Weather Variations, Climate Change, and Demand for in-theater Movie Recreations: Evidence from High-Frequency Movie-Viewing Data in China

Chen Xi Wei Xie Xiaoguang Chen Pan He*

March 2022

Abstract: Accurately assessing the impacts of climate change on each economic sector is essential for designing effective climate policies. Although the impacts of climate change on the agricultural and industrial sectors have been abundantly explored, studies focusing on the service sector are still sparse, especially for emerging economies. Leveraging high-resolution movie-viewing records across 49 cities in China between 2015-2017, this paper examines how in-theater movie recreations are affected by ambient weather variations, mainly temperature and precipitation. We find that, compared with a broader range of moderate temperatures, extremely high temperatures (daily average temperature ≥30°C) led to a 3.27%, 5.94%, and 0.86% reduction in audiences, box office revenues, and attendance rate, respectively. Effects of extremely low temperatures (daily average temperature <-1°C) and precipitations are slightly small. The negative impacts of extreme temperatures are most pronounced in the 3-7 days after a movie premiered, with the performance of movies screened in high-tier cities and on Fridays being more likely to suffer, while demand for high-quality movies suffers less under temperature shocks. Our findings suggest that in 2017, 49 cities across China lost 4.93 (0.13) million audiences and 292.74 (7.24) million Chinese Yuan box office revenues due to extreme temperatures (precipitations). In the medium-term future (years 2041-2060), moviegoing losses due to climate change are predicted to increase by 20%-60% from the current stage.

Keywords: Weather variation, Climate change, Movie viewing demand, China
JEL classification: Q54, L83, Q51

---

* Chen Xi: School of Economics and Management, Tsinghua University (email: xic20@mails.tsinghua.edu.cn); Wei Xie: corresponding author, China Center for Agricultural Policy (CCAP) in the School of Advanced Agricultural Sciences, Peking University (email: xiewei.ccap@pku.edu.cn); Xiaoguang Chen: Research Institute of Economics and Management, Southwestern University of Finance and Economics (email: cxg@swufe.edu.cn); Pan He, School of Earth and Ocean Sciences, Cardiff University (email: HeP3@cardiff.ac.uk). The authors acknowledge supports from the National Natural Science Foundation of China (71873009, 71922002).

1. Introduction

Climate change has been demonstrated to hamper various aspects of society and the economy and is regarded as one of the most severe global challenges in the 21st century. Comprehensively accessing relationships between climatic factors and economic-related outcomes in each sector of the economy is vital for understanding potential economic implications of future climate change and designing economically rational climate policies (Dell et al., 2014; Hsiang et al., 2017). The climate-economy literature is concentrated on agricultural output (Deschênes and Greenstone, 2007; Schlenker et al., 2009; Chen et al., 2016; Zhang et al., 2017) and industrial output (Dell et al., 2012; Zhang et al., 2018; Chen et al., 2019; Somanathan et al., 2021). However, examinations of the impact of weather variations on outcomes in the service sector are limited, especially for emerging economies.

This paper assesses the effects of temperature and precipitation fluctuations on audiences, box office revenues, and the attendance rate in China's film industry. As the world's largest developing country, China has experienced rapid economic growth over the past few decades. The tremendous expansion of the film industry is a testimony of China's transition towards a consumer economy. China is one of the largest movie markets worldwide, and its audiences' preference for actor types may even impact Hollywood castings (Hermosilla et al., 2018).[2] Between 2012-2019, box office revenues, the number of cinema screens, and the number of movie tickets sold in China grew steadily at an average annual growth rate of 21.8%, 27.2%, 22.0%, respectively (Figure 1). The high-speed development of China's film industry demands a critical assessment of its weather vulnerability to formulate effective climate policies.

Weather shocks are likely to change consumers' decisions and indirectly affect the service sector, considering the service sector is mainly driven by demand. Past studies found that households are willing to pay more to avoid extreme temperatures (Albouy et al., 2016) and that they reduce their time outdoors when the temperature becomes

[2] According to box office revenue, China was the second largest movie market worldwide between 2015-2019. 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.

uncomfortable (Zivin and Neidell, 2014). This implies that the more elastic audiences' consumption demand is, the more damage the service sector could suffer from weather variations. Although we focus on the impact of weather variations on in-theater moviegoing in China, considering the representativeness of the film industry for the service sector, the implications of our results may extend to other demand-driven sectors in developing countries.

Leveraging high-frequency movie viewing data, combined with daily weather and air quality data, we causally identified the impact of temperature and precipitation fluctuations on audiences' demand for in-theater movie recreations. Theater-level movie viewing records of 49 cities in China between 2015 and 2017 were obtained from an online box office statistics website. The high-resolution data, both spatial and temporal, comprehensively describe audiences' movie viewing demands. We aggregate theater-level data to the movie-city-day level to conduct our econometric analysis. To accurately describe movies' characteristics, we obtain variables including their overall rating, an appropriate proxy for movie quality, from Douban.com. Meteorological and air quality data are obtained from the China Meteorological Administration and the Ministry of Ecology and Environment of China, respectively. Both data are aggregated to the city-day level to merge with the movie viewing data. Finally, 754,000 observations for 1,273 non-rescreened movies are used in the analysis.

We use day-to-day fluctuations of temperatures and precipitations across cities to causally identify their effect on moviegoing, which are seen as plausible exogenous variations and are widely used as instrumental variables for economic activities in the literature (Mellon, 2021). Although reverse causation is not a major identification concern, estimates may be biased due to potential omitted variables (Dell et al., 2014). Benefiting from our high-resolution movie viewing data, we can control for a wealth of fixed effects, thus removing confounding factors and obtaining a confident causal interpretation of weather variations. In addition, we pay special attention to the identification challenge due to movie supply. The movie distributor chooses the movie's premiere timing to maximize the economic profits, and the concentrated period of the premiere highly overlaps with extremely hot or cold days in a year, which may distort moviegoing through availability for movies. As these time-variant premiering strategy factors are simultaneously related to temperature fluctuations and moviegoing, unfortunately, cannot be absorbed by the fixed effects. We develop a model at the city-day level to carefully examine this identification threat. Results confirm that omitted potential variables related to the movie supply do not substantially shock the identification and actually lead to conservative estimations.

Our flexible semiparametric bin approach indicates an inverted U-shaped relationship between temperature and moviegoing. Significant temperature impacts are found at the head and tail of its distribution, while the effect of a wide range of moderate temperatures is nonsignificant. We define a day as an *extremely hot day*/ *extremely cold day* if the daily average temperature is over 30°C (95th percentile of the temperature distribution)/ below -1°C (5th percentile of the temperature distribution). On an extremely hot day, audiences, box office revenues, and the attendance rate are found 3.27%, 5,94%, and 0.86% lower than on days with moderate temperatures, [-1,30) °C. The effect magnitude of extreme colds is relatively small, with weaker statistical significance (reduction in audiences, revenues, and attendance rate is 2.73%, 3.33%, and 0.99%, respectively). The impact of extreme temperatures is demonstrated to be contemporaneous, as audiences respond less to extreme events lagged up to 10 days. These results are robust under a series of checks. Precipitation is confirmed to reduce audiences' movie-viewing demands linearly under each specification. According to these findings, we further provide a back-of-the-envelop calculation to quantify the economic cost of moviegoing changes caused by weather variations. The calculation suggests that in 2017 extreme temperatures led to 4.93 million losses in moviegoers and a 292.74 million Chinese Yuan loss in box office revenues across 49 cities in China. Although precipitations also harm the film industry, the effect magnitude is far smaller than that of extreme temperatures, that is, 0.13 million loss in audiences and 7.24 million Chinese Yuan loss in revenues.

We further project the effect of medium-term future climate change on China's film industry from the demand side, using response coefficients estimated and city-day level temperature and precipitation data predicted by five global climate models for

2041-2060. Assuming the movie-viewing pattern in the future does not change, we predict the future annual loss from moviegoing will be 1.4-2 times higher than that in the sample period under different representative concentration paths (RCPs), solely caused by the shift in temperature distribution. The effect is strongest for the most severe climate change scenario, RCP8.5. Since accumulated precipitation is expected to decrease in the future, the reduction in movie-viewing demands caused by precipitations is predicted to be 0.87 times that at the current stage.

This paper contributes to the literature on at least three aspects. First, it contributes to a small but growing body of literature identifying the impacts of short-term weather variations on out-of-home recreational activities (Chan and Wichman, 2020; Dundas and von Haefen, 2020). To the best of our knowledge, this is the first paper using high-resolution data to causally examine how recreation demands in developing countries are affected by weather variations. Dundas and von Haefen (2020) found that extreme heat significantly reduced participation in coastal recreational fishing in the US during 2004-2009, and future climate changes imply considerable recreational participation declines and welfare losses. Chan and Wichman (2020) investigate how outdoor cyclings in North American cities are affected by weather variations using 2016 American Time Use Survey data. They found that cyclists prefer to ride on hot rather than cold days, suggesting that more warm days caused by climate change will promote cycling activities in the future. Although extreme heat also decreases cycling, cyclists can mitigate the disadvantage by adjusting their riding time to cooler times of the day. They concluded that medium-term climate changes synthetically lead to surplus benefits for outdoor cycling. Our study distinguishes itself from similar literature that focuses on developed countries. Considering that the rising share of the service sector accounts for aggregate national output in emerging economies, this paper has important economic implications for constructing effective climate policies.

Second, existing literature assessing the impacts of climate change on out-of-home recreational activities mainly concentrates on nonmarket activities (Chan and Wichman, 2018; Dundas and von Haefen, 2020; Chan and Wichman, 2020). However, impacts on transactional market-based recreations are still not fully understood.[3] Since the value standard for market-based leisure consumption is clear, outputs from these recreational activities can be included in the service sector and be a component of aggregate national output. Therefore, market-based recreations are at least as essential as nonmarket recreations in assessing the socio-economic impact of climate change. We add to the literature by evaluating a recreational activity with clear financial indicators.

Third, the effects of temperature variations on different out-of-home recreations are inconsistent in the literature, implying it is difficult to deduce the impact pattern of climate change on the service sector from sparse studies. This paper enriches the discussion on this.

The rest of the paper is organized as follows. Section 2 introduces the data and provides summary statistics. Section 3 presents the empirical strategy. Section 4 reports empirical results and also conducts a series of robustness checks. Section 5 reveals the economic implications of weather variations and predicts the impact of medium-term future climate change. Section 6 concludes the paper.

2. Data

Micro-data from various sources are combined to compile a comprehensive dataset to investigate the impact of weather variations on movie viewings. We further use city-day level temperature and precipitation data estimated for 2041-2060 to predict the effect of medium-term climate change on the film industry from the demand side.

Movie-viewing data. The viewing record micro-data of movies screened in 49 cities across China between 2015-2017 are retrieved from an online box office statistics website. Based on several indicators, 338 Chinese cities are divided into five groups by the YiMagazine.[4] We select 1st-tier cities, new-1st-tier cities, and 2nd-tier cities as samples for our analysis, which account for 68.37% of all 2017 box office revenues in

---

3 One paper that explored market-based leisure consumption is He et al. (2019). Using a dataset of financial records from more than 1,700 hotels in the US between 2016-2018, they found that the profit rate of the hotel industry is decreased by temperatures that deviated from 18°C-20°C.

4 These 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). See https://www.36kr.com/p/1721587073025 for more information.

China's film market.[5] For each screening record, the movie's name, the theater's location, the number of seats, the movie ticket price, the opening time, and the audience numbers are included in the movie-viewing database. We conduct our analysis at the city-date-movie level. By calculating the average audience number per screen, the average box office revenues per screen, and the average attendance rate for each movie in each city, we remove the interference of movie-screening frequency from the estimated results. After excluding the rescreened movie sample from the initial movie-viewing database containing 1,361 movies, 1,273 movie-viewing records are exploited in the baseline analysis.

Movie-rating data. The movie-rating data come from the most popular movie review website in China, Douban.com. The overall rating, i.e., a score between 2 and 10, provides an approximate measure of the movie quality. We also obtain other information about movies' characteristics from the Douban database, including the premiere date, movie language, runtime, number of ratings, and production countries.[6] Based on the premiere date information, we calculate the number of days since the movie has been released.

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, an official institution under the jurisdiction of the China Meteorological Administration.[7] We aggregate the meteorological data to the city-day level using the inverse distance weighting method with a 100km radius setting, a broadly used setting in the literature (Deschênes and Greenstone, 2007; Zhang et al., 2017).[8] In addition to weather conditions, ambient air quality is also a relevant factor in moviegoers' decision-making (He et al., 2022). We include the air quality index (AQI) obtained from the

[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] For instance, the rating interface of *Wolf Warriors* 2 on Douban.com is https://movie.douban.com/subject/26363254/.
[7] More details about the meteorological data can be found at http://data.cma.cn/en.
[8] We also choose 150km and 200km as the radii for robustness checks, and the results are robust.

