have their ads displayed. The contract period typically ranges from a week (mostly for elevator ads) or four weeks (shortest contract length for billboards, street furniture, etc.) to a year, depending on the circumstances.[8] Like in the US, ad agencies or other sellers in China provide various metrics to advertisers, such as venue traffic and weekly impressions, which determine ad rates and total payment together with other factors, such as location, display frequency, and use of a digital screen. Advertisers also monitor the ex-post effectiveness of ads based on metrics provided by third parties. Moreover, under extenuating circumstances, advertisers can negotiate with sellers for ex-post payment adjustments by requesting credit or bonus exposure opportunities. Such contractual arrangements imply that the effect of time-varying conditions, such as environmental changes, should be reflected in advertising spending contemporaneously or with a short time lag. We test this implication directly in our empirical analysis.

Our outdoor advertising data come from CTR Market Research, a joint venture between Kantar Group and China's Central Television. CTR Market Research is a leading market research firm in China and is responsible for industry standard setting jointly with the China Advertising Association. For selected media formats, it provides *ad monitoring* services similar to those offered in US, which track advertising expenditure by geographic market. Our main dataset, which is commercially available, contains information on monthly outdoor advertising spending in 24 major Chinese cities (as shown in Figure 2) from 2008 to 2017. The sample cities account for approximately 20% of China's 1.4 billion population, 37% of the national GDP, and 85% of all outdoor advertising spending. They are considered as China's mega-cities, with an average population of 11 million in 2017 and per-capita income comparable to a high-income developing country like Chile (see Appendix Section A.2 for more details). We further observe advertising spending broken down by venue where ads are displayed, and the venues are categorized based on functionality and road types (e.g.,

8. See CODC (2018), with additional information provided by CTR Market Research.

branch or main roads). The same data are used to generate aggregate statistics reported in the official *China Advertising Yearbooks*; we use the disaggregated data under the hood, which allows us to link the information to time-variant environmental conditions of different geographic markets.

[Figure 2 about here.]

2.2 Air pollution

We obtain air pollution data from satellite-based Aerosol Optical Depth (AOD) retrievals, which measure the extinction of the solar beam by dust and haze and are used to calculate $PM_{2.5}$ (Gupta et al. 2006; van Donkelaar et al. 2010; Buchard et al. 2016). Specifically, our AOD data are from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) maintained by the National Aeronautics and Space Administration (NASA). MERRA-2 reports monthly pollution data at a 50*60-km grid level since 1980. We then downscale the original 50*50-km grid using the bilinear method (Hijmans et al. 2015) and take the average for all downscaled grids within each city. This dataset has been used in several studies (Deschênes et al. 2020; Fu et al. 2021). We do not use ground-based pollution data because they are potentially subject to human manipulation in China (Ghanem and Zhang 2014).

2.3 Thermal inversions

Thermal inversion data are also obtained from MERRA-2, which reports ambient temperature for 42 atmospheric layers, from 110 meters to 36,000 meters, at 6-hour periods for each 50*60-km grid from 1980. We transform the data from grid level to city level using the same method as above. Following Fu et al. (2021), we determine the existence of a thermal inversion if the temperature in the second layer (320 meters) is higher than that in the first layer (110 meters) for each 6-hour period for a city. We define a day with occurrence of ther-

mal inversions if there is at least one thermal inversion in each 6-hour period for that day. Lastly, we count the number of days with occurrence of thermal inversions for each month and each city. We also conduct a robustness check by directly summing all occurrences of thermal inversions from each 6-hour period for each month and each city, and our results continue to hold with the alternative measure of thermal inversions (see Section 4.3).

2.4 Weather

We obtain weather data from the National Meteorological Information Center of China. The data contain daily weather variables, including temperature, precipitation, wind speed, pressure, relative humidity, and sunshine duration for more than 800 weather stations in China. We use the inverse-distance weighting (IDW) method, a common method used in the literature (Deschênes and Greenstone 2011; Deschênes et al. 2020), to interpolate daily weather data from station to city.[9] To account for nonlinear effects of weather variables, we follow Fu et al. (2021) and calculate 20 quantiles for each weather variable based on the daily distribution, and then count the number of days within each quantile for each city-month.

2.5 Summary statistics

Table 1 presents the descriptive statistics of the main variables. We have a slightly unbalanced panel due to missing observations from the original dataset. The average monthly spending on outdoor advertising per city is CNY 83.6 million. The standard deviation is CNY 91.3 million, indicating a large degree of dispersion in advertising spending across cities and over time.

The average monthly $PM_{2.5}$ concentration is 89.06 $\mu g/m^3$, which is 8 times higher than the WHO standard of 10 $\mu g/m^3$ (WHO 2006). The average number of days with thermal

9. Specifically, we take weighted averages of all weather stations within the centroid of a city with a radius of 200 km, and the weights are the inverse distance from a station to the city's centroid. Our results are robust to different radii. We do not use the same interpolation method used for air pollution and thermal inversions data because the weather data are at the station level, not at the grid level.

inversions in a month is 12.84, or roughly 40% of a month.

[Table 1 about here.]

3 Empirical Strategy

The main challenge in estimating the causal effect of air pollution on advertising spending is the potential endogeneity caused by omitted variable bias. Air pollution is typically correlated with local economic variables, such as industrial activities, which also directly affect advertising spending. Therefore, omitting such confounding variables could result in a spurious correlation between air pollution and advertising.

To overcome this issue, we use thermal inversions, a meteorological phenomenon, as an IV for air pollution. Normally, temperature decreases with higher altitude. Thus, air pollutants could be transmitted from the ground to the upper layer and further be spread out. A thermal (or temperature) inversion occurs when the temperature in the upper layer is higher than the ground temperature, and thus pollutants are trapped near the ground. Since thermal inversions are a complex high-atmosphere phenomenon, their occurrence is generally independent of economic activity. In Figure 3, we show that the annual GDP of the sample cities has a clear upward trend, while the number of thermal inversions does not. Thermal inversions are widely used as an IV for air pollution in the literature (Arceo et al. 2016; Jans et al. 2018; Deschênes et al. 2020; Fu et al. 2021).

[Figure 3 about here.]

Formally, we use the following 2SLS model to estimate the causal effect of air pollution on advertising spending:

$$Y_{cmt} = \beta_0 + \beta_1 P_{cmt} + \beta_2 \mathbf{W}_{cmt} + \theta_{ct} + \omega_{mt} + \varepsilon_{cmt} \tag{1}$$

$$P_{cmt} = \alpha_0 + \alpha_1 I_{cmt} + \alpha_2 \mathbf{W}_{cmt} + \theta_{ct} + \omega_{mt} + \nu_{cmt} \tag{2}$$

where Y_{cmt} is the log of outdoor advertising spending in city c in month m of year t. The

main explanatory variable, P_{cmt}, is the current month's average $PM_{2.5}$ concentration. In Section 4.4, we use alternative exposure windows to examine the lagged and lead effects. We instrument P_{cmt} using the number of days with thermal inversions in a month, denoted by I_{cmt}. $\mathbf{W}_{cmt}$ represents the vector of weather variables described in Section 2.4. We include city-year fixed effects, θ_{ct}, to absorb any city-specific yearly factors (including variables such as GDP and population), and month-year fixed effects, ω_{mt}, to capture year-specific seasonality. Standard errors are clustered at the city level to account for serial and spatial correlation within each city.

