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### Article

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## Article

# The Role of Air Pollution in Shaping Urban Cultural Consumption: An Empirical Investigation of PM<sub>10</sub> and Movie Consumption in Chinese Cities

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## Abstract

This study investigates the nonlinear effects of air pollution on urban entertainment consumption by analyzing daily PM<sub>10</sub> levels and movie box office data across 334 Chinese cities from 2012 to 2022, resulting in a total of 1,250,339 observations. Utilizing a two-way fixed effects model and threshold regression framework, we identify three key findings: (1) elevated PM<sub>10</sub> concentrations significantly reduce movie attendance, with a 1-unit increase decreasing consumption by 0.0797 units; (2) the inhibitory effect intensifies during weekends and holidays, reflecting heightened sensitivity to pollution during leisure periods; (3) threshold effects emerge, where PM<sub>10</sub> exceeding 0.0229  $\mu\text{g}/\text{m}^3$  triggers a sharp decline in attendance, while temperature moderates this relationship, amplifying pollution's negative impact. By integrating meteorological, environmental, and socioeconomic datasets, this research reveals substitution patterns between digital and offline entertainment under pollution stress. The results underscore the necessity for region-specific pollution mitigation strategies, cinema infrastructure upgrades, and dynamic pricing policies to counteract environmental disruptions. These insights advance the interdisciplinary nexus of environmental economics and cultural consumption, offering actionable pathways for sustainable urban development.



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## 1. Introduction and Literature Review

Increasing globalization and urbanization have resulted in declining air quality, which has become a major global environmental challenge. [Andrei et al. \(2024\)](#) and [Yan et al. \(2019\)](#) found that urban air pollution not only poses threats to ecosystems and human health but also has far-reaching impacts on economic activities and social behavior.

The impact of air quality on human health is significant and multifaceted, encompassing both acute and chronic conditions. Atmospheric pollutants such as PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>2</sub>, CO, and O<sub>3</sub> have been linked to various health problems, including cardiovascular disease, respiratory disease, stroke, and lung cancer ([Mannucci et al., 2015](#); [Maung et al., 2022](#); [Zhong et al., 2019](#)). For instance, [Yang et al. \(2020\)](#) found that PM<sub>2.5</sub> pollution is associated with about 20% of lung cancer cases, and long-term exposure to high concentrations of PM<sub>2.5</sub> may reduce life expectancy.

Beyond health effects, air quality also influences people's daily behavior. [G. Zhang et al. \(2021\)](#) demonstrated that individuals' efforts to avoid air pollution can constrain their

consumption and spending patterns. [X. Lu et al. \(2019\)](#) analyzed the relationship between PM<sub>2.5</sub> pollution and health problems caused by urban and rural residents' consumption in China, revealing an intrinsic association between consumption behaviors and air pollution-induced health issues.

Cultural consumption is another domain significantly affected by air quality. The organization and participation in cultural events often rely on favorable air quality conditions. For example, areas with high levels of air pollution. For example, [Robaina et al. \(2020\)](#) found that Beijing has experienced substantial declines in cultural activity participation during peak pollution periods. Furthermore, research has highlighted the substantial impact of air quality and climate change on the movie industry. [Jin and Shen \(2022\)](#) found that climate conditions, particularly heatwaves, can lead to reduced movie attendance. They also noted that air quality has varying effects on different types of films. For example, high-quality or action-oriented movies are less susceptible to temperature changes due to their unique viewing experiences. [X. He et al. \(2022\)](#) analyzed movie attendance data from 60 Chinese cities between 2012 and 2014, revealing a negative correlation between pollution levels and movie attendance. [Xi et al. \(2023\)](#), using high-frequency movie attendance data from 49 major Chinese cities between 2015 and 2017, found that extreme temperatures and heavy rainfall can reduce movie attendance.

In addition to movie consumption, air pollution has been found to influence digital entertainment consumption patterns. For example, [Shu \(2024\)](#) examined how internet technology, particularly streaming platforms, has expanded people's entertainment options, allowing them to access movies and games on their mobile devices. This shift reduces the impact of environmental factors such as air quality on offline movie consumption. When air quality is poor, consumers tend to fulfill their cultural and entertainment needs through virtual experiences, which may increase the usage of streaming platforms ([Shu, 2024](#)).

In summary, existing studies have thoroughly documented the multifaceted pathways through which urban air pollution shapes human well-being and market outcomes. At the health margin, a robust body of work links PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>2</sub>, CO, and O<sub>3</sub> exposures to both acute and chronic conditions—ranging from cardiovascular and respiratory diseases to stroke and lung cancer ([Mannucci et al., 2015](#); [Maung et al., 2022](#); [Zhong et al., 2019](#)). At the behavioral margin, evidence shows that individuals adjust consumption and leisure patterns to avoid polluted environments, constraining both offline spending ([G. Zhang et al., 2021](#); [X. Lu et al., 2019](#)) and participation in cultural events ([Robaina et al., 2020](#)), while shifting toward digital alternatives such as streaming platforms ([Shu, 2024](#)). In the entertainment sector, studies of China's film industry reveal that pollution and weather shocks exert heterogeneous effects across movie-attendance distributions and film genres ([X. He et al., 2022](#); [Xi et al., 2023](#); [Jin & Shen, 2022](#)).

Despite these advances, three critical gaps remain. First, most analyses focus on average effects and overlook how pollution's impact varies across cities with different baseline box-office performance. Second, causal identification often relies on long-term panel or cross-sectional variation, leaving short-term endogeneity unaddressed. Third, the potential for nonlinear or threshold responses—beyond simple linear specifications—has not been systematically explored in a high-frequency, multi-city context.

To address these gaps, this study poses the following research question: how does air pollution—specifically PM<sub>10</sub>—affect movie attendance, and does this effect exhibit a nonlinear threshold? Additionally, how do temperature and the availability of digital streaming platforms (e.g., Netflix) moderate or substitute for offline movie consumption under varying pollution conditions?

This study makes four key contributions. First, by applying threshold regression to a high-frequency panel of 334 Chinese cities from 2012 to 2022, it reveals a nonlinear

threshold effect: once  $PM_{10}$  concentrations exceed  $0.0229 \mu g/m^3$ , their inhibitory impact on movie attendance intensifies sharply, challenging the conventional linear view. Second, we document the moderating role of temperature, showing that high heat amplifies  $PM_{10}$ 's negative effect on cinema-going, thereby integrating meteorological stressors into environmental-economics analysis. Third, we compile a novel multi-source dataset—merging daily  $PM_{10}$  readings, meteorological variables, nighttime light indices, and box-office revenues—overcoming prior spatial and temporal limitations and providing a methodological blueprint for future environmental-behavior research. Fourth, we derive differentiated policy recommendations based on spatial and temporal heterogeneity, including region-specific film-industry support, air-quality warning systems for winter and holiday peaks, cinema air-purifier mandates, and ticket subsidies to encourage offline attendance despite digital-platform substitution. Together, these contributions advance theoretical understanding and offer actionable insights for sustainable urban development and cultural policy in the face of worsening air quality.

## 2. Theoretical Analysis and Research Hypotheses

### 2.1. Linear Effect of Air Quality on Movie Attendance

[Fang et al. \(2021\)](#), using the stimulus–organism–response (S-O-R) framework, found that air pollution, as an exogenous stimulus, affects consumers' internal states (organism), such as their emotional and cognitive perceptions, which, in turn, leads to different behavioral responses. Under poor air quality, individuals experience heightened risk perception, feeling that their health and safety needs are threatened. Consequently, they develop a negative attitude toward leaving home and reduce discretionary activities like going to the cinema ([X. Zhang et al., 2017](#)). In this context, the Theory of Planned Behavior ([J. Li & Han, 2025](#)) suggests that when perceived environmental risk increases, subjective norms and perceived behavioral control shift, leading to lower intention and actual attendance at movie theaters.

Short-term air pollution can prompt people to go out less and instead focus their recreational activities and spending within the home, guided by a substitution effect from Consumer Choice Theory ([Ren et al., 2024](#)): they choose safer, private alternatives over public venues. Long-term air pollution further triggers protective actions (e.g., purchasing masks) and reduces expenditure on entertainment ([X. Zhang et al., 2017](#)). After initial consumption decisions have been made, individuals evaluate alternative consumption possibilities, such as streaming services, thereby influencing final consumption.