Ministry of Ecology and Environment of China as a control variable.[9] Air quality data are aggregated to the city-day level by averaging hourly AQI for each day.

Temperature and precipitation prediction data. Predicted data on daily average temperatures and daily accumulated precipitations for 49 cities between 2041-2060 are extracted from five Global Climate Models (GCMs), i.e., GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM, and NorESM1-M, released by the Inter-Sectoral Impact Model Intercomparison Project (ISI-MPI). The ISI-MPI provides a framework for comprehensively understanding the impact of climate change on the earth's surface processes and human societies.[10] Relevant data have been adopted by the Intergovernmental Panel on Climate Change (IPCC) for simulating the profound effects of climate change (Warszawski et al., 2014; Frieler et al., 2017). Differing on the severity of climate warming, each climate model includes four representative concentration paths (RCPs), RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The resolution of the gridded meteorological prediction data is $0.5° \times 0.5°$, and we assign the prediction data to each city according to the city's geographic center.

Table 1 shows the summary statistics of our data. Unsurprisingly, the average ticket price is 36.89 Chinese Yuan, close to the national level between 2015-2017, reflecting that our sample is representative of the general population.[11]

3. Empirical strategy

3.1 *Baseline specification*

We focus on exploring the impact of weather variations on the film industry from the demand side, mainly investigating temperature and precipitation. Based on the high-frequency movie-reviewing records of 1,273 non-rescreened movies in 49 cities between 2015-2017 and following a high-dimensional fixed-effects model, Eq.(1) is proposed to assess the influence of weather variations:

---

[9] Compared with individual air pollutants such as PM10 or PM2.5, people pay more attention to the comprehensive indicator, AQI (Zhang and Mu, 2018). We also replace AQI with PM2.5 and PM10 as air quality controls for robustness checks, which shows consistent results. The official website releasing air quality data is: http://106.37.208.233:20035/.

[10] For a more detailed introduction about the ISI-MPI, see https://www.isimip.org/.

[11] 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 released by chinabaogao.com. See: http://data.chinabaogao.com/chuanmei/2019/12304H3162019.html.

$$
\begin{aligned}
V_{icd} = \alpha f(Temp_{cd}) + \boldsymbol{W}_{cd}\beta_1 + \beta_2 AQI_{cd} + \boldsymbol{M}_{icd}\gamma \\
+ \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd}
\end{aligned}
\tag{1}
$$

where V_{icd} denotes movie-viewing behaviors, consisting of the logarithmic average audience number per screen, the logarithmic average number of box office revenues per screen, and the average attendance rate for movie i screening in city c on date d. $f(Temp_{cd})$ represents the general function of the daily average temperature of city c on date d, where our primary interest is in the parameter α. Considering the non-linear response of socio-economic variables to temperature fluctuations extensively found in the literature, we apply various temperature measurements (the setting of the temperature variable is explained in detail later).

$\boldsymbol{W}_{cd}$ is a vector of city-day level weather variables except for temperature, including precipitation and other meteorological variables described above. The comprehensive indicator for ambient air quality AQI_{cd} is also included as a confounder in the baseline specification. Since we aim to estimate the effects of weather variations from the demand side, confounders related to the supply side $\boldsymbol{M}_{icd}$ are also controlled to mitigate potential estimation bias. $\boldsymbol{M}_{icd}$ includes movie- and time-varying screening frequency and average ticket price, which signal movies' popularity and may affect moviegoers' interest and admission chances.

The movie-city-day level specification allows us to eliminate the estimation bias caused by time-invariant unobservables by including abundant fixed effects. The movie fixed effect θ_i captures observable time-invariant movie characteristics, including movie quality and runtime, and all other time-invariant unobservable movie attributes not available in the Douban database. City-level movie-viewing characteristics that do not change over time are controlled by the city fixed effect τ_c, i.e., the heterogeneity of the administrative level, population structure, and preference for movie types across cities. National-level shocks common to all cities but varying across time are absorbed by the date fixed effect ρ_d. For instance, these include the effect of weekends and holidays, as well as the market trends during summer holidays and the Spring Festival. There may be a non-linear relationship between moviegoers' number and the days since the movie premiered. We use DsP (days-since-premiered) fixed effects to capture this non-linear relationship, allowing more flexible movie-viewing reactions. In the baseline analysis, we cluster standard errors at the movie level, with additional two-way clustering being performed as a robustness check.

3.2 *Definition of temperature measures*

Ongoing literature reveals the profound impact of extreme temperatures on human behaviors from multiple perspectives, including time allocation (Zivin and Neidell, 2014), recreational cycling (Chan and Wichman, 2020), criminal activities (Ranson, 2014), electricity consumption (Auffhammer, Baylis, and Hausman, 2017; Li et al., 2019), and human health and mortality across countries (Deschênes and Greenstone, 2011; Karlsson and Ziebarth, 2018; Yu et al., 2019), highlighting the non-linear relationship between extreme temperatures and human activities. Therefore, we adopt various methods to measure temperatures $f(Temp_{cd})$. We prefer to flexibly capture the non-linear effects of temperature by the broadly used temperature-bins model.[12] Eq.(1) thus can be explicitly written as:

$$\begin{aligned} V_{icd} = \sum_j \alpha_j TempBin_{cd}^j + \boldsymbol{W}_{cd}\beta_1 + \beta_2 AQI_{cd} + \boldsymbol{M}_{icd}\gamma \\ + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd} \end{aligned} \quad (2)$$

To ensure enough temperature bins to depict the response to temperature fluctuations accurately and that the number of observations in each bin is comparable, we divide temperatures into 18 bins with a 2℃ interval[13]. $TempBin_{cd}^j$ contains a group of dummy variables, which equal one if city c's daily average temperature falls into the

[12] We also use a concise quadratic temperature setting, where $f(Temp_{cd})$ includes $Temp_{cd}$ and its quadratic term $Temp_{cd}^2$.

[13] The 18 temperature bins are <-2, [-2,0), [0,2), [2,4), [4,6), [6,8), [8,10), [10,12), [12,14), [14,16), [16,18), [18,20), [20,22), [22,24), [24,26), [26,28), [28,30), and ≥30°C.

j-th bin on date d. We designate [20,22) °C as the reference bin, generally seen as the optimal ambient temperature range for the human body and associated with the weakest influence on movie-viewing decisions. Thus, the coefficients of bins α_j measure the relative impact of temperature fluctuations on movie-viewing compared with the reference temperature zone.

To investigate the effect of extremely high and low temperatures, we define two dummy variables according to the head and tail of the temperature distribution, similarly to Karlsson and Ziebarth (2018) and Chan and Wichman (2020). We indicate a day with the daily average temperature over 30°C as an *extremely hot day* and a day with the daily average temperature below -1°C as an *extremely cold day*, representing the 95th and 5th percentiles in the distribution of temperatures. This specification is close to the definition of extreme temperatures in the context of recreational cycling (over 80°F for extremely hot days and below 30°F for extremely cold days; Chan and Wichman, 2020), but slightly different from the standard used in a temperature-mortality study (30°C and -10°C as criteria for extremely hot and extremely cold days; Karlsson and Ziebarth, 2018). Following the definition above, we further extend our baseline specification as follows:

$$\begin{aligned} V_{icd} = &\alpha_1 ExtreHighTemp_{cd} + \alpha_2 ExtreLowTemp_{cd} + \boldsymbol{W}_{cd}\beta_1 \\ &+ \beta_2 AQI_{cd} + \boldsymbol{M}_{icd}\gamma + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd} \end{aligned} \tag{3}$$

The interpretation of α_1 and α_2 in Eq.(3) is slightly different from coefficients α_j in the temperature-bins model because the reference is no longer the bin [20,22) °C, but a broader range of moderate temperatures, i.e., [-1,30) °C. Coefficients of extremely hot and extremely cold temperatures here capture movie-viewing changes relative to common temperatures, which will be further used in predicting the impact of medium-term climate change on the film industry.

3.3 *Challenges from the movie-supply side*

Our analysis of the shock on the film industry induced by weather variations is based on the demand side. The main concerns about the validity of the above specifications come from potential correlations between temperature patterns and the distributors' decision on the timing of a movie's release, i.e., supply-side threats. Although there is no literature on the direct impact of temperatures on movie releases to our knowledge,[14] some studies on seasonality in movie release strategies provide indirect insights for this connection. King et al. (2017) established a signaling model and deduced that the best releasing period differs between high-quality and low-quality movies. That is, a high-demand and quality-elastic market is better for high-quality movies, while a low-demand and quality-inelastic market is a better choice for low-quality movies. Because extreme temperatures overlap with the popular release periods of the film market, with extremely high temperatures corresponding to summer periods and extremely low temperatures corresponding to the Spring Festival, this suggests a high correlation between temperatures and the timing of movie releases. The release decision made by the distributors affects audiences' availability for the movie from both the extensive and the intensive margin in the specific period, which alerts us that our specifications may biasedly estimate the effect of temperature fluctuations on moviegoing if supply-side movie-release decisions related to temperature measures but are not controlled for in our models.

Figure 2 shows the pattern of movies premiered in days across a week and months across a year for non-rescreened movies. The movie premiere day is predominantly Friday, which is not surprising. A reasonable explanation is that a movie released on Friday can attract audiences from Friday night to Sunday, contributing to higher early-period box office revenues. Movies released in two windows- July to September and November to December, account for a large percentage of movies released throughout a year, corresponding to the summer period and the Spring Festival, respectively. Our descriptive findings are highly consistent with Eivan (2010), which documents that movie-release dates are densely clustered around weekends and holidays. Additionally, we select the top 22 days between 2015-2017 based on the number of movies released that day (see Table A2). Interestingly, all the 22 popular premiere days are Fridays, echoing the pattern presented in Figure 2.

[14] Chisholm et al. (2015) provides a brief overview of ongoing economic research related to the film industry, although meteorological factors are not investigated.

These pieces of evidence suggest that distributors' strategy for timing movie premieres is principally driven by the probability of obtaining high box office revenues immediately after the movie is premiered, while subtle meteorological factors are not a primary consideration. Furthermore, specific features of film premiers strengthen our confidence in these revenue-based inferences. A movie's premiering date is always decided a few months ahead and announced to the public to enhance their expectations, and information is available for audiences through news reports or websites.[15] While short-term temperatures can be obtained from the weather forecast, it is quite challenging to precisely predict weather conditions months ahead. This suggests that movie-release decisions are unlikely to be meteorologically influenced, even though weather shocks potentially affect movies' performance through social and observational learning (Moretti, 2011; Gilchrist and Sands, 2016).

To formally address the relationship between temperature fluctuations and movie supply, we implement the following temperature-bins specification at the city-day level, echoing models above:

$$\begin{aligned} S_{cd} = & \sum_j \alpha_j TempBin_{cd}^j + \boldsymbol{W}_{cd}\beta_1 + \beta_2 AQI_{cd} \\ & + \tau_c + \sigma_{year} + \pi_{DoW} + \lambda_{MoY} + \varepsilon_{cd} \end{aligned} \tag{4}$$

S_{cd} denotes a series of variables for movie premiere and screening. The number of movies screened in city c on date d is the movie-screening indicator. A dummy variable for whether movies premiered on date d reflects the availability of movies from the extensive margin, while the number of movies premiered on date d represents movie availability from the intensive margin. Although the same movie has the same premiere date across cities, adding the city fixed effect τ_c and year fixed effect σ_{year} helps clarify the relationship between temperature and movie premieres. To illustrate, preferences for movie types and viewing habits in hotspots are usually

[15] For example, THE NUMBERS provides release schedules for movies that will be released in the U.S. or Canada. Similar information for China's film market can be found on Douban.com. For more details, see: https://www.the-numbers.com/movies/release-schedule.

considerations for movie distributors, captured by the city fixed effect. Moreover, movie demand density throughout the years is correlated with movie distributors' strategy (King et al., 2017), implying the necessity of year fixed effects. We further include day-of-week fixed effects π_{DoW} and month-of-year fixed effects λ_{MoY} to control for the pattern described in Figure 2. The setting of temperature bins in Eq.(4) is the same as that in Eq.(2). Correlations between temperatures and the movie supply are represented by the coefficients α_j. Meteorological factors and air quality are still controlled. Standard errors are clustered at the city level.