4 Results

4.1 First-stage results

Table 2 reports the first-stage estimates. Our estimates show significant positive effects of thermal inversions on $PM_{2.5}$ concentrations. Columns (1) and (2) use different fixed effect specifications. The coefficients are comparable across specifications and highly significant. The Kleibergen-Paap (KP) F-statistics for weak identification are much larger than the Stock-Yogo critical value of 16.38 (Stock and Yogo 2005), indicating a strong first-stage relationship. The estimate in column (2), our preferred specification, indicates that one additional day with thermal inversions in a month increases the average monthly $PM_{2.5}$ concentration by 0.55 $\mu g/m^3$ (0.62% of the mean), implying an elasticity of 0.08.

[Table 2 about here.]

4.2 Effect of $PM_{2.5}$ on outdoor advertising

Table 3 summarizes the main results. Columns (1) and (2) report the OLS estimates. Without any fixed effects (column (1)), $PM_{2.5}$ is positively correlated with outdoor advertising spending. When we include city-year and month-year fixed effects (column (2)), the

coefficient becomes close to 0 and insignificant, suggesting that the spurious correlation between $PM_{2.5}$ and advertising spending is likely to be caused by unobserved factors.

Columns (3) and (4) show the second-stage results of the 2SLS estimation. Across specifications, the estimates are negative and highly significant. The estimate in column (4), our preferred specification, indicates that outdoor advertising decreases by 0.25%, or CNY 0.21 million per city, with a 1 $\mu g/m^3$ increase in the current-month's $PM_{2.5}$ concentration. Using the mean $PM_{2.5}$ in the sample (89.06 $\mu g/m^3$), the estimate implies an elasticity of -0.22. Compared with the OLS estimates, the 2SLS estimates are significantly more negative, suggesting that OLS severely biases the results towards 0.

[Table 3 about here.]

Our estimates represent a substantial effect of $PM_{2.5}$ on outdoor advertising spending. First, the loss of advertising dollars in the sample cities per month (CNY 50.2 million) due to a 10 $\mu g/m^3$ (30% of one standard deviation) increase in $PM_{2.5}$ is more than 20% of China's monthly spending on magazine advertising in 2008.[10] Second, during the sample period, the biggest threat to traditional advertising markets is competition from Internet media. Shi and Li (2021) estimate that a 1 percentage point increase in broadband Internet penetration causes a decrease in monthly television and radio advertising spending in China of CNY 0.15–0.22 billion. Our estimated effect of a 1-standard-deviation increase in air pollution is comparable to the effect of the Internet on broadcast media.

4.3 Robustness checks

Table 4 presents the robustness results, with the baseline results replicated in column (1). To test for robustness to differential time trends, in column (2), we add city-specific quadratic monthly trends. In column (3), we control for monthly city-level CPI to capture the short-term variation in local economic conditions. The estimates are similar.

10. The size of China's magazine advertising market was CNY3 billion in 2008.

Columns (4) and (5) test the robustness of our IV construction. In column (4), we use an alternative measure by counting the total number of thermal inversions in one month. In the baseline model, we define thermal inversions based on the temperature difference between the ground layer (110 meters) and the second layer (320 meters). In column (5), we replace the second layer with the third layer at 540 meters. The main results continue to hold with the alternative thermal inversion measures. In column (6), we cluster the standard errors at both city and year level (two-way clustering). This allows for serial correlation in errors within cities and spatial correlation within each year. The result remains significant.

[Table 4 about here.]

4.4 Heterogeneous effects by ad location

To shed light on the consumer exposure effect that we postulate, we examine the heterogeneity in the pollution effect by location. Table 5 summarizes the results using the same IV method.

By functional area. Panel A shows that $PM_{2.5}$ has significant negative effects on outdoor advertising in residential and shopping areas. For shopping areas, the effect is more pronounced: a 10 unit increase in $PM_{2.5}$ reduces monthly outdoor spending by 3.9% or CNY 0.9 million, which is about 43% of the total loss of outdoor advertising money due to air pollution. For business areas, the estimate is marginally significant (p-value = 0.107). For train stations, industrial and government areas, the effects are not significant. The results are consistent with our hypothesis that air pollution reduces outdoor advertising spending because it renders outdoor ads less effective, with people being more likely to remain indoors (Neidell 2009) and cut visits to restaurants and shopping areas rather than work-related trips on polluted days (Barwick et al. 2019; Sun et al. 2019).

By road type. Panel B reports the estimates for ads displayed on three types of roads. In China, main and secondary arterial roads have speed limits of 40–60 km/h and 30–50 km/h, respectively, and branch roads are roads connecting secondary arterial roads and

community pathways with lower speed limits.[11] While we do not find a significant effect of air pollution for main and secondary arterial roads, the effect for branch roads is significantly negative. Previous studies find that on polluted days, residents in China are less likely to walk to school or work (Deschênes et al. 2020) and would instead take "indoor" commuting options like public transport or private vehicles (Fan et al. 2021). As consumers' outdoor activities are possibly more sensitive to pollution in areas near branch roads than on main roads and boulevards—where people can use vehicles—the pollution effect should be more pronounced for ads on branch roads, which is what we find empirically. This set of findings again supports the consumer exposure effect.

[Table 5 about here.]

4.5 Lagged and lead effects

In the main analysis, we find a significant contemporaneous effect of air pollution on outdoor advertising. Figure 4 explores the lagged and lead effects of $PM_{2.5}$. Specifically, we examine separately the effect of $PM_{2.5}$ in 1 to 6 months before the current period and 1 to 6 months after.[12] The estimates are denoted by dots, and the 95% confidence intervals are denoted by whiskers. Table A.4 reports the first-stage and second-stage estimates in detail.

[Figure 4 about here.]

We find no significant effects of air pollution 2 to 6 months before the current period. For the lags, only the estimate for $PM_{2.5}$ with a 1-month lag is significantly positive. The results show that outdoor advertising is only affected by $PM_{2.5}$ in the current month and the previous month, which is consistent with the contractual arrangements described in Section 2.

11. See China's *2012 Code for Design of Urban Road Engineering*.
12. For any month m (say, April 2010), the 2-month lag indicates the effect of $PM_{2.5}$ in $m-2$ (February 2010).

