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The impact of air pollution on movie theater admissions[☆]

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ABSTRACT

We provide new evidence of pollution avoidance in the movie theater market. Our analysis is based on a unique dataset of high-frequency movie ticket sales in China at the movie- and city-level during 2012–2014. We estimate that one pollution day reduces the market share of a movie by 2.26%, other things being equal. The effect is mainly through ambient pollution exposure during transportation to the theater. On average, popular movies are inelastic to air pollution. However, as air quality deteriorates, even blockbuster movies start to suffer a box-office loss during the heavy pollution episodes.

1. Introduction

Individuals take costly actions to mitigate the adverse health impact of air pollution. On the one hand, consumers shift budget towards defensive expenditures on facemasks, air purifiers, and medical services (Deschênes et al., 2017; Barwick et al., 2018; Zhang and Mu, 2018; Ito and Zhang, 2020). On the other hand, people adjust outdoor activities to reduce personal exposures to harmful air contaminants (Graff Zivin and Neidell, 2009; Neidell, 2009; Keiser et al., 2018). The shift in consumer preference induced by air pollution avoidance affects various economic sectors disproportionately as some consumer sectors are particularly vulnerable. Therefore, it is important to assess the sectoral impact of pollution for a better understanding of the distribution of pollution costs.

In this paper, we analyze how air pollution affects the demand for a service sector in the short run by focusing on the movie theater market. We face two empirical challenges in identifying the effect of air pollution on box-office sales. First, there is virtually no price competition in the movie industry. The demand for a movie is largely determined by movie quality (Chintagunta et al., 2010). In addition, movie attendance also hinges on consumer-generated marketing such as the word-of-mouth effect (Moul, 2007; Moretti, 2011; Gilchrist and Sands, 2016). However, the quality of a movie and the word-of-mouth effect are not entirely observable. Second, air pollution exposure for moviegoers could be endogenous. Studios tend to time the market to maximize audiences (Einav, 2007). For example, the peak movie seasons are summer and winter in China, but summer is the most polluted season for ozone and winter for all other pollutants. In addition, most movie tickets are sold in big cities, which are more likely to be pollution centers.

We overcome these challenges by taking advantage of a unique dataset on box-office performance in China. Specifically, we have assembled a dataset with daily movie ticket sales for 829 movies released in 60 cities from 2012 to 2014. The sample accounts

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for about 40% of audiences and 74% of revenues in the Chinese motion picture exhibition market in 2014. We have also collected movie characteristics and viewer ratings from a leading movie review website. The movie ticket sales and characteristics data are then merged with daily air pollution and weather variables, including temperature, precipitation, dew point, and wind speed. In the end, our dataset contains 426,757 observations.

The identification is enabled by the data for multiple goods in multiple markets over multiple periods. Since a movie is on show in multiple cities for multiple days, this allows us to include a movie fixed effect to control for unobservable quality. The high-frequency data in multiple cities also allow us to include a day fixed effect that absorbs the temporal shocks common to all cities, such as the word-of-mouth effect for the movies shown on the same day. The day fixed effect can also control for holidays, weekends, and national events. With multiple movies over time in a city, we can include a city fixed effect to absorb all geographic factors that determine local box-office sales.

The high-frequency data across cities provide plausibly exogenous variation in air quality to identify the impact of air pollution on box-office sales. To deal with the challenge of endogenous movie release decisions, we utilize the fact that a movie is simultaneously released in all cities in China. By controlling for weather and movie-, city-, and day-fixed effects, the variation of air quality within the period of the show for a movie across cities is likely exogenous. In addition, although the aggregate variation in air quality can be driven by economic activities, which is a confounding factor for ticket sales, daily variation in air pollution is presumably random (Graff Zivin and Neidell, 2012).

Our results show unambiguous evidence that air pollution reduces box-office sales. The baseline result suggests that one day of air pollution (with air pollution index, or API, above 100) reduces the market share of a movie by 2.26% in China. This result survives numerous robustness checks. In comparison, Neidell (2009) estimates that smog alerts reduce the attendance of the Los Angeles Zoo by 15% and 6% for the Griffith Park Observatory. Our estimate is smaller for several reasons. Moviegoing is a combination of indoor and outdoor activities, and movie theaters usually have air conditioning and filtration. In addition, movie theaters are mainly frequented by young adults in China and other countries.[1] Compared to more sensitive groups such as children and seniors, young adults do not face as many immediate adverse effects when exposed to air pollution (He et al., 2016). Furthermore, people in developing countries may be less responsive to pollution because their valuation for environmental quality is generally lower than that in developed countries (Greenstone and Jack, 2015; Freeman et al., 2019).

We explore potential mechanisms that can explain the negative effect of air pollution on box-office performance. Moviegoers respond to air pollution exposure during the transportation to the theater; those who live farther away from theaters are more likely to forgo a movie theater visit during pollution days. In addition, mixed entertainment – such as eating and shopping – can amplify the adverse effect of pollution on movie attendance. Furthermore, we find that air quality in a theatrical environment is closely related to ambient pollution, even though the theater has installed air purifiers.

We find significant heterogeneity in moviegoers' responses to air pollution. Most interestingly, we find that air pollution avoidance hinges on movie quality. The blockbusters, with top 25% viewer's ratings, are insensitive to air pollution, while the bottom rated movies suffer the most from bad air quality. The responses to air pollution are also nonlinear. As air quality deteriorates, more and more people reduce movie theater visits; even blockbuster movies suffer a loss during the worst pollution episodes.

Our research contributes to several strains of the literature. First, to the best of our knowledge, we provide the first empirical evidence of air pollution avoidance in a consumer sector using nationwide data. We reinforce the importance of characterizing avoidance behavior in quantifying the cost of environmental pollution (Graff Zivin and Neidell, 2009; Neidell, 2009; Janke, 2014). Second, we contribute to the exploitation of unconventional data from the Internet to study the behavioral responses to air pollution in developing countries where data availability is a major obstacle. Related studies in China include e-commerce mask sales (Sun et al., 2017; Zhang and Mu, 2018), smartphone application-based exercise data (Hu et al., 2017), online search records (Liu et al., 2018; Qin and Zhu, 2018), and social media posts (Zheng et al., 2019). Third, our analysis also contributes to the growing literature on understanding the demand in the movie industry (Einav, 2007; Dahl and DellaVigna, 2009; Buchheim and Kolaska, 2017). Many studies in the literature use data aggregated to certain temporal and spatial levels. Our data with daily variation across different cities for every single movie enable us to control for the unobservables that cannot be captured by the aggregate data.

The rest of this paper is organized as follows. Section 2 describes the data and Section 3 introduces specification and identification. The main results are reported in Section 4. Section 5 discusses policy implications. The last section concludes.