4. Empirical results

4.1 *Baseline findings*

We begin by analyzing the impact of weather variations on moviegoing. The temperature-bins model flexibly estimates the dose-response function of temperature fluctuations on moviegoing, as illustrated in Figure 3.[16] The point estimation result of each bin should be interpreted as the marginal change of the logarithm of audiences, the logarithm of box office revenues, and the attendance rate, compared with the reference group, [20,22) °C. We find that statistically significant effects appear at the upper and lower ends of the temperature distribution, while bins between -2°C to 28°C are nonsignificant or weakly significant, suggesting the impact of temperature fluctuations on moviegoing is mainly driven by extreme temperatures and only weakly affected by moderate temperatures.[17] An extremely hot day with the daily average temperature higher than (or equal to) 30°C decreases audiences and box office revenues by 4.15% and 6.17% relative to the reference group, equivalent to 0.72 persons and 40.08 Chinese Yuan, also leading to a 1.25% reduction in the attendance rate. Extremely low temperatures reduce audiences' demand for movie viewing with a magnitude similar to extremely high temperatures, although the change is less significant. Audiences, box office revenues, and attendance rates are 4.42%, 9.28%, and 1.06% lower than for the reference group on days with the daily average temperature lower

[16] For detailed regression results, see Table A3.

[17] The quadratic temperature setting also implies an inverted U-shaped relationship between temperatures and moviegoing, as shown in Panel A of Table 2.

than -2℃, equivalent to a 0.72 reduction in audiences and 60.29 Chinese Yuan revenue losses. We find strongly significant effects of extremely high temperatures on moviegoing. However, the negative effect of extremely low temperatures is marginally significant, which implies that moviegoers are more sensitive to extreme heat. The heterogeneous effects of extreme heat and extreme cold on socio-economic outcomes are broadly found in the literature, such as Zivin and Neidell (2014), Li et al. (2019), and Chan and Wichman (2020). We further extended these findings in the context of market-based recreational activities.

The fact that moviegoing does not respond to temperature bins except in extreme cases encourages us to extend the reference interval, thus directly estimating the impact of extreme temperatures rather than temperature fluctuations on movie viewings. Estimation results according to Eq.(3) are presented in Panel B of Table 2. Temperature extremes are defined as days when the daily average temperature is above 30°C or below -1°C. Again, we find substantial negative effects on extremely hot days and less significant effects on extremely cold days. The effect on audiences, box office revenues, and attendance rate is a reduction by 0.56 (0.46) persons, 38.24 (21.63) Chinese Yuan, and 0.86% (0.99%) on extremely hot days (extremely cold days) when compared to moderate temperatures (between -1°C and 30 °C). We continue to adopt this definition of extreme temperatures when evaluating future economic implications and predicting losses to the film industry induced by climate change, considering our findings are consistent with the temperature-bins model and the convenience of calculations. Moreover, we find that the daily cumulative precipitation, another indicator commonly adopted to reflect climate change, also negatively impacts moviegoing. We further confirm this approximately linear effect of precipitation by using a quadratic precipitation setting and a precipitation-bins model, detailed in Table A4.

It is worth noting that air pollution promotes moviegoers' viewing habits by assuming air quality fluctuations are exogenous and random, contrary to He et al. (2022). This effect is robust to an air quality bins setting and to PM2.5 and PM10 as alternative air quality indicators.[18] The difference between our study and He et al. (2022) is that their sampling period ended in 2014,[19] the year when China established real-time air quality monitoring sites nationwide and transparently disclosed air pollution information to the public. Barwick et al. (2019) documented that this information program profoundly enhanced residents' awareness of air pollution and triggered their avoidance behaviors. We argue that, although movie-viewing is an out-of-home recreational activity similar to supermarket shopping and outdoor dining, it also offers shelter from damages from particulate matters for the duration of the activity. That is to say, movie-viewing on days with severe pollution levels can be seen as a choice to avoid short-term air pollution in the context of out-of-home activities. Columns 1-3 in Table A5 further support this inference, showing audiences' movie-viewing willingness increases non-linearly with the increase in air pollution severity. Unfortunately, due to the lack of information on the whereabouts of audiences when they decide to see a movie (indoors or outdoors), more in-depth exploration of this question is unfeasible.

4.2 *Robustness checks*

In this section, we apply various specifications to check the robustness of our baseline findings. First, 88 movies rescreened during 2015-2017 are excluded from the baseline analysis, considering that audiences' differential preferences for rescreened versus newly released movies may cause an ambiguous effect on the results. Here, we use all 1,361 movies (including rescreened movie samples) and rerun the analysis to test the sensitivity of our baseline results. For this estimation, we no longer include the fixed effects for days since premiered (DsP). Second, the cloud cover variable from the meteorological vector has a large number of missing observations, as shown in the descriptive statistics. We drop this variable and rerun the baseline model. Third, although each movie has a unified national premiere date recorded on Douban.com, the first release of a movie is not the same for each city. Profit-maximizing theaters may be

[18] Detailed results are provided in Table A5.

[19] The sample period of He et al. (2022) is 2012-2014, while we use a sample between 2015-2017. He et al. (2022) use the air pollution index (API) to measure air quality because nationwide AQI information is not completely available until 2014, which is inconsistent with our AQI setting.

affected by the preferences of potential audiences in their city and thus postpone the release date of new films. We calculate the minimum value of DsP within movie-city groups and drop the observations in movie-city groups with a minimum DsP larger than ten days for the robustness check. Fourth, we further refine our samples by excluding observations with a movie ticket price below the 1% quantile or above the 95% quantile of the whole distribution. The cutoff point is 22.42 Chinese Yuan and 65 Chinese Yuan, respectively. Fifth, the abnormal screening behavior of theaters may have unexpected effects on the results. Therefore, we exclude movie samples screened for fewer than seven days between 2015-2017 within each city. In addition, Movies have experienced a big success at the box office and have word of mouth may be postponed to go offline, thus having screening days far exceeding other movies.[20] To avoid results being biased by these blockbuster movies, movie samples screened for more than 80 days in each city are also excluded. Moreover, the standard errors are clustered at the movie level to control for autocorrelation within each movie in the baseline analysis. We now adopt the two-way clustered standard errors to cluster them at the movie-city level.

The effect of extreme temperatures under various robustness checks is presented in Figure 4. Extreme temperatures still have a negative and stable effect on moviegoing, reflecting that the baseline results are robust. Again, the negative impact of extreme temperatures is mainly driven by extremely high temperatures, while extremely low temperatures have a smaller negative influence on moviegoing, coinciding with findings in Panel B of Table 2.[21]

Another concern is that the ambient air quality AQI_{cd} is an endogenous variable that may bias air pollution estimation in Table 2 and leads to inconsistent results with He et al. (2022). To make matters worse, if temperature and air quality are not independent, the endogenous air quality variable also leads to biased estimates of

[20] Generally, the average screening period for a movie is 30-40 days, although this depends 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, although 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.

[21] The results of the robustness checks for extremely high and extremely low temperatures are shown in Figures A1 and A2, respectively.

temperature effects. We use thermal inversion as an instrumental variable (IV) for air quality, a popular method in the literature, and conduct HDFE-2SLS estimation to alleviate this concern (Fu et al., 2021; Godzinski and Castillo, 2021). The 3-hour-period, 50×60 km grid-level thermal inversion data are obtained from the MERRA-2 satellite of the National Oceanic and Atmospheric Administration (NOAA).[22] The thermal inversion condition of each city is identified based on its geographic center location. We establish that a thermal inversion occurs if the temperature in the second atmospheric layer (320m) is higher than that in the first layer (110m) for each 3-hour-period observation. For a specific city, if a thermal inversion occurs more than four times in the eight satellite observations taken during a day, TI_{cd} is assigned the value of one. Otherwise, this variable equals zero. HDFE-2SLS estimation results are reported in Table A6. The Cragg-Donald Wald F-statistic is 2222.174, which is large enough to exclude thermal inversion as a weak IV for air pollution. Under this IV strategy, the magnitude of the AQI is estimated to be nearly four times larger than that in Table 2. However, the impact of air quality on moviegoing is no longer significant. Once more, we find no changes in the estimations for temperature variations, as findings in Table A6 are close to the pattern presented in Figure 3.

4.3 *Correlation between temperature and movie-screenings*

Out of concern that movie premieres and screening might be correlated with temperatures which may bias the baseline estimations represented in Figure 3, we examine the relationship between temperature fluctuations and movie premieres/screening frequency under the guidance of Eq.(4). Investigations from the movie-supply side are carried out at the city-day level. Explained variables here are the number of movies screened/premiered and the dummy variable for whether movies premiered. All weather variables, as well as the AQI, are controlled for in the regressions. Since analyses here are at the city-day level, fixed effects controlled for are different from those on the demand side, year fixed effects, city fixed effects, day-of-week fixed

[22] A detailed description of the thermal inversion data can be found at: https://disc.gsfc.nasa.gov/datasets/M2I3NVAER_V5.12.4/summary. We use the product M2I3NVAER version 5.12.4.

effects, and month-of-year fixed effects are included. We still use the OLS estimation for the convenience of explanation when the explained variable is the dummy variable for whether movies premiered, i.e., a linear probability model (LPM).

As shown in Figure 5,[23] we find a dramatically opposite correlation pattern between movie screenings/ movie premieres and temperature fluctuations. The total number of movies screened in a city each day increases significantly with a decrease in the daily average temperature from the reference group. However, screenings are not significantly correlated with temperatures higher than 22°C. The number of movies premiered in a day, as the intensive marginal indicator of movie premieres, has a significant positive correlation with temperatures above the reference group, with an almost nonsignificant correlation with temperatures lower than 20°C. The temperature-movie premiere pattern at the extensive margin is similar to that at the intensive margin, except for the nearly nonsignificant coefficients. Considering the findings depicted in Figure 3 that moviegoing decreases significantly on extreme temperature days but does not respond to moderate temperatures, the significant positive correlations between extreme temperatures and screenings/premieres in Panel A and Panel B of Figure 5 indicate that the impact of extreme temperatures on moviegoing is underestimated. Therefore, even when considering the potentially complex relationship between temperatures and movie screenings from the supply side, our baseline results should be explained as conservative estimations.

4.4 *Lagging effects*

The baseline analysis examines the impact of extreme temperatures on moviegoing under the assumption that audiences only respond to contemporaneous extreme temperatures. In this part, we relax the assumption by introducing the lag term of extreme temperatures up to 10 days to investigate potentially intertemporal effects.[24] The model to examine the lagging effect of extreme heat/cold is the following:

[23] For detailed regression results, see Table A7.

[24] We also examine extreme temperature lags of more than 10 days. However, coefficients of higher-order lag terms are found to be almost nonsignificant.

$$
\begin{aligned}
V_{icd} = & \sum_{\eta=0}^{10} \alpha_{1\eta} ExtreHighTemp_{c,d-\eta} + \sum_{\eta=0}^{10} \alpha_{2\eta} ExtreLowTemp_{c,d-\eta} \\
& + \boldsymbol{W}_{cd}\beta_1 + \beta_2 AQI_{cd} + \boldsymbol{M}_{icd}\gamma + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd}
\end{aligned} \tag{5}
$$

Both $ExtreHighTemp_{c,d-\eta}$ and $ExtreLowTemp_{c,d-\eta}$ are a series of dummy variables that denote whether the η-th day before date d in city c was either extremely hot/ cold or moderate. The other variables of Eq.(5) are similar to Eq.(3).

We also combine the definitions of extremely high and extremely low temperatures to generate a comprehensive extreme temperature variable, which leads to the following Eq.(6):

$$
\begin{aligned}
V_{icd} = & \sum_{\eta=0}^{10} \alpha_{\eta} ExtreTemp_{c,d-\eta} + \boldsymbol{W}_{cd}\beta_1 + \beta_2 AQI_{cd} \\
& + \boldsymbol{M}_{icd}\gamma + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd}
\end{aligned} \tag{6}
$$

The lagging effects of extreme heat/cold and generalized extreme temperatures on moviegoing are presented in Figure 6.[25] We find no evidence that extreme temperatures affect moviegoing on a specific day in the past ten days. The coefficients of extreme temperatures are statistically significant when $\eta = 0$, but almost nonsignificant for any $\eta > 0$. This finding confirms that audiences' movie-viewing demand responds strongly to contemporaneous temperature shocks but is less sensitive to extreme temperature exposure in the recent past.

4.5 *Heterogeneity*

4.5.1 Days after the movie premiered

The audience scale for a movie is not stable during its life cycle but gradually declines, as an exponential decline predicted by Gilchrist and Sands (2016). We illustrate the relationship between audiences per screen and days after the movie premiered in Figure 7 after removing the city and day-of-week factors. As expected, an exponential curve with three parameters fits the relationship well.[26]

[25] Detailed regression results are provided in Table A8.