We also examine the lead effects as a falsification test because outdoor advertising should not be affected by *future* air pollution. Figure 4 shows that the estimates are not significant for all post periods. Overall, the findings bolster our confidence that our main results are not driven by spurious correlations between $PM_{2.5}$ and advertising spending.

4.6 Does air pollution affect advertising in other media?

In this section, we investigate whether air pollution affects advertising in other media markets. Our following analysis focuses on newspaper advertising because, first, newspapers are one of the most important advertising markets in China; we use newspaper data from 2007 to 2012, during which newspapers were the second-largest advertising market (see Figure 1); second, the localized nature of city newspapers allows us to exploit available data by linking monthly environmental data to newspaper advertising in geographic markets.

We study commercial municipal newspapers serving the 24 sample cities with segmented geographic markets. These newspapers do not circulate outside their home-city markets; therefore, their advertisements only reach local readers. We use newspaper-level data from (Qin et al. 2018), with additional details described in the Supplementary Appendix A.3.

Table 6 reports the 2SLS estimates. Column (1) looks at 52 commercial city newspapers. Column (2) includes 12 additional party-line city newspapers with available data. Party-line newspapers are heavily subsidized by local governments and rely less on ad revenues. The estimates in both columns are small and insignificant. We include more robustness results in Table A.3. In summary, we find no significant effect of $PM_{2.5}$ on newspaper advertising.

[Table 6 about here.]

How do we interpret this set of findings? First, previous environmental studies (e.g., Block and Calderón-Garcidueñas 2009; Fonken et al. 2011) imply that air pollution may also affect "indoor" media advertising because it impairs consumers' mental ability to process information. Here, our findings do not support that mechanism, suggesting that consumer

exposure is the driving force behind the pollution effect on outdoor advertising. Second, the results indicate a lack of substitution between outdoor advertising and newspapers. While we cannot say much about other media (e.g., the Internet), given the importance of newspapers as a traditional media—especially for the elderly and digitally disadvantaged consumers—the lack of substitution is appealing. It suggests that at least some of the total value of consumer attention lost from the outdoor market disappears and is not (re)captured by print media.

5 Concluding Remarks

We provide a novel study on the causal impact of ambient air pollution on advertising. Using monthly city-level data for 10 years and an IV approach based on thermal inversions, we establish large-scale evidence that air pollution significantly reduces outdoor advertising spending in big Chinese cities. Further analyses support the exposure effect that air pollution reduces the reach of outdoor advertising as consumers avoid going outdoors on days of severe pollution, especially for consumption purposes—a widespread phenomenon facing many cities around the world.

By exploring the marketing implications of air pollution and pollution avoidance behavior, our study has rich implications for future work. First, we expect that the pollution effect detected in our context is also relevant for other important marketing activities, such as in-store promotions and geo-targeted mobile advertising. Recent studies show that local activities and consumption trips are crucial for Mobile geo targeting (see, e.g., Ghose et al. (2012) and Chen et al. (2017) for empirical and theoretical analyses). In addition, using detailed bank-card transaction data, Barwick et al. (2019) shows that even accounting for intertemporal substitution, $PM_{2.5}$ still has a net negative effect on the number of weekly shopping trips by consumers.

Second and relatedly, the increased time spent at home and indoors caused by air pollution has important implications for understanding consumption decisions in the digital era.

In many emerging economies, drastic environmental changes and the rapid penetration of the Internet are concurrent phenomena. While we do not find evidence of inter-media substitutions in this study, we believe it remains worthwhile to examine whether and how air pollution diverts consumer attention to the online world, thus contributing to the changing Internet media landscape.

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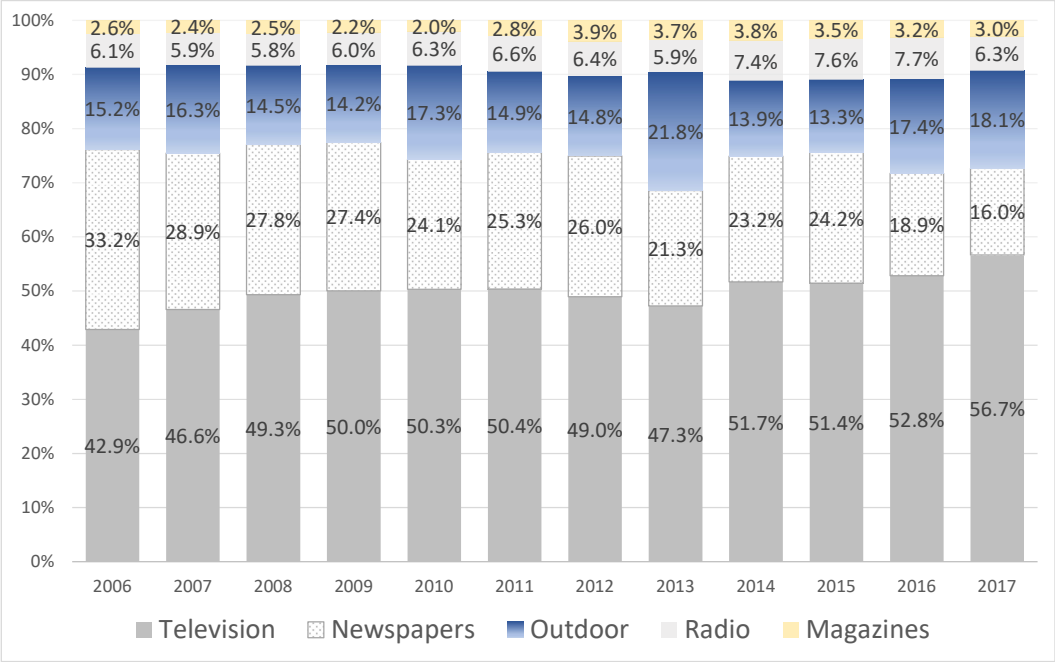
Figures and Tables