2. Data

2.1. Movie data

The theatrical market data came from two sources. The first source is an online movie ticket vendor, company W, which acts as a ticket sales agent for many movie theaters. As of July 2019, company W covers more than 7000 movie theaters in over 450 cities in China.[2] The second source is a subsidiary of a large entertainment conglomerate, company D. Company D targets high-end consumers and generally has no more than two theaters, with multiple screens, in a city, except in some large cities like Beijing

[1] 84% of moviegoers in China in 2018 are between 18–40 (Source: http://www.bigdata-research.cn/content/201901/915.html, Last retrieved on April 5, 2020). In comparison, 53% of frequent moviegoers in North America in 2019 is between 12–39 (Motion Picture Association, 2020).

[2] Our raw data from company W consist of 49, 55, and 54 cities in 2012, 2013, and 2014, respectively. The number of theaters is 205, 330, and 626.

and Shanghai. As of July 2019, company D owns 541 theaters in over 140 cities throughout China.[3] During the period of our study, these two sources do not have overlapped theaters since company D sold tickets exclusively on its website.[4]

While both companies allow tickets to be bought through the website, telephone, or smartphone applications,[5] there are some differences in addition to their targeted types of consumers. In most circumstances, company W allows consumers to buy tickets only two days in advance[6] but all sales are final, and no return is permitted. Company D, on the other hand, only sells same-day tickets except to VIP members, who may buy tickets one day in advance. Company D also claimed itself as the only online movie ticket vendor that accepts returns for the period of our data. With the non-refundable policy of company W and the convenience of buying tickets on smartphone applications, the portion of consumers that would buy tickets a few days ahead must be small, even though they may have planned to watch a movie ahead of time.

Movie characteristics and viewer ratings were retrieved from Douban.com, a Chinese online rating and reviewing website. The information used in this paper includes the day of premier and viewer ratings on a 10-point scale.[7]

2.2. Pollution and weather data

The air pollution data are from China's Ministry of Ecology and Environment (MEE), previously named Ministry of Environmental Protection (MEP). The data contain the retrospective measurement of air pollution levels instead of forecasts; the latter is unavailable. Prior to 2013, Chinese cities reported air pollution index (API), which is a composite index of three criteria pollutants including sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter with a diameter of 10 micrometers or less (PM_{10}). Since 2013, China has switched to the new system of air quality index (AQI), which is based on six criteria pollutants, with CO, $PM_{2.5}$, and ozone as newly added pollutants.

Although our study period straddles the change of the air pollution reporting system, we take the face values of API and AQI directly since people mainly respond to pollution alerts that are issued when API or AQI is above 100. To save notations, we use API to refer to both API and AQI throughout the paper. Pollution alerts are disseminated through newspapers, TV, radio, and the Internet. Real-time air quality information is available in all Internet portals, including major websites, smartphone apps, and social media.

The weather data are provided by the National Center for Environmental Information (NCEI, formerly National Climatic Data Center) under the National Oceanic and Atmospheric Administration (NOAA) of the United States.[8] The NCEI documents essential weather information from land-based weather stations in the US and around the world. The Chinese weather data that we use include weather information for 499 weather stations that are reported every 3 h. The weather variables include temperature, precipitation, dew point, and wind speed. All these variables measure how comfortable it feels in the outdoor environment.[9]

2.3. Supplementary data

We collected indoor and outdoor air quality field data in a movie theater in Kunshan city, which is close to Shanghai, from April 30 to May 17, 2021. The theater has eight projection halls with air conditioning and filtration. We deployed 31 monitoring devices in all projection halls, theater lobby, and outdoor environment. The sensors continuously reported $PM_{2.5}$ concentrations to the server via the 4G network every 10 min. Section A.1 in the Online Appendix shows the detailed information.

We also gathered information on 8374 shopping malls in 60 cities from Dianping.com, a leading Chinese website for customer reviews of businesses. Using the geospatial information in the 2015 Chinese Population Census, we can compute the distance between a household and the nearest in-mall movie theater. We use %(1 km radius) and %(2 km radius) to designate the proportions of households in a city with an in-mall theater within 1 or 2 km of residence. We can also use the proportion of malls with a movie theater as a proxy for mixed entertainment such as shopping and dining.

2.4. Descriptive statistics

Our dataset is compiled from four different sources: theatrical market statistics, air quality, weather conditions, and movie characteristics. The movie data are merged from two sources. There are overlapping cities by companies W and D, but some cities have box-office statistics from only one of the sources, mostly company W. According to our calculation, the movie data used in this

[3] Our raw data from company D consists of 64, 73, and 93 cities in 2012, 2013, and 2014, respectively. The number of cinemas is 106, 133, and 161.

[4] As of October 2016, company W also covers tickets from company D in certain cities.

[5] According to the State Administration of Press, Publication, Radio, Film, and Television of The People's Republic of China, in 2013, the top choice of buying a movie ticket was through online venues such as website or smartphone applications.

[6] The website shows search results for as many as five days ahead, but schedules are only available two days in advance except for premier of highly anticipated movies.

[7] Date of access: August 14, 2016.

[8] https://www.ncdc.noaa.gov.

[9] Dew point and humidity have a functional relationship under various temperatures and pressure. According to the National Weather Service, the dew point is a better indicator for the feeling of moisture in the air by human bodies, compared with relative humidity. https://www.weather.gov/arx/why_dewpoint_vs_humidity, last retrieved on April 5, 2020.