[26] We first regress the average number of audiences on the day-of-week and city dummies with standard errors clustered at city level to obtain residual audiences per screen. Then we plot residual audiences per screening days

We infer that audiences who go to a movie at different periods in its life cycle have heterogeneous prior preferences. In the early days after a movie is released, audiences who flood the theater are its most devoted fans, seeking to view the movie as soon as it is released and is minimally affected by others' reviews. In contrast, subsequent audiences are more likely to decide whether to view the movie depending on the feedback of early adopters, which highlights the effects of network externalities and social learning (Moretti, 2011; Gilchrist and Sands, 2016). We explore the heterogeneous impacts of extreme temperatures on moviegoing in various periods of a movie's life cycle by interacting indicators of days after the movie was released with extreme temperature indicators following Zheng et al. (2019). Formally, the equation is expressed as:

$$\begin{aligned} V_{icd} = \sum_{\omega=0}^{10} \alpha_\omega ExtreTemp_{cd} \times 1(DsP_{i\omega}) + \boldsymbol{W}_{cd}\beta_1 + \beta_2 AQI_{cd} \\ + \boldsymbol{M}_{icd}\gamma + \theta_i + \tau_c + \rho_d + \xi_{DsP} + \varepsilon_{icd} \end{aligned} \tag{7}$$

In Eq.(7), $1(DsP_{i\omega})$ are dummy variables representing whether date d is the ω-th day since the movie i premiered nationwide. Estimation results of α_ω are then interpreted as the impact of extreme temperatures on moviegoing on the ω-th day after the movie premiered.

The results are shown in Figure 8.[27] The significant negative impact of extreme temperatures on moviegoing mainly appears about 3-7 days after a movie is released. Estimations for early screening periods and days after the 8-day mark are nonsignificant, an effect that remained robust when extending the window to 30 days. As discussed above, viewings in the early period after a movie's premiere reflect enthusiasts' expectations in advance of the opening day. After early adopters view the movie, their experience will be passed on to potential audiences who have not yet viewed it through network externalities or social learning, further influencing non-viewers' prior

after the movie premiered in Figure 7. An exponential curve with three parameters is used to fit the relationship, that is, $Residual\_audiences = k_0 + k_1 \times k_2^{Days\ after\ premiered}$.

[27] Detailed regression results are provided in Table A9. By decomposing extreme temperatures in Eq.(7) into extremely high and extremely low temperatures, we find that the heterogeneity effects shown here are mainly driven by extremely low temperatures. See Table A9 for more information.

expectations, especially for audiences who hold diffuse expectations. We show that during the fermentation period of word-of-mouth, moviegoing is vulnerable to extreme temperatures. When a movie's reputation becomes stable, audiences' demand for the movie also smoothly declines, as shown in the tails of the exponential fitting curve in Figure 7. The nonsignificant influence of extreme temperatures can be partly attributed to the lack of variation in the size of audiences during the stable period. Unlike Gilchrist and Sands (2016), which focused on the relationship between weather shocks and abnormal viewership during opening weekends, our analysis demonstrates that the temperature shocks that occur during the social spillover of movie information also weaken audiences' demand for moviegoing, which provides new insights for understanding the box office performance and life cycle of movies from the demand side.

4.5.2 City tiers

The film market in high-tier cities is normally more active than in low-tier cities. The box office revenues of four 1st-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen) accounted for 20.23% of all nationwide box office revenues in 2017; those of fifteen new-1st-tier cities accounted for 26.26%; while revenues in thirty 2nd-tier cities accounted for 21.88% of all revenues. It is worth noting that high-tier cities are usually more developed, as suggested by the high correlation between the city's GDP and its tier classification,[28] which means residents in high-tier cities have a higher ability to pay for recreational activities and can more flexibly choose to attend in-theater movie screenings or not. When encountering extreme temperature shocks, they are thus more likely to substitute in-theater movies with indoor activities requiring less travel, such as pay-to-watch movies on online video websites. Considering that preference for in-theater movie viewing varies across audiences, audiences in high-tier cities are hypothesized to be more affected on average, as movie audiences are disproportionately clustered in these cities. To verify our deduction, we divided 49 sample cities into three

---

[28] This relationship is not surprising because a city's economic development level is one of the main factors considered by the YiMagazine when classifying cities. For each city's GDP information in China in 2017, please see: https://en.m.wikipedia.org/wiki/List_of_Chinese_prefecture-level_cities_by_GDP.

groups according to their classification by the YiMagazine. Similarly, we interact city tier indicators with extreme temperatures and investigate the estimation results of interaction terms.

Table 3 shows the heterogeneous impact of extreme temperatures on moviegoing across different city tiers. Coefficients for the interaction between extreme temperatures and 1st-tier cities/ new-1st-tier cities are negative and significant, suggesting that the negative effect of extreme temperatures on moviegoing mainly appears in high-tier cities. The effect magnitude of extremely high and extremely low temperatures in 1st-tier cities is larger than that in other cities, further confirming that the movie-viewing demand of audiences in higher-tier cities has a higher temperature elasticity, i.e., is more sensitive to extreme temperatures (see Panel B and Panel C of Table 3).

4.5.3 Day-of-week

The daily audience size varies greatly within a week, as shown in Figure 9. Consistent with Dahl and DellaVigna (2009) and He et al. (2022), movie attendance is concentrated on Fridays and weekends, when individuals have more leisure.[29] To explore the heterogeneous effect of extreme temperatures on each day of the week, we continue to construct interaction terms between extreme temperatures and each day of the week following the method described above. The results are reported in Table 4.

We find substantial heterogeneous effects of extreme temperatures on moviegoing for each day of the week. The negative effects of extreme temperatures are concentrated on Monday, Tuesday, Wednesday, and Friday, while coefficients for Thursday, Saturday, and Sunday are barely significant. Across all days, movies screened on Fridays are most affected, followed by movies screened on Wednesdays. The underlying explanation is that people's mood fluctuates across weekdays (Areni and Burger, 2008), leading them to tend to participate in recreational activities on Wednesdays. However, unsuitable temperatures may prompt them to give up that idea. As Fridays are generally followed by two free days, people have more time for moviegoing and alternatives such as resting at home and participating in other recreational activities. When the demand for movie-

[29] This fact also explains why analyses using market-level movie-viewing data focus on weekend audiences, such as Dahl and DellaVigna (2009), Moretti (2011), and Gilchrist and Sands (2016).

viewing is flexible, the external weather conditions are nudging factors in their decision-making process. On weekends, crowds of audiences flood into theaters due to plenty of leisure time, making moviegoing demand less elastic to extreme temperatures.

4.5.4 Movie quality

Quality is an important determinant of box office success for a movie (Prag and Casavant, 1994). High-quality movies are always associated with intriguing scripts, sufficient production budgets, and star appearances, which are more attractive to audiences. When suffering extremely hot or cold waves, high-quality movies are expected to have fewer losses. To verify this hypothesis, we use the Douban ratings and production countries of movies as proxies for the quality of movies, following the abovementioned specification for the heterogeneity analysis. Results are illustrated in Figure 10.

The Douban rating is an overall evaluation of a movie provided by Douban.com. The Douban rating is scaled between 2 and 10 points, and the movie with higher quality owns a larger rating. Douban.com is the most popular movie review website in China, where many audiences communicate their feelings about movies and publish short or long comments online. Our 1,106 non-rescreened movies were rated by 55,513.32 people on average (with a large SD, 117,634.4), suggesting that the Douban rating is a reliable approximation of movie quality from the demand perspective.[30] According to the overall rating, all observations in the baseline analysis are divided into four equal groups. The group 'Bottom 25%' includes movies that are least favored by audiences, while movies in the group 'Top 25%' are most sought after. Besides that, we divide medium-quality movies to obtain groups '25%-50%' and '50%-75%.' As shown in Figure 10, extreme temperatures significantly decrease audiences' demand for medium-quality movies but only slightly affect high-quality and low-quality movies. The mechanisms behind this inelastic response to extreme temperatures are the strong demand for high-quality movies and the insufficient demand for low-quality movies. It is worth noting that in our sample, movies in the group 'Top 25%' attracted 6.81 million

[30] Among 1,273 non-rescreened movies, 167 were not assigned a rating because of too few commenters to compute the statistics. We exclude these observations from the heterogeneity analysis.

audiences on average, with 6.45 million, 5.62 million, and 3.44 million individuals viewing movies in the groups '50%-75%', '25%-50%', and 'Bottom 25%'. Audiences are more enthusiastic about high-quality movies, and extreme temperatures have little effect on the box office performance of such movies. However, audiences are more reluctant to watch low-quality movies. The size of audiences for low-quality movies is stabilized at a low level and lacks variation, which causes moviegoing to be insensitive to extreme temperatures. In contrast, medium-quality movies have a moderate attractiveness but are not attractive enough for audiences to ignore the negative impact of extreme temperatures. When extreme temperatures occur, medium-quality movies are significantly impacted.

We continue to explore the differential impact of extreme temperatures on moviegoing by production countries/regions. Based on the production countries, all movie samples are sorted into three categories: produced by China alone (group 'China'), produced by countries other than China (group 'countries except for China'), and jointly produced by China and other countries (group 'joint production').[31] Since we focus on data from movies screened in China, domestic movies dominate the sample. Out of 1,273 non-rescreened movies, 74.71% of them were produced by China alone (951 movies), 17.91% of them were produced by countries other than China (228 movies), and 7.38% of them were joint productions (94 movies). As an important component of the cultural industry, the film industry is affected by the administrative power in China. A series of formal and informal measures have been introduced to support the development of Chinese movies. For instance, the National Radio and Television Administration encourages theaters to project Chinese movies instead of imported movies during the summer period each year (always from June to August), known as the 'domestic film protection month.' Moreover, the 'regulations on administration of films' formally stipulate that the annual time spent on the projection of Chinese movies shall not be less than 2/3 of the total projection time for the same

[31] We classify movies according to the production countries/regions label on Douban.com. For example, the production countries of *The Great Wall* include mainland China and the United States, so it is a joint production movie.

film projection unit.[32] Under these regulations, it is quite difficult for imported movies to enter China, which explains why movie distributors mainly import high-quality movies to maximize profits. Our sample confirms that imported movies (group 'countries except for China') have the highest Douban ratings (mean = 6.90) and the smallest variance (SD = 1.08) of the three groups. The average rating of movies jointly produced by China and other countries is 5.76 (SD = 1.55). However, the quality of domestic movies is uneven. Movies in this group have the smallest average quality (mean = 4.58), with the largest quality fluctuations (SD = 1.65). The effect of extreme temperatures on movie-goings conditional on production countries is consistent with that of overall ratings. Figure 10 shows that extreme temperatures significantly decreased the number of moviegoers for movies produced by either China alone or for those jointly produced, while there is no effect on imported movies.

To sum up, under the shock of extreme temperatures, moderate-quality movies are more likely to suffer revenue losses due to moviegoers' flexible viewing demand. Extreme temperatures have less impact on high-quality movies because of already packed audiences, with a similarly small impact on low-quality movies because of their lack of appeal.

5. Economic implications and climate predictions

5.1 *Economic implications*

We provide a back-of-the-envelope calculation to intuitively reveal the economic loss of in-theater movie consumption due to extreme temperatures. The idea is to take advantage of temperature variations at the city level, combining the response modes of movie-goings on extreme temperatures estimated above. Considering that not all in-theater movie consumption is included in our movie-viewing database, we rescale the economic loss estimations to the city level based on the ratio between annual audiences (or annual box office revenues) in our sample and those officially announced.[33] Since the statistics on audiences and box office revenues for each city are not available for

[32] Article 45 of the Regulations. See: http://www.asianlii.org/cn/legis/cen/laws/roaof382/

[33] Based on the statistics on audiences and box office revenues in each city, we calculated that our sample accounts for 5.01% of total audiences and 5.21% of total box office revenues across 49 cities in 2017. Thus, restricting the calculation to sample data only explains a part of the decrease in moviegoing because of extreme temperatures.

2015 and 2016, we focus our analysis on 2017. Moreover, the asymmetric effects of extreme heat and extreme cold are calculated separately. We apply the following Eq.(8) and Eq.(9) to calculate losses in audiences and box office revenues induced by extreme temperatures across 49 cities in 2017:

$$\begin{aligned} Loss\ in\ audience = & \sum_c \sum_d \eta_c \times \mathbf{1}(ExtreHighTemp_{cd}) \times Audience_{cd} \times \left(\frac{1}{1-0.0327} - 1\right) \\ & + \sum_c \sum_d \eta_c \times \mathbf{1}(ExtreLowTemp_{cd}) \times Audience_{cd} \times \left(\frac{1}{1-0.0273} - 1\right) \end{aligned} \tag{8}$$

and

$$\begin{aligned} Loss\ in\ box\ office = & \sum_c \sum_d \varphi_c \times \mathbf{1}(ExtreHighTemp_{cd}) \times Boxoffice_{cd} \times \left(\frac{1}{1-0.0594} - 1\right) \\ & + \sum_c \sum_d \varphi_c \times \mathbf{1}(ExtreLowTemp_{cd}) \times Boxoffice_{cd} \times \left(\frac{1}{1-0.0333} - 1\right) \end{aligned} \tag{9}$$

$\mathbf{1}(ExtreHighTemp_{cd})$ denotes whether date d in city c was an extremely hot day with a daily average temperature above 30℃, while $\mathbf{1}(ExtreLowTemp_{cd})$ denotes whether date d in city c was an extremely cold day with the daily average temperature below -1℃. Since we re-aggregate movie records from the movie-city-day level to the city-day level, $Audience_{cd}$ and $Boxoffice_{cd}$ are city c's total audiences and box office revenues on date d. The strength of extreme heat and extreme cold effects on moviegoing differs, as estimated in Table 2. The audience size of a city suffers a 3.27% (2.73%) reduction when a day is extremely hot (extremely cold), while the reduction in box office revenues is 5.94% for extremely hot days and 3.33% for extremely cold days. η_c and φ_c are parameters used to scale up the estimation of moviegoing losses from sample level to city level. η_c is defined as the ratio between the number of moviegoers officially announced in city c in 2017 and the number of moviegoers in our sample. φ_c is similarly defined but based on box office revenues.

