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Weather shocks and movie recreation demand in China

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ABSTRACT

Understanding the impacts of weather shocks on various economic sectors is crucial for designing effective climate policies. While previous studies have focused mainly on the agricultural and industrial sectors, there has been limited exploration of weather effects on the service sector, particularly in emerging economies. This study addresses this research gap by analyzing high-frequency movie-viewing records of 49 major cities in China between 2015 and 2017 to examine the effects of weather shocks on in-theater movie recreation. The findings reveal that both extreme temperatures and pouring rains significantly reduce movie demand. We also investigate the relationship between weather and movie supply at both extensive and intensive margins, and confirm the weather-movie demand results are not driven by supply-side dynamics. The back-of-the-envelope calculation indicates that extreme temperatures led to a loss of 5.14 million moviegoers and a 311.32 million Chinese Yuan loss in box office revenue for the Chinese film market in 2017, while losses due to pouring rains amounted to 1.28 million audiences and 69.16 million Chinese Yuan in revenues. This paper highlights the significant damage caused by current extreme weather conditions to China's film market and emphasizes that such damage is expected to worsen in the future with the intensification of climate change.

1. Introduction

The increasing frequency of weather shocks has detrimental effects on various aspects of society. In order to develop effective policies to address the climate challenge, it is crucial to have a comprehensive understanding of how weather affects all sectors of the economy (Dell et al., 2014; Hsiang et al., 2017). However, the existing literature primarily focuses on the agricultural sector (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Chen et al., 2016; Zhang et al., 2017) and the industrial sector (Dell et al., 2012; Zhang et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021). Unfortunately, studies examining the impact of weather on the service sector using high-frequency micro-data are still limited.

Examining the effects of weather conditions on consumer demand in the service sector poses unique challenges due to two key attributes. Firstly, while consumer demand for agricultural and industrial products remains relatively stable over long periods, such as quarterly or yearly scales, demand for services can be influenced by weather changes occurring at shorter frequencies. This observation is supported by Lai et al. (2022), who find that food consumption exhibits less sensitivity to temperature fluctuations than entertainment spending, as evidenced by detailed bank card transaction data in China. This characteristic suggests that relying on coarse time-aggregated data may overly smooth out consumers' immediate responses to weather, underscoring the need for more granular data to identify weather impacts accurately. Secondly, the effects of weather on both the demand and supply of the service sector are intertwined, making it challenging to isolate the demand effect from the whole. For example, precipitation not only leads to an increase in demand for taxi services but also incentivizes taxi drivers to turn their leisure time into work time (Connolly, 2008), thereby augmenting the supply of taxi services (Brodeur and Nield, 2018). Failing to account for such supply-side behaviors could introduce biases in estimating the impact of weather on consumer demand in the service sector. Consequently, it is imperative to employ appropriate methodologies to disentangle rigorously the direction of these biases and provide accurate assessments.

This study aims to address these research gaps by utilizing high-frequency movie-viewing data from 49 cities in China between 2015 and 2017. We focus on examining the impact of weather shocks, i.e., temperature and precipitation, on the demand for movie recreation. The

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choice to focus on China's film industry offers unique advantages in understanding the relationship between weather conditions and service demand. Firstly, China is one of the largest consumers of recreational services globally (Hermosilla et al., 2018),[1] and the film industry is a rapidly growing sector within China's service industry. As shown in Fig. 1, between 2012 and 2019, China witnessed significant growth in box office revenues, cinema screens, and the volume of movie tickets sold, with average annual growth rates of 21.8%, 27.2%, and 22.0%, respectively. Exploring the context of China can enable us to understand how weather shocks can influence recreational services. Secondly, box office data provide accurate electronic records, serving as the foundation for revenue sharing between filmmakers and theaters, and it is publicly available. This readily available data ensures convenience in compiling and analyzing the relevant information while minimizing measurement errors associated with movie attendance variables. Lastly, the fine-grained data allow us to examine the causal effects of weather on movie demand by leveraging the plausibly exogenous variations in weather conditions. Furthermore, the data allow us to explore whether the relationship between weather and movie supply has any confounding effects on our results, ensuring the robustness of our findings.

To examine the effects of temperature and precipitation on movie demand, we aggregate movie attendance data from the theater to the city level, adopt a widely used semi-parametric approach, and control for various spatial, temporal, and movie fixed effects. The results indicate that compared to the reference category, 20–25 °C, extreme heat with a daily average temperature exceeding 25 °C reduces 3.38%, 5.61%, and 1.02% in audience numbers, box office revenues, and attendance rates, respectively. Extreme cold with temperatures below −5 °C results in a more substantial impact, causing a decrease of 7.87%, 13.51%, and 1.83% in audience numbers, box office revenues, and attendance rates, respectively. Precipitation also significantly dampens movie demand, and its effects become stronger as the intensity of rainfall increases. This relationship indicates that movie attendance is negatively affected by rain, with heavier rainfall resulting in more substantial decreases in demand.

We develop a framework at the city-day level to address concerns about potential biases in our weather-movie demand estimates due to the omission of contemporaneous movie supply variables. This framework allows us to explore the relationship between weather conditions and movie supply from both extensive and intensive perspectives. We find extreme weather is almost unrelated to movies' premiere frequency and screening frequency after controlling for the city, year, month-of-year, day-of-week, and national holiday fixed effects. This finding suggests that the relationship between weather and movie supply does not affect our baseline results, reinforcing the robustness of our findings regarding weather's impact on movie demand.

Our findings carry significant policy implications. By conducting a back-of-the-envelope calculation, we estimate that extreme temperatures (pouring rains) led to a loss of 5.14 (1.28) million moviegoers and a loss of 311.32 (69.16) million Chinese Yuan in box office revenues to China's film market in 2017. These monetized results indicate substantial economic losses experienced by the film industry in China due to current weather shocks. Furthermore, as the intensity and frequency of extreme weather increase under future climate change, we anticipate that the damage inflicted by extreme weather events will escalate further. Therefore, addressing the challenges posed by climate change not only has environmental implications but also becomes crucial for developing the service sector in the economy. Additionally, our findings suggest that the service sector will transform in response to future climate change. As climate change intensifies, residents' demand for offline recreation services is expected to face continued limitations. This, in turn, will reshape the energy requirements of physical entertainment businesses and influence energy consumption patterns during the travel process.

In a related study by He et al. (2022), the impact of air pollution on movie attendance was examined, with weather conditions included as controls. However, our paper differs from He et al. (2022) in several key aspects. Firstly, we utilize more recent movie attendance data from 2015 to 2017, and we have a larger sample size with 1273 non-rescreened movies. In contrast, He et al. (2022) used a 2012 to 2014 dataset encompassing 829 movies. Secondly, in addition to the audience scale used by He et al. (2022), we also incorporate two other variables, i.e., box office revenues and attendance rates, to provide a more comprehensive understanding of consumers' movie demand. Thirdly, our study takes a more rigorous approach to examine the potential bias in demand-side estimates due to the association between movie supply and weather. In contrast, He et al. (2022) primarily overlooked this consideration. Lastly, as a supplementary analysis, we go a step further by employing thermal inversion as an instrumental variable for air pollution and report the impact of air pollution on move attendance in Supplementary Analysis.

This paper is connected to a broader body of literature and contributes to the existing literature in several ways. Firstly, it stands out as the first study to examine the causal impact of weather shocks on demand for a specific service industry in an emerging economy. Previous studies have predominantly focused on developed economies (Dundas and von Haefen, 2020; Chan and Wichman, 2020) or aggregated expenditures (Lai et al., 2022). By addressing this research gap, our study sheds light on the unique dynamics of weather effects on the service sector in emerging economies. Moreover, we introduce an empirical framework that allows us to uncover the direction and magnitude of biases that may arise from supply-side responses when evaluating the impact of weather on service demand from the demand-side perspective. This consideration is crucial for analyzing service activities where demand and supply are intertwined, such as the behavior of taxi drivers (Brodeur and Nield, 2018), courier services (Wang et al., 2022), and food delivery riders.