When the air pollution index exceeds a specific threshold, the perceived severity and susceptibility become so high that people choose to stay home, reducing movie attendance. In addition, deteriorating air quality can affect people's health status, increasing anxiety and vulnerability, which further decreases willingness to visit public places, including cinemas. Furthermore, the development of the Internet and digital media has significantly expanded the range of entertainment options available ([Shu, 2024](#); [Lee, 2016](#)). Under the substitution mechanism of Behavioral Economics, consumers readily access movies and games on their mobile devices when outdoor conditions deteriorate, thereby reducing the impact of environmental factors, such as air quality, on offline movie consumption behavior. Today, especially when air quality is poor, consumers are more inclined to fulfill their cultural and entertainment needs through virtual experiences. Thus, we propose the following hypothesis:

**H1.** *Deteriorating air quality reduces people's movie attendance.*

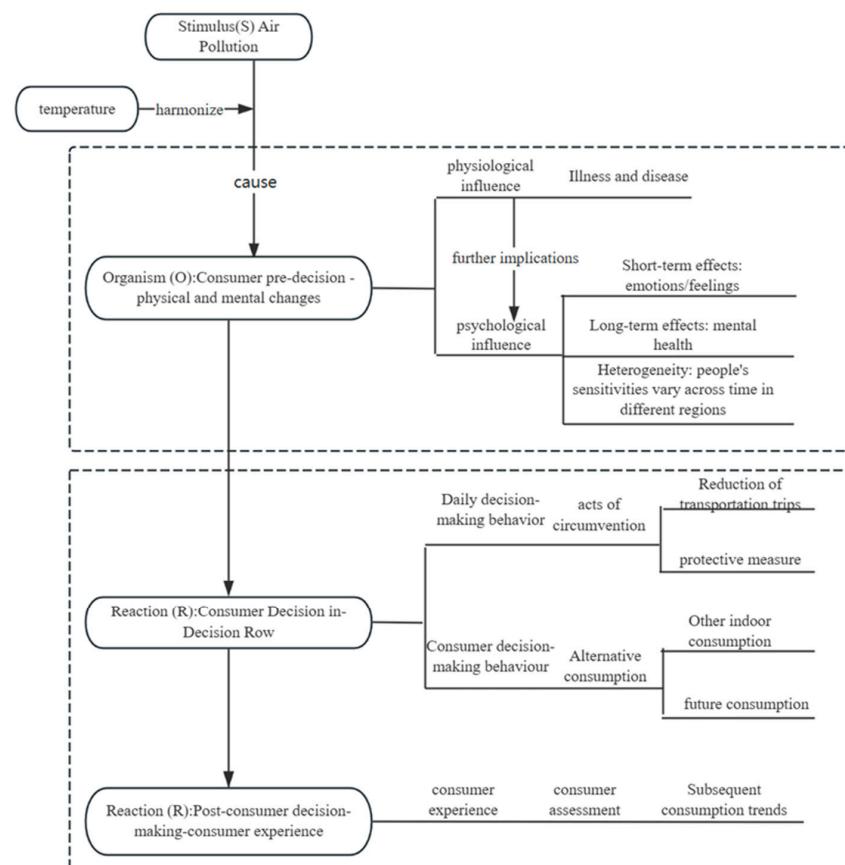
### 2.2. Moderating Role of Temperature

According to expected utility theory ([Q. He, 2024](#)), when making decisions, individuals aim to maximize positive utility (such as happiness or economic benefits) and minimize

negative utility (such as pain or economic losses). In the context of movie consumption, people weigh the pros and cons of going out to a theatre versus staying home. If both temperature and air quality are favorable, the expected emotional utility of the cinema experience (social enjoyment, escapism) outweighs the monetary cost of a ticket and the opportunity cost of staying home, leading individuals to choose to go out for entertainment. Conversely, if conditions are unfavorable, anticipated disutility (health risks, discomfort) outweighs the benefits, and they reduce movie attendance.

Temperature plays a critical role in determining thermal comfort—a concept from environmental psychology—which directly influences the positive utility derived from outdoor activities. Under optimal thermal comfort, people perceive higher well-being when leaving home, reinforcing the decision to attend a movie.

However, at lower temperatures, two processes unfold. First, cold weather is typically associated with a more stable atmospheric boundary layer and weaker wind speeds (Mahrt, 2010), which fits within the atmospheric physics theory of pollutant dispersion: lower wind speeds and a stable boundary layer hinder the dispersion of pollutants, causing them to accumulate locally (Samad et al., 2023). Second, during cold seasons, people use heating systems that rely on coal, natural gas, or other fuels; the combustion process releases secondary pollutants such as nitrogen oxides and sulfur dioxide (Xiao et al., 2015; Fan et al., 2020). Combining these two factors, environmental economics theory suggests that in colder weather, ambient air quality deteriorates more severely, increasing the perceived health risk and protective behavior—a concept drawn from Protection Motivation Theory—where individuals adopt behaviors to reduce exposure to threats. Therefore, people may choose to limit outdoor activities, including moviegoing, to avoid adverse health effects. The impact mechanism is illustrated in Figure 1. Based on this, the paper proposes the following hypothesis:



**Figure 1.** Influence mechanism.

**H2.** *High temperatures amplify the negative impact of poor air quality on people's movie theatre attendance.*

### 2.3. Threshold Effect of Air Quality on Movie Attendance

According to Expected Utility Theory (J. Zheng & Zhao, 2023), when air quality reaches a mild pollution level, people will feel slight discomfort, but this usually does not completely prevent them from going to the cinema. Under bounded rationality, individuals make satisficing choices: most still opt to go out, weighing the perceived benefits of social and emotional utility against the cost of mild discomfort. However, at this stage, according to environmental psychology (H. Shen et al., 2025), consumers may experience physical unease, such as breathing difficulties and dry eyes, which can generate a negative affective state. According to Cognitive Appraisal Theory (Y. Zhu & Wu, 2023), individuals assess coping options and may view the cinema as a relatively safe, indoor refuge. In this context, the cinema's social and hedonic value (behavioral economics) slightly outweighs the discomfort, resulting in a modest increase in attendance; yet, the overall impact remains statistically insignificant.

As pollution intensifies and enters a severe stage, the perceived severity and preventive appraisal become dominant: health risks—especially to respiratory and cardiovascular systems—significantly increase. Under Risk Homeostasis Theory (Y. Zhang & Cai, 2024), individuals adjust their behavior to maintain acceptable risk levels, leading to a sharp drop in willingness to go out. According to the Theory of Planned Behavior (J. Li & Han, 2025), elevated pollution diminishes perceived behavioral control and shifts subjective norms toward avoidance of public spaces. At this point, cinemas—once regarded as a temporary refuge—lose their appeal, and movie attendance declines markedly. Therefore, further deterioration in air quality results in a significant reduction in cinema consumption. Based on this, we propose the hypothesis:

**H3.** *There is a threshold effect of air quality on movie attendance.*

## 3. Data and Modelling

### 3.1. Variables

#### 3.1.1. Explanatory Variable

Air pollution ( $PM_{10}$ ). This study uses  $PM_{10}$  as the primary indicator of air quality. The main reason is that  $PM_{10}$  particles are larger and more visible to the human eye, making them more intuitively perceivable. In contrast,  $PM_{2.5}$  is less visible, and AQI, as a composite index, is not directly felt in real-time by individuals. Since going to the cinema is typically an impulsive, short-term consumption behavior, people are more likely to be influenced by environmental conditions they can directly observe at the moment of decision-making. Therefore,  $PM_{10}$  is better suited to capture the perceived air quality that affects consumer behavior in this context. Therefore, in this study, the daily average  $PM_{10}$  concentration of a certain prefecture-level city is used to measure the air quality of that city on a given day. We collected daily  $PM_{10}$  data from 2012 to 2022 for 334 cities above the prefecture level from the high-resolution, high-quality near-surface air pollutant dataset published by Dr. Wei Jing and Professor Li Zhanqing's team on the National Qinghai-Tibet Plateau Scientific Data Center website. The data are in units of  $\mu g/m^3$ . We then matched the  $PM_{10}$  data for each city with corresponding cinema consumption data, meteorological data, and socio-economic data to conduct the next phase of analysis.

### 3.1.2. Dependent Variable

The dependent variable was movie consumption. Drawing on the study of [Xi et al. \(2023\)](#), we obtained daily movie box office receipts for China's 334 prefecture-level and above cities from 2012 to 2022 from the Yien database (currently the most professional and authoritative database of film and television entertainment in China) and used these to represent movie attendance.

### 3.1.3. Control Variables

This paper utilizes daily minimum and maximum temperatures, daily average wind speeds, and daily precipitation data from 334 cities above the prefecture level across China from 2012 to 2022 as control variables for meteorological factors. Meteorological factors significantly influence people's travel behavior. When the temperature is too high or too low, wind speed is too fast, or precipitation increases, people's travel tends to decrease, which, in turn, affects movie consumption. Therefore, this paper obtains daily precipitation raster data for the entire country from Dr. Wei Jing and Professor Li Zhanqing's team, which was published on the National Tibetan Plateau Science Data Center website. The resolution is  $1^{\circ}$ , and the data are converted into Excel format using ArcGIS, with units in millimeters (mm). Additionally, daily wind speed and temperature data from global stations between 2012 and 2022 were obtained from the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA) in the United States. The daily temperature data from all meteorological observation stations for each year (2012–2022) were processed and merged, extracting data from stations located within China. This resulted in daily minimum, maximum, and average temperature data for meteorological stations across China from 2012 to 2022. Furthermore, the wind speed data were converted from knots to kilometers per hour, yielding daily average wind speed data for meteorological stations across China from 2012 to 2022.