Calculations show that extreme temperatures caused a 4.93 million people reduction in audiences and a 292.74 million Chinese Yuan loss in box office revenues across 49 cities in 2017, both of which are tremendous economic losses.[34] Precipitation is another main variable that reflects the effects of climate change. Its economic impacts on moviegoing are monetized in a slightly different way.[35] We find that precipitations reduced moviegoers' numbers by about 0.13 million people and reduced box office revenues by about 7.24 million Chinese Yuan in 2017, a far smaller effect than the economic losses caused by extreme temperatures.

Our results are part of China's film industry costs caused by extreme temperatures. We focus on quantifying the loss in box office revenues in response to extreme temperatures, while no related costs besides movie ticket sales are measured due to a lack of information (e.g., snacks sales or movie peripheral products sales). Thus, our results can be interpreted as the lower bound of losses from in-theater movie recreations due to extreme temperatures. Moreover, a broader range of activities within the service sector is vulnerable to uncomfortable temperatures, such as outdoor recreational activities like fishing (Dundas and von Haefen, 2020) and cycling (Chan and Wichman, 2020), the hotel industry (He et al., 2019), and the catering industry. However, the response pattern of extreme temperatures is inconsistent across these sectors. This paper extends the ongoing literature by adding the perspective of in-theater movie viewings, and it also provides new insights for understanding how the service sector in emerging economies is affected by climate conditions from the demand side.

5.2 *Prediction of the medium-term climate change impacts*

We further predict the influence of climate change on China's film industry in the medium-term future, years 2041-2060, by assuming that future movie-viewing patterns

[34] In 2017, there were 31 days of missing weather data for Taizhou, Jiaxing, Ningbo, Hangzhou, Wenzhou, Shaoxing, Chongqing, Jinhua, and 61 days of missing weather data for Shijiazhuang andWulumuqi. Due to the data missing, we cannot calculate if the loss in moviegoing on these days was caused by potential extreme temperatures. We argue that this deficiency does not substantively bias our results. In fact, that underestimates the effect of extreme temperatures.

[35] Losses in audiences and box office revenues caused by precipitations are calculated by:

$$Loss\ in\ audience = \sum_c \sum_d \eta_c \times Audience_{cd} \times \left[\frac{1}{2 - \exp\left(Precipitation_{cd} \times 0.000553\right)} - 1 \right]$$

and

$$Loss\ in\ box\ office = \sum_c \sum_d \varphi_c \times Boxoffice_{cd} \times \left[\frac{1}{2 - \exp\left(Precipitation_{cd} \times 0.000892\right)} - 1 \right].$$

-0.000553 and -0.000892 are coefficients of the impact of precipitations on audiences and box office revenues, respectively, estimated in Table 2.

remain consistent with the current period. The popularity of China's film market is expected to grow steadily in the short term, as described in Figure 1, while the development of movie consumption patterns in the long term is difficult to predict due to uncertainty. We emphasize that the rough predictions made here do not aim to quantify the effect of climate change precisely but to provide a deeper understanding of its impact on China's service sector by investigating the scale of economic losses in the future compared to the sample period. The quantitative framework we provided is not restricted to the film industry but applicable to broader industries driven by audience demand. We no longer rescale the prediction results to the city level but calculate the effects at the sample level to achieve the aims mentioned above.

To predict the impact of climate change on movie-goings in the future, we obtain daily average temperature and precipitation information for 49 cities between 2041-2060, under four RCPs: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. Five different GCMs are used comprehensively to smooth out the prediction bias caused by any single model. The IPCC (2014) states that heatwaves and extreme precipitation events are very likely to occur more often in the future, while the frequency of extremely cold temperatures will decrease. The pattern pointed out by the IPCC (2014) is clearly visible in our prediction data. As shown in Panel A of Figure 11, the medium-term future is predicted to have a higher proportion of extremely hot days than the sample period under each RCP, particularly for RCP8.5.[36] However, the future pattern of extremely low temperatures is similar to the sample period, while a slightly lower frequency of extremely cold days is found under RCP8.5. For precipitation, extreme conditions will be more likely to occur in the future, as presented in Panel D of Table 1, but the average value is slightly lower than that in the sample period.

We then predict the economic losses from decreases in moviegoing between 2041-2060 under the medium-term climate change conditions, following the procedure used to calculate the economic losses in the sample period. The calculation is implemented

[36] RCP8.5 is the scenario with intensive fossil fuel use and no climate mitigation policies, contributing to a nearly 5℃ increase in temperature by the end of the century. RCP8.5 indicates the worst-case climate change scenario among the four RCPs.

at the city-day level by assuming that future movie-viewing demands in each city do not deviate sharply to the current state. We first obtain the city-day level observations for moviegoers and box office revenues by aggregating the original movie-city-day level data. Then, for each specific city, we calculate the average audiences and box office revenues per day for each month in the sample period and assign that as the pattern of movie-viewing demands in the prediction period. That is to say, in the medium-term future, the moviegoing pattern is allowed to vary by month-of-year and by cities, while the movie-viewing demands of a specific city are homogeneous across days within a month. The response of moviegoing to extreme temperatures is assumed to be the same as above, which derives the following approach to predict the yearly loss in audiences and box office revenues across 49 cities between 2041-2060:

$$Predicted\ loss\ in\ audience = \frac{1}{20} \times \left[\begin{array}{l} \sum_c \sum_d \mathbf{1}(ExtreHighTemp_{cd}) \times \overline{Audience_{c,d\in m}} \times \left(\frac{1}{1-0.0327} - 1 \right) \\ + \sum_c \sum_d \mathbf{1}(ExtreLowTemp_{cd}) \times \overline{Audience_{c,d\in m}} \times \left(\frac{1}{1-0.0273} - 1 \right) \end{array} \right] \quad (10)$$

and

$$Predicted\ loss\ in\ box\ office = \frac{1}{20} \times \left[\begin{array}{l} \sum_c \sum_d \mathbf{1}(ExtreHighTemp_{cd}) \times \overline{Boxoffice_{c,d\in m}} \times \left(\frac{1}{1-0.0594} - 1 \right) \\ + \sum_c \sum_d \mathbf{1}(ExtreLowTemp_{cd}) \times \overline{Boxoffice_{c,d\in m}} \times \left(\frac{1}{1-0.0333} - 1 \right) \end{array} \right] \quad (11)$$

In Eq.(10) and Eq.(11), definitions of $ExtreHighTemp_{cd}$ and $ExtreLowTemp_{cd}$ are the same as above, except temperatures are now predicted for the medium-term future under each RCP. $\overline{Audience_{c,d\in m}}$ and $\overline{Boxoffice_{c,d\in m}}$ represent the city-/date-specific audiences and box office revenues. Once the city c is defined, moviegoing on each day d that belongs to the month m in that city is identical. For each RCP-GCM combination, the calculation procedure is repeated. We then take the average result across the different GCMs as the prediction of annual moviegoing losses caused by future climate change under each RCP, which helps avoid the potential prediction biases from adopting a single climate model.

The yearly impact of climate change on moviegoing in the medium-term future is graphically depicted in Figure 12. Under each RCP, extreme temperatures are expected to cause higher losses in audiences and movie ticket revenues between 2041-2060 when compared with the current period, mainly due to more frequent extreme heat.[37] The predicted reduction in audiences and box office revenues is strongest for RCP8.5, namely about 1.93 times and 2.06 times that of the current sample period, respectively. For other RCPs, the ratio varies from 1.43 to 1.58 for the loss in audiences and from 1.47 to 1.65 for the loss in box office revenues. We also calculate the yearly loss in moviegoing caused by precipitations between 2041-2060, which is found to be weaker than that in the current period (Figure A3). The ratio between annual moviegoing losses due to precipitations in the future and losses in the sample period remains steadily around 0.87 for audiences and 0.86 for box office revenues. As discussed above, although the frequency of extreme precipitation events is expected to increase in the future, the annual cumulative precipitation is predicted to be somewhat lower than that in the current stage. Considering that moviegoing responds linearly to precipitation changes, as found in Table A4, lower annual cumulative precipitations lead to less of a negative impact on moviegoing in the future.

We roughly estimated the economic losses from moviegoing induced by future climate changes by assuming all other conditions besides meteorological factors remain unchanged. As future movie consumption patterns are uncertain, it is difficult to attest to the accuracy of this estimation, which causes the prediction based on the sample period to either overestimate or underestimate the impact of future climate change. To make matters worse, if the movie demand pattern changes dramatically in the medium-term future, the effects on moviegoing from extreme temperatures or precipitations estimated by the baseline specifications would no longer be suitable for the prediction purposes, making the prediction more ambiguous. However, our predictions found suggestive evidence that future climate change will cause considerable economic losses to the film industry from the demand side, a finding which is robust across GCMs under each RCP. When including both extreme temperatures and precipitations into the calculation, the loss in moviegoing caused by future climate changes is suggested to be

[37] The predicted annual loss of audiences and movie ticket revenues induced by extreme temperatures shown in Figure 12 is the average of the loss calculated by the five GCMs. For predictions by each GCM, see Table A10.

1.2-1.6 times higher than that in the current stage, being the strongest for the worst-case climate change scenario RCP8.5. We stress that our brief prediction provides an approach to intuitively understand the economic cost of climate changes on the demand-driven film industry and even the service sector, which has positive implications for the formulation of policies aimed to address the challenges of future climate changes.

6. Conclusion and discussion

Understanding how each sector in the economy is affected by climate change is essential for effective climate policy development, and we contribute to the literature by providing information about the film industry, an important component of the service sector. Moreover, we also enrich the literature that discusses links between climate change and out-of-home recreations, especially focusing on market-based recreational activities.

In doing so, we use high-resolution movie-viewing data from 49 cities across China between 2015-2017 to causally identify that extreme temperatures sharply reduce audiences' demand for in-theater movie viewings. However, moviegoing does not respond to temperature variations across a broader range of temperature distribution. We also find that the effects of precipitations on moviegoing follow an approximately linear pattern, which differs from findings on recreational fishing (Dundas and von Haefen, 2020). Findings in this study have distinct economic implications. Our back-of-the-envelop calculations show that weather variations have caused considerable economic losses to China's film industry from the demand side in the sample period. Worse still, losses in the medium-term future are predicted to be 1.2-1.6 times those of the sample period under different climate change scenarios. These results suggest that implementing policies to mitigate future climate change will release consumers' demand for service industries and contribute to economic profit.

There are two potential limitations of our paper. First, we cannot completely distinguish the mechanisms behind the abovementioned response of moviegoing to weather variations. Theoretically, when the outdoor temperature deviates from the range that the human body perceived as comfortable, [20,22) °C, two confounding mechanisms lead to the movie viewing pattern observable in the data. If the audience is indoors, deterioration of the outdoor temperature may prevent the opting for out-of-home in-theater movie viewing, an *avoidance behavior* that damages movies' performance. In contrast, if the audience is outdoors, moving into theaters could also be an *avoidance response* because most theaters are equipped with air conditioning. Therefore, the uncomfortable outdoor temperature may nudge the demand for an in-theater movie. Ultimately, the effect of temperature shocks on the performance of movies depends on the proportion of potential audiences that are located indoors or outdoors. These two effects can offset and finally aggregate at the theater level and captured by our data, presenting as audiences and box office revenues for the specific screening. Since personal-level data is not available, our specifications cannot distinguish between the two mechanisms. However, the abovementioned response pattern of moviegoing based on temperature variations gives us some suggestive results. At the head and tail of the temperature distribution, extreme temperatures cause significant decreases in moviegoing, indicating that the dominant power is the first mechanism. For other ranges across the temperature distribution, the two effects are entangled and lead to almost nonsignificant coefficients. Exploring the mechanisms behind the impact of ambient weather on recreational consumption is an interesting topic for future research. Since this paper aims to assess the overall impact of weather variations, this limitation does not shake the policy implications.