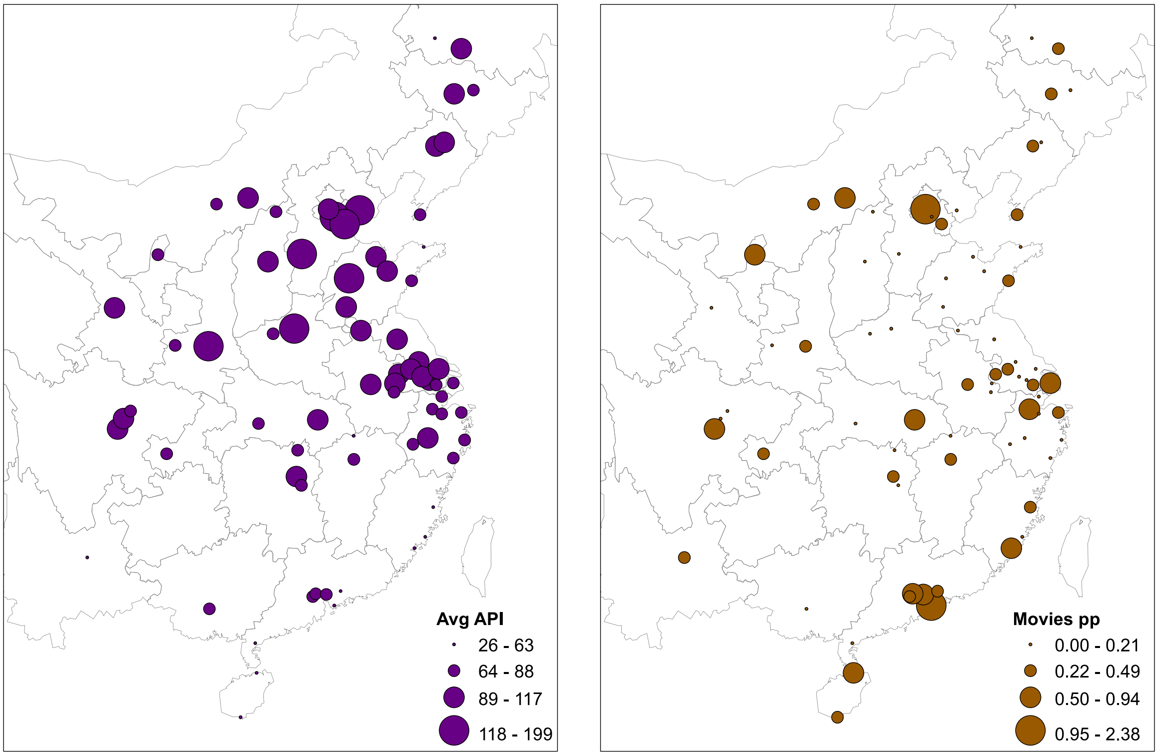

Fig. 1. The Spatial Distribution of Cities in Our Sample of Analysis. The left panel illustrates each city's annual average Air Pollution Index (API). The right panel depicts the annual average number of movies an urbanite watches in cinema. Numbers are calculated based on the dataset used in this paper.

study account for about 38% of audiences and 65% of revenues in the Chinese market in 2012 and 2013, 40% and 74% in 2014.[10] The final dataset covers 829 movies shown in 60 cities throughout China between January 1, 2012 and December 31, 2014. Fig. 1 shows the geographic distribution of these cities.

The upper bound of API in China is 500, which occurred 32 times in our sample: once in 2012, 10 times in 2013, and 21 times in 2014. The average API is around 88, with 25.9% of observations in a pollution day. The average API among pollution days (API > 100) is 156.26, while that among "blue-sky" days (API≤100) is 64.54. Pollution in China does not exhibit significant day-of-week variations. As shown in Fig. 2, the average API throughout a week is very stable, while movie theater admissions vary across a week.

The daily average number of movie audiences in a city is 1599 per film. An average movie drew 0.02% of a city's population on an average day. At the extreme, one movie attracted 2.4% of a city's population in a single day. This happened in Wuhan on June 29, 2014, for the movie "Transformer: Age of Extinction".

3. Empirical strategy

3.1. Motivation

A consumer makes the daily decision of choosing among multiple movies as well as not going to any movie at all. It is natural to use a random utility framework to describe this individual moviegoing behavior. Although we do not intend to estimate an individual discrete choice model, the stylized framework enables us to derive the aggregate market share at the movie-, city-, and day-level. Let u_{ijct} designate the utility of consumer i going to movie j in city c on date t, which can be specified as

$$u_{ijct} = \alpha \mathrm{API}_{ct} + v_{jct} + \varepsilon_{ijct}, \tag{1}$$

where the variable of central interest, API_{ct}, denotes various measures of air pollution levels. The term v_{jct} gives the observable component of the valuation assigned by individual i to movie j. The term ε_{ijct} is an unobservable component of this valuation, which is assumed with an $i.i.d.$ extreme value distribution.

[10] Sources: http://www.199it.com/archives/91183.html for 2012, http://biz.zjol.com.cn/system/2014/01/03/019791233.shtml for 2013, and http://paper.people.com.cn/rmrbhwb/html/2015-01/02/content_1516620.htm for 2014. Last retrieved on April 5, 2020.

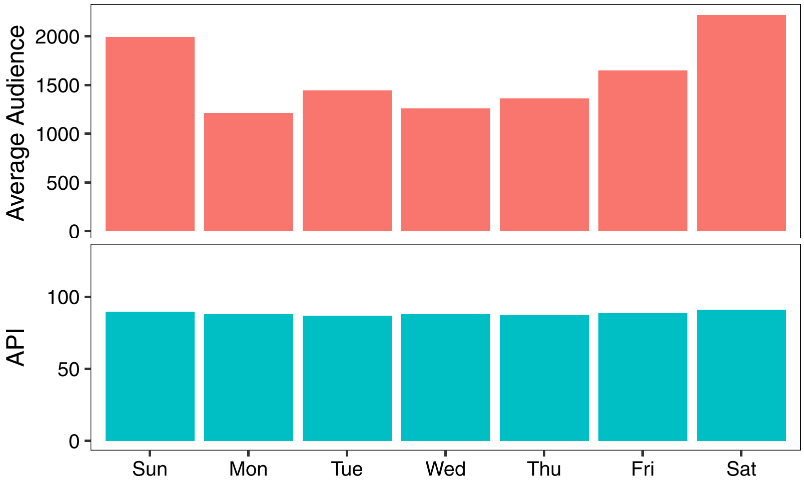

Fig. 2. Weekly API and Movie Audience Distribution. Numbers are calculated based on the dataset used in this paper.

We normalize the utility of not going to any movie on date t to be zero in all markets, which is a typical specification in discrete choice modeling. It is worth noting that this assumption is not overly restrictive since we include a large number of fixed effects in Eq. (1). In particular, the inclusion of flexible city and time fixed effects can partially account for the variation in the utility of the outside goods caused by seasonality. The setup of this framework leads to a multinomial logit model, which can be transformed into a linear model and estimated with aggregate data (Berry, 1994; Berry et al., 1995). Under this specification, the market share of movie j in city c on date t is given by

$$s_{jct} = \frac{\exp(\alpha \mathrm{API}_{ct} + v_{jct})}{1 + \sum_{k \in J_{ct}} \exp(\alpha \mathrm{API}_{ct} + v_{kct})}, \tag{2}$$

where J_{ct} is the set of all movies that are showing in city c at time t. Let s_{0ct} designate the share of the outside goods, that is, not going to any movie. The above model can be linearized as

$$\ln\left(\frac{s_{jct}}{s_{0ct}}\right) = \alpha \mathrm{API}_{ct} + v_{jct}, \tag{3}$$

where the left-hand side variable denotes the log ratio of market share of movie j to the share of the outside good. In the next section, we will spell out the observable component of the utility v_{jct} to facilitate econometric estimation.