**Socioeconomic Control Variables.** This paper uses daily nighttime light data from 334 prefecture-level cities between 2012 and 2022 as a factor influencing people's movie consumption. Nighttime light data can, to some extent, measure the economic activity level of a city. The brighter the nighttime lights in a city, the more active the city is at night, which is associated with an increase in movie consumption. The nighttime light data come from NASA in the United States.

### 3.1.4. Instrumental Variable

Drawing on the study of [C. Shen et al. \(2024\)](#), we used the inverse temperature as an instrumental variable to address the endogeneity problem and to enable us to study the relationship between air quality and movie attendance. The level of air pollution influences economic activity. When air pollution is severe, people tend to reduce their outings in an effort to avoid health problems associated with exposure to polluted air, which in turn reduces economic activity. In the troposphere, under normal conditions, temperature decreases with increasing altitude. However, when the air near the ground cools more rapidly than the upper layers, resulting in the upper air being warmer than the air near the surface, an inversion occurs ([Feng et al., 2020](#)). The presence of an inversion layer hampers the upward movement of air, causing pollutants to remain in place and resulting in prolonged pollution. Because inversion phenomena affect local air quality but are unrelated to people's movie attendance, they can be used as an instrumental variable.

This paper downloads inversion data from NASA's MERRA-2 and extracts the near-surface data from the first, second, and third layers of the downloaded netCDF data. If the temperature of the second and third layers of air is higher than the temperature of the first layer on a given day, an inversion exists. In this paper, data from the first and second layers

are used. If the temperature of the second layer is higher than that of the first layer on a given day, the value is set to 1; otherwise, it is set to 0.

### 3.2. Data Sources

This paper selects 334 cities above the prefecture level as the research subjects. The movie box office data used in this study come from the EntGroup database (currently the most professional and authoritative film and entertainment database in China).  $PM_{10}$  and precipitation data are from the dataset published by Dr. Wei Jing's and Professor Li Zhanqing's team on the National Tibetan Plateau Science Data Center website. The temperature and wind speed data for the control variables come from the National Centers for Environmental Information (NCEI) under the National Oceanic and Atmospheric Administration (NOAA) in the United States. Nighttime light and inversion data are provided by NASA. In addition, to eliminate extreme values, the dependent, independent, and control variables are standardized using the Min–Max (MMX) normalization method. A detailed description of the data used in this paper is provided in Table 1.

**Table 1.** Results of descriptive statistics.

Variable	Description	Calculation Method	Mean	Std. D.	Min	Max
BO	Movie consumption	Standardized movie consumption	0.00454	0.0150	0	1
$PM_{10}$	Air quality	Standardized air quality	0.509	0.500	0	1
Rain	Precipitation	Standardized precipitation amount	0.139	0.0564	0	1
NI	Economic vitality	Standardized nighttime light brightness value	0.675	0.157	0	1
Htem	Max temperature	Standardized daily max temperature (°F)	0.708	0.157	0	1
Ltem	Min temperature	Standardized daily min temperature (°F)	0.0113	0.0299	0	1
Atem	Average temperature	Standardized daily average temperature (°F)	0.0410	0.0676	0	1
Wind	Wind speed	Standardized daily average wind speed	0.0280	0.0212	0	1
NW	Temperature inversion	=1 if a temperature inversion occurs	0.701	0.150	0	1

### 3.3. Model Construction

#### 3.3.1. Baseline Regression

To study the impact of air quality on residents' entertainment consumption, this paper selects 334 prefecture-level cities in China as the research subjects, using daily movie consumption data from 19 January 2012, to 31 December 2022, combined with daily  $PM_{10}$  data to form a panel dataset for the prefecture-level cities. An econometric model is constructed under the OLS framework as follows:

$$BO_{it} = \alpha_0 + \alpha_1 PM_{10, it} + \alpha_2 Control_{it} + \mu_t + \delta_i + \varepsilon_{it} \quad (1)$$

In the model,  $BO_{it}$  represents the movie consumption of city  $i$  on day  $t$ , and  $PM_{10, it}$  represents the  $PM_{10}$  concentration in city  $i$  on day  $t$ .  $Control$  refers to a set of control variables, which mainly include daily weather data and annual economic data at the prefecture-level city. The weather data include average temperature, precipitation, wind speed, etc., while the economic data include nighttime light data.  $\mu_t$  represents time-fixed effects, and  $\delta_i$  represents city-fixed effects. We performed the Huber–White test and found the  $p$ -value to be 0, indicating the presence of heteroscedasticity. To address issues of heteroscedasticity, cluster analysis is conducted at the prefecture-level city level to robustly estimate the standard errors in all models of this paper. We conducted the Wooldridge test and found evidence of autocorrelation in the model. Consequently, we introduced instrumental variables into the regression and observed that the results remained consistent with those of the baseline regression.

### 3.3.2. Instrumental Variable Regression

In this study, we used established research methodologies and, in an effort to address endogeneity issues, used a dummy variable for daily inversion at the prefecture level as an instrumental variable for air quality. If an inversion occurred on a given day, the variable was assigned a value of 1; otherwise, it was assigned a value of 0. The impact of air pollution on movie attendance was then identified using the two-stage least squares (2SLS) method. The regression model is as follows:

$$PM10_{it} = \gamma_0 + \gamma_1 NW_{it} + \gamma_2 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$BO_{it} = \theta_0 + \theta_1 \widehat{PM10}_{it} + \theta_2 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

In model (2), the first stage of the instrumental variable approach, the dependent variable is the daily  $PM_{10}$  concentration of city  $i$  on day  $t$ , which represents the air pollution level. The instrumental variable,  $NW_{it}$ , indicates whether an inversion phenomenon occurred in city  $i$  on day  $t$ . Model (3) represents the second stage regression, where the dependent variable is the movie consumption in city  $i$  on day  $t$ , and  $PM10_{it}$  is the corrected  $PM_{10}$  concentration for city  $i$  on day  $t$  from model (2). Additionally, a set of control variables,  $Control_{it}$ , is included, which is defined the same as in model (1).

In Model (2), the first stage of the instrumental variable method, the dependent variable is the  $PM_{10}$  concentration level in city  $i$  on day  $t$ . The instrumental variable  $NW_{it}$  indicates whether an inversion occurred in city  $i$  on day  $t$ . In Model (3), the second stage of the regression model, the dependent variable is movie attendance in city  $i$  on day  $t$ , and  $\widehat{PM10}_{it}$  is the  $PM_{10}$  concentration level in city  $i$  on day  $t$  as per Model (1).

### 3.3.3. Threshold Model

In this study, we used the following panel threshold model to investigate the potential non-linear relationship between air quality and movie attendance:

$$BO_{it} = \beta_0 + \beta_1 PM10_{it} \cdot I(q \leq \tau_1) + \beta_2 PM10_{it} \cdot I(\tau_1 < q \leq \tau_2) + \beta_3 PM10_{it} \cdot I(q > \tau_2) + \beta_4 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

where  $I(\cdot)$  denotes an indicator function that is allocated a value of 1 if the condition specified within the parentheses is satisfied, and 0 otherwise. Here,  $\tau$  signifies the threshold level and the other symbols are the same as outlined in relation to Model (1).

## 4. Empirical Analysis

### 4.1. Baseline Regression

#### 4.1.1. Analysis of Baseline Regression Results

Table 2(1) presents the baseline regression results without control variables and without time and city fixed effects. Table 2(2) shows the regression results without control variables but with the inclusion of time and city fixed effects and city clustering. Table 2(3)–(6) display the regression results after adding control variables step by step, following the clustering at the city level and controlling for time and city effects. Thus, the above results verify H1.

We find that the effect of  $PM_{10}$  on movie consumption is consistently significantly negative, indicating that air quality has a significant negative impact on movie consumption. First, air pollution negatively affects people's health, particularly harming the respiratory and cardiovascular systems. When pollution levels are high, many people may choose to stay indoors to avoid harmful substances in the air, thereby reducing outdoor activities. While this might encourage people to spend more time at home, poor air quality can

also affect people's mood and physical condition, leading to reduced interest in movie consumption. Specifically, when air quality deteriorates, people may be more inclined to engage in low-intensity activities such as resting, watching TV, or using their phones, rather than going to the cinema.

**Table 2.** Analysis of baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
pm10	−0.0195 *** (−30.8216)	−0.0024 ** (−2.4224)	−0.0023 ** (−2.3445)	−0.0025 ** (−2.5028)	−0.0025 ** (−2.4496)	−0.0024 ** (−2.4203)
wind			−0.0020 *** (−3.5726)	−0.0020 *** (−3.5622)	−0.0020 *** (−3.6391)	−0.0020 *** (−3.5926)
rain				−0.0007 (−1.4233))	−0.0007 (−1.3828)	−0.0007 (−1.4701)
ltem					−0.0001 (−0.2610)	−0.0000 (−0.0460)
hitem						−0.0001 (−0.1239)
nl						0.0106 ** (2.1999)
Observations	(229.1768) 1,250,399	(169.3620) 1,250,375	(66.8204) 1,250,375	(65.2152) 1,250,375	(16.4300) 1,250,375	1,250,375
Adjusted R-squared	0.0008	0.5688	0.5688	0.5688	0.5688	0.5688
City FE	No	Yes	Yes	Yes	Yes	Yes
Date FE	No	Yes	Yes	Yes	Yes	Yes

t-statistics clustered at the city level are shown in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ .

Second, travel becomes inconvenient during haze or smog (Congyin, 2015). Many people may choose to cancel or delay outdoor entertainment activities due to concerns about discomfort or traffic issues when going outside. Although the popularity of online streaming platforms offers an alternative in-home movie experience, poor air quality generally makes people more likely to stay home rather than go out to watch a movie. Furthermore, poor air quality can cause discomfort such as anxiety and fatigue, which can impact people's consumption behavior.

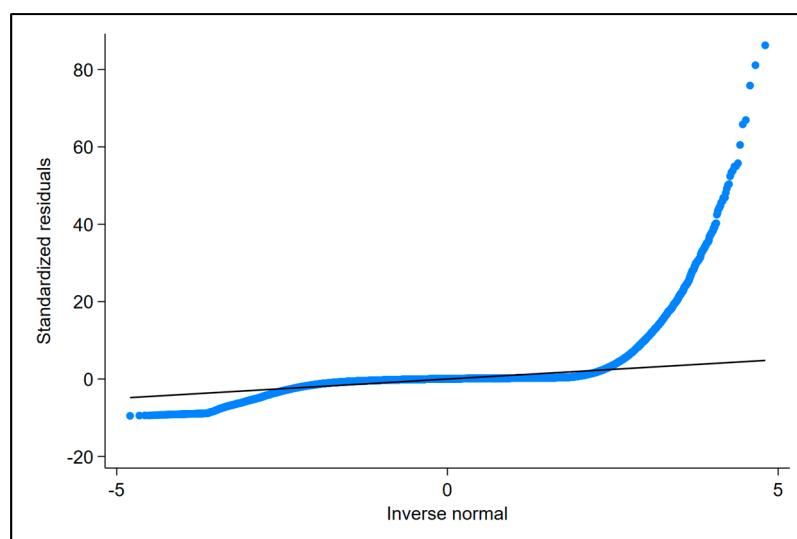
Third, psychological studies show that air pollution not only affects physical health but also has a negative impact on emotions and cognitive abilities. Polluted weather may cause feelings of oppression and unhappiness (J. Lu, 2020), which could lead people to be less willing to engage in leisure consumption, including watching movies.

Fourth, cities with severe air pollution are often associated with increased economic pressures and higher living costs. For example, pollution may force governments and businesses to increase energy consumption or implement clean-up measures, thereby raising living costs (Bisadi et al., 2018). In such cases, residents' disposable income might be redirected toward more health- and safety-related expenses (e.g., air purifiers, health check-ups, medical costs) rather than entertainment consumption, such as movie tickets or streaming subscriptions. Therefore, poor air quality leads to a reduction in movie consumption.

#### 4.1.2. Residual Analysis

Figure 2 presents the Q-Q plot of the standardized residuals from our OLS regression model. As shown, the residuals deviate markedly from the theoretical normal line at both tails: on the left, multiple observations fall below  $-10$  in standardized units, while on the right, some exceed  $+50$ . These large deviations indicate significant non-normality and the presence of extreme values in the residual distribution. Importantly, these outliers are not data errors but genuine reflections of the market environment. First, during the COVID-19 lockdowns, many cities experienced consecutive days of zero ticket revenue

because theaters were temporarily closed. Second, during major holidays such as Chinese New Year and National Day—especially in first-tier cities like Beijing, Shanghai, and Guangzhou—daily box office revenue can surge dramatically, creating extreme high values. Third, the film market inherently exhibits seasonal ups and downs (off-peak vs. peak seasons), and the consumption capacity and viewing habits differ greatly between large metropolises and smaller prefecture-level cities, further widening the gap between “normal” daily revenues and extreme spikes. Although these observations appear as statistical outliers in the residuals, they are economically meaningful and accurately capture real fluctuations. To mitigate the influence of these extreme residuals on our OLS estimates of the average effect, we complement the OLS analysis with a quantile regression framework. By estimating effects across multiple quantiles of the dependent-variable distribution, quantile regression reduces the bias introduced by very low or very high box office observations and provides a more robust assessment of how air quality influences box office revenue at different points of the distribution.



**Figure 2.** Q-Q plot of the standardized residuals. The black line in the figure represents the theoretical normal distribution. The blue line and dots represent the distribution of the actual residuals.

#### 4.2. Quantile Regression

The preceding estimation of the baseline model is based on mean regression, and the resulting coefficients reflect the average effect of air quality on movie consumption. However, if the distribution of box-office revenue is asymmetric, this average effect cannot fully capture how air quality influences movie consumption. In contrast, quantile regression is not affected by outliers in box-office data and does not impose strong assumptions on the error-term distribution. Therefore, drawing on the work of [Xiong et al. \(2025\)](#), this paper further employs quantile regression. We specify the following quantile regression model:

$$Q_q(BO_{it}|PM10_{it}) = \partial_{q0} + \partial_{q1}PM10_{it} + \partial_{q2}Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

In the above equation,  $q$  represents the quantile index. This paper conducts regressions at the 0.25, 0.5, and 0.75 quantiles. All other symbols have the same meaning as in Equation (1). The quantile regression results are shown in Table 3.

Columns (1) and (2) of Table 3 indicate that at the 0.25 and 0.50 quantiles, the coefficient on air quality is significantly negative, mirroring the negative average effect found in the baseline (mean) regression. In other words, for cities and days where the box-office revenue falls in the lower and median ranges, worse air quality is associated with a

statistically significant drop in movie attendance. However, at the 0.75 quantile, the estimated coefficient on air quality is not statistically significant. This suggests that on days or in cities with relatively high box-office revenue (the upper tail of the distribution), variations in air quality do not have a discernible impact on movie consumption.

**Table 3.** 2SLS Quantile regression results.

Variables	(1) Q(25)	(2) Q(50)	(3) Q(75)
pm10	−0.0003 * (−1.9287)	−0.0011 *** (−3.9262)	0.0016 (0.7791)
wind	−0.0000 (−0.3371)	0.0000 (0.1563)	−0.0002 (−1.2749)
rain	0.0001 ** (2.4258)	0.0000 (0.1719)	0.0003 (1.6389)
ltem	−0.0001 (−0.9876)	0.0001 (0.6199)	0.0009 * (1.7321)
hitem	0.0001 *** (3.0016)	0.0001 (1.0783)	0.0005 * (1.8679)
nl	0.0004 (0.8362)	−0.0001 (−0.1321)	−0.0036 (−1.3902)
Observations	1,250,399	1,250,399	1,250,399
Number of groups	334	334	334
City FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes

t-statistics in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

When box-office revenue is already high—often driven by blockbuster releases, major holidays, or strong local demand in large metropolitan areas—viewers may be less deterred by poor air quality. In such cases, the strong underlying demand for popular films or the special occasion itself may override concerns about pollution. In contrast, when box-office revenue is lower or around the median, consumers appear more sensitive to air quality conditions: poorer air quality discourages cinema visits, and this effect shows up as a significant negative coefficient at the 0.25 and 0.50 quantiles.

Overall, these quantile results reveal heterogeneity in how air pollution affects movie consumption. While the average (OLS) effect correctly captures the negative relationship for typical (lower-to-median) revenue scenarios, it overstates air quality's influence during high-revenue days. The absence of a significant effect at the 0.75 quantile implies that, under conditions of strong box-office demand, other factors dominate consumer behavior, and air quality becomes less relevant.

#### 4.3. Instrumental Variable Regression

Columns (1) and (2) of Table 4 present the estimation results for the first and second stages of the instrumental variable approach. In the first-stage regression, we find that the estimated coefficient for the instrumental variable NW is 0.0014, which is significantly positive at the 1% level. Additionally, we test whether the instrumental variable NW is a weak instrument. The F-statistic in the first-stage regression is far greater than the critical value provided by Stock and Yogo (2005) (16.38). The K-P LM statistic and C-D LM statistic are both greater than the critical value of 16.93 at the 10% level for the weak instrument identification test from Stock-Yogo, overcoming the test for instrument relevance. The  $p$ -value for Hansen's J test is 0.000, allowing us to reject the null hypotheses of "NW is a weak instrument" and "over-identification", thereby validating the appropriateness of the chosen instrumental variable.