Secondly, this paper also extends the previous weather-recreation demand literature in the context of one of the largest recreation markets worldwide. Previous studies evaluate weather impacts on recreational activities but focus on non-market-based activities, such as recreational fishing (Dundas and von Haefen, 2020) and recreational cycling (Chan and Wichman, 2020). Since these activities are non-market-based, they bring challenges in assessing the welfare consequences of weather shocks.[2] Our study focuses on a market-based recreation activity, and welfare changes are thus calculated explicitly leveraging the price signal. Moreover, since the value standard of market-based recreation is clear, revenues of these activities can be classified into the service sector output and be a component of aggregate national output. Therefore, market-based recreation is at least as essential as non-market-based recreation in assessing the socioeconomic impacts of weather and climate. This paper also enriches the literature that explores weather impacts on recreation at the aggregated level, such as Graff Zivin and Neidell (2014) and Lai et al. (2022).

Thirdly, this paper also dialogues with studies exploring network externalities and learning effects on movie consumption, in which plausible exogenous weather shocks are instrumented for abnormal

[1] According to box office revenue, China was the second largest movie market worldwide between 2015 and 2019. In 2020, benefiting from the effective control of the coronavirus epidemic, China overtook North America for the first time to become the world's largest movie market. See: https://www.globaltimes.cn/page/202101/1211591.shtml.

[2] These stuides use the value of a recreational trip estimated by prior studies, combined with weather-recreation response patterns to approxly calculate welfare changes. Dundas and von Haefen (2020) assume the value of a lost fishing trip is 30$ based on results from meta-analysis studies. Chan and Wichman (2020) approximate the average consumer surplus for cycling according to the Recreation Use Values Database.

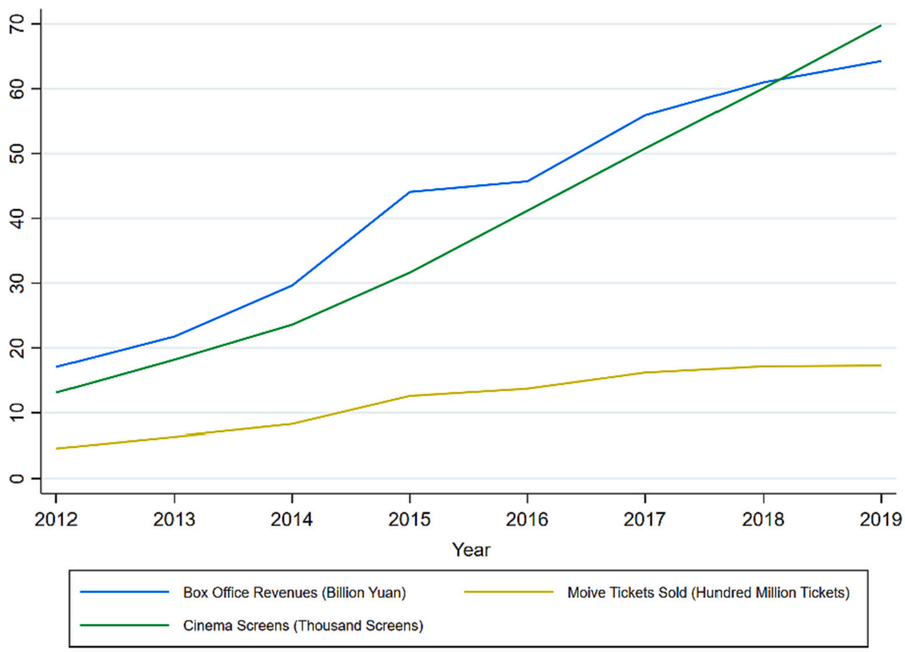


Fig. 1. The booming film market in China from 2012 to 2019.
Notes: Data are from https://www.statista.com/.

moviegoing, such as Moretti (2011) and Gilchrist and Sands (2016).[3] This paper finds that weather effects on moviegoing are contemporaneous and not homogeneous across days after the movie premiere. This pattern suggests the role of ex-ante priors and ex-post information in shaping weather effects and also deepens our understanding of the validity of instruments in aforecited studies.

2. Data

To examine the impacts of weather conditions on movie viewings, we compile a comprehensive dataset by combining micro-data from multiple sources.

2.1. Movie-viewing data

The viewing record micro-data of movies screened in 49 cities across China from 2015 to 2017 are retrieved from an online box office statistics website. The dataset provides valuable information such as the movie's name, the location of the theater, the number of seats, the ticket price, the opening time, and the audience numbers for each screening. Next, 338 Chinese cities are divided into five groups by the China Business Network, a leading financial media group in China.[4] For our analysis, we select from the 1st-tier cities, new-1st-tier cities, and 2nd-tier cities, which collectively accounted for 68.37% of all box office revenues in China's film market in 2017.[5] We conduct our analysis at the movie-city-day level. To mitigate the influence of movie-screening frequency on our estimates, we calculate the average audience number per screen, the average box office revenues per screen, and the average attendance rate for each movie in each city. To ensure the reliability of our results, we exclude the rescreened movies from the initial movie-viewing database, narrowing it down to 1273 newly released movies (out of the initial 1361 movies) for our baseline analysis.

2.2. Movie-rating data

The movie-rating data come from Douban.com, one of China's most popular movie review websites. The overall rating, i.e., a score between 2 and 10, measures the quality of a movie. The website also provides other characteristics of movies, including the premiere date, movie language, runtime, number of ratings, and production countries. Based on the premiere date information, we calculate the number of days since the movie premiered.

2.3. Meteorological and air quality data

Station-day level meteorological data, including temperature, precipitation, atmospheric pressure, relative humidity, wind speed, and cloud cover, are obtained from the China Meteorological Data Service Center.[6] We aggregate the meteorological data to the city-day level using the inverse distance weighting method with a 100 km radius, as broadly used in the literature (Deschênes and Greenstone, 2007; Zhang et al., 2017). Our baseline results are robust to other radius settings, such as 150 and 200 km. Considering that air quality may affect moviegoers' decision-making (He et al., 2022), we obtain the air quality index (AQI),

[3] Moretti (2011) uses weather conditions on the day of a movie release and the day before the release as instrumental variables for the movie-specific surprise in the first week, with surprise measured by the residual from a regression of the first-week ticket sales on the number of screens. Gilchrist and Sands (2016) use weather shocks on opening weekend as instrumental variables for contemporaneous abnormal viewership. Both studies find weather shocks are related to movie consumption, and the IV strategy helps to distinguish confounding network externalities and learning effects.

[4] These indicators include commercial resources, transportation convenience, resident activity, lifestyle variety, and future adaptability. The five groups of cities are 1st-tier cities (4 cities), new-1st-tier cities (15 cities), 2nd-tier cities (30 cities), 3rd-tier cities (70 cities), 4th-tier cities (90 cities), and 5th-tier cities (129 cities). Table A1 provides the detailed city ranking list. See https://www.yicai.com/news/5293378.html for more information.

[5] The box office revenues data for each city in 2017 are from https://www.askci.com/news/chanye/20180116/094421116104.shtml. Also see Table A1.

[6] CMDSC is an official institution under the jurisdiction of the China Meteorological Administration. More details about the meteorological data can be found at http://data.cma.cn/en.

Table 1
Summary statistics.

	Mean	SD	Min	Max	Sample size
Panel A: Movie-viewing variables					
Average number of audiences per screen (Persons)	17.04	27.59	0	1324	789,807
Average box office revenues per screen (Chinese Yuan)	637.59	1089.18	0	65,490.2	789,807
Average attendance rate (%)	15.35	20.83	0	100	789,807
Number of screenings	16.32	32.97	1	866	789,807
Average ticket price (Chinese Yuan)	36.89	8.99	4	223	789,807
Number of days since the movie premiered (days)	13.75	13.00	0	100	789,780
Panel B: Movie quality and attributes					
Douban rating (2–10 scores)	5.20	1.82	2.1	9.3	1193
Number of ratings (Persons)	50,884.74	115,337.1	0	1,071,835	1361
Runtime (minutes)	99.68	13.99	64	192	1361
Panel C: Meteorological and air quality variables					
Temperature (°C)	17.10	9.97	−26.1	36.5	53,274
Precipitation (mm)	3.61	11.91	0	253	53,274
Atmospheric pressure (kPa)	99.15	4.54	80.41	104.32	53,274
Relative humidity (%)	72.02	16.84	8	100	53,274
Wind speed (m/s)	2.27	1.09	0	10.7	53,274
Cloud cover (%)	66.30	16.62	0	90	49,222
AQI	75.57	46.02	12	500	53,704
PM2.5 (μg/m^3)	47.04	39.34	0	881	53,704
PM10 (μg/m^3)	80.53	58.51	0	1398	53,704
TI (1 = thermal inversion occurs more than four times in a day, 0 = otherwise)	0.34	0.48	0	1	53,704

Notes: The observations in Panel A are viewing records for each movie at the city-day level. In Panel B, Douban ratings for 163 movies are missing because of too few reviews.

a comprehensive air quality measure, from the Ministry of Ecology and Environment of China. Air quality data are aggregated to the city-day level by averaging hourly AQI within a day.