3.2. Specification

Motivated by Eq. (3), we derive the following baseline specification:

$$\ln\left(\frac{s_{jct}}{s_{0ct}}\right) = \alpha \mathrm{API}_{ct} + \beta w_{ct} + \gamma_1(t - \tau_{jc}) + \gamma_2(t - \tau_{jc})^2 + \theta_j + \delta_c + \pi_t + \psi_{jct}. \tag{4}$$

In this form, w_{ct} is a vector of weather variables that are city- and time-varying; τ_{jc} is the release date of movie j in city c. To account for the fact that the interest in a movie decays over time, we use a quadratic decay function to capture the nonlinear relationship between movie theater admissions and the number of days passed since its release ($t - \tau_{jc}$). In addition, θ_j, δ_c, and π_t designate movie, city, and day fixed effects, respectively. The idiosyncratic propensity of watching a movie is denoted by ψ_{jct}, which is an unobservable error term. In all estimations, standard errors are clustered at the movie level to accommodate the serial correlation of movie attendance across cities and periods.

The quality of movie j is designated by θ_j. Movie quality is unobservable. Since we can observe box-office performance for the same movie in different markets, it allows us to use movie fixed effect θ_j to control for unobservable movie attributes. Residents in different cities have different preferences for movies. We include city fixed effect δ_c to control for time-invariant city attributes, such as geographical location, history, social norms, and other unobservables that do not change over time but affect movie theater admissions. In addition, we include day fixed effect π_t to control for daily shocks that are identical across cities, such as holidays, seasonality, and national events.

Weather affects movie theater visits. We include daily temperature, precipitation, wind speed, and dew point. The dew point measures the moisture in the air, which has a nonlinear effect on the comfort of human bodies. Therefore, we include a quadratic term of dew point in the regression. There is also a comfortable zone for temperature, so a quadratic term of temperature is also included. Our conjecture is that extreme weather – such as extreme temperature and humidity, intense precipitation, and strong wind – makes people less likely to go outside, thus lowering movie theater admissions.

In addition to the baseline specification, we also test an alternative specification that regresses the number of the audience (in logarithm) on air pollution and a set of other control variables. Let y_{jct} designate the number of audiences for movie j in city c on date t. The specification below is similar to model (4) except for the dependent variable:

$$\ln\left(y_{jct}\right) = \alpha \mathrm{API}_{ct} + \beta w_{ct} + \gamma_1(t-\tau_{jc}) + \gamma_2(t-\tau_{jc})^2 + \theta_j + \delta_c + \pi_t + \psi_{jct}. \tag{5}$$

In the estimation, we drop the observations with 0 tickets. The log model cannot deal with 0 very well. One has to drop the observations with 0 or use $\log(1+y)$.

3.3. Challenges and strategies

The first identification challenge is that moviegoers' valuation of a movie, which depends on movie quality, is not entirely observable (Einav, 2007). Consumers might determine the quality ex-ante based on the characteristics such as cast, director, budget, genre, and ratings. However, these observable characteristics are not perfect predictors of movie quality; otherwise, there would be no surprises. We deal with this challenge by using high-frequency ticket sales data, which allow us to include the movie fixed effect to control for the unobservable movie quality. In addition, the movie fixed effect can also control for firm-initiated marketing efforts such as advertising (Chintagunta et al., 2010).

The second challenge is that box-office performance also hinges on consumer-generated marketing such as word of mouth (Moul, 2007; Gilchrist and Sands, 2016). Social learning amplifies the elasticity of aggregate demand to movie quality compared with the elasticity of the individual demand (Moretti, 2011). To deal with this complication, one strategy is to include the day fixed effect. The day fixed effect can lump in all the reviews about all movies shown on a particular day, which is constant across cities but variable over time. Another strategy is to separate the first week of the release from other weeks. The first-week box office may depend on expectations, while the performance of the remaining weeks is more influenced by realized reviews.

The third challenge is the concern of endogenous release time decisions, which plagues the analysis that uses the data that are aggregated to certain temporal and market levels. Movies, especially those big hits, are likely to be released during the two prime seasons in summer and winter. However, winter is by far the most polluted season in China for all pollutants except for ground ozone; summer is the peak for ozone pollution. In addition, movie theaters are mostly located in population centers, where air pollution tends to be more severe. Therefore, a naive regression that uses aggregate data to test the effect of air pollution on movie theater admissions will lead to conspicuous conclusions.

Movie distributors may have some flexibility in choosing the release time, but the decision is mainly based on the global market reception. To the best of our knowledge, there is no evidence that air quality is a significant factor in their decisions of release in the Chinese market, especially many big hits are facing the global market. Even if a distributor tries to factor in the air pollution effect, air quality forecasting in specific weeks is unavailable. More importantly, most movies are released to all cities on the same day. Once a movie is released, the daily air quality fluctuations are random. Therefore, conditional on weather, geography, and seasonality, the daily variation of pollution within the show window is presumably an exogenous driver for box-office sales.

3.4. Air pollution effect

The central research question is to measure the effect of air pollution on movie theater admissions. Therefore, the key explanatory variable is air pollution index API_{ct}. In the baseline model, we use categorical API with the cut-off at 100. Because a day with API higher than 100 is a polluted day, and a pollution alert is issued, the coefficient α then quantifies the impact of a "polluted" day on a city's theatrical market. Alternatively, we also use the continuous API as the explanatory variable directly.

The economic significance of the effect needs to be quantified by the marginal effect of pollution on box-office performance. Let $s_{jct}^{\mathrm{API}>100}$ and $s_{jct}^{\mathrm{API}\le 100}$ designate the market shares of movie j in city c at time t with and without pollution. The marginal effect of pollution on movie theater admissions is defined as the percentage change of the movie share attributed to air pollution. According to Eq. (3), the marginal effect can be derived as:

$$\frac{s_{jct}^{\mathrm{API}>100} - s_{jct}^{\mathrm{API}\le 100}}{s_{jct}^{\mathrm{API}\le 100}} = (e^{\alpha}-1)\left(1 - \sum_{k\in J_{ct}} s_{jct}^{\mathrm{API}\le 100}\right). \tag{6}$$

In the above equation, $1-\sum_{k\in J_{ct}} s_{jct}^{\mathrm{API}\le 100}$ represents the share of outside option during non-pollution days, or the share of population not going to a movie theater.