Second, one may argue that our prediction of the medium-term climate change impacts is inaccurate because we held all things unchanged except for the meteorological factors. We show that this limitation does not fundamentally change the policy implications. The film industry is one of the booming service sectors in China, and it is challenging to predict its future development, which is beyond the scope of this paper. For this reason, we restrict the prediction period to the medium-term future, years 2041-2060, rather than extending it to the end of this century, which is the methodology usually adopted by the literature focused on the agricultural sector (see Chen et al., 2016; Zhang et al., 2017). Moreover, in our prediction, we are interested in the ratio between the economic losses in the future and those in the sample period caused by weather variations rather than in an exact amount. Ceteris paribus, the ratio isolates the essential impact of climate change on in-theater movie-viewing demands and can be extended to other sectors mainly driven by demand. More importantly, if China's film industry is optimistic that it will continue growing as described in Figure 1, assuming the movie-viewing pattern in the future is the same as in the sample period actually underestimates the impacts of future climate change. That means the ratio may be much greater than we estimated above, and implementing effective climate change policies has potentially greater economic benefits. Once an accurate prediction of future movie-viewing patterns is available, the above procedure can quickly generate new calculations and update the results.

References

Areni, Charles, and Mitchell Burger. 2008. "Memories of "Bad" Days Are More Biased Than Memories of "Good" Days: Past Saturdays Vary, but Past Mondays Are Always Blue." *Journal of Applied Social Psychology*. 38(6): 1395-1415.

Albouy, David, Walter Graf, Ryan Kellogg, and Hendrik Wolff. 2016. "Climate Amenities, Climate Change, and American Quality of Life." *Journal of the Association of Environmental and Resource Economists*, 3(1): 205-246.

Auffhammer Maximilian, Patrick Baylis, and Catherine Hausman. 2017. "Climate Change is Projected to Have Severe Impacts on the Frequency and Intensity of Peak Electricity Demand across the United States." *Proceedings of the National Academy of Sciences*, 114(8): 1886-1891.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Zou. 2019. "From Fog to Smog: the Value of Pollution Information." NBER Working Papers 26541. Available at: https://www.nber.org/papers/w26541.

Chisholm, Darlene, Víctor Fernández-Blanco, Abraham Ravid, and David Walls. 2015. "Economics of Motion Pictures: the State of the Art." *Journal of Cultural Economics*, 39: 1-13.

Chen, Shuai, Xiaoguang Chen, and Jintao Xu. 2016 "Impacts of Climate Change on Agriculture: Evidence from China." *Journal of Environmental Economics and Management*, 76: 105-124.

Chan, Nathan, and Casey Wichman. 2018 "Valuing Nonmarket Impacts of Climate Change: From Reduced-Form to Welfare. " Resources for the Future Working Paper 18-06. Available at: https://www.rff.org/publications/working-papers/valuing-nonmarket-impacts-of-climate-change-from-reduced-form-to-welfare/

Chen, Xiaoguang, and Lu Yang. 2019. "Temperature and Industrial Output: Firm-level Evidence from China." *Journal of Environmental Economics and Management*, 95: 257-274.

Chan, Nathan, and Casey Wichman. 2020. "Climate Change and Recreation: Evidence from North American Cycling." *Environmental and Resource Economics*, 76: 119–151.

Deschênes, Olivier, and Michael Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review*, 97 (1): 354-385.

Dahl, Gordon, Stefano DellaVigna. 2009. "Does Movie Violence Increase Violent Crime?" *Quarterly Journal of Economics*. 124(2): 677–734.

Deschênes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics*, 3(4): 152-185.

Dell, Melissa, Benjamin Jones, and Benjamin Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics*, 4(3): 66-95.

Dell, Melissa, Benjamin Jones, and Benjamin Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature*, 52(3): 740-798.

Dundas, Steven, and Roger von Haefen. 2020. "The Effect of Weather on Recreational Fishing Demand and Adaptation: Implications for a Changing Climate." *Journal of the Association of Environmental and Resource Economists*. 7(2): 209-242.

Einav, Liran. 2010. "Not All Rivals Look Alike: Estimating an Equilibrium Model of the Release Date Timing Game." *Economic Inquiry*. 48(2): 369-390.

Frieler, Katja, et al. 2017. "Assessing the Impacts of 1.5 °C Global Warming – Simulation Protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b)." *Geoscientific Model Development*, 10(12): 4321-4345.

Fu, Shihe, Brian Viard, and Peng Zhang. 2021. "Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China.", *Economic Journal*. Forthcoming.

Gilchrist, Sheppard, and Emily Sands. 2016. "Something to Talk About: Social Spillovers in Movie Consumption." *Journal of Political Economy*. 124(5): 1339-1382.

Godzinski, Alexandre, and Milena Suarez Castillo. 2021. "Disentangling the Effects of Air Pollutants with many Instruments." *Journal of Environmental Economics and Management*. 109: 102489.

Hsiang, Solomon, et al. 2017. "Estimating Economic Damage from Climate Change in the United States." *Science*, 356(6345): 1362-1369.

Hermosilla, Manuel, Fernanda Gutierrez-Navratil, and Juan Prieto-Rodriguez. 2018. "Can Emerging Markets Tilt Global Product Design? Impacts of Chinese Colorism on Hollywood Castings." *Marketing Science*, 37(3): 356-381.

He, Pan, Yueming Qiu, Yi David Wang, Cihan Cobanoglu, Olena Ciftci, and Zhu Liu. 2019. "Loss of Profit in the Hotel Industry of the United States Due to Climate Change." *Environmental Research Letters*, 14(8): 084022.

He, Xiaobo, Zijun Luo, and Junjie Zhang. 2022. "The Impact of Air Pollution on Movie Theater Admissions." *Journal of Environmental Economics and Management*, 112: 102626.

IPCC. 2014. "Climate Change 2014 Synthesis Report." https://www.ipcc.ch/report/ar5/syr/.

King, Amanda, John King, and Michael Reksulak. 2017. "Signaling for Access to High-Demand Markets: Evidence from the US Motion Picture Industry." *Journal of Cultural Economics*. 41: 441–465.

Karlsson, Martin, and Nicolas Ziebarth. 2018. "Population Health Effects and Health-Related Costs of Extreme Temperatures: Comprehensive Evidence from Germany." *Journal of Environmental Economics and Management*, 91: 93-117.

Li Yating, William Pizer, and Libo Wu. 2019. "Climate Change and Residential Electricity Consumption in the Yangtze River Delta, China." *Proceedings of the National Academy of Sciences*, 116(2): 472-477.

Moretti, Enrico. 2011. "Social Learning and Peer Effects in Consumption: Evidence from Movie Sales." *Review of Economic Studies*. 78(1): 356-393.

Mellon, Jonathan. 2021. "Rain, Rain, Go Away: 176 Potential Exclusion-Restriction Violations for Studies Using Weather as An Instrumental Variable." Available at SSRN: https://ssrn.com/abstract=3715610.

Prag, Jay, and James Casavant. 1994. "An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry." *Journal of Cultural Economics*. 18(3): 217-235.

Ranson Matthew. 2014. "Crime, Weather, and Climate Change." *Journal of Environmental Economics and Management*, 67(3): 274-302.

Schlenker, Wolfram, and Michael Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences*, 106(37): 15594-15598.

Somanathan, Eswaran, Rohini Somanathan, Anant Sudarshan, and Meenu Tewari. 2021. "The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian

Manufacturing." *Journal of Political Economy*, 129(6): 1797-1827.

Warszawski, Lila, Katja Frieler, Veronika Huber, Franziska Piontek, Olivia Serdeczny, and Jacob Schewe. 2014. "The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP): Project Framework." *Proceedings of the National Academy of Sciences*, 111(9): 3228-3232.

Yu, Xiumei, Xiaoyan Lei, and Min Wang. 2019. "Temperature Effects on Mortality and Household Adaptation: Evidence from China." *Journal of Environmental Economics and Management*, 96: 195-212.

Zivin, Graff, and Mattew Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics*, 32(1): 1-26.

Zhang, Peng, Junjie Zhang, and Minpeng Chen. 2017. "Economic Impacts of Climate Change on Agriculture: The Importance of Additional Climatic Variables Other than Temperature and Precipitation." *Journal of Environmental Economics and Management*, 83: 8-31.

Zhang Junjie, and Quan Mu. 2018. "Air Pollution and Defensive Expenditures: Evidence from Particulate-Filtering Facemasks." *Journal of Environmental Economics and Management*, 92: 517-536.

Zhang, Peng, Olivier Deschênes, Kyle Meng, and Junjie Zhang. 2018. "Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants." *Journal of Environmental Economics and Management*, 88: 1-17.

Zheng, Siqi, Jianghao Wang, Cong Sun, Xiaonan Zhang, and Matthew Kahn. 2019. "Air Pollution Lowers Chinese Urbanites' Expressed Happiness on Social Media." *Nature Human Behaviour.* 3: 237–243.

Figures and tables in the text

Figures

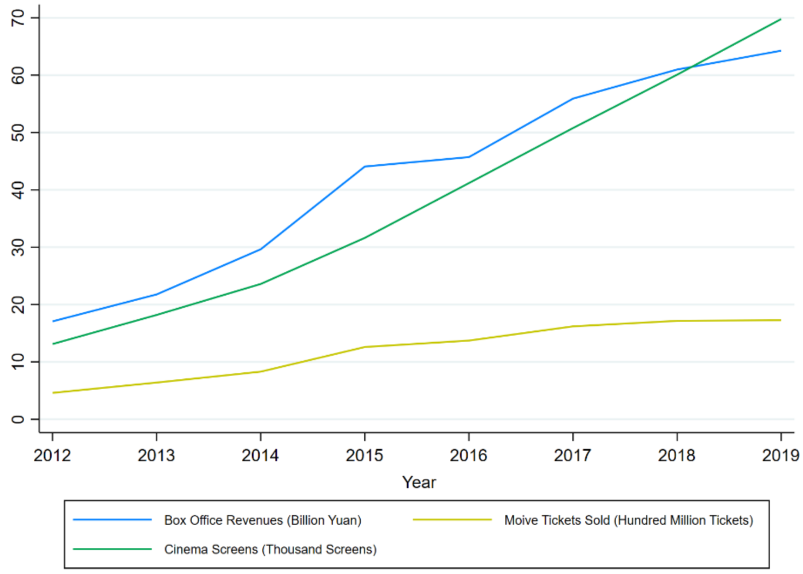
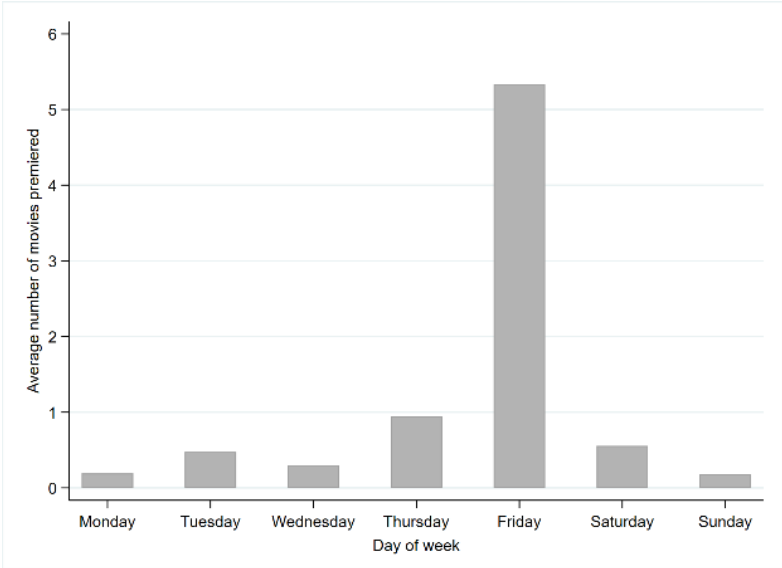


Figure 1 Development of China’s film industry: 2012-2019.

Notes: Data are from https://www.statista.com/.