**Table 4.** 2SLS as well as threshold regression results.

Variables	(1) The First Stage pm10	(2) The Second Stage bo	(3) Threshold Regression bo
pm10		−0.0797 *** (−2.7807)	
NW	0.0014 *** (9.3488)		
pm10 < 0.0074			0.0726 *** (7.5364)
0.0074 < pm10 < 0.0229			0.0200 *** (10.8093)
pm10 > 0.0229			−0.0174 *** (−26.6722)
wind	0.0024 (0.7710)	−0.0019 *** (−9.0204)	0.0007 *** (3.2425)
rain	−0.0473 *** (−21.4726)	−0.0044 *** (−5.0508)	−0.0037 *** (−10.0139)
ltem	−0.0006 (−0.1024)	−0.0001 (−0.4262)	0.0010 *** (4.1047)
hitem	0.0115 *** (3.7185)	0.0010 *** (3.0071)	−0.0030 *** (−13.2505)
nl	0.0052 (0.9128)	0.0098 *** (16.4226)	0.0163 *** (27.2338)
Constant			0.0053 *** (67.0061)
Observations	1,250,375	1,250,375	1,250,399
Adjusted R-squared			0.0027
F-value	87.40		
C-D Wald F		1896.817	
R-K Wald F		87.401	
Hansen J statistic		0.000	
City FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes

t-statistics clustered at the city level are shown in parentheses. \*\*\*  $p < 0.01$ .

In the second-stage regression, the coefficient for  $PM_{10}$  is significantly negative at the 1% level. The economic interpretation indicates that for each 1-unit increase in  $PM_{10}$ , movie consumption decreases by 0.0797 units, which confirms H1.

#### 4.4. Threshold Model Results and Analysis

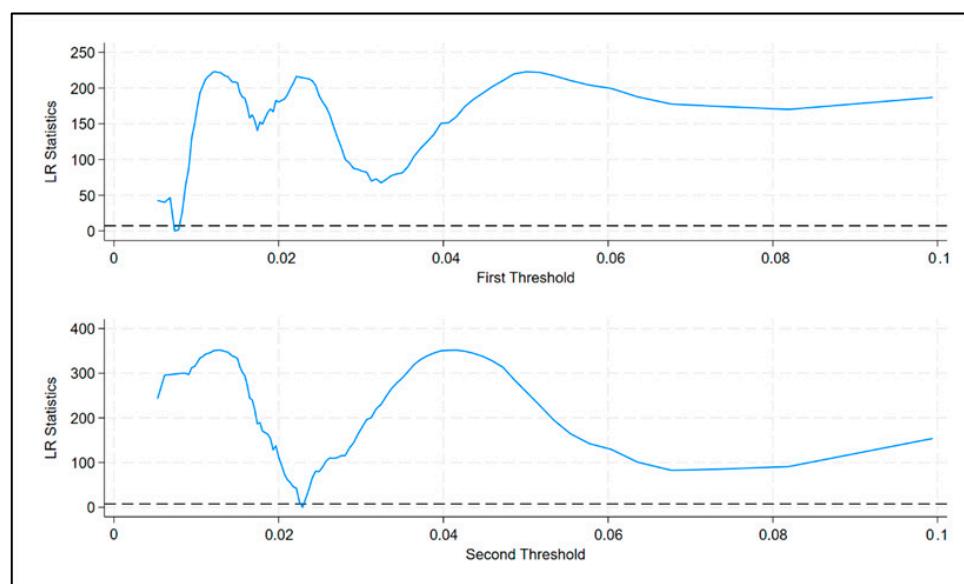
##### 4.4.1. Threshold Effect Test

To further examine the threshold effect of air quality on people's movie consumption, we test for the threshold effect in the model following the approach of Hansen (1999). First, we test whether there is a threshold effect of different levels of  $PM_{10}$  on movie consumption, and then we assess the impact of air quality on movie consumption at various  $PM_{10}$  levels. In this paper,  $PM_{10}$  is used as the threshold variable and the core explanatory variable. The model (4) is estimated under the null hypotheses of a single threshold, dual thresholds, and triple thresholds, and the F-statistic is obtained, with  $p$ -values derived using the bootstrap method. The results in Table 5 show that both the single threshold and dual threshold effects are significant at the 1% level, while the triple threshold does not pass the 10% significance test. Therefore, the subsequent analysis will be based on the dual-threshold model.

**Table 5.** Threshold effect test results.

Model	Fstat	Prob	Crit1	Crit5	Crit10
Single Threshold	483.67	0.000	15.398	11.461	9.806
Double Threshold	223.52	0.000	13.961	10.618	9.114
Triple Threshold	102.67	0.320	291.049	266.931	247.404

Next, we identified the two threshold values in the double threshold model. Table 6 presents the estimated values of these two thresholds along with their corresponding 95% confidence intervals. Based on the principles of the threshold model, the estimated threshold values correspond to the x-axis values where the likelihood ratio (LR) approaches zero. The dashed line in Figure 3 represents the critical value of the LR at the 5% significance level, and the region below the dashed line represents the 95% confidence interval for the threshold values. The upper and lower panels in Figure 3 display the LR function values for threshold values of 0.0074 and 0.0229, respectively. The minimum point of the LR indicates the true threshold value, and it can be seen that this point roughly aligns with the estimated thresholds. Additionally, because the critical value of 7.35 is significantly greater than both threshold estimates, it can be concluded that the model exhibits a double threshold effect, with estimated threshold values of 0.0074 and 0.0229.

**Figure 3.** LR plot of the threshold model.**Table 6.** Threshold effect test results.

Model	Threshold Value	Corresponding Value for $PM_{10}$	95% Confidence Interval
Single Threshold	0.0074	23.4601	(0.0072, 0.0075)
Double Threshold	0.0229	62.0473	(0.0226, 0.0230)

#### 4.4.2. Analysis of Threshold Estimate Results

The results of the dual-threshold regression are shown in Table 4(3). The impact of  $PM_{10}$  at different levels on people's movie consumption varies significantly. When  $PM_{10} < 0.0074$ , the impact on movie consumption is positive, with a coefficient of approximately 0.0726. When  $0.0074 < PM_{10} < 0.0229$ ,  $PM_{10}$  still has a positive effect on movie consumption, but the impact decreases, with a coefficient of 0.02. When  $PM_{10} > 0.0229$ , the effect of air quality on movie consumption turns negative, with a coefficient of  $-0.0174$ .

We speculate that when  $PM_{10}$  concentration is relatively low, the impact of air quality on the human body is limited, and people's willingness to go out is less affected, so they are still likely to engage in outdoor activities. As  $PM_{10}$  concentration increases, indoor entertainment venues like cinemas become a temporary option for people to avoid air pollution. However, when  $PM_{10}$  concentration exceeds a certain threshold and air pollution reaches a certain level, people tend to reduce outdoor activities, and in the higher  $PM_{10}$  concentration range, air quality has a negative impact on movie consumption.

#### 4.5. Robustness Testing

To ensure the robustness of the above results, this paper conducts robustness checks by changing the dependent variable, replacing the instrumental variable, altering the sample period, adjusting the sample size, and modifying the data processing methods.

##### 4.5.1. Replacement of Explanatory Variables

This paper replaces the dependent variable  $PM_{10}$  with the finer particulate matter,  $PM_{2.5}$ . Although  $PM_{2.5}$  is less visible to the naked eye, it poses a greater threat to human health. Therefore, the core explanatory variable is replaced with  $PM_{2.5}$  for regression, and the data is standardized. The regression results, shown in column (1) of Table 7, are largely consistent with the previous findings, confirming the robustness of the results.

**Table 7.** Robustness testing.

	(1)	(2)	(3)	(4)	(5)
Variables	Replacement of $PM_{10}$ bo	Replacement of NW bo	Troubleshooting External Shocks bo	Changing the Sample Size bo	Changes in Data Processing lnbo
pm10		−0.0528 *** (−3.0036)	−0.0033 *** (−5.1611)	−0.0022 *** (−5.8075)	
lnpm10					−0.0133 *** (−3.7651)
pm25	−0.0008 *** (−2.7974)				
wind	−0.0021 *** (−9.9176)	−0.0019 *** (−9.2213)	−0.0024 *** (−11.1576)	−0.0011 *** (−8.7808)	−0.0897 *** (−3.8052)
rain	−0.0006 * (−1.8130)	−0.0031 *** (−3.3646)	−0.0008 ** (−2.2009)	−0.0005 ** (−2.5015)	−0.1801 *** (−4.6550)
Item	0.0002 (0.6396)	−0.0000 (−0.1143)	0.0003 (1.0548)	0.0002 (1.2929)	−0.1456 *** (−4.3738)
hitem	−0.0002 (−0.8391)	0.0006 * (1.7586)	−0.0004 (−1.5106)	−0.0001 (−0.4154)	−0.1711 *** (−6.4231)
nl	0.0093 *** (15.8805)	0.0096 *** (16.1933)	0.0202 *** (33.6162)	0.0055 *** (15.3888)	−4.7751 *** (−70.7258)
Constant	0.0045 *** (32.0184)		0.0043 *** (30.0928)	0.0026 *** (31.6879)	11.2579 *** (543.1380)
Observations	1,250,375	1,250,375	1,223,027	1,135,381	1,135,381
Adjusted R-squared	0.5689	−0.0081	0.5781	0.5523	0.7552
City FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes

t-statistics clustered at the city level are shown in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

#### 4.5.2. Replacement of Instrumental Variables

To further confirm the robustness of the instrumental variable regression, this paper replaces the instrumental variable with the inversion temperature data from the first and third layers of the atmosphere. If the temperature of the third layer is higher than that of the first layer on a given day, it is considered a temperature inversion, with a value of 1; otherwise, the value is 0. The regression results, shown in column (2) of Table 7, indicate that the impact of air quality on movie consumption remains significantly negative at the 1% level, further validating the robustness of the regression results.