However, the interpretation of marginal effects is different when pollution is specified as a continuous variable. With this specification, the marginal effect of air pollution on movie theater admissions, measured by the percentage change of the movie market share attributed to air pollution, is

$$\frac{\partial\left(s_{jct}/s_{0ct}\right)}{\partial p_{ct}} = \alpha\left(1 - \sum_{k\in J_{ct}} s_{kct}\right). \tag{7}$$

In this form, $1-\sum_{k\in J_{ct}} s_{kct}$ is the share of the outside option, or the population not going to a movie theater at all.

We use both categorical and continuous APIs as explanatory variables. However, the categorical API is preferred because the Chinese government issues pollution alerts dependent on pollution levels. Most individuals can receive pollution alerts from numerous media sources such as TV and the Internet. In addition, using categorical API allows us to measure the nonlinear effect of air pollution on movie theater admissions. The summary statistics of the main variables used in regressions are reported in Table 1.

Table 1
Summary statistics.

Variable	N	Mean	Std. Dev.	Min.	Max.
Air pollution					
Air Pollution Index (API)	426,757	88.3287	54.4069	0	500
$I(\text{API} > 100)$	426,757	0.2593	0.4383	0	1
Pseudo API (2013–2014)	236,211	82.2711	42.2577	11	500
Movies					
Audience (persons)	426,757	1599	5625	1	264,578
s_{jct} (movie market share)	426,757	0.0002	0.0006	0.0000	0.0240
s_{0ct} (outside good share)	426,757	0.9977	0.0031	0.9585	0.9999
Douban rating	426,595	6.0400	1.5270	2.3	9.4
In-Mall movie theaters					
%(1 km radius)	426,757	0.2415	0.1077	0.0307	0.5277
%(2 km radius)	426,757	0.4438	0.1521	0.0688	0.7972
%(Mall w/theater)	426,757	0.3365	0.0757	0.1304	0.5873
Weather					
Temperature (kelvin)	426,757	288.3150	11.0226	244.15	309.37
Precipitation (inches)	426,757	0.1097	0.3781	0	11.15
Dew point (kelvin)	426,757	281.1339	12.4901	239.7	301.9
Wind speed (knots)	426,757	4.9938	2.3406	0	36.9
Visibility (miles)	423,701	7.4538	4.3303	0	18.6

Notes: Our main dependent variable is $\ln(s_{jct}/s_{0ct})$, where s_{jct} is the market share of movie j in city c on date t and s_{0ct} is the share of the outside goods, i.e., not going to any movie. The variables %(1 km radius) and %(2 km radius) designate the proportions of households within 1 and 2 km of in-mall theaters. The variable %(Mall w/theater) designates the proportion of malls with theater.

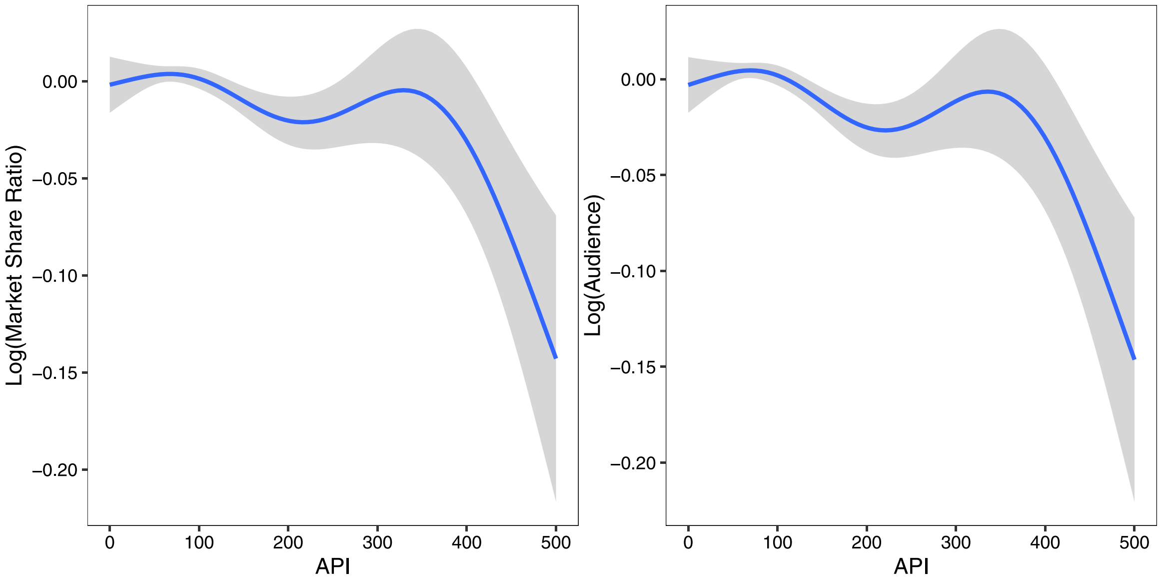

Fig. 3. The Relationship between Movie Theater Admissions and API. The left panel plots log(market share ratio), and the right panel plots log(audience). The plots are based on residuals. We control for all covariates and fixed effects except for API in the baseline model specification. The left panel depicts residuals from Eq. (4). The right panel depicts residuals from Eq. (5). The smoothing function is generalized additive mode smoothing with $k = 7$. The shaded area represents a 95% confidence interval.

4. Empirical results

4.1. Main results

First of all, we illustrate the responses of moviegoers to air pollution in Fig. 3. To do so, we obtain the residuals from Eqs. (4) and (5), respectively, controlling for all weather variables, time trends, and fixed effects of date, city, and movie. The figure shows, after controlling for all the fixed effects and covariates, how the movie market share ratio and audiences (in logarithm) change as air pollution becomes severe. In general, people reduce theater visits as pollution deteriorates; avoidance behavior is the most pronounced during the worst pollution days.

Table 2
Main results for the effect of air pollution on movie theater admissions.

Dependent	log (Market share ratio)			log (Audience)		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$I(\text{API} > 100)$	−0.0233***			−0.0275***		
	(0.0075)			(0.0075)		
API/100		−0.0242***			−0.0279***	
		(0.0074)			(0.0074)	
1/Visibility			−0.0218*			−0.0225*
			(0.0130)			(0.0129)
Marginal effect	−0.0226***	−0.0242***				
	(0.0072)	(0.0074)				
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Movie FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Time trends	Yes	Yes	Yes	Yes	Yes	Yes
N	426,757	426,757	426,757	426,757	426,757	426,757
R^2	0.738	0.738	0.738	0.741	0.741	0.741

Notes: All specifications include weather variables (temperature, temperature^2, precipitation, wind speed, dew point, and dew point^2), movie specific linear and quadratic time trends, and dummies of city, movie, and day. For columns (1)–(3), the dependent variable is the log of the ratio of market share of movie j in city c at time t to the outside good: $\ln(s_{jct}/s_{0ct})$. For columns (4)–(6), the dependent variable is the log of number of audience of movie j in city c at time t. Columns (1) and (4) use binary pollution index of whether API > 100 as the main explanatory variable. The marginal effect, defined in Eq. (6), is the percentage change of the market share for a movie due induced by one pollution day. Columns (2) and (5) use continuous measure of API as the main explanatory variable. The marginal effect, defined in Eq. (7), is the percentage change in movie market share due to a 100 points increase in API. Columns (3) and (6) use the reciprocal of visibility as the main explanatory variable. Standard errors in parentheses are clustered at the movie level. The standard errors for the marginal effects are calculated using the Delta method. ***, **, and * denote 1%, 5%, and 10% significance level.