Table 1 shows the summary statistics of our data. The average ticket price of the sample is 36.89 Chinese Yuan, close to the national level between 2015 and 2017, reflecting that our sample is external comparability.[7]

3. Empirical strategy

3.1. Baseline specification

We focus on examining the effects of temperature and precipitation on audiences' movie demand. Considering the nonlinear relationship between weather and recreation activities as found by ongoing studies (Chan and Wichman, 2020; Dundas and von Haefen, 2020; Lai et al., 2022), we propose the Eq.(1), a semi-parametric model with high-dimensional fixed-effects (HDFE) to identify the impact of plausible-random weather variations on moviegoing:

$$\mathbf{V}_{icd} = \sum_j \alpha_j Tbin^j_{cd} + \sum_k \beta_k Pbin^k_{cd} + \mathbf{W}_{cd}\gamma + \phi AQI_{cd} + \mathbf{M}_{icd}\lambda + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd} \quad (1)$$

$\mathbf{V}_{icd}$ refers to a set of movie-viewing demand variables, including the log of the number of audiences per screen, the log of box office revenues per screen, and the attendance rate for movie i screening in city c on date d.[8] $Tbin^j_{cd}$ represents a set of temperature bins that equal one if the daily average temperature of city c on date d falls into the j-th bins and zero otherwise. To explore the effects of the entire temperature distribution on moviegoing, we construct nine bins with 5 °C as the interval. The nine temperature bins are <-5, −5–0, 0–5, 5–10, 10–15, 15–20, 20–25, 25–30, and >30 °C. In practice, as revealed by our data, the 20–25 °C bin is designated as the reference group, in which the human body usually feels comfortable and owns the largest number of audiences. Therefore, the coefficient α_j we are interested in should be interpreted as the relative impact of temperatures within the j-th bins on moviegoing compared to the reference temperature range. $Pbin^k_{cd}$ indicates a set of precipitation bins, and five bins are constructed based on the official classification of precipitation grades.[9] According to the daily 24-h accumulated precipitation, <0.1, 0.1–10, 10–25, 25–50, and >50 mm are assigned to 'drizzle', 'light' rain, 'moderate' rain, 'heavy' rain, and 'torrential' rain bins, respectively. We omit the 'drizzle' bin as the reference group, which accounts for 65.9% of the observations. Therefore, the coefficient β_k captures the relative effects of various rainfall intensities on moviegoing compared to no-rain days.

$\mathbf{W}_{cd}$ is a vector of weather controls, including air pressure, humidity, wind speed, and cloud cover. We further control for AQI_{cd} to remove the confound of air pollution on weather effects identification (He et al., 2022). To mitigate potential estimation bias caused by movie-supply factors that are simultaneously related to weather and viewing availability, we include two movie-and-date-varying variables $\mathbf{M}_{icd}$: average ticket price and the total number of screenings. Taking advantage of the high-frequency data, we control for abundant fixed effects to make weather variations plausibly exogenous to time-variant unobservables to identify the causal effects of weather on moviegoing. The movie fixed effects θ_i capture all time-invariant movie attributes. City-level features related to moviegoing and do not change over time are absorbed by city fixed effects τ_c, such as the administrative level and preference for movie types. We use the day fixed effects ρ_d to strictly control for time-varying shocks common to all cities, such as weekends and holidays, and national-level seasonal changes in movie market popularity. At last, we control for days-since-premiered (DsP) fixed effects ξ_{DsP} to remove the decaying trend of movie demand after a movie premiered (Gilchrist and Sands, 2016), as shown in Fig. A1. Standard errors are clustered at the movie level to allow demand for the same movie to be arbitrarily correlated over time and across cities.

[7] The average movie ticket price in China was 35.0, 33.3, and 34.5 Chinese Yuan in 2015, 2016, and 2017, respectively, based on the China Film Industry Analysis Report. See: http://data.chinabaogao.com/chuanmei/2019/12304H3162019.html.

[8] Specifically, the average audience number per screen is defined as (total # of audiences watching the movie i screening in city c on date d)/ (total # of screens showing movie i in city c on date d). The average number of box office revenues per screen is defined as (total box office revenues of movie i screening in city c on date d)/ (total # of screens showing movie i in city c on date d). The average attendance rate is defined as (total # of audiences watching the movie i screening in city c on date d)/ (total # of seats in screening rooms showing movie i in city c on date d).

[9] China Meteorological Administration publishes the standard GB/T 28592–2012 for precipitation grades. See: https://www.cma.gov.cn/zfxxgk/gknr/flfgbz/bz/202209/t20220921_5097915.html.

3.2. Parsimonious model and moviegoing losses due to weather shocks

The bins specification of Eq.(1) allows us to examine the effects of the entire temperature distribution and precipitation on movie demands. Motivated by Barreca et al. (2016) and Burgess et al. (2017), we apply a more parsimonious model focusing on extreme temperatures and pouring rains. This approach is convenient for exploring the heterogeneity of weather on moviegoing, and more importantly, it provides a realistic counterfactual for calculating moviegoing losses due to weather shocks in China during the sample period. The parsimonious model is proposed as Eq.(2):

$$V_{icd} = \delta_1 ExtreHighT_{cd} + \delta_2 ExtreLowT_{cd} + \pi PouringR_{cd} + W_{cd}\gamma + \phi AQI_{cd} + M_{icd}\lambda + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd} \quad (2)$$

$ExtreHighT_{cd}$ and $ExtreLowT_{cd}$ are two dummy variables that indicate the upper and lower tails of the daily temperature distribution, and cutoffs for extremely cold and hot days are −5 and 30 °C, respectively. Therefore, coefficients δ_1 and δ_2 are interpreted as the effects of extreme heat and cold on movie demand, compared to a broader reference temperature range: -5–30 °C. In addition, we combine the extreme heat and cold in subsequent analyses to obtain a comprehensive extreme temperature variable, $ExtreT_{cd}$, which equals one if the daily mean temperature is below −5 °C or above 30 °C. $PouringR_{cd}$ is a pouring rain day dummy and equals one if daily accumulated precipitation exceeds 25 mm, accounting only for 3.97% of our sample. Thus, π depicts the impact of extreme precipitations on moviegoing, compared to mild precipitation situations, including drizzle, light, and moderate rains. The other settings in Eq.(2) are the same as in Eq.(1).

Moreover, the specification of Eq.(2) provides a counterfactual context to calculate moviegoing losses caused by weather shocks in China. For temperature shocks, the intuition is to calculate the increase in audiences and box office revenues if all extreme temperatures are altered to moderate temperatures, −5–30 °C. The difficulty in the calculation is that not all in-theater movie consumption in sample cities is covered by our data. Thus we recover the calculation from the sample level to the city level by using the ratio of moviegoers/revenues in our sample to numbers officially announced. Specifically, Eq.(3) is applied to calculate the loss in audience scales in all sample cities caused by extreme heat and cold:

$$\Delta AudienceT = \sum_c \eta_c \times \left\{ \begin{array}{l} \sum_d 1(ExtreHighT_{cd}) \times Audience_{cd} \times \left(\frac{1}{1+\hat{\delta}_1} - 1 \right) \\ + \sum_d 1(ExtreLowT_{cd}) \times Audience_{cd} \times \left(\frac{1}{1+\hat{\delta}_2} - 1 \right) \end{array} \right\} \quad (3)$$

where η_c denotes that for city c, the ratio of the official audience scale listed in Table A1 to the annual number of moviegoers recorded by our data. $Audience_{cd}$ represents the total number of moviegoers in city c on date d. $\mathbf{1}(ExtreHighT_{cd})$ and $\mathbf{1}(ExtreLowT_{cd})$ indicate whether date d in city c is an extremely hot/cold day. $\hat{\delta}_1$ and $\hat{\delta}_2$ are estimated by Eq.(2).