#### 4.5.3. Troubleshooting External Shocks

The COVID-19 pandemic brought about unprecedented economic and social changes, many of which were atypical and may differ from behavior patterns and economic laws during normal times (Delardas et al., 2022). In particular, during the pandemic, many industries and consumption patterns underwent dramatic changes (Donthu & Gustafsson, 2020), such as the closure of cinemas, shifts in entertainment consumption patterns (e.g., a surge in streaming media consumption), and government-imposed lockdowns and quarantine measures. These changes could lead to significant differences between the sample data during the pandemic and the data from normal periods. If data from the pandemic period are not excluded, these abnormal fluctuations could distort the results of regression analysis and affect the accurate determination of causal relationships. Therefore, to ensure that the analysis more accurately reflects the economic behavior and market trends during normal times, and to avoid unnecessary impacts from external shocks during exceptional periods, this paper excludes the sample data from the pandemic period. The years 2020 to 2022, when the COVID-19 pandemic was most severe, are considered the pandemic period, and the corresponding samples are removed for regression. The regression results, shown in column (3) of Table 7, indicate that after removing the pandemic's impact, the effect of air quality on people's movie consumption remains significantly negative, further validating the robustness of the regression results.

#### 4.5.4. Changing the Sample Size

Provincial capital cities often exhibit significant differences from other cities in terms of economy, policies, culture, and infrastructure, which may lead to different behavioral patterns in some aspects. For example, provincial capitals generally have higher income levels, more developed public services, stronger consumption capacity, and more concentrated business and cultural activities (Z. Li et al., 2016). These factors may cause the sample from provincial capitals to differ from that of other cities in terms of certain economic behaviors or consumption patterns. To ensure that the research results are not influenced by these unique attributes of provincial capitals, and to verify whether the conclusions can be generalized to a broader range of regions with different characteristics, this paper excludes the samples from provincial capitals to enhance the generalizability and robustness of the findings. The regression results, shown in column (4) of Table 7, indicate that after excluding the samples from provincial capitals, the impact of air quality on movie consumption remains significantly negative, further validating the robustness of the regression results.

#### 4.5.5. Changes in Data Processing

Standardization is typically used to transform variables into a form with the same dimension and scale, but it may overlook the nonlinear relationships between variables or fail to handle extreme values effectively. On the other hand, applying a log transformation ( $\log(x + 1)$ ) can effectively deal with extreme values in the data and, in many cases, can

transform nonlinear relationships between variables into linear ones, thus making them better suited for regression models (Mishra & Datta-Gupta, 2018). By using this approach, the robustness of the model under different data transformations can be tested, ensuring that the research conclusions do not solely rely on a particular data processing method. If the results obtained after applying the log transformation ( $\log(x + 1)$ ) align with the conclusions derived from standardization, it indicates that the model's conclusions are more robust and can adapt to different data preprocessing methods. Therefore, the original standardized explanatory and dependent variables are replaced with their log-transformed versions ( $\log(x + 1)$ ) to examine the impact of the data processing method on the results. The regression results, shown in column (5) of Table 7, indicate that after applying the log transformation to the explanatory and dependent variables, the effect of air quality on movie consumption remains significantly negative, further validating the robustness of the regression results.

#### 4.6. Moderating Effect

##### 4.6.1. Model Construction

The average temperature can moderate people's expectations regarding travel in relation to air quality. When air quality is poor, but the average temperature is suitable, people may take protective measures and still choose to go out for movie consumption. However, when the temperature is unsuitable, even if air quality is good, people's willingness to go out may decrease, leading to a reduction in movie consumption. Therefore, this paper constructs an interaction term by multiplying air quality and average temperature to explore the role of average temperature in influencing the effect of air quality on people's movie consumption. The following model is constructed:

$$BO_{it} = \eta_0 + \eta_1 PM10_{it} + \eta_2 PM10_{it} * atem_{it} + \eta_3 atem_{it} + \eta_4 Control_{it} + \mu_t + \delta_t + \varepsilon_{it} \quad (6)$$

The moderating variable  $atem_{it}$  represents the average temperature in city  $i$  on day  $t$ , and  $PM10_{it} * atem_{it}$  is the interaction term between air quality and average temperature. The meanings of the other terms are the same as in Equation (1).

##### 4.6.2. Analysis of Regression Results

The results of the moderating effect regression are shown in column (1) of Table 8. The interaction term between average temperature and air quality is significantly negative at the 1% level, indicating that average temperature strengthens the negative effect of air quality on people's movie consumption. Extreme high-temperature weather may make going outside uncomfortable, especially without air conditioning. In such cases, more people might choose to engage in indoor entertainment at home (Amindeldar et al., 2017), such as watching movies through streaming platforms. Although the air conditioning system in cinemas might provide temporary comfort, it is less appealing compared to being at home, particularly when outdoor air quality is poor, as people are more likely to avoid going outside. Extreme weather conditions (especially prolonged high temperatures) may have a negative impact on people's psychological state (Cruz et al., 2020; Chique et al., 2021). Extended hot weather combined with air pollution may trigger emotional issues such as anxiety and depression, which could reduce people's interest in outdoor entertainment activities, including going to the cinema. On the contrary, people may be more inclined to engage in leisure activities at home, such as watching streaming content.

**Table 8.** Regression results for thermoregulatory effects.

Variables	(1) Moderating Effect	(2) Cold	(3) Moderate	(4) Hot
pm10	0.0220 *** (8.7565)	−0.0029 *** (−2.9833)	−0.0040 *** (−3.9582)	−0.0034 (−1.5115)
pm10*atemp	−0.0394 *** (−10.1021)			
atemp	−0.0030 *** (−3.1058)			
wind	−0.0019 *** (−9.2746)	−0.0032 *** (−7.8527)	−0.0022 *** (−6.5910)	−0.0015 *** (−3.2493)
rain	−0.0010 *** (−3.0110)	−0.0034 ** (−2.2079)	−0.0012 ** (−2.1371)	0.0000 (0.0384)
ltemp	0.0022 *** (4.0880)	0.0021 *** (3.4249)	−0.0010 * (−1.9235)	0.0023 ** (2.4631)
htemp	0.0021 *** (3.9244)	−0.0016 *** (−3.3174)	−0.0006 * (−1.6774)	0.0017 *** (2.6891)
nl	0.0091 *** (15.6559)	0.0592 *** (36.0397)	0.0053 *** (6.0439)	−0.0013 (−1.3844)
Constant	0.0037 *** (21.6950)	0.0025 *** (9.8171)	0.0054 *** (14.3762)	0.0025 *** (3.4029)
The <i>p</i> -value for the difference			0.000	
Observations	1,250,375	374,957	500,145	374,756
Adjusted R-squared	0.5690	0.5509	0.5667	0.6062
City FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes

t-statistics clustered at the city level are shown in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

#### 4.6.3. Regressions Grouped According to Temperature

To investigate the varying responses of movie consumption to air quality under different temperature ranges, we follow the approach of [Eom et al. \(2020\)](#) and others, dividing the daily average temperature into three groups for grouped regression analysis: the top 30% of average temperatures represent “hot” weather, the bottom 30% represent “cold” weather, and the middle 40% represent “moderate” weather.

The regression results are shown in columns (2) and (3) of Table 8. Under both cold and moderate temperatures, air quality has a significant negative effect on people’s movie consumption. However, the negative effect is stronger under cold conditions than under moderate conditions. Moreover, the *p*-value for the difference in coefficients is 0.000, indicating that there is a significant difference between the coefficients of the three groups.

In cold weather, on one hand, low temperatures are often associated with stable atmospheric stratification and weaker wind speeds, which result in a longer retention time of air pollutants in the atmosphere. Lower temperatures and weak winds hinder the dispersion and dilution of air pollutants, causing them to accumulate in localized areas. On the other hand, during the cold season, people typically use heating systems to maintain indoor warmth. These systems often rely on fuels such as coal and natural gas, which release harmful substances like nitrogen oxides and sulfur dioxide during combustion. In colder weather, people tend to increase both the duration and intensity of heating usage to stay warm, leading to more pollutant emissions. Therefore, in cold weather, air pollution is more severe, which leads people to reduce outdoor activities and movie consumption due to concerns about health risks.