Figure 1: Outdoor share of offline advertising spending in China, 2006–2017

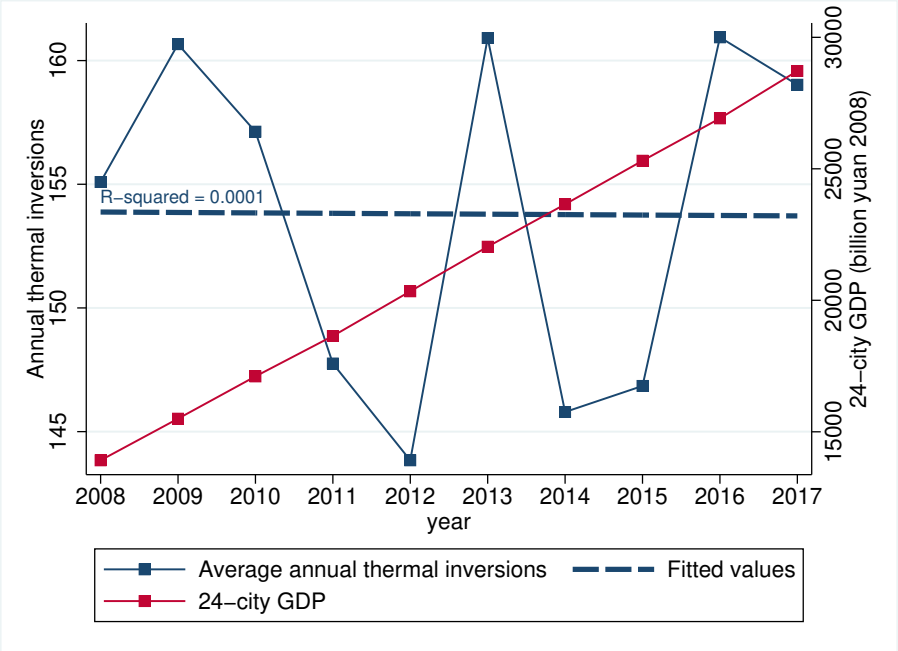


Notes: Data come from the *China Advertising Yearbooks* and *China Broadcasting and Television Yearbooks*, 2007–2018. The total spending on traditional offline advertising amounted to CNY 110 billion in 2007 and CNY 230 billion in 2017 (see Figure A.1). USD 1 = CNY 6.95 in 2008.

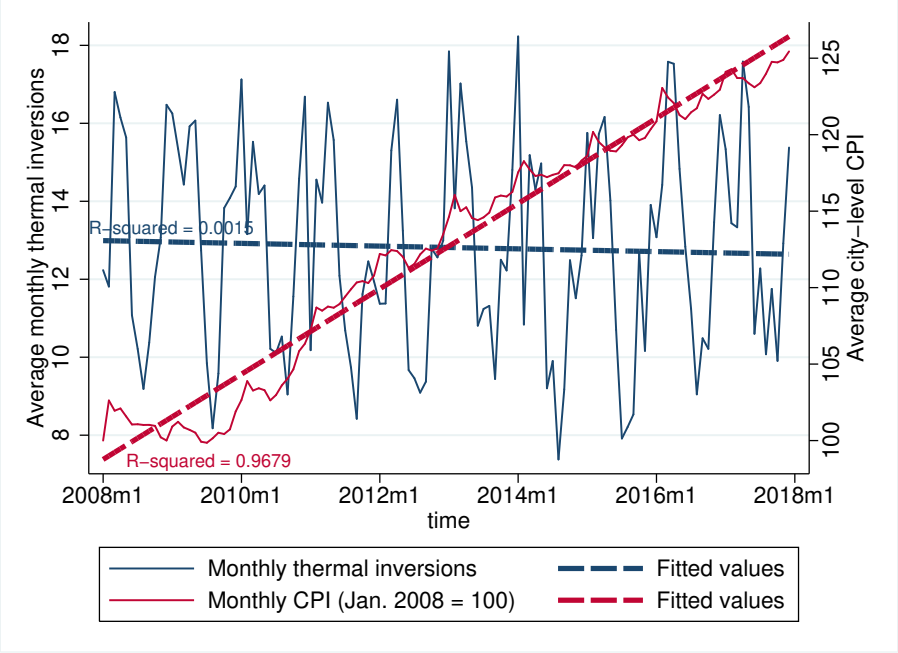
Figure 2: Sample cities in China

Notes: This figure shows the location of the 24 sample cities in China.

Figure 3: Trends of thermal inversions, GDP and CPI in China during 2008–2017



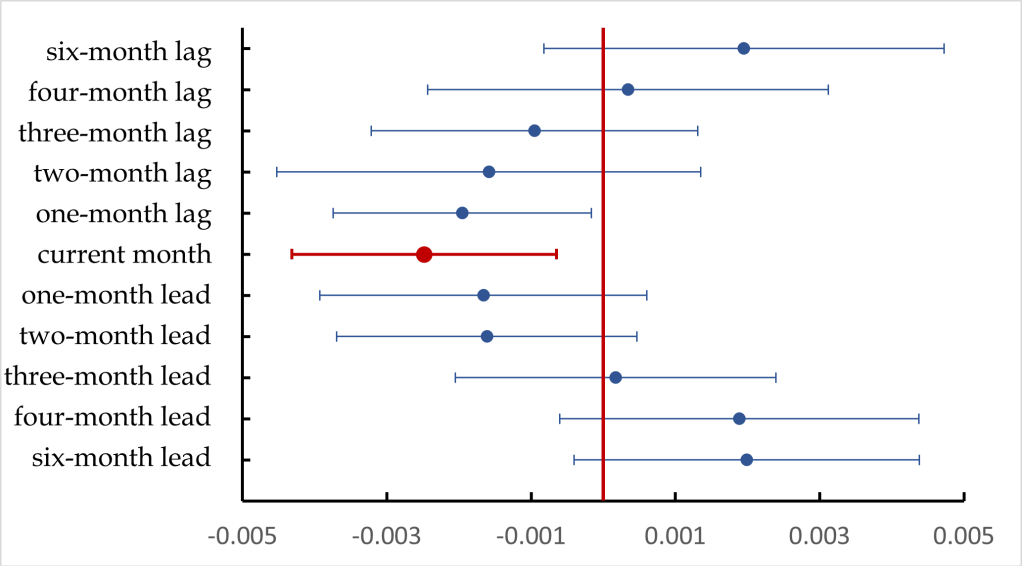
(a) Annual days with thermal inversion and 24-city GDP



(b) Average monthly days with thermal inversion and CPI

Notes: Monthly CPI information includes only 23 cities with available monthly data, except Suzhou. GDP is deflated to 2008 constant CNY.

Figure 4: Lagged and lead impacts



Notes: This figure shows the lagged and lead effects of $PM_{2.5}$ on the current month's outdoor advertising spending. Circles denote the point estimates reported in Table A.4, and the whiskers denote the 95% confidence intervals.

Table 1: Summary statistics

Variables	Obs.	Mean	S.D.	Min	Max
Outdoor ad spending (2008 CNY million)					
City-wide total	2,664	83.56	91.28	5.10	447.17
By functionality					
Residential	2,553	14.54	21.86	0.47	141.91
Shopping	2,553	22.95	29.97	0.33	207.53
Business	1,998	7.22	10.29	0.08	55.21
Industrial area	1,679	3.97	6.95	0.02	39.73
Train station	1,991	1.67	1.83	0.005	9.70
Government	1,869	1.53	1.74	0.01	7.81
By type of road					
Main arterial road	2,109	30.95	33.15	2.95	266.48
Secondary arterial road	2,073	15.78	17.45	0.003	161.18
Branch road	2,538	20.50	30.50	1.11	191.47
Air pollution					
$PM_{2.5}$ ($\mu g/m^3$)	2,664	89.06	33.40	13.65	216.98
Thermal inversions					
Inversion days in one month	2,664	12.84	7.62	0	31

Notes: Each observation is a city-month-year. Advertising data cover 24 Chinese cities from 2008 to 2017. USD 1 = CNY 6.95 in 2008.