We run the main regression to measure the effect of air pollution on movie theater admissions. The baseline results, following Eq. (4) that regresses the ratio of market shares on air pollution and a set of other control variables, are presented in the first two columns in Table 2. Column (1) shows the result when the binary API measure is used, i.e., whether daily API is above 100. The estimated coefficient suggests that air pollution leads to a statistically significant decrease in the market share of the movie on show. The estimate of the average marginal effect of API on movie market share is about −0.0226, significant at the 1% level. This estimate implies that one pollution day (API > 100) reduces the market share of a movie by 2.26%, other things being equal.

Column (2) in Table 2 presents the result of using continuous API scores as an independent variable. Dividing API scores by 100, the estimated coefficient is shown as the percentage change in the ratio of market shares of a movie when API changes by 100 points.[11] The result corroborates the previous conclusion that pollution reduces movie theater admissions. The average marginal effect of API on movie market share is about −0.0242, significant at the 1% level. This estimate suggests that a 100-point increase in API leads to a 2.42% decline in a movie's market share.

Besides official air quality reports, individuals also resort to ancillary information to make decisions on pollution avoidance. A frequently used proxy is visibility, which is negatively correlated with air pollution as particulate matter and gaseous pollutants can impair visibility. Visibility and air pollution have an inverse correlation, so we include the reciprocal of visibility in the regression. In column (3) of Table 2, visibility is used as the main explanatory variable in the regression. The estimate is negative, suggesting that people reduce movie theater visits as visibility declines. However, the estimate is less significant since visibility is a noisy proxy for air quality.

We also test the alternative specification in Eq. (5) that regresses the log of the number of audiences on air pollution and a set of other control variables. The results are presented in columns (4)–(6) in Table 2. Similarly, column (4) shows that one pollution day reduces the audience by 2.75%; column (5) suggests that a 100-point increase in the air pollution index reduces the audience by 2.79%. Both results are statistically significant at the 1% level. Column (6) confirms that increasing visibility, a proxy for better air quality, will improve box-office performance. All these results support our main conclusions.

4.2. Potential channels

We explore plausible mechanisms that help to explain our finding that moviegoers avoid polluted days. We first show that transportation to the theater is a plausible channel through which pollution reduces movie attendance. People would not go to the theater to avoid being exposed to ambient pollution during transportation to the theater no matter by walking, driving, or public transit. To test this, we examine if transportation time amplifies the pollution effect. We use the proportion of households living

[11] A 100-point increase in API is not an unusual change in China during 2012–2014, which is about the average change of API from non-polluted days to polluted days. The mean API for non-polluted days is 64.54, while that for polluted days is 156.26.

Table 3
Potential channels through which air pollution reduces movie attendance.

Variable	(1)	(2)	(3)
$I(\text{API} > 100)$	−0.1295***	−0.1500***	0.1117***
	(0.0212)	(0.0280)	(0.0314)
$I(\text{API} > 100) \times \%(1\ \text{km radius})$	0.4477***		
	(0.0865)		
$I(\text{API} > 100) \times \%(2\ \text{km radius})$		0.2867***	
		(0.0628)	
$I(\text{API} > 100) \times \%(\text{Mall w/theater})$			−0.4000***
			(0.0893)
Weather variables	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Movie FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Time trends	Yes	Yes	Yes
N	426,757	426,757	426,757
R^2	0.738	0.738	0.738

Notes: The dependent variable is the log of the ratio of market share of movie j in city c at time t to the outside good: $\ln(s_{jct}/s_{0ct})$. All estimations include weather variables (temperature, temperature^2, precipitation, wind speed, dew point, and dew point^2), movie specific linear and quadratic time trends, and dummies of city, movie, and day. The variables %(1 km radius) and %(2 km radius) designate the proportions of households within 1 and 2 km of in-mall movie theaters. The variable %(Mall w/theater) designates the proportion of malls with theater. Standard errors in parentheses are clustered at the movie level. ***, **, and * denote 1%, 5%, and 10% significance level.

within 1 km of movie theaters, denoted by %(1 km radius), as a proxy for transportation time. The estimation result is presented in columns (1) of Table 3. The estimated coefficient for the interaction term is positive, statistically significant at the 95% level. It suggests that cities with more households living close to movie theaters tend to have a less negative pollution effect on movie attendance. Furthermore, if we increase the radius to 2 km, %(2 km radius), the magnitude of the estimate becomes smaller. The result suggests that pollution has a more negative effect on movie attendance as the population distributes farther away from the theater.

In addition, we test if other entertainment activities such as shopping and dining affect pollution avoidance. We use the proportion of shopping malls in a specific city that has a movie theater, denoted %(Mall w/theater), as a proxy for mixed entertainment. In column (3) of Table 3, the estimated coefficient for the interaction term is negative and statistically significant. This suggests that as the proportion of malls with a theater increases, the avoidance response to a pollution day also increases. The result implies that mixed entertainment amplifies the pollution effect on movie attendance.

It is worth noting that although many movie theaters in China have installed air purifiers, pollution in the theater is still dependent on ambient pollution because air pollutants such as $PM_{2.5}$ do penetrate indoors (Cyrys et al., 2004). Using the field data collected from a movie theater, we find that the filtered air quality in the theater varies with ambient pollution, although its pollution level is lower, which suggests that moviegoers can still be exposed to indoor air pollution (see Section A.1 in the Online Appendix). Nevertheless, pollution in the theater is unlikely a channel to discourage moviegoers from visiting a theater; air quality at home may still be better than that in the theater.

4.3. Movie quality

The forgone utility of a movie theater visit is the opportunity cost of pollution avoidance. For high-quality movies, moviegoers are less likely to give up movie theater visits for the given level of air pollution. To examine how movie quality affects pollution avoidance, we use viewer ratings to measure movie quality. Specifically, we use the scores provided by Douban, China's IMDB, which rates every movie premiered on a 10-point scale, higher scores for better movies. We divide all movies into three groups by their Douban scores. The "good movies" are defined as those with the top quartile of viewer ratings, and the "bad movies" have the bottom quartile of ratings. Alternatively, we also use movie popularity, measured by aggregate audience size, as a proxy for quality. Both measures are defined on movies premiered in the same calendar year.