Panel A: By day-of-week



Panel B: By month-of-year

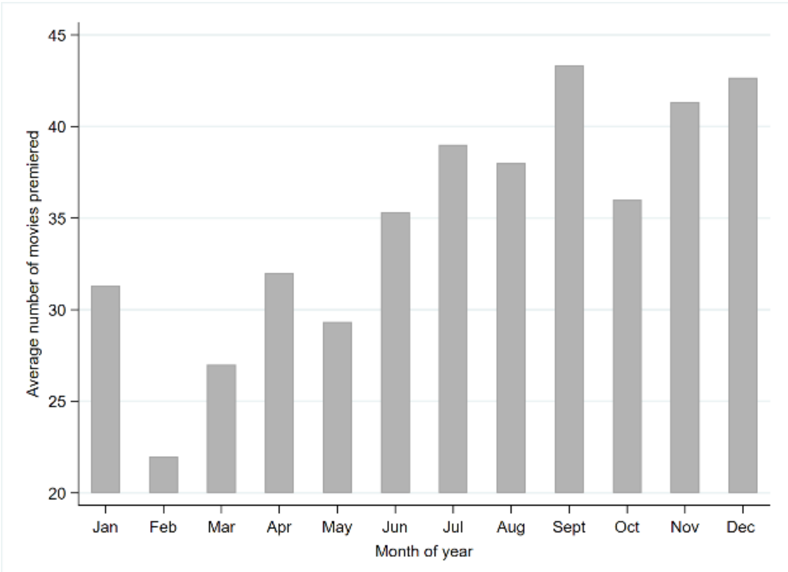
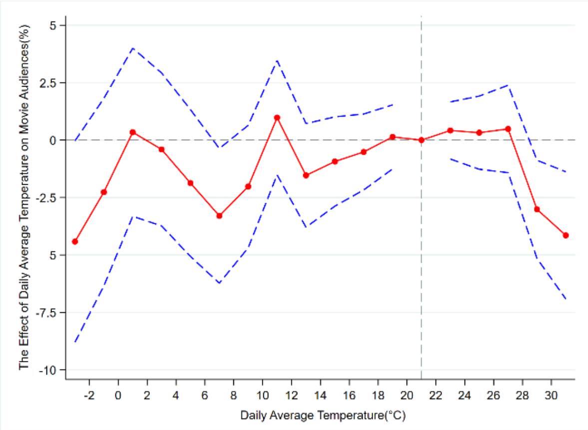
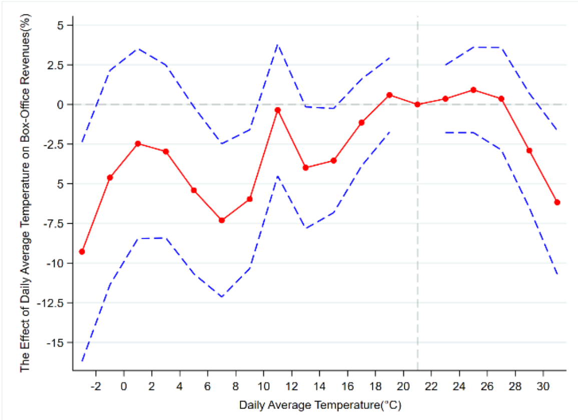


Figure 2 The average number of movies premiered by day-of-week and month-of-day in 2015-2017. *Notes:* The premiere date of non-rescreened movies comes from the movie-rating database. In 1273 non-rescreened movie samples, 21 movies are excluded when plotting the figure since their premiere year is 2014.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

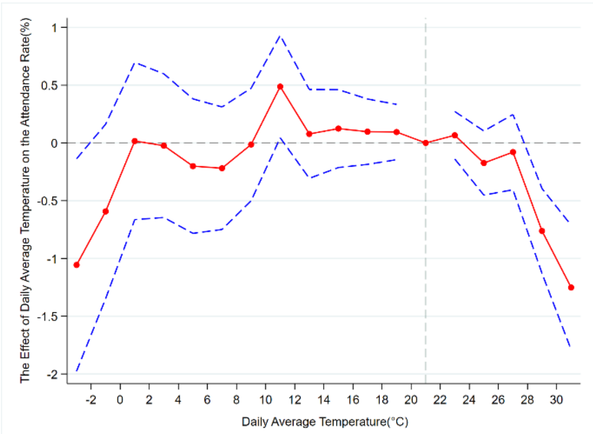


Figure 3 The impact of temperature fluctuations on movie-goings by the temperature-bins model. *Notes:* The red points represent the impact of temperatures falling into corresponding bins on movie-goings, compared with that in the reference group [20,22) ℃. The blue dash lines indicate the 95% confidence interval.

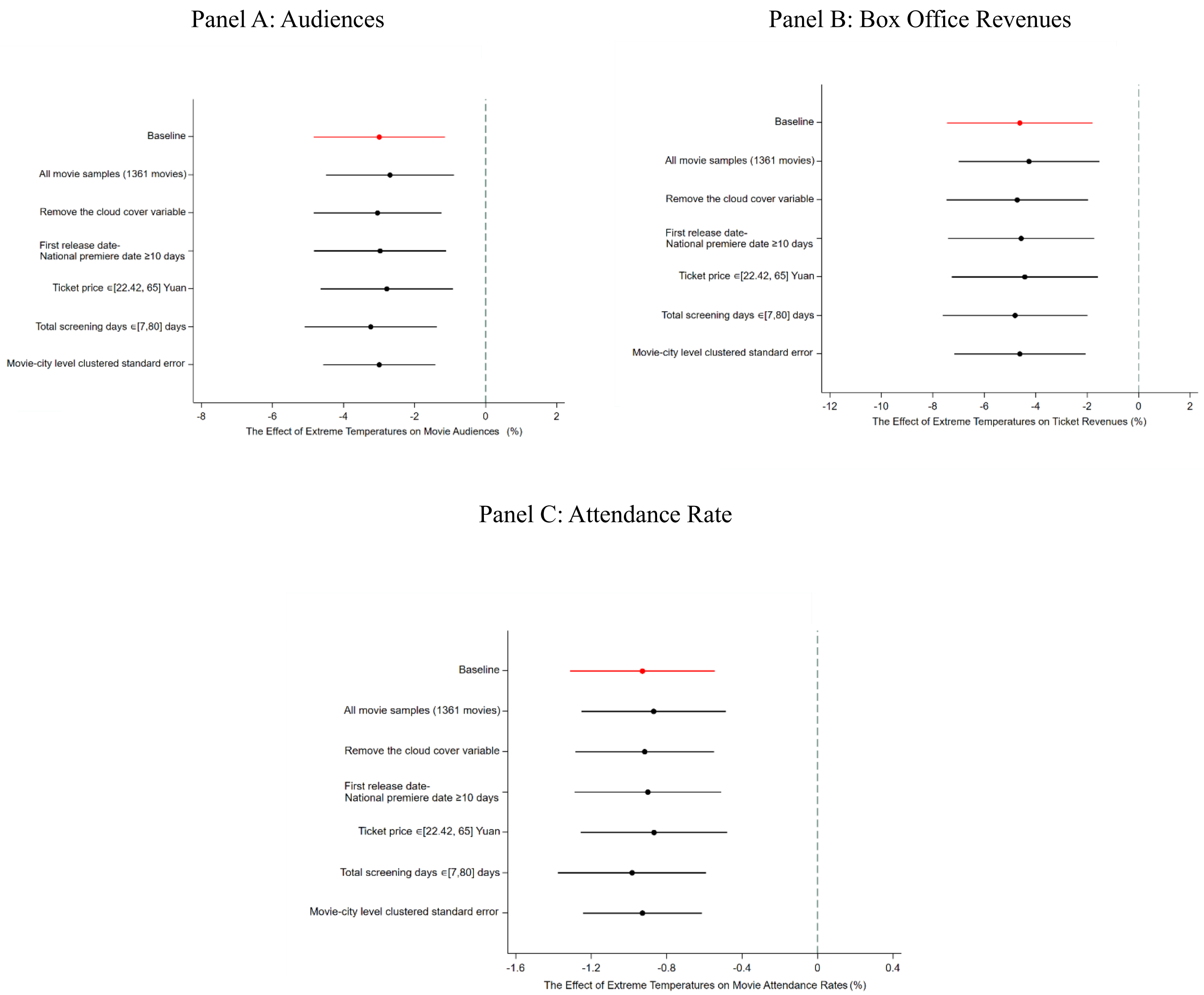
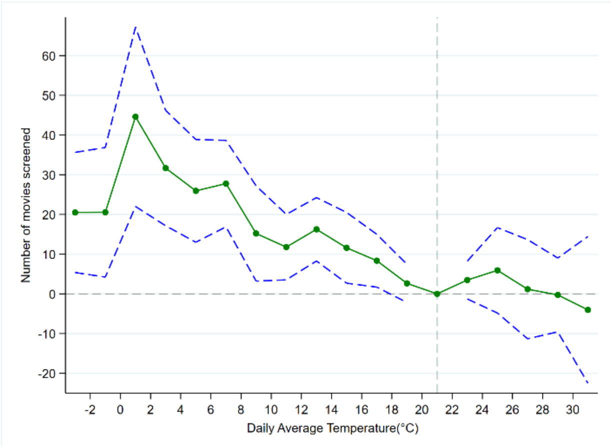


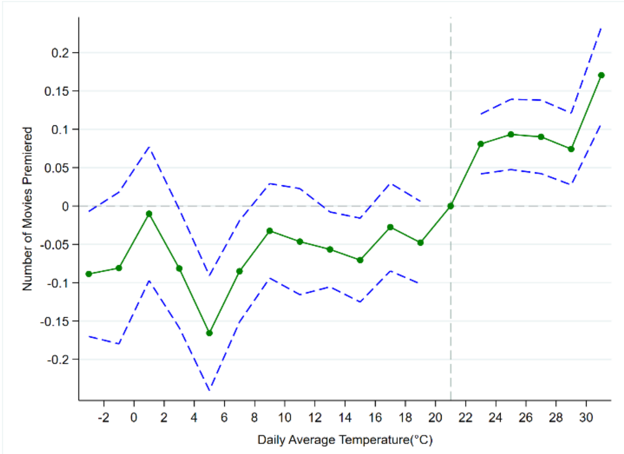
Figure 4 Effects of extreme temperatures on movie-goings: robustness checks.

Notes: The figure illustrates the effect of extreme temperatures on movie-goings under various robustness check settings. Points represent the point estimation results, and horizontal solid lines indicate the 95% confidence interval.

Panel A: The Number of Movies Screened



Panel B: The Number of Movies Premiered



Panel C: At Least One Movie Premiered

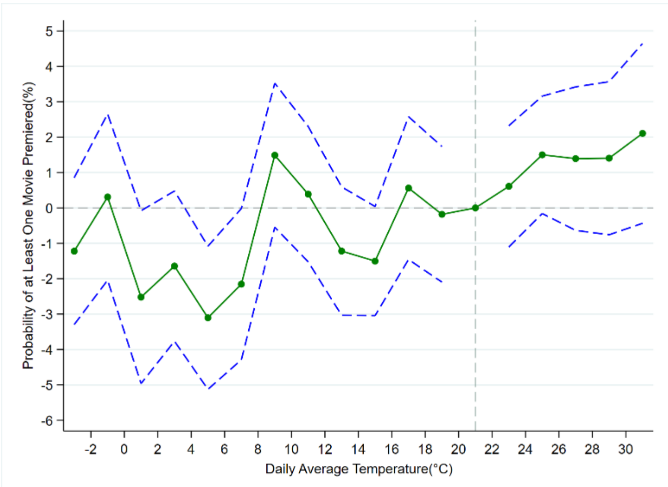
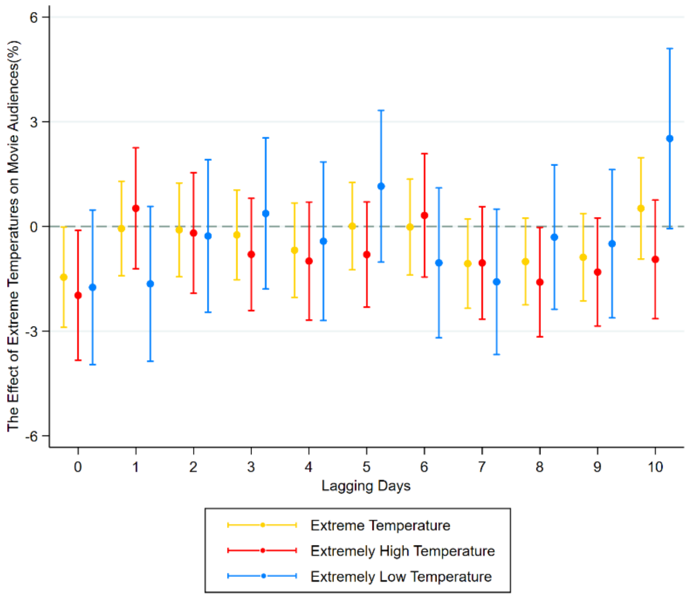


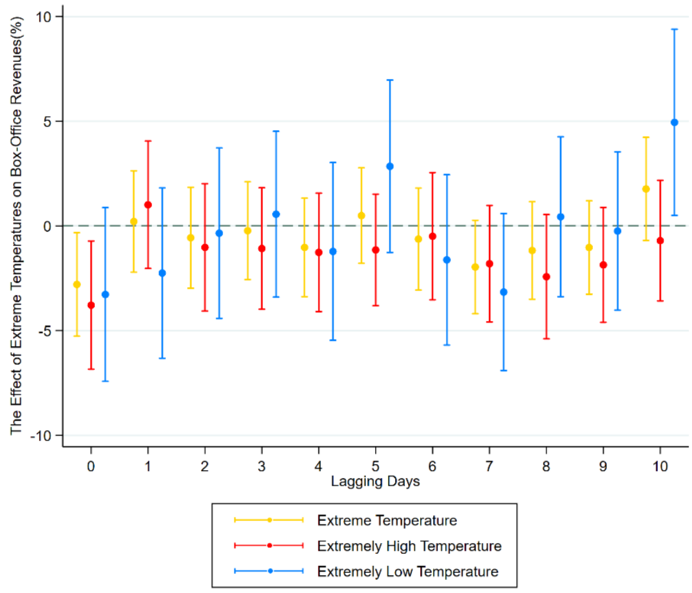
Figure 5 Correlation between temperatures and movie premiere/ screening.