Table 2: First-stage regression results

Dependent variable:	$PM_{2.5}$	
	(1)	(2)
Thermal inversions	0.6191***	0.5531***
	(0.0955)	(0.0999)
City-year FE	Yes	Yes
Month FE	Yes	No
Month-year FE	No	Yes
Weather controls	Yes	Yes
KP *F-stat.*	42.01	30.66

Notes: $N = 2,664$. The dependant variable is the current month's average $PM_{2.5}$ concentration. Robust standard errors clustered at the city level are in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table 3: Effects of $PM_{2.5}$ on outdoor advertising spending

Dependent variable:	ln(outdoor ad spending)			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.0118***	-0.0001	-0.0016**	-0.0025***
	(0.0042)	(0.0002)	(0.0007)	(0.0009)
KP *F-stat.*	-	-	42.01	30.66
City-year FE	No	Yes	Yes	Yes
Month FE	No	No	Yes	No
Month-year FE	No	Yes	No	Yes
Weather controls	Yes	Yes	Yes	Yes

Notes: $N = 2,664$. 2SLS estimations use the number of days with thermal inversions as an instrument for $PM_{2.5}$. Robust standard errors clustered at the city level are in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table 4: Robustness results

Dependent variable:	ln(outdoor ad spending)					
	Baseline	Add city-specific trends	Control for CPI	Alternative measure of inversion	Alternative layer of inversion	Two-way clustering
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.0025***	-0.0033**	-0.0025**	-0.0018**	-0.0024**	-0.0025*
	(0.0009)	(0.0012)	(0.0010)	(0.0008)	(0.0010)	(0.0012)
KP *F-stat.*	30.66	24.57	26.07	46.17	19.34	25.37
N	2,664	2,664	2,553	2,664	2,664	2,664
City-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates are obtained using 2SLS estimations. Column (2) includes city-specific quadratic monthly trends. Column (3) controls for monthly CPI of each city (with one less city (Suzhou) due to missing monthly CPI data). Column (4) changes the measure of thermal inversions by using the total number of inversions in a month. Column (5) changes the IV by coding thermal inversions based on temperature difference between the ground (110 meters) and the third layers (540 meters). Except in column (6), robust standard errors clustered at the city level are in parentheses. Column (6) uses two-way clustering at both city and year level. Significance at * 10%, ** 5%, and *** 1% levels.

Table 5: Effect of $PM_{2.5}$ by location

(a) By functional area

Functional area	Residential	Shopping	Business	Industrial	Train station	Government
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.0020*	-0.0039***	-0.0027	-0.0037	-0.0030	-0.0031
	(0.0012)	(0.0012)	(0.0016)	(0.0020)	(0.0022)	(0.0019)
KP *F-stat.*	28.70	26.56	25.64	30.67	29.09	19.62
N	2,442	2,553	1,998	1,679	1,991	1,869
City-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes

(b) By type of road

Urban road type	Main arterial	Secondary arterial	Branch road
Vehicle speed (km/h)	$40-60$	$30-50$	$20-40$
	(1)	(2)	(3)
$PM_{2.5}$	-0.0002	-0.0023	-0.0023*
	(0.0008)	(0.0017)	(0.0012)
KP *F-stat.*	19.82	17.35	29.46
N	2,109	2,073	2,538
City-year FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes

Notes: Estimates are obtained using 2SLS estimations. The dependent variables include the log of outdoor advertising spending in different locations. Robust standard errors clustered at the city level are in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table 6: Effect of $PM_{2.5}$ on newspaper advertising

Dependent variable:	ln(newspaper ad revenue)	
	Commercial newspapers	Commercial + party line newspapers
	(1)	(2)
$PM_{2.5}$	0.0010	-0.0006
	(0.0037)	(0.0034)
KP *F-stat.*	17.88	18.12
N	2991	3618
No. newspapers	52	64
Newspaper FE	Yes	Yes
City-year FE	Yes	Yes
Month-year FE	Yes	Yes
Weather controls	Yes	Yes

Notes: Estimates are obtained using 2SLS estimations. Each observation is a newspaper-month-year. Time period is 2007–2012. Robust standard errors clustered at the city level are in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Supplementary Appendix

A.1 A Simple Model of Pollution and Advertising Spending

This section sketches a simple model to illustrate how pollution may affect firms' optimal advertising decision. We consider a monopolistic firm with endogenous production and advertising spending. In particular, the firm chooses price p and advertising expenditure a, which jointly determine the equilibrium output level. The profit maximization problem is given by

$$\max_{p,a} \pi(p, a; \Omega) = [p - c]q(p, a; \Omega) - a; \tag{3}$$

We use $q(\cdot)$ to denote the product demand function with $q_p \equiv \frac{\partial q}{\partial p} < 0$ (i.e., a downward-sloping demand curve). Advertising functions to increase product demand, so $q_a \equiv \frac{\partial q}{\partial a} > 0$. Without loss of generality, we assume a constant marginal cost of production, c.

The main novelty of this paper is to investigate the role of air pollution in shaping the advertising decision. Our model allows the marketing efficiency to depend on air pollution concentrations captured by Ω. We postulate that air pollution can reduce the effectiveness of advertising; i.e., $q_\Omega \equiv \frac{\partial q}{\partial \Omega} < 0$ and $q_{a\Omega} \equiv \frac{\partial}{\partial \Omega}\frac{\partial q}{\partial a} < 0$.

What are the microeconomic underpinnings of the demand function $q(p, a; \Omega)$? We consider two different views on advertising and show that both are consistent with the general demand form we propose.

First, consider Butters (1977)'s classic model of *informative advertising*. In this case, $q(p, a; \Omega)$ takes the following form (with our modifications):

$$F\big(\psi(\Omega)a\big) \cdot s(p), \tag{4}$$

where $F\big(\psi(\Omega)a\big)$ is the probability that product information reaches a consumer through advertising, which depends on the advertising technology $\psi(\Omega) > 0$ with $\psi' < 0$, and advertising spending a. $s(p)$ is the total sales conditional on that consumers are aware of the product (and its price) with $s' < 0$. As is previously noted in the literature (Butters 1977; Bagwell 2007), in this framework, advertising does not affect price elasticity of demand; i.e., $\epsilon_p \equiv q_p * p/q = ps'/s$, which is independent of a.