For precipitation shocks, we aim to calculate the additional gains in moviegoing from replacing realistic pouring rains with normal precipitation. Still using audience size as an instance, the calculation is presented by Eq.(4):

$$\Delta AudienceP = \sum_c \eta_c \times \left\{ \sum_d \mathbf{1}(PouringR_{cd}) \times Audience_{cd} \times \left(\frac{1}{1+\hat{\pi}} - 1 \right) \right\} \quad (4)$$

where $\mathbf{1}(PouringR_{cd})$ denotes whether the accumulated precipitation of city c on date d is above 25 mm and $\hat{\pi}$ is estimated by Eq.(2). The other settings in Eq.(4) are the same as in Eq.(3). The above logic also applies to calculating the loss in box office revenues caused by weather shocks.

3.3. Challenges from the weather-movie supply nexus

We exploit plausible random weather shocks that deviate from local norms to causally identify the impact of weather on movie demand after controlling for abundant spatial and temporal fixed effects. However, a challenge is raised that our specification as Eq.(1) does not fully include movie-supply factors, and the estimate of weather-movie demand may be biased if omitted factors are also linked to the weather. We ease this challenge in two ways. First, we control for movie supply variables available in our database $\mathbf{M}_{icd}$, ticket price, and screening frequency for the specific movie to mitigate the omission bias as much as possible. Second, we directly examine the relationship between weather and movie supply behaviors in this section and thereby clarify the direction and extent of potential bias in weather-movie demand estimates.

The weather may be associated with both extensive and intensive margins of movie supply. From the extensive margin, weather status may be correlated with movie premiere decisions. King et al. (2017) theoretically suggest optimal premiere strategies vary across movie quality.[10] Since audiences' enthusiasm and sensitivity to movie quality are not uniform within a week and across a year, the distribution of premieres is expected to reflect hotspots of movie demand- mainly on weekends and holidays (Einav, 2010). Our data provide a more detailed description of this inference. In Panel A of Fig. A2, movie premieres are dominantly concentrated on Fridays within a week, and an explanation is that it helps to attract weekend audiences and contribute to a higher early-stage box office. Moreover, across a year, as shown in Panel B of Fig. A2, the peak of movie premieres mainly occurs in July to September and November to December, which correspond to summer vacation and Lunar New Year, respectively. Since extreme heat usually happens in the summer and extreme cold usually happens in the winter, extreme temperatures overlap with the peak of movie premieres. While premiere timing may not be **causally** affected by the weather but rather by producers' and distributors' pursuit of word-of-mouth, awards, and box office, the **correlation** between weather and premieres can moderate the availability of a specific movie and further transmit to audience demand.

For the intensive margin, the nexus of weather and movie supply is more nuanced. Once a movie has premiered, theater owners can adjust screening schedules based on their expectations of movie performance, reflected in screening frequency changes for a specific movie within a day, in which subtle real-time weather conditions can be essential factors. Weather shocks affect the spread of word-of-mouth for a movie and dampen subsequent demand (Moretti, 2011; Gilchrist and Sands, 2016), which further leads theaters to reduce scheduling to mitigate financial losses. Nevertheless, the weather-movie screening relationship remains to be empirically examined.

We apply the specification of Eq.(5) to explore the association between weather and movie supply at the city-day level:

$$\mathbf{S}_{cd} = \sum_j \alpha_j Tbin_{cd}^j + \sum_k \beta_k Pbin_{cd}^k + \mathbf{W}_{cd}\gamma + \phi AQI_{cd} + \tau_c + \vartheta_{year} + \zeta_{MoY} + \varpi_{DoW} + \chi_{holiday} + \varepsilon_{cd} \quad (5)$$

where $\mathbf{S}_{cd}$ is a vector of movie supply variables. Outcomes for the extensive margin are the number of premiere movies in city c on date d, and a dummy for at least one movie premiered. For the intensive margin,

[10] King et al. (2017) demonstrate that high-quality movies are suitable for premieres during high-demand and high-quality elasticity periods, while low-demand and less quality-sensitive periods are appropriate for premieres of low-quality movies.

the outcome is the total number of movies screened in city c on date d. We flexibly control for the city (τ_c), year (ϑ_{year}), month-of-year (ζ_{MoY}), day-of-week (ϖ_{DoW}), and national holiday ($\chi_{holiday}$) fixed effects to capture the distribution of the movie premieres presented in Fig. A2.[11] Therefore, α_j and β_k describe the linkage between temperature and precipitation to movie supply, respectively. Standard errors are clustered at the city level in Eq.(5).

4. Empirical results

4.1. Baseline findings

Fig. 2 illustrates the impact of weather shocks on moviegoing using the semi-parametric bins specification, while detailed results can be found in Table A2. We observe an inverted U-shaped dose-response relationship between temperature and moviegoing (Fig. 2A), which aligns with previous studies on specific outdoor recreation in North America (Chan and Wichman, 2020; Dundas and von Haefen, 2020), as well as research on aggregated recreation time use (Graff Zivin and Neidell, 2014) and entertainment consumption (Lai et al., 2022). Furthermore, the statistically significant effects of temperature on movie demand are primarily observed in the extreme temperature ranges. Specifically, temperatures below −5 °C and above 30 °C show significant impacts on moviegoing, while a large range of moderate temperatures, −5 to 30 °C, yield insignificant or marginally significant coefficients. The effects of extreme heat and cold on moviegoing are asymmetrical, with extreme cold having a slightly stronger dampening effect. For instance, compared to the reference category, an extremely cold day with a temperature below −5 °C is associated with a 7.87%, 13.51%, and 1.83% reduction in audience numbers, box office revenues, and attendance rate, respectively. On the other hand, extreme heat with a temperature over 30 °C leads to a 3.38% decrease in audiences, a 5.61% decline in box office revenues, and a 1.02% drop in the attendance rate.

We turn to the effect of precipitation shocks on moviegoing, as presented in Panel B of Fig. 2. According to the official criteria, the daily 24-h accumulated precipitation is classified into five groups, and ‘drizzle’ with precipitation below 0.1 mm is adopted as the reference category. As rainfall rises, the reduction effect of precipitation on moviegoing increases monotonically. In terms of audience scale, the move from no rain to light rain is accompanied by a 1.45% drop in audience. When precipitation intensifies to moderate rain, audience size experiences an additional 0.92% reduction. Under the most severe conditions- heavy and torrential rain, audiences significantly decreased by 3.49% and 4.62%, respectively, compared to the no rain status. The damage of precipitation on other movie demand outcomes also exists, as indicated by the detailed estimated coefficients in Table A2.

The feature that moviegoing responds almost entirely to temperature extremes motivates us to extend the interval of temperature reference. Therefore, we employ the parsimonious model presented by Eq.(2) to directly estimate the effect of extreme temperatures rather than temperature variations. Based on the estimated temperature response pattern, we define temperatures below −5 °C as extremely low and above 30 °C as extremely high. We further combine two dummies to obtain an integrated extreme temperatures measure. Since precipitation monotonically damages movie demand, we conservatively define the pouring rain day with daily accumulated precipitation over 25 mm.

Table 2 reports the results from the parsimonious specification, where we use two separate extreme temperature variables in Panel A and the combined variable in Panel B. We found that both extremely high and low temperatures reduce moviegoing compared to a broader range of moderate temperatures, −5–30 °C, and the magnitude is slightly greater for extreme cold, consistent with the insights from the temperature bins specification above. Panel B indicates that on a day with an extreme temperature, moviegoers, revenues, and the up rate significantly decline by 3.80%, 6.21%, and 1.07%, respectively. Moreover, even compared to a more normal range of precipitation, the pouring rain still significantly reduces demand for movie recreation. Given that the parsimonious specification has clear economic meaning and convenience of interpretation, we will primarily rely on that for the subsequent analysis.

4.2. Robustness checks

We conduct various attempts to check the robustness of the above baseline findings, including altering the specification setting and being cautious about potential outliers.

4.2.1. Model specification

In the baseline model, we establish causal identification by relying on exogenous weather fluctuations while controlling for various fixed effects. Here we further control for city-by-month fixed effects, which can flexibly help to capture local time trends and isolate residual weather shocks that deviate more randomly from the local norm. It is important to note that stricter control can limit the available variations and potentially lead to attenuation bias in weather estimates (Fisher et al., 2012). The results of the model with city-by-month fixed effects are graphically presented in Fig. 3. Due to space constraints, we only report the estimates for movie audiences, but it is worth mentioning that the results for other movie demand outcomes are very similar and are reported in Fig. A3. We observe that after the inclusion of city-by-month fixed effects, the magnitude of weather shock effects decreases slightly than baseline results but remains statistically significant.