As shown in column (4) of Table 8, under high-temperature conditions, air quality does not have a significant effect on people’s movie consumption. High temperatures typically

cause people to avoid going outside (Ebi et al., 2021), especially during extreme heat or heatwaves. To escape the intense heat, many prefer to stay in air-conditioned environments. In such cases, although the air quality may be poor, cinemas, being air-conditioned and comfortable places, can offer a relatively cool and comfortable movie-watching experience. In hot weather, cinemas may become more attractive as a place to escape the heat. Therefore, even if air quality is poor, high temperatures may still encourage people to go to the cinema to avoid the combined effects of high heat and pollution outside. In contrast, the motivation for going to the cinema may be more about escaping the heat rather than concerns about air quality. However, once people have chosen an indoor environment to escape the heat, their movie consumption behavior (whether through online streaming platforms or in cinemas) may not be significantly influenced by air quality. In other words, even if air quality is poor, people may still choose to watch movies as a way to cool off and entertain themselves, especially when cinemas have air conditioning.

## 5. Heterogeneity Analysis

### 5.1. Differences in the Negative Effects of Air Pollution at Various Times

We expect that the impact of air quality on movie consumption differs during time periods with distinct characteristics. Specifically, when people have more flexible time, air quality is likely to have a greater impact on their movie consumption. During periods of greater time flexibility, if air quality is poor, people may tend to choose time periods with better air quality for movie consumption. To analyze time heterogeneity, we use two time-related indicators: first, whether it is a holiday or weekend period; second, we perform heterogeneity analysis based on seasons, selecting summer (July, August, and September) and winter (November, December, and January). In model (1), we conduct group regressions based on the two classification indicators mentioned above. We use the Chow test to examine the differences between groups, that is, we construct an interaction term between the grouping variable and  $PM_{10}$ , and include it in model (1) for regression analysis, observing whether the coefficient of this interaction term is significant. And the regression results are shown in Table 9.

Columns (1) and (2) of Table 8 show the regression results for non-holidays and holidays, respectively. The impact of air quality on movie consumption is negative in both cases, but the negative effect is stronger during holiday periods than during non-holiday periods. We speculate that this may be due to several reasons. During holidays, people generally have more free time for outdoor activities, entertainment, and leisure (De Bloom et al., 2017), and they tend to have more entertainment options, which increases the availability of alternative activities to movie watching. Therefore, when air quality is poor, especially during haze or high-pollution weather, many people may choose to stay indoors, particularly those with respiratory issues. In such cases, their willingness to go out and watch a movie significantly decreases, and they may opt for other indoor leisure activities at home. Additionally, during holidays, there is a significant increase in population movement (such as visiting relatives or traveling), which leads to higher travel frequency and longer travel times (H. Zhu et al., 2022; Cools et al., 2010). In cases of poor air quality, congestion and pollution worsen, especially in large cities, where the combined effects of air pollution and traffic pressure reduce people's willingness to go out. As a result, more people may prefer to stay indoors, leading to fewer opportunities to go to the cinema and a reduction in movie consumption. Moreover, the *p*-value for the difference in coefficients is 0.000, indicating that there is a significant difference between the coefficients of the two groups. Therefore, the negative impact of air quality on movie consumption is greater during holidays than during non-holidays.

**Table 9.** Results of temporal heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)
pm10	−0.0007 *** (−2.7504)	−0.0049 *** (−5.2486)	−0.0049 *** (−4.3100)	−0.0181 *** (−16.9174)
wind	−0.0002 ** (−2.3473)	−0.0031 *** (−10.4004)	−0.0002 (−0.8261)	−0.0048 *** (−13.5644)
rain	−0.0000 (−0.0185)	−0.0012 ** (−2.4919)	−0.0003 (−1.2858)	−0.0031 *** (−2.6495)
Item	−0.0007 *** (−5.6749)	0.0016 *** (3.8300)	0.0010 ** (2.1370)	−0.0017 *** (−2.9963)
htem	0.0001 (0.6258)	−0.0002 (−0.5431)	0.0003 (0.8837)	−0.0015 *** (−3.8387)
nl	−0.0040 *** (−16.0334)	0.0275 *** (32.2484)	−0.0043 *** (−6.7793)	0.0206 *** (21.9743)
Constant	0.0025 *** (43.6259)	0.0032 *** (16.0926)	0.0021 *** (6.3261)	0.0059 *** (23.0534)
The <i>p</i> -value for the difference		0.000		0.000
Observations	778,468	356,913	285,512	281,987
Adjusted R-squared	0.6008	0.6513	0.6282	0.5341
City FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes

t-statistics clustered at the city level are shown in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ .

Columns (3) and (4) of Table 9 show the regression results for summer and winter, respectively. We find that in both summer and winter, air quality has a negative impact on movie consumption, but the negative impact is greater in winter than in summer. On the one hand, winter temperatures are lower, and many areas, especially in northern cities, turn on their heating systems. The burning of large amounts of heating fuels, such as coal and natural gas, during the heating process releases pollutants, leading to a deterioration in air quality. Additionally, low temperatures often coincide with temperature inversion (thermal inversion) in the atmosphere, which prevents pollutants from dispersing and causes them to accumulate, resulting in even worse air quality (W. Zhu et al., 2018). Therefore, air pollution in winter is typically more severe than in summer, which reduces people's willingness to go out. On the other hand, winter air pollution is usually more persistent, particularly when haze lasts for long periods and the weather is cold and humid, with little wind to clear the pollutants (Song et al., 2020). As a result, prolonged pollution in winter leads to worse air quality, which has a greater negative impact on both people's psychological and physical health. This prolonged exposure to air pollution can increase people's health awareness, making them more likely to reduce outdoor leisure activities. In contrast, while poor air quality in summer also causes discomfort, the duration of such conditions is usually shorter and the impact more dispersed. Furthermore, the low temperature and dry air in winter may make people's respiratory systems more vulnerable to pollutants, with more severe irritation to the respiratory system, especially for the elderly, children, and those with underlying conditions. Poor air quality can worsen symptoms such as coughing and shortness of breath. In comparison, in summer, higher temperatures allow people to regulate their body temperature through sweating and other mechanisms (Wang et al., 2020), making them more tolerant of air pollution. Therefore, in winter, poor air quality poses a greater health threat, and consumers may be more cautious, reducing the frequency of going out to watch movies. Moreover, the *p*-value for the difference in coefficients is 0.000, indicating that there is a significant difference between the coefficients

of the two groups. As a result, the negative impact of air quality on movie consumption is greater in winter than in summer.

### 5.2. Differences in the Negative Effects of Air Pollution in Various Regions

We expect that the impact of air quality on people's movie consumption varies across regions with different characteristics. We use three regional characteristic indicators to conduct regional heterogeneity analysis. First, we divide cities in China into northern and southern cities based on the Qinling-Huaihe line. Second, we categorize cities into coastal and non-coastal cities according to the provinces they belong to. Third, we differentiate between provincial capital cities and non-provincial capital cities for heterogeneity analysis. In model (1) and its basic form, we conduct group regressions based on the above classification indicators, and the regression results are shown in Table 10.

The regression results for northern and southern cities are shown in columns (1) and (2) of Table 10, respectively. We find that air quality negatively impacts movie consumption in both northern and southern cities, but the negative impact is greater in southern cities than in northern cities. On the one hand, the climate in southern cities is generally more pleasant than in northern cities, so factors like temperature have less impact on people's willingness to go out. Therefore, in southern cities, especially in industrially influenced areas such as the Pearl River Delta, poor air quality becomes a significant factor affecting residents' willingness to go out. In contrast, although northern cities experience severe air pollution in winter, this period is typically dominated by cold air, with lower temperatures and shorter outdoor activity periods. As a result, while the negative impact of poor air quality is still present, it is less pronounced compared to that in southern cities (K. Zheng & Zhang, 2023). On the other hand, the causes of air pollution in southern cities tend to be more complex. In addition to heating and industrial pollution in winter, southern cities have higher humidity, and with the dense urban layout, pollutants are not easily dispersed, leading to prolonged smog and higher levels of air pollution. In northern cities, however, strong cold air during winter helps disperse pollutants (Liu et al., 2020), and the pollution tends to be more short-lived. Moreover, the *p*-value for the difference in coefficients is 0.000, indicating that there is a significant difference between the coefficients of the two groups. Therefore, the negative impact of air quality on movie consumption is greater in southern cities than in northern cities.

The regression results for coastal and non-coastal cities are shown in columns (3) and (4) of Table 10, respectively. We find that air quality negatively impacts movie consumption in both coastal and non-coastal cities, but the negative impact is greater in coastal cities than in non-coastal cities. We hypothesize the following reasons: Firstly, coastal areas generally have a humid climate, especially in summer and autumn, with higher humidity levels in the air (Ramesh et al., 2021). High humidity makes it more difficult for pollutants such as PM<sub>2.5</sub> and PM<sub>10</sub> to disperse and settle, leading to prolonged haze and pollutant retention. The high humidity environment worsens the perception of air quality, which reduces residents' willingness to go out, thus affecting their movie consumption. Secondly, coastal cities are typically densely populated and highly urbanized, leading to greater traffic pressure (Ozturk, 2024). Pollution from vehicle emissions, industrial discharges, and other sources is more severe in these areas. In such high-density, rapidly developing environments, air pollution tends to reach higher levels, with concentrations of atmospheric pollutants often being higher, directly affecting residents' health and suppressing their willingness to engage in outdoor activities and entertainment. In contrast, non-coastal cities generally have lower population density, fewer pollution sources, and lower health risks for residents, meaning the negative impact of poor air quality on movie consumption is less pronounced. Thirdly, coastal cities are usually China's economic centres and have a higher

degree of internationalization, attracting large numbers of foreign-invested enterprises and expatriates (Gong, 1995). These cities are not only affected by local industrial and traffic pollution but also by transboundary pollutants from neighbouring countries or regions, such as Japan, South Korea, and Southeast Asia. As a result, air quality in coastal cities is often worse than in non-coastal cities, especially due to seasonal pollution and meteorological conditions. This heightened pollution exacerbates residents' perception of poor air quality, further decreasing their willingness to go out for entertainment and consumption. Moreover, the *p*-value for the difference in coefficients is 0.000, indicating that there is a significant difference between the coefficients of the two groups.