Another way is to model advertising as a *complementary* feature that affects consumers' subjective perception of product quality, in the tradition of Stigler and Becker (1977). For instance, as in recent discrete choice models, advertising can be modeled as entering consumers' indirect utility function like a product attribute. In this case, the demand function takes the following form:

$$s\big(p - \psi(\Omega)a\big), \tag{5}$$

where $\psi(\Omega) > 0$ measures how effective advertising increases consumers' perceived product quality and consequently reduces the dis-utility of price.

For either model, an interior solution to the firm's problem, (p^*, a^*), satisfies the following first-order conditions (FOCs):

$$\pi_p \equiv [p - c]q_p + q = 0, \tag{6}$$

$$\pi_a \equiv [p - c]q_a - 1 = 0. \tag{7}$$

The FOCs imply that $q_a = -q_p/q$. We also assume that the associated second-order conditions (SOCs) are satisfied. For instance, the SOCs imply that $\pi_{pp} < 0$ and $\pi_{aa} < 0$, so $q_{aa} < 0$ in optimum.

Differentiating (6) and (7) and applying the Cramer's rule, we can derive the following comparative static result:

$$\frac{da^*}{d\Omega} = \frac{[p-c](q_a q_{p\Omega} - q_p q_{a\Omega}) + [p-c]^2(q_{pa} q_{p\Omega} - q_{pp} q_{a\Omega})}{D}; \tag{8}$$

where D denotes the determinant of the Hessian matrix and is guaranteed positive by the SOCs.

For informative advertising, we re-arrange the two terms in equation (8) to obtain

$$\frac{[p-c](q_{p\Omega}(q_a + [p-c]q_{pa}) + q_\Omega q_{pa} - q_p q_{a\Omega} - [p-c]q_{pp} q_{a\Omega})}{D}. \tag{9}$$

The FOCs imply $q_a = \psi f s = -Fs'/Fs = -q_p/q$, so $\psi f s^2 + s' = 0$. Also by the FOC, $q_a + [p-c]q_{pa} = \frac{q_a^2 + q_{pa}}{q_a}$, which equals zero because $q_a^2 + q_{pa} = \psi f(\psi f s^2 + s') = 0$. For the next term, we have $q_a q_{p\Omega} - q_p q_{a\Omega} = a s s' \psi' f(a\psi f - F) - a\psi^2 F f' s s' < 0$ because of $f' < 0$ at the optimum. Then $-[p-c]q_{pp} q_{a\Omega}$ is also negative when $s(p)$ is concave (i.e., $s'' < 0$). Overall, expression (8) is negative under informative advertising.

For complimentary advertising, it is straight forward to show that $q_{p\Omega} = -a\psi' s'' < 0$, $q_{pa} = -\psi s'' > 0$, and $q_{pp} = s'' < 0$, so both terms in (8) are negative. Expression (8) is negative again in this case.

Put together, the impact of pollution on ad spending via the marketing efficiency channel is unambiguously negative under both models of advertising. We show that air pollution should negatively affect the firm's advertising spending, which is our main hypothesis. In our empirical analysis, we test the hypothesis and its underlying mechanisms using data from the outdoor advertising industry.

A.2 Sample Cities in China

For empirical analysis, we examine the outdoor advertising markets in 24 large Chinese cities for which advertising data are available. Figure 2 shows their locations in China. They include Beijing, Chongqing, Tianjin, and Shanghai (four municipalities directly governed by China's central government); Changchun, Dalian, Harbin, Shenyang (in Northeast China); Changsha, Shijiazhuang, Wuhan, Zhengzhou (in North and Central China); Xi'an (in Northwest China); Chengdu and Kunming (in Southwest China); Fuzhou, Hangzhou, Jinan, Nanjing, Ningbo, Qingdao, Suzhou (in East China); Guangzhou and Shenzhen (in South China).

According to our calculation and market information provided by CODC (2018), the sample cities account for more than 85% of nationwide spending on outdoor advertising in China.

Table A.1 presents summary statistics of GDP and population of the sample cities. In particular, the 24 cities account for roughly 20% of China's 1.4 billion population, with an average population of 10–11 million; the smallest city had over 5 million people in 2008. Their population accounts for 20% of China's total population, more than the fourth most populous country in the world (Indonesia). In terms of economy, they contribute around 37.5% of China's national GDP, which is comparable to the GDP of Germany.

Table A.1: GDP and population of the sample cities

Year	Mean	S.D.	Min	Max	Total	Share in national total
		Nominal GDP (CNY trillion)				
2008	0.48	0.28	0.16	1.37	11.41	37.68%
2017	1.29	0.71	0.49	3.06	30.93	37.40%
		Population (million)				
2008	10.13	5.13	5.83	28.39	243.21	18.31%
2017	11.91	6.01	5.95	31.43	285.92	20.57%

Notes: Statistical data are collected from the official municipal yearbooks of various years. Population refers the number of long-term residents living in urban and suburban areas of a city; for Changchun and Dalian, we use the number of officially registered residents with *hukou*.

A.3 Effect of Air Pollution on Newspaper Advertising

To test whether $PM_{2.5}$ has a significant effect on newspaper advertising, we merged newspaper-level advertising information obtained from Qin et al. (2018) with our environmental data. The merged data cover 52 commercial city newspapers and 12 party-line newspapers in the 24 sample cities. For historical and political reasons, China's newspaper markets have a hierarchical structure resembling its government system (Qin et al. 2018). This study excludes national and provincial newspapers that are sold across municipalities. For a list of the newspapers, see Table A.2.

Table A.2: Sample newspapers

City	Commercial	Party-line
Beijing	*Beijing Entertainment Messenger, Beijing Morning Post, Beijing Evening News*	*Beijing Daily*
Chongqing	*Chongqing Business Daily, Chongqing Times, Chongqing Morning Post, Chongqing Evening News*	*Chongqing Daily*
Tianjin	*Tonight News, Chengshi Kuaibao, Meiri Xinbao*	*Tianjin Daily*
Shanghai	*Xing Bao*	
Changchun	*City Evening News, Changchun Evening News*	
Dalian	*Peninsula Morning Post, Dalian Evening News*	
Harbin	*New Evening Post*	
Shenyang	*Huashang Morning Post, Shidai Shangbao, Shenyang Evening News*	*Shenyang Daily*
Changsha	*Changsha Evening News*	
Shijiazhuang	*Yanzhao Evening News*	
Wuhan	*Wuhan Morning Post, Wuhan Evening News*	*Changjiang Daily*
Zhengzhou	*Zhengzhou Evening News*	*Zhengzhou Daily*
Xi'an	*Xi'an Evening News*	
Chengdu	*West China City News, Tianfu Morning Post, Chengdu Business Daily, Chengdu Evening News*	*Chengdu Daily*
Kunming	*Dushi Shibao, Chuncheng Evening News*	
Fuzhou	*Fuzhou Evening News*	
Hangzhou	*Morning Express, Daily Business, City Express*	*Hangzhou Daily*
Jinan	*Jinan Times*	
Nanjing	*Dongfang Wei Bao, Nanjing Morning Post, Yangtse Evening Post, Jinling Evening News*	*Nanjing Daily*
Ningbo	*Ningbo Evening News*	*Ningbo Daily*
Qingdao	*Bandao Dushi Bao, Qingdao Morning News, Qingdao Evening News*	
Suzhou	*Gusu Evening News*	*Suzhou Daily*
Guangzhou	*Information Times, Xin Kuai Bao, Yangcheng Evening News*	*Guangzhou Daily*
Shenzhen	*Jing Bao, Shenzhen Special Zone Daily, Shenzhen Business Daily, Shenzhen Evening News*	