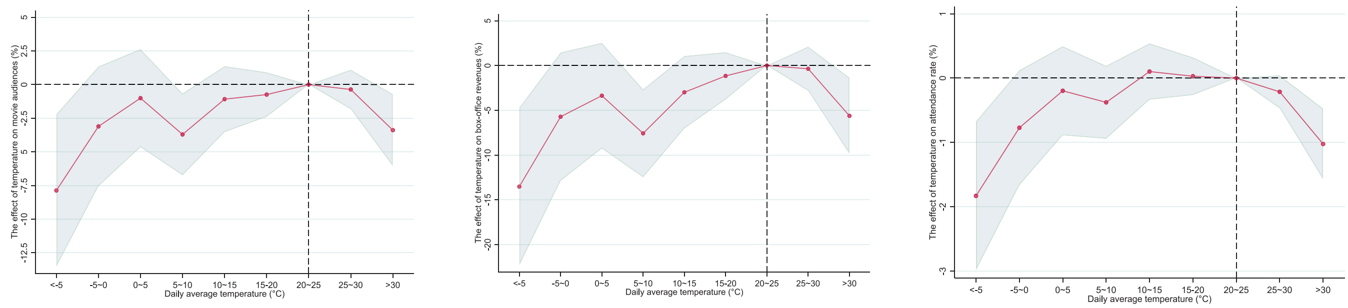
Moreover, since we control for day fixed effects in the preferred specification to absorb common daily shocks across sample cities, one may be concerned that the setting is too stringent for available weather residuals. We then adjust day fixed effects to a set of the year, month-of-year, day-of-week, and holiday fixed effects and confirm estimates from the temporal-relaxed specification are very close to baseline results. We also change the cluster level of standard errors from the movie to the city, which allows for serial correlation of movie demand within a city and audiences’ contemporaneous choosing across multiple movies. The city-level clustering specification leads to less precise estimations of weather shocks, but statistical significance is still maintained. The cloud cover rate is essential for weather control since it is correlated with temperature and rain, and cloudiness is often thought to be linked to subtle emotions. The cloud cover variable faces a proportion of 7.9% missing in the sample. We remove the cloud cover from weather controls and confirm that its missing observations do not shake baseline results.

To test whether baseline results are sensitive to the bandwidth of temperature bins, we replace the temperature bin width in Eq.(1) with 3 °C to allow for a more flexible response of moviegoing to temperature, and the category 30–33 °C is omitted as the reference group. Fig. 4A shows that results under a narrower temperature bin width are consistent with the baseline findings, with almost only extreme temperatures significantly reducing moviegoers.[12] We then check whether baseline findings still hold under alternative nonlinear specifications. Similar to Cui (2020), we propose a fourth-order polynomial function to flexibly capture the global nonlinear effect of weather on movie demand, that is:

[11] We are grateful to the referee for suggesting control for holiday fixed effects. Holiday information for 2015–2017 is from the State Council website. See: https://www.gov.cn/zhengce/content/2014-12/16/content_9302.htm; https://www.gov.cn/zhengce/content/2015-12/10/content_10394.htm; https://www.gov.cn/zhengce/content/2016-12/01/content_5141603.htm.

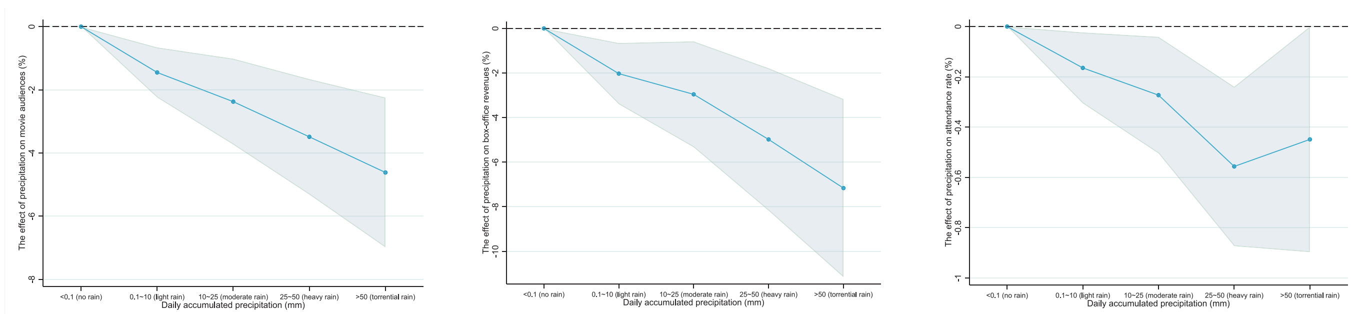
[12] Due to the space limitation, Figure 4 only reports results for audience size, and results for other moviegoing outcomes are reported in Figures A4.

Panel A: temperature



(a) audiences (b) box office revenues (c) attendance rate

Panel B: precipitation



(a) audiences (b) box office revenues (c) attendance rate

Fig. 2. Impacts of temperature and precipitation on movie demand.
Notes: The points are estimated by Eq.(1), and shaded areas are the 95% confidence interval. In Panel A, the reference temperature bin is 20– 25 °C. In Panel B, the reference precipitation bin is 0– 0.1 mm (light drizzle).

Table 2
The effects of weather shocks on movie demand.

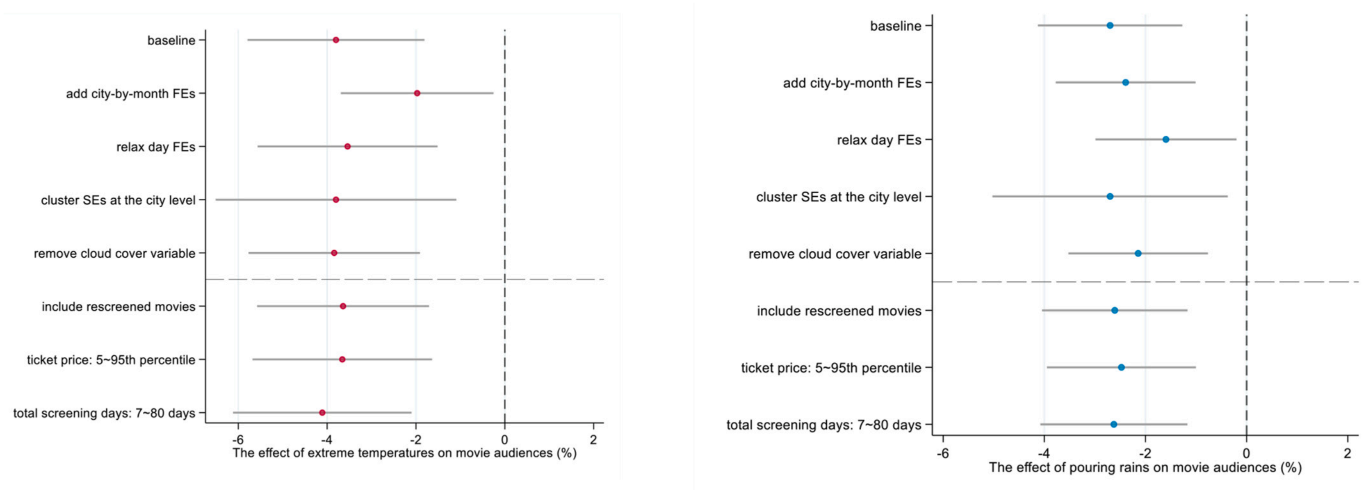
	ln(audience)	ln(box office revenues)	attendance rate
	(1)	(2)	(3)
Panel A: Separated extreme temperature variables			
ExtreHighT	−0.0315***	−0.0571***	−0.8650***
	(0.0111)	(0.0168)	(0.2495)
ExtreLowT	−0.0488***	−0.0704**	−1.4209***
	(0.0188)	(0.0292)	(0.3346)
PouringR	−0.0266***	−0.0418***	−0.3930***
	(0.0073)	(0.0125)	(0.1312)
Controls	Y	Y	Y
Fixed effects	Y	Y	Y
Observations	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2042
Panel B: Combined extreme temperature variables			
ExtreT	−0.0380***	−0.0621***	−1.0736***
	(0.0102)	(0.0155)	(0.2076)
PouringR	−0.0270***	−0.0422***	−0.4067***
	(0.0073)	(0.0125)	(0.1316)
Controls	Y	Y	Y
Fixed effects	Y	Y	Y
Observations	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2042