**Table 10.** Regional heterogeneity regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	North	South	Coastal	Inland	Capital	Non-Capital
pm10	−0.0022 *** (−3.6707)	−0.0114 *** (−5.7908)	−0.0082 *** (−4.6996)	−0.0012 ** (−2.0798)	0.0043 (0.9315)	−0.0022 *** (−5.8075)
wind	−0.0011 *** (−4.5028)	−0.0037 *** (−9.8486)	−0.0026 *** (−6.1621)	−0.0001 (−0.4889)	−0.0056 *** (−4.0510)	−0.0011 *** (−8.7808)
rain	0.0001 (0.1010)	−0.0013 *** (−2.7147)	−0.0014 ** (−2.3087)	−0.0003 (−0.7702)	−0.0041 * (−1.6616)	−0.0005 ** (−2.5015)
ltem	0.0025 *** (6.9043)	0.0005 (0.7773)	−0.0019 *** (−2.7861)	0.0014 *** (4.6165)	0.0001 (0.0269)	0.0002 (1.2929)
mhtem	−0.0006 ** (−2.1417)	−0.0014 *** (−3.2341)	0.0007 (1.1806)	−0.0009 *** (−3.7848)	−0.0013 (−0.7432)	−0.0001 (−0.4154)
nl	0.0410 *** (32.5582)	0.0059 *** (8.1443)	0.0036 *** (4.4018)	0.0372 *** (30.5247)	0.0167 *** (5.0174)	0.0055 *** (15.3888)
Constant	0.0011 *** (6.2416)	0.0068 *** (17.4807)	0.0085 *** (25.0521)	0.0020 *** (14.6078)	0.0225 *** (21.3479)	0.0026 *** (31.6879)
The <i>p</i> -value for the difference		0.000		0.000		0.001
Observations	585,618	645,582	432,622	817,742	114,978	1,135,381
Adjusted R-squared	0.5820	0.5708	0.5902	0.5722	0.6697	0.5523
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes

t-statistics clustered at the city level are shown in parentheses. \*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1.

The regression results for capital cities and non-capital cities are shown in columns (5) and (6) of Table 10, respectively. We find that air quality negatively impacts movie consumption in non-capital cities, but in capital cities, there is no significant effect of air quality on movie consumption. We hypothesize the following reasons: Firstly, capital cities typically have better transportation and public facilities. These cities are generally more developed, and public transportation systems (such as subways and buses) are usually more efficient (Chen et al., 2021), which helps mitigate the impact of traffic pollution on residents. Additionally, since cinemas are often located in commercial centres and busy areas, people visiting cinemas are usually not exposed to outdoor pollution for extended periods. The efficient public transportation and urban planning in capital cities make air quality a less significant factor affecting residents' willingness to go out. Secondly, capital cities are usually cultural and entertainment hubs with a strong demand for the movie market (Ji et al., 2009). The demand for movies is higher, and residents are more willing to consume movies. Cinemas in these cities often offer a wider range of movie options, and ticket prices are relatively affordable, making movie-going a part of people's daily lives. In this context, air quality may not be the primary factor influencing movie-watching behavior, as demand for movie consumption driven by other social and economic factors often outweighs the negative impact of air quality. Thirdly, in capital cities, movie consumption is often not just for personal entertainment, but also has strong social and family elements. Many people go to cinemas with family or friends, and even when air quality is poor, they

still opt for this form of social entertainment. Especially on weekends or public holidays, watching movies has become a common family and social activity, which is less likely to be interrupted by air quality concerns. Fourthly, capital cities are generally more digitally advanced (Du et al., 2024). With the development of digital marketing, movie promotion has increasingly moved online through platforms like social media and video streaming sites, which can boost movie exposure and audience expectations, reducing the direct impact of air quality on movie-going decisions (Liao & Huang, 2021; A & Felisiya, 2024). In contrast, non-capital cities tend to have poorer infrastructure, lower social and movie consumption demands. Moreover, the *p*-value for the difference in coefficients is 0.000, indicating that there is a significant difference between the coefficients of the two groups. And thus, air quality has a more significant negative impact on movie consumption.

## 6. Conclusions

This study uses data from 334 cities at or above the prefecture level in China from 2012 to 2022, with inversed temperature as an instrumental variable. It employs the two-way fixed-effects instrumental variable approach and threshold regression method to explore the impact of air quality on people's movie consumption. The findings reveal that an increase in a city's PM<sub>10</sub> concentration leads to a decrease in movie consumption in that city. Moreover, the suppressive effect of PM<sub>10</sub> on movie consumption varies across different time periods and regions. During holidays and weekends, the suppressive effect of PM<sub>10</sub> on movie consumption is greater compared to non-holiday periods. In winter, the suppressive effect of PM<sub>10</sub> on movie consumption is stronger than in summer. Furthermore, in southern cities and coastal cities, the suppressive effect of PM<sub>10</sub> on movie consumption is more pronounced. In capital cities, however, no significant effect of PM<sub>10</sub> on movie consumption is observed. Additionally, we conduct a threshold effect test using PM<sub>10</sub> as the threshold variable. We find that as PM<sub>10</sub> concentration increases, people initially increase their movie consumption. However, when the PM<sub>10</sub> concentration exceeds a certain level, further increases in PM<sub>10</sub> lead to a reduction in movie consumption. Finally, average temperature enhances the suppressive effect of air quality on movie consumption.

Based on the above conclusions, this study proposes the following recommendations:

First, strengthen air quality regulation and improvement. Policy suggestion: The government should intensify its efforts in regulating air pollution by implementing stricter emission standards and enhancing control over major pollution sources such as industry and transportation. At the same time, it should increase investment in the research and development of clean energy and environmental protection technologies, and provide policy support to encourage enterprises and individuals to adopt low-carbon, eco-friendly production and living practices, thereby reducing the emission of air pollutants.

Second, optimize the supply of the movie market during holidays. During periods when air quality is poor, such as holidays and weekends, the movie industry should release more high-quality films that cater to viewers' tastes and increase the diversity of available films to attract people to theaters. Additionally, various promotional activities, such as offering discounted tickets and movie packages, should be conducted to reduce the cost of moviegoing for audiences and increase their willingness to go to the movies.

Third, improve the moviegoing experience. Cities with higher overall development should invest more in the construction and renovation of cinemas, enhancing both the hardware facilities and service levels. For example, improving air quality in theaters by installing air purifiers and creating a more comfortable and healthy viewing environment, while also providing more user-friendly services such as comfortable seating and superior sound systems, can significantly enhance the moviegoing experience for audiences.

Fourth, adopt differentiated measures for different regions. Based on the air quality conditions and consumption characteristics of residents in various regions, differentiated policies and measures should be implemented. For instance, in southern and coastal cities where air quality is poorer, more support should be provided to the movie industry, including policy incentives and financial assistance, to promote the development of the film sector. In contrast, in northern and non-coastal cities where air quality is relatively better, the focus should be on strengthening the regulation of the movie market, standardizing market order, and improving the overall quality of the movie industry.

Fifth, strengthen public awareness campaigns and public participation. The government and relevant departments should strengthen environmental awareness campaigns to raise the public's consciousness of environmental protection and increase their participation. Through various channels and methods, the public should be educated on the hazards of air pollution and its prevention, and encouraged to participate in environmental protection actions, such as reducing private car usage and conserving energy, in order to reduce the emission of air pollutants from the source.

Sixth, promote integration of digital and physical cinema experiences. In light of the shift in consumer behavior—particularly during periods of poor air quality or public health concerns—there is significant potential to leverage digital streaming platforms as a complementary mechanism to support the film industry. Policymakers and industry stakeholders should encourage partnerships between cinemas and major streaming services (e.g., iQIYI, Tencent Video, Netflix) to offer hybrid distribution models. For example, select films could be released simultaneously or sequentially in theaters and online, allowing consumers in areas with poor air quality to participate in new film releases without needing to travel. This approach could help stabilize industry revenues during periods of low in-person attendance while expanding access for vulnerable groups. At the same time, by bundling in-theater experiences with digital benefits (e.g., digital vouchers, bonus content), the industry could strengthen its resilience and enhance audience engagement across both physical and digital platforms.

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