To identify the effect of $PM_{2.5}$, we use the same IV strategy based on thermal inversions. As we now incorporate newspaper-level data, the second-stage equation becomes

$$Y_{imt} = \beta_0 + \beta_1 P_{c(i)mt} + f(W_{c(i)mt}) + \nu_i + \theta_{c(i)t} + \omega_{mt} + \varepsilon_{imt} \tag{10}$$

where Y_{imt} is the log of advertising revenue of newspaper i serving its home city $c(i)$. Here, we control for newspaper fixed effects in addition to the city-year and month-year fixed effects. The standard errors are clustered at the city level.

Table 6 reports the baseline results for newspaper advertising. We also conduct a set of robustness checks, which results are reported in Table A.3. Column (1) tests for a lagged effect, where we use the previous month's average $PM_{2.5}$ concentration as the main explanatory variable. In column (2), we also control for monthly city-level CPI. In column (3), we use an alternative measure by counting the total number of thermal inversions in one month. In baseline regressions, we define thermal inversions based on the temperature difference between the ground layer (110 meters) and the second layer (320 meters). In column (4), we replace the second layer with the third layer at 540 meters. All estimates remain statistically insignificant, indicating no significant effect of air pollution on newspaper advertising.

Table A.3: Effect of $PM_{2.5}$ on newspaper advertising: robustness results

Dependent variable:	ln(newspaper ad revenue)			
	One-month lag	Control for CPI	Alternative measure of inversion	Alternative layer of inversion
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.0008	0.0008	-0.0028	0.0007
	(0.0032)	(0.0040)	(0.0035)	(0.0039)
KP *F-stat.*	16.38	16.46	24.50	9.57
N	3085	2931	2991	2991
No. newspapers	52	51	52	52
Newspaper FE	Yes	Yes	Yes	Yes
City-year FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	No	Yes
Weather controls	Yes	Yes	Yes	Yes

Notes: Estimates are obtained using 2SLS estimations. Column (1) uses the previous month's average $PM_{2.5}$ concentration. Column (2) controls for monthly CPI of each city. Column (3) changes the measure of thermal inversions by using the total number of inversions in a month. Column (4) changes the IV by coding thermal inversions based on temperature difference between the ground (110 meters) and the third layers (540 meters). Robust standard errors clustered at the city level are in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

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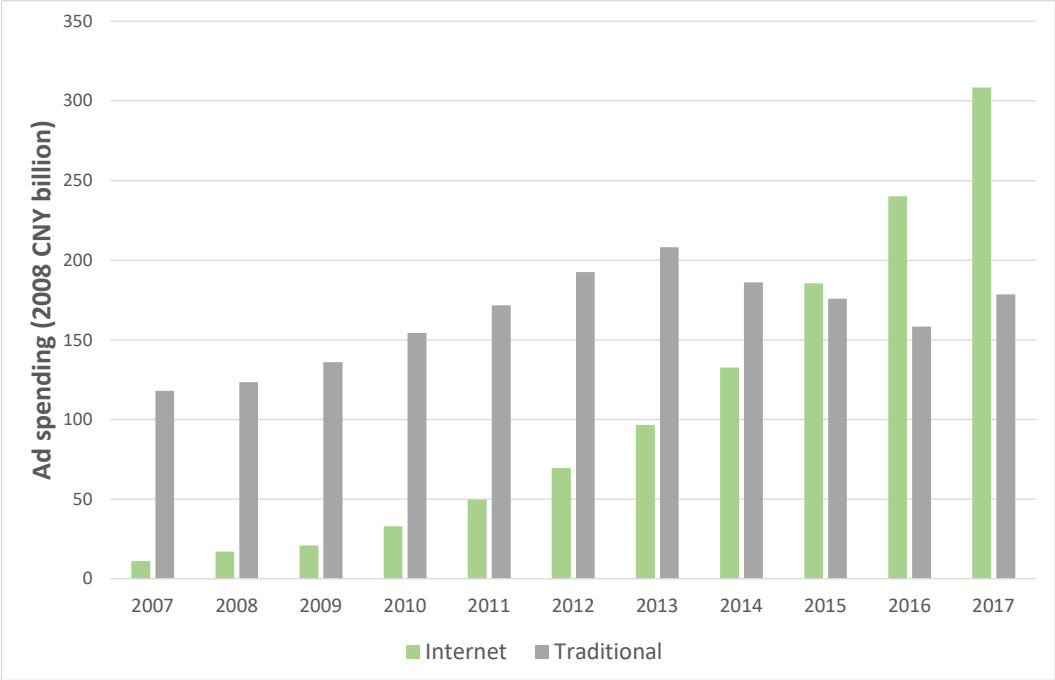
Stigler, GJ, and GS Becker. 1977. "De Gustibus Non Est Disputandum." *American Economic Review* 67:76–90.

A.4 Additional Figures and Tables

Figure A.1: Traditional and online media in China, 2007–2017



Notes: Data come from iResearch and the *China Advertising Yearbooks*, 2008–2018. Traditional media include television, newspapers, outdoor advertising, radio, and magazines. USD 1 = CNY 6.95 in 2008.

Figure A.2: A screenshot of Google search results for "outdoor advertising" and "smog"

Notes: The figure presents a screenshot of a Google search results page using the keywords of "outdoor advertising" and "smog" in Chinese (accessed on August 12, 2021). It shows the headlines of a few online articles (including possible advertorials) discussing the impact of smog on pricing and the effectiveness of outdoor advertising.

A.5 Unused materials

Specification II: IND-D1M3 + County-year & month FEs

Table A.5: First-stage results

	$PM_{2.5}$		
	(1)	(2)	(3)
Thermal inversions (IND)		0.4587***	0.4127***
		(0.0861)	(0.0869)
County-year FE		Yes	Yes
Month FE		Yes	No
Year-month FE		No	Yes
Weather controls		Yes	Yes
KP *F-stat.*		28.39	22.57

Notes: $N = 2,664$. Significance at * 10%, ** 5%, and *** 1% levels.