Notes: Controls include weather controls- air pressure, humidity, wind speed, cloud cover, and AQI, and movie-supply controls- ticket price and screening frequency; Fixed effects include movie FE, city FE, day FE, and days-since-premiered FE; The reference group for extreme temperature variables is −5–30 °C, and the reference group for *PouringR* is 0-25 mm. Standard errors in parentheses are clustered at the movie level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

$$\mathbf{V}_{icd} = \sum_{k=1}^{4}\left(\alpha_k T_{cd}^{k} + \beta_k P_{cd}^{k}\right) + \mathbf{W}_{cd}\gamma + \phi AQI_{cd} + \mathbf{M}_{icd}\lambda + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd} \tag{6}$$

and apply marginal effects $\partial \mathbf{V}_{icd}/\partial T_{cd}$ and $\partial \mathbf{V}_{icd}/\partial P_{cd}$ to describe the weather effects on moviegoing, which depend on the specific weather level at which to be estimated, rather than anchoring to a fixed reference weather interval as in Eq.(1). Fig. 4B indicates that on the left side of comfort temperatures, a decrease in temperature continuously hampers audience size, with a stable but marginally significant estimate of marginal effects. When the temperature exceeds 25 °C, the marginal increase in temperature significantly reduces moviegoers. These findings are consistent with the relationship between temperature and movie demand revealed by the bin model. Fig. 4C shows that additional precipitation reduces movie demand throughout the distribution, but estimates of heavy rain with daily cumulative precipitation above 30 mm are less precise due to limited observations. These results confirm that the nonlinear effects of weather on moviegoing are robust under the alternative polynomial specification.

In the baseline analysis, temperature bins are constructed by the daily average temperature. To extract useful information provided by diurnal variation in temperature, we conduct a sinusoidal interpolation between daily maximum and minimum temperatures following Tack et al. (2015) and obtain the temperature for each hour within a day. Table A3 presents the results of the temperature bins model constructed by hourly level temperatures within a day. Extreme heat and cold are still found to own the most pronounced and statistically significant marginal damages on movie demand, which reflects our baseline findings are robust under the aggregated hourly temperature measurement.



Panel A: extreme temperature **Panel B: pouring rain**

Fig. 3. Robustness checks: the effects of weather shocks on movie audiences.
Notes: Solid dots represent the point estimate results, each from a separate regression. Horizontal solid lines indicate the 95% confidence interval.

4.2.2. Exclude potential outliers

We exclude potential outliers from the following aspects to investigate their disturbance to baseline results. First, considering audiences' preferences for rescreened movies may differ from newly released movies, 88 rescreened movies are excluded from the baseline analysis. Now we reinclude these rescreened movies and no longer control for days-since-premiered fixed effects. Second, we exclude observations with ticket prices above the 95th percentile or below the 5th percentile of the movie ticked price distribution, and then samples with a price range from 21.13 to 52.62 Chinese Yuan are used to produce estimates.

At last, the abnormal screening behavior of theaters may cause unexpected results. Therefore, we exclude movie samples screened for fewer than seven days during the sample period. Movies that have experienced considerable success at the box office or have had word-of-mouth may be postponed to go offline, thus having screening days far exceeding other movies.[13] We remove movie samples screened for >80 days in each city to avoid biased results by these blockbuster movies. As shown in Fig. 3, the magnitude of weather effects on movie demand is still stable after considering potential outliers.

Another concern is that the air quality variable in the baseline specification may be endogenous, which may mislead estimates of weather effects. We overcome the challenge by using thermal inversions to instrument air quality (Fu et al., 2021; Godzinski and Castillo, 2021) and reaffirm the robustness of baseline weather effects. We provide a more detailed discussion in Appendix Supplementary Analysis and compare our air pollution-moviegoing findings with He et al. (2022).

4.3. Exploration of the channel

The observed relationship between weather shock and movie demand suggests a pattern of avoidance behavior among residents. When faced with extreme weather conditions, individuals tend to adjust their activities to minimize exposure and potential damage (Graff Zivin and Neidell, 2014). Nevertheless, the decision to go to movies during extreme weather is influenced by the initial location of potential audiences. On the one hand, if individuals are already indoors when extreme weather occurs, the inconvenience and discomfort of going outside to the theater may dampen their enthusiasm for moviegoing. On the other hand, if the audience is outdoors when extreme weather strikes, the unpleasant conditions may actually encourage them to seek shelter and entertainment in the comfort of a theater, as most theaters offer air-conditioned environments. As a result, the weather-movie demand relationship is shaped by these two opposing channels, which depend on the population's location within the city at a specific moment. Unfortunately, we cannot explicitly separate and analyze these two channels due to the lack of real-time information on population locations, such as data from mobile phone records (Li et al., 2023).

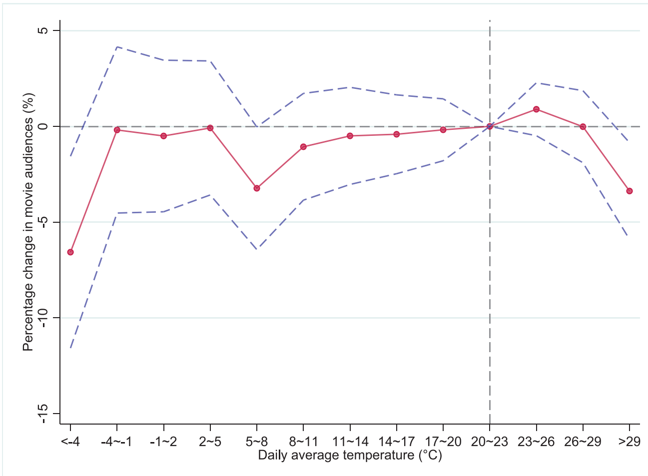
We adopt an indirect approach to explore the mechanism. Our idea is that on weekends or holidays, the initial location of most residents is at home, and if extreme weather occurs at this time, its impact is expected to be dominated by the first channel. We interact weather shocks with the weekends or holidays dummy and report results in Table 3. The result shows that when recreational peaks are met with severe weather, the damage of extreme temperatures and pouring rains on movie demand is amplified. Moreover, once interactions are introduced, the estimate of the single extreme temperature variable is no longer significant, indicating that the effect of extreme temperatures on moviegoing is almost concentrated at the peak period of recreational demand. The coefficients of precipitation interactions remain negative but are weaker in statistical significance. The exploration demonstrates that the impacts of weather shocks on movie demand, as illustrated in Fig. 2, are at least partially explained by the disutility caused by unpleasant weather on the way out. The channel echoes the literature on avoidance behaviors to weather shocks (Deschênes, 2014).

4.4. Back-of-the-envelope calculation

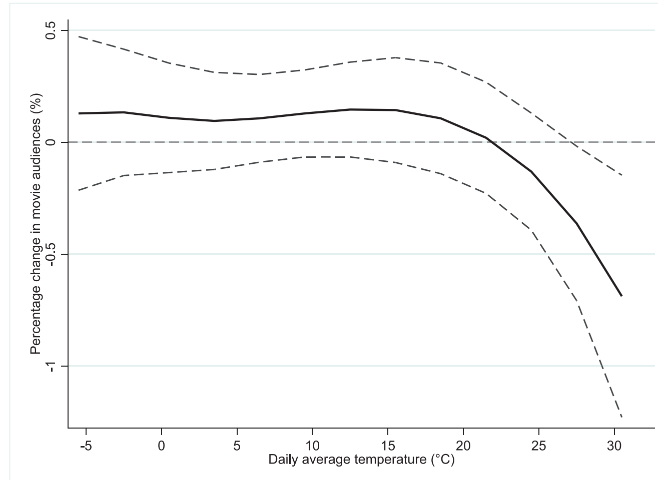
Leveraging the parsimonious model proposed in section 3.2, we calculate the loss of moviegoers and box office revenues in 49 cities caused by weather shocks. Since official statistics on movie audiences and revenues for each city are unavailable for 2015 and 2016, we focus the calculation on 2017 in this section. Estimates of extreme temperatures, $\widehat{\delta}_1$ and $\widehat{\delta}_2$, and pouring rain, $\widehat{\pi}$, are reported in Table 2.