The regression results, summarized in Table 4, suggest that the baseline result is mainly driven by the least popular movies; the demand for high-quality movies is inelastic to air pollution. In column (1) of panel A, it shows that air pollution has a statistically insignificant effect on the box performance of good movies. As movie quality declines, the bad movies are negatively affected by air pollution, as is shown in column (3). The results that use the total audience as a proxy for movie quality, reported in panel B, are consistent with the previous conclusion.

4.4. Nonlinear responses

Individuals respond to air pollution nonlinearly. The worst pollution episodes, or the so-called airpocalypse, induce most pollution avoidance behavior (Zhang and Mu, 2018). To investigate moviegoers' nonlinear responses to air pollution, we divide air pollution

Table 4
The effect of air pollution on movie theater admissions by movie quality.

Sample	(1) Top 25%	(2) Middle 50%	(3) Bottom 25%
	Panel A: Douban rating		
$I(\text{API} > 100)$	−0.0178	−0.0146	−0.0420**
	(0.0138)	(0.0099)	(0.0169)
N	104,227	211,858	104,505
R^2	0.806	0.750	0.659
	Panel B: Movie attendance		
$I(\text{API} > 100)$	−0.0068	−0.0289**	−0.1186***
	(0.0092)	(0.0119)	(0.0339)
Weather variables	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Movie FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Movie-city time trends	Yes	Yes	Yes
N	224,224	179,144	23,328
R^2	0.786	0.600	0.381

Notes: The dependent variable is the log of the ratio of market share of movie j in city c at time t to the outside good: $\ln(s_{jct}/s_{0ct})$. All estimations include weather variables (temperature, temperature^2, precipitation, wind speed, dew point, and dew point^2), movie specific linear and quadratic time trends, and dummies of city, movie, and day. All columns use binary pollution index of whether API > 100 as the main explanatory variable. In panel A, movie quality is measured by Douban ratings. In panel B, movie quality is measured by box-office performances. Columns (1) presents results of the top quartile, columns (2) presents results of the middle 50%, and columns (3) presents results of the bottom quartile. Standard errors in parentheses are clustered at the movie level. ***, **, and * denote 1%, 5%, and 10% significance level.

Table 5
Nonlinear effects of air pollution on movie attendance.

Sample		Douban rating		
	(1) Whole	(2) Top 25%	(3) Middle 50%	(4) Bottom 25%
$I(\text{API} \in [101, 200])$	−0.0205***	−0.0175	−0.0134	−0.0379**
	(0.0074)	(0.0138)	(0.0098)	(0.0167)
$I(\text{API} \in [201, 300])$	−0.0446***	−0.0015	−0.0231	−0.0691*
	(0.0158)	(0.0275)	(0.0206)	(0.0359)
$I(\text{API} \in [301, 500])$	−0.0584**	−0.1031**	−0.0280	−0.1197*
	(0.0271)	(0.0449)	(0.0361)	(0.0670)
Weather variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Movie FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Time trends	Yes	Yes	Yes	Yes
N	426,757	104,227	211,858	104,505
R^2	0.738	0.807	0.750	0.659

Notes: The dependent variable is the log of the ratio of market share of movie j in city c at time t to the outside good: $\ln(s_{jct}/s_{0ct})$. All estimations include weather variables (temperature, temperature^2, precipitation, wind speed, dew point, and dew point^2), movie specific linear and quadratic time trends, and dummies of city, movie, and day. The main explanatory variables are dummies of three different pollution levels. The reference group is API ≤ 100. Movie quality is measured by Douban ratings. Columns (2)–(4) present results of the top quartile, middle 50%, and bottom quartile. Standard errors in parentheses are clustered at the movie level. ***, **, and * denote 1%, 5%, and 10% significance level.

days into four groups: "blue sky" (API ≤ 100), slightly polluted (100 < API ≤ 200), polluted (200 < API ≤ 300), and heavily polluted (API > 300). "Blue sky" is used as the reference group.[12] These categories correspond to the official levels of air pollution alerts issued by the Chinese government. This specification allows us to identify the nonlinear effect of air pollution. The estimation results are shown in Table 5.

Column (1) reports the estimates for the whole sample. The coefficients are negative and statistically significant at all levels of pollution. In addition, the coefficients grow larger when pollution becomes more severe. It corroborates the conjecture that moviegoers are more likely to forgo a movie theater visit as air quality deteriorates. The good movies, with Douban ratings in the

[12] In our sample of 426,757 observations, 110,670, or 25.93%, are considered "polluted" with API greater than 100. Among them, 91,075, or 21.34%, are slightly polluted (100 < API ≤ 200); 15,291, or 3.58%, are polluted (200 < API ≤ 300); and 4304, or 1.01%, are heavily polluted (API > 300).

top quartile in column (2), become sensitive during the worst pollution days. The bad movies, bottom 25% in terms of Douban ratings in column (4), are negatively affected by all pollution levels, while movie theater admissions are decreased more during heavy pollution days.

In the Online Appendix, we present additional analyses examining moviegoers' heterogeneous responses to air pollution. The heterogeneity analyses include spatial heterogeneity such as northern versus southern cities (A.2), nonlinear effect by cities (A.3), movie decay effect since the interest of audience decays overtime (A.4 and A.5), movie types in their sources/origins and languages (A.6), and holiday and weekend effect (A.7). In general, results from these additional analyses support the main finding of pollution avoidance in the movie theater market in China.

4.5. Robustness checks

We conduct a series of sensitivity analyses to check the robustness of the results (see Section A.8 in the Online Appendix). First, the credibility of air pollution data in China is a major concern (Ghanem and Zhang, 2014; Ghanem et al., 2020). Although data quality has improved dramatically since 2013, thanks to the reform of the environmental monitoring and information reporting system, we still conduct a robustness check to rule out the concern of data quality. Since Chinese cities were involved in threshold manipulation when the pollution index is around 100, we run the regressions in Table 2 for a sub-sample that excludes the observations with API between 95 and 105. The results in Table A10 are close to the baseline estimates. It suggests that data quality is not a concern.

Second, individuals may plan ahead for movies. Although the lead time for planning a movie is limited, consumers might use the pollution information on the day of purchase instead of the day of the show. To test this effect, we include lagged air pollution information for up to three days in the baseline model. The results in Table A11 suggest that air pollution has a one or two-day lagged effect, but the magnitude of the contemporaneous effect is quite robust for the preferred specification, although the total effect becomes slightly higher.