Table A.8: Effects of air pollution on outdoor ad revenue: by location

	Commercial	Residential	Colleges	Science park	Train station	Airport
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.0032***	-0.0016	-0.0029	-0.0042	-0.0036	-0.0033
	(0.0011)	(0.0012)	(0.0020)	(0.0030)	(0.0027)	(0.0030)
KP *F-stat.*	24.77	26.81	23.84	41.98	19.80	31.88
N	2,553	2,442	2,553	1,753	1,991	2,437
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Significance at * 10%, ** 5%, and *** 1% levels.

For informative advertising,

$$
\begin{aligned}
q_p &= Fs'\big(<0\big), & q_a &= \psi fs\big(>0\big), & & \\
q_{pp} &= Fs'', & q_{aa} &= \psi^2 f's\big(<0\big), & q_{pa} &= \psi fs'\big(<0\big), \\
q_{p\Omega} &= a\psi' fs'\big(>0\big), & q_{a\Omega} &= \psi' fs + a\psi^2 f's\big(<0\big) & q_{\Omega} &= a\psi' fs\big(<0\big).
\end{aligned}
$$

For complimentary advertising,

$$\begin{aligned} q_p &= s', & q_a &= -\psi s', & & \\ q_{pp} &= s''\big(<0\big), & q_{aa} &= \psi^2 s''\big(<0\big), & q_{pa} &= -\psi s''\big(>0\big), \\ q_{p\Omega} &= -a\psi' s''\big(<0\big), & q_{a\Omega} &= -\psi'(s' - a\psi s'')\big(<0\big) & q_{\Omega} &= -a\psi' s'\big(<0\big). \end{aligned}$$

The first bracketed term $q_a q_{p\Omega} - q_p q_{a\Omega} = \psi'(s')^2 < 0$. The second bracketed term is also negative, as is guaranteed by the SOCs. Overall, the net effect is negative.

For informative advertising,

$$\begin{aligned} q_p &= Fs'\big(<0\big), & q_a &= \psi f s\big(>0\big), \\ q_{pp} &= Fs'', & q_{aa} &= \psi^2 f' s, & q_{pa} &= \psi f s'\big(<0\big). \end{aligned}$$

Therefore,

$$q_a q_{pp} - q_p q_{pa} = \psi F f\big((ss'' - (s')^2\big) < 0; \tag{11}$$

where $ss'' - (s')^2 < 0$ holds if and only if the demand function $s(p)$ is log-concave.

For complimentary advertising,

$$\begin{aligned} q_p &= s', & q_a &= -\psi s', \\ q_{pp} &= s''\big(<0\big), & q_{aa} &= \psi^2 s''\big(<0\big), & q_{pa} &= -\psi s''\big(>0\big). \end{aligned}$$

So, Therefore,

$$q_a q_{pp} - q_p q_{pa} = -\psi s' s'' + s' \psi s'' = 0. \tag{12}$$

Table A.4: Lagged and lead effects

(a) Estimated lagged effects

	1-month lag	2-month lag	3-month lag	4-month lag	6-month lag
First-stage results	*dependent variable*: $\text{PM}_{2.5t-l}$				
Thermal inversions$_{t-l}$	0.5709***	0.5604***	0.5594***	0.5308***	0.4485***
	(0.1022)	(0.1044)	(0.1080)	(0.1086)	(0.1110)
KP *F-stat.*	31.22	28.83	26.84	23.91	16.33
Second-stage results	*dependent variable*: $\ln(\text{outdoor ad spending})_t$				
$\text{PM}_{2.5t-l}$	-0.0020*	-0.0016	-0.0010	0.0003	0.0020
	(0.0009)	(0.0014)	(0.0011)	(0.0013)	(0.0013)
N	2,664	2,664	2,664	2,664	2,664
City-year FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes

(b) Estimated lead effects

	1-month lead	2-month lead	3-month lead	4-month lead	6-month lead
First-stage results	*dependent variable*: $\text{PM}_{2.5t+l}$				
Thermal inversions$_{t+l}$	0.5051***	0.5105***	0.5645***	0.5285***	0.5138***
	(0.1060)	(0.1135)	(0.1295)	(0.1097)	(0.1154)
KP *F-stat.*	22.72	20.25	19.00	23.20	19.84
Second-stage results	*dependent variable*: $\ln(\text{outdoor ad spending})_t$				
$\text{PM}_{2.5t+l}$	-0.0017	-0.0016	0.0002	0.0019	0.0020
	(0.0011)	(0.0010)	(0.0011)	(0.0012)	(0.0012)
N	2,640	2,640	2,616	2,592	2,544
City-year FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes

Notes: Estimates are obtained using 2SLS estimations. Robust standard errors clustered at the city level are in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.

Table A.6: Effects of air pollution on outdoor ad revenue

	OLS		IV	
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.0118***	-0.0000	-0.0021**	-0.0027***
	(0.0042)	(0.0002)	(0.0009)	(0.0010)
KP *F-stat.*	-	-	28.39	22.57
County-year FE	No	Yes	Yes	Yes
Month FE	No	No	Yes	No
Year-month FE	No	Yes	No	Yes
Weather controls	Yes	Yes	Yes	Yes

Notes: $N = 2,664$. Significance at * 10%, ** 5%, and *** 1% levels.

Table A.7: Robustness checks

	Baseline (IND-D1M3)	Alternative aggregation methods (D1M2)	(D1M1)	Alternative layers for IV (D2M3)	Alternative measure (NUM-D1M3)	SO_2
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.0021**	-0.0018**	-0.0016**	-0.0015*	-0.0017*	-0.0084*
	(0.0009)	(0.0009)	(0.0007)	(0.0008)	(0.0009)	(0.0045)
KP *F-stat.*	28.39	21.81	42.01	25.17	29.69	5.72
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: $N = 2,664$. Significance at * 10%, ** 5%, and *** 1% levels.

Table A.9: Controlling for CPI with leads

Dependent variable:	ln(total outdoor ad spending)				
	Baseline	CPI w/ a 6-month lead	CPI w/ a 12-month lead	CPI w/ a 18-month lead	CPI w/ a 24-month lead
	(1)	(2)	(3)	(4)	(5)
$PM_{2.5}$	-0.0025***	-0.0028**	-0.0026**	-0.0027**	-0.0025**
	(0.0009)	(0.0011)	(0.0010)	(0.0010)	(0.0011)
KP *F-stat.*	30.66	25.32	26.10	26.40	25.93
City-year FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes

Notes: $N = 2,553$. The estimates are obtained using 2SLS estimations. Robust standard errors clustered at the city level are reported in parentheses. Significance at * 10%, ** 5%, and *** 1% levels.