The back-of-the-envelope calculation indicates that for 49 cities, extreme heat caused a 4.36 million loss in moviegoers and a 273.43

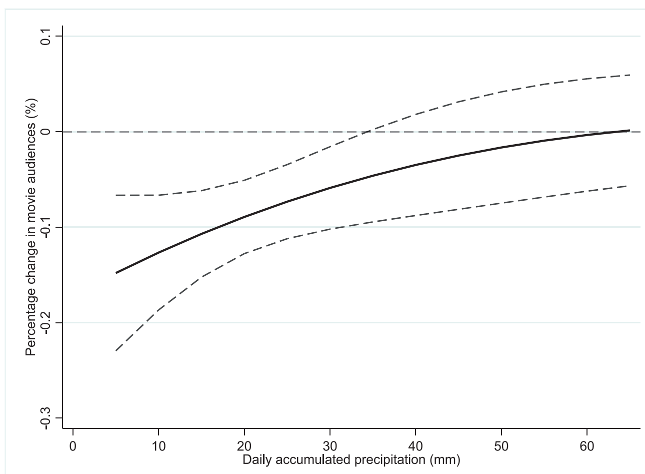
[13] Generally, the average screening duration for a movie is 30–40 days depending on its popularity. Part of high reputation movies are sometimes postponed to go offline, but repeated postponement crowd out other movies and may cause dissatisfaction from audiences. For example, *Wolf Warriors 2* premiered on July 27, 2017 nationwide, and the distributor announced that it would be postponed for one more month on August 15 and September 28, respectively. These decisions caused dissatisfaction among viewers on Weibo, with some of them even believing that postponements are politically motivated.



Panel A: temperature bins with 3°C as the interval



Panel B: global nonlinear temperature function



Panel C: global nonlinear precipitation function

Fig. 4. Robustness checks: temperature effects on movie audiences under alternative specifications.
Notes: In panel A, red points denote point estimates based on Eq.(1), but alter 3 °C as the interval and 20– 23 °C as the reference group. Blue dashed lines represent the 95% confidence interval. In Panels B and C, the solid black line represents the marginal effect of temperature/ precipitation under a fourth-order global nonlinear specification, as proposed by Eq.(6), and black dashed lines denote the 95% confidence interval.

million loss in box office revenues, and extreme cold led to a 0.78 million loss in audiences and a 37.89 million loss in revenues in 2017. If heavy and torrential rains were replaced with mild precipitation, it would gain an additional 1.28 million moviegoers and a 69.16 million revenue. These results suggest that weather shocks cause a tremendous toll on movie demand nationwide.

Two notes on the calculation are provided here. First, the calculation focuses on quantifying the loss of moviegoers and revenues, while other consumption attached to movie recreation, such as snacks sales and movie peripheral products sales, is not included due to the lack of information. Therefore, the concise calculation should be interpreted as a lower bound of the impact of weather shocks on the offline film industry. Second, we restrict the analysis year to 2017 due to data limitations. However, once the data are available, the calculation logic can be extended to other periods and regions.

5. Further analysis

5.1. *Examine the weather-movie supply relationship*

Following the specification of Eq.(5), we examine the relationship between weather and movie supply from both the extensive and intensive margins after controlling for the city, year, month-of-year, day-of-week, and national holiday fixed effects. Results are reported in Fig. 5.

From the extensive margin, there is no significant difference in the number of movies premiering on days with a temperature below 20 °C. However, the premiere frequency positively correlates with the temperature after the temperature exceeds 20 °C. When altering the outcome to the premiere dummy, estimates of temperature indicators are almost insignificant, as shown in subfigure (b) of Panel A. We find the premiere frequency is slightly higher on days of heavy and torrential rains (subfigure (a) of Panel B), and one explanation is that pouring rains are more frequent in summer, which is also the peak season for movie demand. Nevertheless, the dummy for at least one movie premiere is not correlated with precipitation (subfigure (b) of Panel B). These findings suggest that weather conditions are mostly unrelated to movie supply

Table 3
Mechanism exploration.

	ln (audience)	ln(box office revenues)	attendance rate
	(1)	(2)	(3)
*ExtreT*weekends or holidays*	−0.0409***	−0.0568***	−0.8625***
	(0.0120)	(0.0199)	(0.2525)
*PouringR*weekends or holidays*	−0.0234*	−0.0307	−0.5128**
	(0.0136)	(0.0231)	(0.2580)
ExtreT	−0.0090	−0.0217	−0.4616
	(0.0134)	(0.0204)	(0.3117)
PouringR	−0.0194**	−0.0322**	−0.2409
	(0.0086)	(0.0150)	(0.1573)
Controls	Y	Y	Y
Fixed effects	Y	Y	Y
Observations	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2043

Notes: Controls include weather controls- air pressure, humidity, wind speed, cloud cover, and AQI, and movie-supply controls- ticket price and screening frequency; Fixed effects include movie FE, city FE, day FE, and days-since-premiered FE; The reference group for extreme temperature variables is −5–30 °C, and the reference group for *PouringR* is 0-25 mm. Standard errors in parentheses are clustered at the movie level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

does not shake our findings. Subfigure (c) of Panel B presents that precipitation is not significantly correlated with movie screening frequency.

In summary, we find extreme weather is less connected with movie supply, and if any, the weather-movie supply relationship only leads to conservative estimates of weather shocks on movie demand.

5.2. Lagging effects

We further explore whether the past weather shocks have affected the current movie demand. To examine this, we extended Eq.(2) by including the lag terms of extreme temperatures and pouring rains for up to ten days.[14] The graphical representation of the lagged effects of weather shocks on movie audiences is shown in Fig. 6. Similar patterns for other movie outcomes can be observed and are illustrated in Fig. A5. In Fig. 6A, we observe that only extreme temperatures occurring on the current day significantly negatively affect movie audiences. However, the effects of extreme temperatures from the past ten days are estimated to be statistically insignificant. Fig. 6B demonstrates that current heavy rainfall has a pronounced negative impact on movie demand. Interestingly, we find that a rainstorm occurring one week prior slightly increases the current number of audiences. One possible explanation is that the unexpected rainfall prompts individuals with pre-planned movie viewings to reschedule and already-planned audiences to shift

Panel A: temperature

(a) number of premiere movies (b) dummy for movie premieres (c) number of movies screened

Panel B: precipitation

(a) number of premiere movies (b) dummy for movie premieres (c) number of movies screened

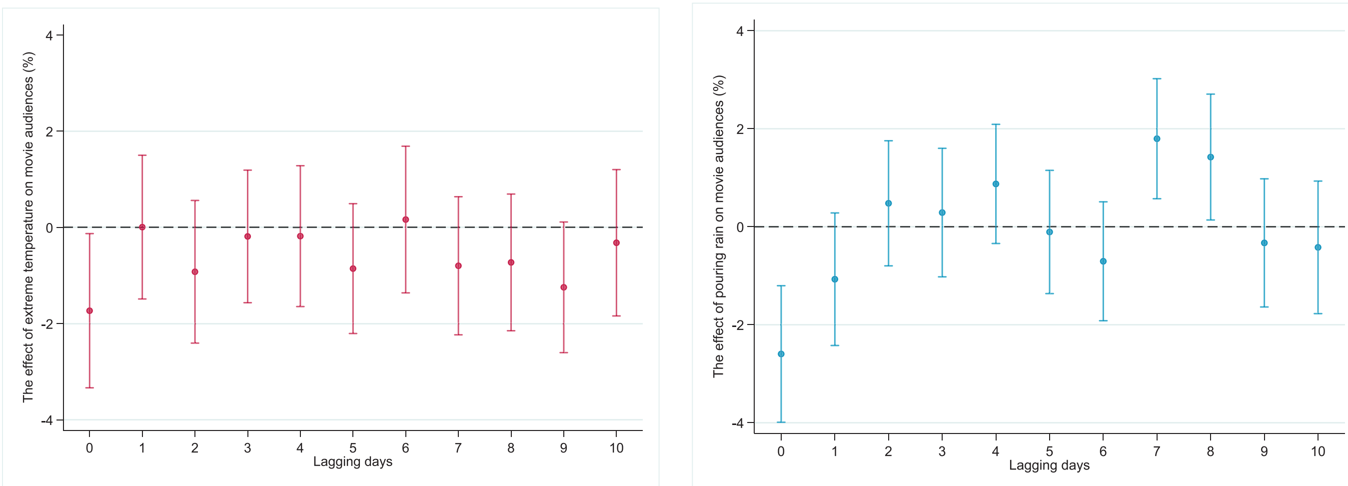
Fig. 5. The relationship between weather and movie supply.
Notes: The points are estimated by Eq.(5), and shaded areas are the 95% confidence interval. In Panel A, the reference temperature bin is 15– 20 °C. In Panel B, the reference precipitation bin is 0– 0.1 mm (light drizzle).

from the extensive margin. Although heat days are associated with a higher frequency of movie premieres, this linkage implies a higher movie availability on extreme heat days, and hence, Eq.(2) only underestimates the damage of extreme temperatures on movie demand.