Third, we differentiate API and AQI. Chinese cities started switching from API to AQI in 2013. Adopting the empirical strategy similar to Barwick et al. (2019) and Wang and Zhang (2021), we create a dummy variable, at the city level, that equals 1 for the cities disclosing AQI after 2013 and 0 otherwise. This dummy variable is then interacted with the pollution dummy, and the results are reported in column (1) of Table A12. The negative and statistically significant coefficient for the interaction term, $I(\text{API} > 100) \times I(\text{Year} \geq 2013)$, suggests that information disclosure stimulates more pollution avoidance, which is consistent with the literature.

Finally, we generate pseudo API scores for the cities that switched to AQI after 2013. API is the maximum pollution index of three criteria pollutants (i.e., SO_2, NO_2, and PM_{10}). The API before 2013 was reported by the government; after 2013, we constructed pseudo API from original daily average pollutant concentrations. In column (2) of Table A12, we re-run the baseline regression using API for the non-switchers and pseudo API for the switchers. The main conclusion still holds.

5. Policy implications

Our analysis has several policy implications. First, we reinforce the revealed-preference evidence that individuals take costly actions to avoid their exposure to harmful air pollutants. Some might expect the movie theater market, primarily for young adults in the indoor environment, may be insensitive to air pollution. One might even argue that air pollution could increase movie theater visits because other outdoor entertainment activities become less attractive. We find that the opposite is true: air pollution unambiguously reduces movie theater admissions in Chinese cities. Since many popular movies are released in winter, the most polluted season in a year, reducing air pollution during these periods can mitigate the welfare cost associated with adjusting the preferred allocation of time. In addition, without accounting for the cost of the avoidance behavior, it is likely to underestimate the cost of environmental pollution.

Second, we quantify the economic impact of pollution on a sector using nationwide data. The existing literature has demonstrated that air pollution affects labor supply by reducing individual's work hours and labor productivity and hence adversely impacts the income (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Chang et al., 2016, 2019). Our analysis suggests that air pollution shrinks the demand for a service sector as people forgo activities with exposure risks. Our back-of-the-envelope calculation shows that air pollution could reduce movie theater visits by about 5 million for the three years in our dataset,[13] or a loss of movie theater revenues by about 69.2 million USD.[14]

[13] We use the following formula to calculate the loss in the audience in a city in a given year:

$$\frac{\text{Days with pollution}}{365} \times (\text{Annual total audience}) \times \left(\frac{1}{1-.0226} - 1\right),$$

where the last term is approximately .0231. For example, Beijing had 193 polluted days in 2014 and a total of just over 36 million viewers in our data. As a result, loss in audience in Beijing in 2014 can be calculated by $(193/365) \times 36{,}000{,}000 \times .0231 \approx 440{,}000$. We implemented this calculation for all cities in our sample for the three-year period, and the aggregated total is about 5 million.

[14] Assuming average ticket price at 60 RMB and concession sales about half of the ticket price. Exchange rate 6.5RMB = 1USD.

The theatrical market is a small but fast growing sector in China.[15] The economic impact of movie theater goes beyond movie ticket sales. Movie theaters profit not only from admissions from film exhibitions but also from concession sales.[16] In addition, visiting a movie theater will create a spillover effect on other service sectors such as restaurants, bars, and shopping malls. These sectors are likely to follow a similar pattern under air pollution (Liu et al., 2021). For the illustration purpose, we further apply the environmental consumption effect estimated in the movie theater market to the dining and tourism industries, which share many common characteristics with the theatrical market. We estimate that air pollution could cause a loss in the dining industry by about 1.6 billion USD while 9.4 billion USD for the domestic tourism industry in 2012–2014.[17]

Third, reducing environmental pollution can improve urban quality of life and then boost urban consumption. Cities play a vital role in the Chinese economy. The ten largest cities in China contributed to about a quarter of the national GDP in 2018. These Chinese cities used to be the centers of manufacturing. With income growth and industrial transformation, consumption has emerged as an increasingly important factor for the success of these cities. Economists argue that the quality of life is an instrumental determinant of the attractiveness of cities and the willingness of urbanites to spend money (Glaeser et al., 2001). In particular, as environmental quality deteriorates, people become reluctant to go out for consumption, which diminishes the benefit of high urban density. Therefore, improving urban environmental quality is aligned with China's incentive to further grow its urban economy.

6. Conclusion

In this paper, we provide new evidence of air pollution avoidance behavior in the movie theater market in China. Taking advantage of a unique dataset that includes daily ticket sales at the movie- and city-level, our analysis shows unambiguous evidence that air pollution lowers movie theater admissions. We find that one pollution day reduces the market share of a movie by 2.26%, other things being equal. This result is robust to numerous alternative assumptions, specifications, and sub-sample analyses. Notably, the avoidance behavior hinges on movie quality and pollution severity. The box office performance of blockbuster movies is much less affected by pollution alerts than that of less popular ones. However, even the most popular movies suffer from significant box office losses during the worst pollution days or the so-called airpocalypse. To the best of our knowledge, we are among the first to measure the impact of air pollution on consumption in a service sector, especially in the context of China.

Several issues remain. First, using ambient air pollution as a proxy for pollution exposure introduces measurement errors in the case of a combination of both indoor and outdoor activities. Second, environmental pollution can induce a substitution effect. For example, potential moviegoers can turn to online streaming services, paid or pirated during a pollution day. We cannot measure the overall economic impact of substituting local consumption, such as movie theater visits with online services. Last but not least, the reduced-form approach can only identify the combined effect of air pollution on movie attendance, which may lump in illness effect and avoidance effect. Those who fall ill to air pollution may not go to the movie theater. All these will be left for future studies.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2022.102626.

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[15] To put it in context, the total movie ticket sales in China reached 9.3 billion USD in 2019, compared to 11.4 billion USD in the North American market (Motion Picture Association, 2020).

[16] In the US market, the revenue from food and beverage sales is more than half of the revenue from ticket sales. Source: US Census Bureau, 2019. Annual Services Report.

[17] According to data from the National Bureau of Statistics of China, the three-year total revenue from the dining industry is 1356.8 billion RMB, while total expenditure of domestic tourism is 7929.4 billion RMB. Also, based on our data, about 1/3 of city-day observations had a polluted day in these three years. As a result, we calculated that the loss in the dining industry is $(1,356.8 \times .0231)/3 \approx 10.45$, while that of the domestic tourism is $(7,929.4 \times .0231)/3 \approx 61.06$. Exchange rate 6.5RMB = 1USD.

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