From the intensive margin, the frequency of movie screenings is slightly higher on days with a temperature range from 0 to 15 °C. Since we mainly focus on the effect of extreme temperatures, this correlation the demand to a week later. However, this relationship disappears when examining the attendance rate, as indicated in Panel B of Fig. A5.

In conclusion, audiences' movie recreational demand primarily

[14] We also try weather lags of more than ten days, and coefficients of higher-order lag terms are found to be almost insignificant.



Panel A: extreme temperature **Panel B: pouring rain**

Fig. 6. Lagging effects of weather on movie audiences.
Notes: Solid dots represent the point estimate results, and vertical solid lines indicate the 95% confidence interval. Panel A and Panel B are obtained from a combined regression.

responds to contemporaneous weather shocks and is less sensitive to extreme weather realized in the recent past.

5.3. *Heterogeneity*

We examine the heterogeneity of weather effects across city tiers, movie quality, and movie life cycle by interacting weather dummies with heterogeneity indicators following Zheng et al. (2019). The heterogeneity results are illustrated in Figs. 7 and 8. Due to the space limitation, we only show the results with the outcome as audience size, and results for other moviegoing outcomes are provided in Figs. A6 and A7.

5.3.1. *City tiers*

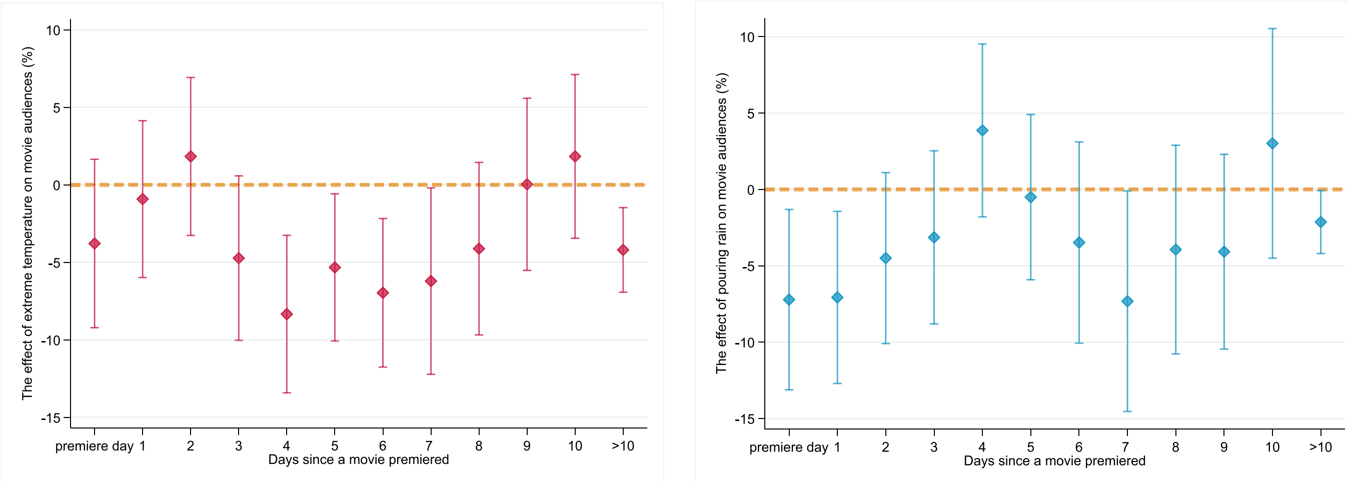
Based on the China Business Network classification, 49 sample cities are divided into 1st-tier, new 1st-tier, and 2nd-tier cities. The film market is more active in high-tier cities on average. In 2017, 1st-tier cities accounted for 20.23% of national box office revenues, while the share in new 1st-tier and 2nd-tier cities are 26.26% and 21.88%. Fig. 7 confirms that the damage of weather shocks on movie demand appears in 1st-tier and new 1st-tier cities, with the former owning a slightly larger magnitude. This result is consistent with findings in Table 3, suggesting that markets with strong demand for moviegoing are more vulnerable to external weather shocks. While in 2nd-tier cities, estimates of weather shocks are insignificant due to the limited fan base and lower market activity.

5.3.2. *Movie quality*

According to Douban ratings, movie samples are divided equally into four groups to examine the heterogeneity of movie quality. Fig. 7 indicates that the effect of weather is concentrated in medium-quality movies, while estimates for the highest (top 25%) and lowest (bottom 25%) quality movies are insignificant. High-quality movies often boast intriguing scripts, sufficient production budgets, and star appearances,

Panel A: extreme temperature **Panel B: pouring rain**

Fig. 7. Heterogeneity effects of weather on movie audiences: city tiers and movie quality.
Notes: Solid diamonds and squares represent point estimation results, each group from a separate regression. Horizontal dashed lines indicate the 95% confidence interval.



Panel A: extreme temperature

Panel B: pouring rain

Fig. 8. Heterogeneity effects of weather on movie audiences: movie life cycle.
Notes: Solid diamonds represent point estimation results, and all are from a combined regression. Vertical solid lines indicate the 95% confidence interval.

which attract audiences to attend theaters, even if they may be exposed to unpleasant weather. As a comparison, the audience size for low-quality movies stagnates at a low level and is insensitive to weather shocks since audiences are reluctant to go for them.

5.3.3. Movie life cycle

The audience of a movie is not constant but gradually declines after its premiere, as shown in Fig. A1. Fig. 8 illustrates the impact of weather shocks on audience size in the early stage of a movie's life cycle, i.e., in the first ten days after its premiere. We find that the significant dampening of extreme temperatures on movie demand occurs within 3–7 days after the premiere, while the effects of pouring rain are concentrated in the first three days after the premiere. On the one hand, audience demand for a movie is strongest in the opening week, and unexpected weather shocks significantly reduce movie recreation. On the other hand, for potential audiences with imprecise priori of the movie, their attending decisions are affected by feedback from early adopters through network externalities and social learning (Moretti, 2011; Gilchrist and Sands, 2016). That means the sudden weather shocks during the fermentation period of word-of-mouth can profoundly damage its performance. We provide new insights for understanding the effect of weather conditions on movie performance by focusing on the early period of its life cycle rather than on opening weekends, as Gilchrist and Sands (2016).

6. Conclusion and discussion

In this study, we analyze the impact of weather shocks on movie demand using a comprehensive dataset of high-frequency moviegoing records for 49 major cities in China from 2017 to 2019. Our results reveal that both extreme temperatures and pouring rains have significant negative effects on audiences' demand for movies, with the impact more pronounced during weekends and holidays. Hence, avoiding disutility from extreme weather in outgoing is an essential explanation for the reduction of movie audiences. To ensure the validity of results, we develop a rigorous framework that addresses potential biases arising from the interplay between weather and movie supply. We emphasize the importance of considering these supply-side factors when studying the relationship between weather demand for services. By providing a reference empirical framework, we contribute to the existing literature and encourage further research to explore the theoretical market correlations and characterize these behaviors through structural estimates.

Two caveats should be considered regarding our study. First, our analysis focuses on a relatively short sample period of three years, which may limit the generalizability of our findings. Audiences' offline movie demand can be dramatically affected by economic policies and systemic preference changes, such as the COVID-19 pandemic and travel restrictions. Therefore, caution should be exercised when interpreting the external validity of our results. To fully understand the long-term effects of climate change on movie recreation, an accurate projection of the future development of China's film industry would be necessary. However, such projections fall out of the scope of the paper, and we do not attempt to extrapolate our baseline results to the end of the century, as commonly done in climate literature.

Second, we use the reduced-form specification to identify the causal effect of weather on offline movie demand. However, the increasing frequency of extreme weather may benefit online movie viewing demand and other indoor recreational activities. Exploring the reshaping of climate for recreational demands relies on more detailed data and structural estimation designs.

CRediT authorship contribution statement

Chen Xi: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Wei Xie:** Conceptualization, Methodology, Resources, Supervision, Writing – review & editing. **Xiaoguang Chen:** Conceptualization, Methodology, Resources, Supervision, Writing – review & editing. **Pan He:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.107038.

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