Notes: The green points represent the change in the number of movie screenings/ premieres and the probability of at least one movie premiered on days in which temperatures fall into corresponding bins, compared with that in the reference group [20,22) ℃. The blue dash lines indicate the 95% confidence interval.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

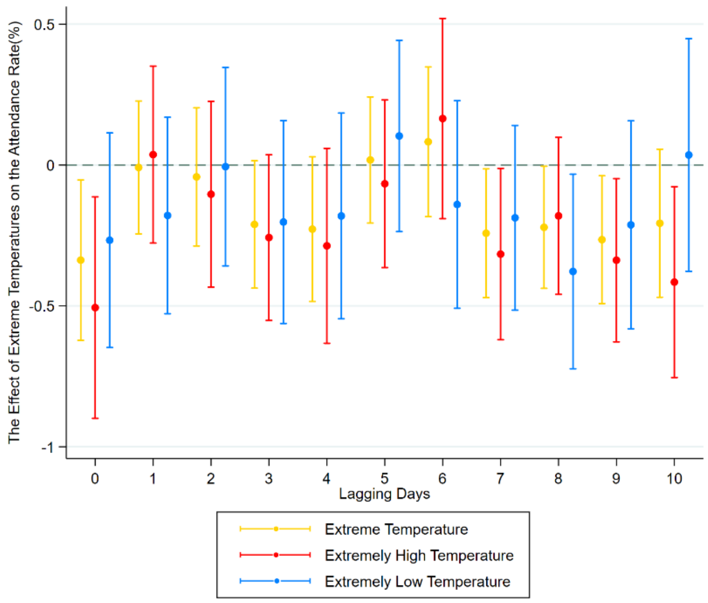


Figure 6 The lagging effects of extreme temperatures on movie-goings up to 10 days.

Notes: Yellow, red, and blue points represent the point estimation results of extreme temperatures, extremely high temperatures, and extremely low temperatures, respectively. The vertical solid lines indicate the 95% confidence interval.

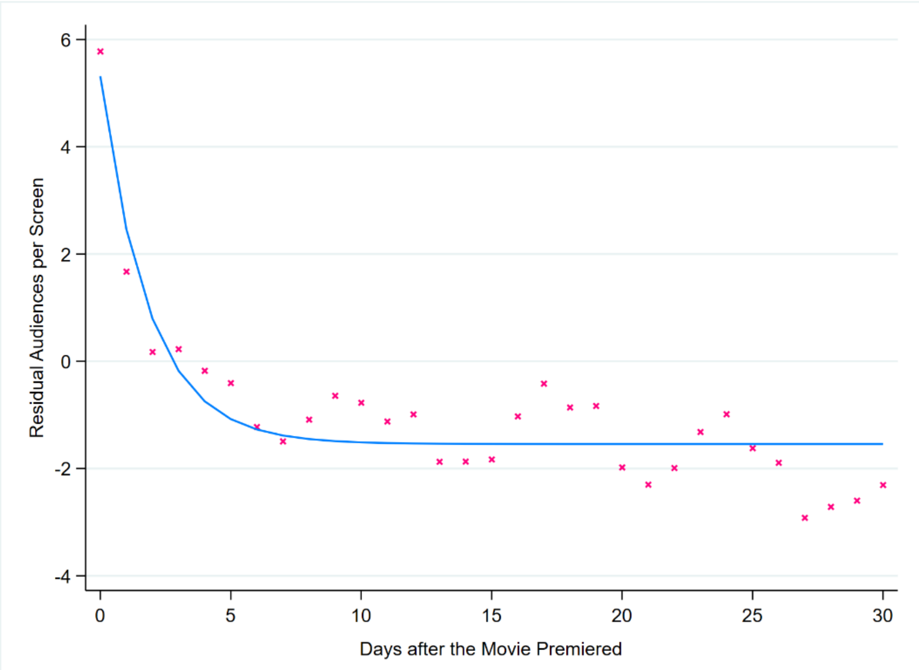
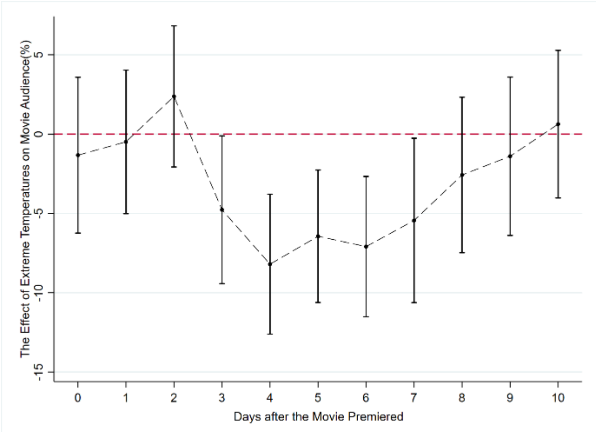
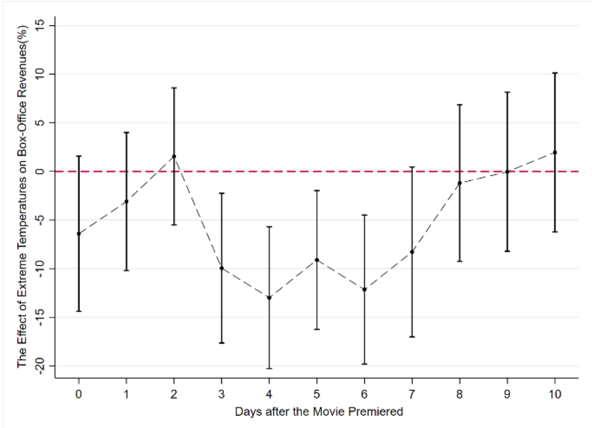


Figure 7 The relationship between audiences per screen and days after the movie premiered.
Notes: Red points denote the audiences per screen after removing day-of-week fixed effects and city fixed effects. The blue curve is an exponential fitting with three parameters.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

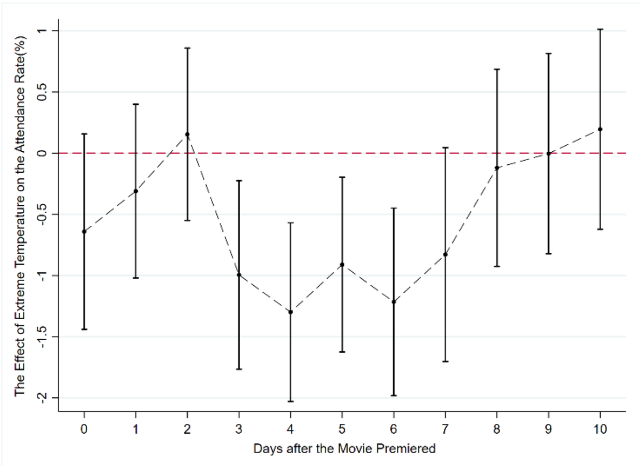


Figure 8 Heterogeneous effects of extreme temperatures on movie-goings on different days after the movie premiered.

Notes: Black points represent the point estimation results of the interaction extreme temperatures and days after the movie premiered dummies. The vertical solid lines indicate the 95% confidence interval.

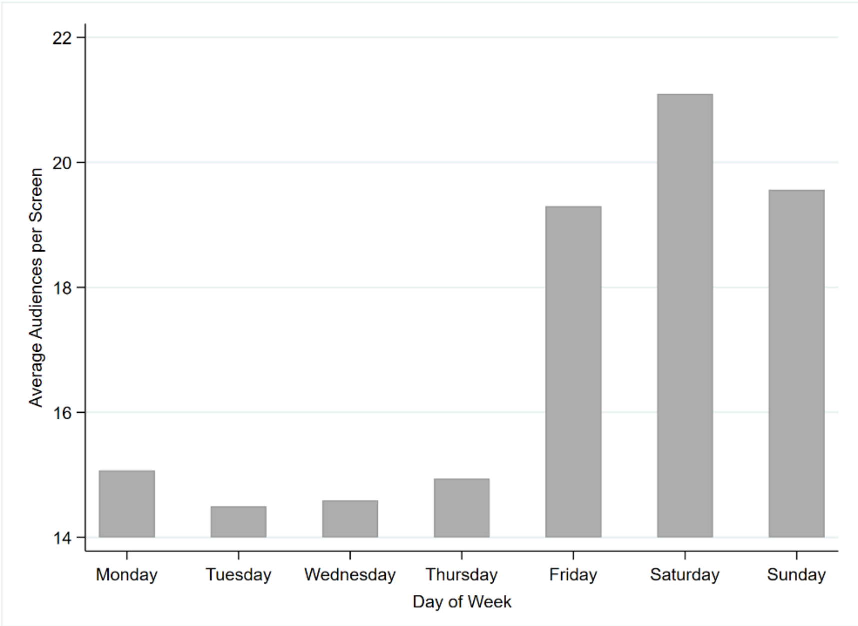
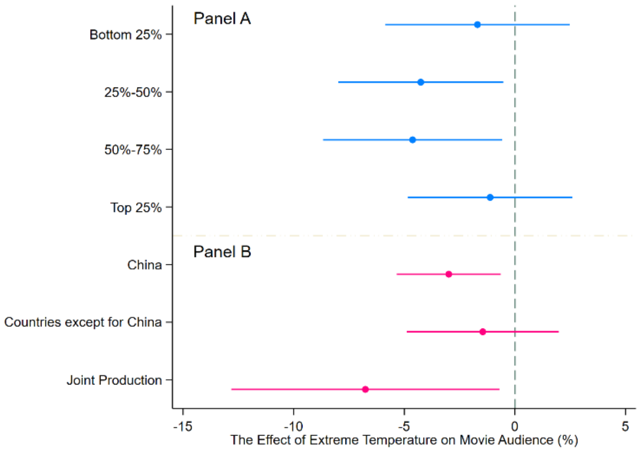


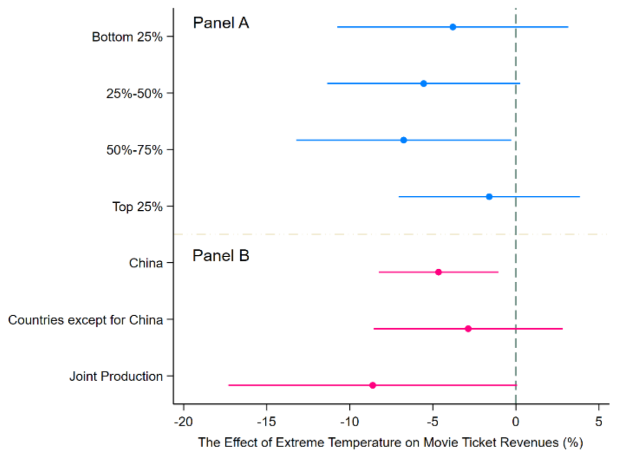
Figure 9 Average audiences per screen by day-of-week.

Notes: This figure is plotted based on observations of non-rescreened movies in 2015-2017. Observations of rescreened movies are excluded.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

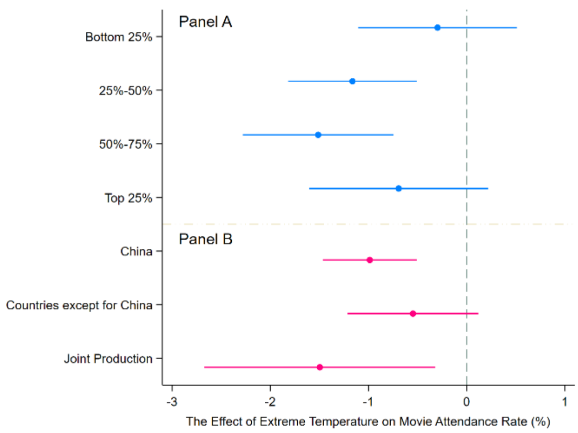


Figure 10 Effects of extreme temperatures on movie-goings: movie quality heterogeneity.

Notes: In each subfigure, Panel A illustrates heterogeneous effects of extreme temperatures on movie-goings for movie subsamples with different qualities, represented by the quartile of the Douban rating. Panel B illustrates the effect of extreme temperatures on movie-goings by filmmaking countries. According to the production country, all movie samples are divided into three groups: China, other countries (except for China), and jointly produced by China and other countries. Points represent the point estimation results, and horizontal solid lines indicate the 95% confidence interval.

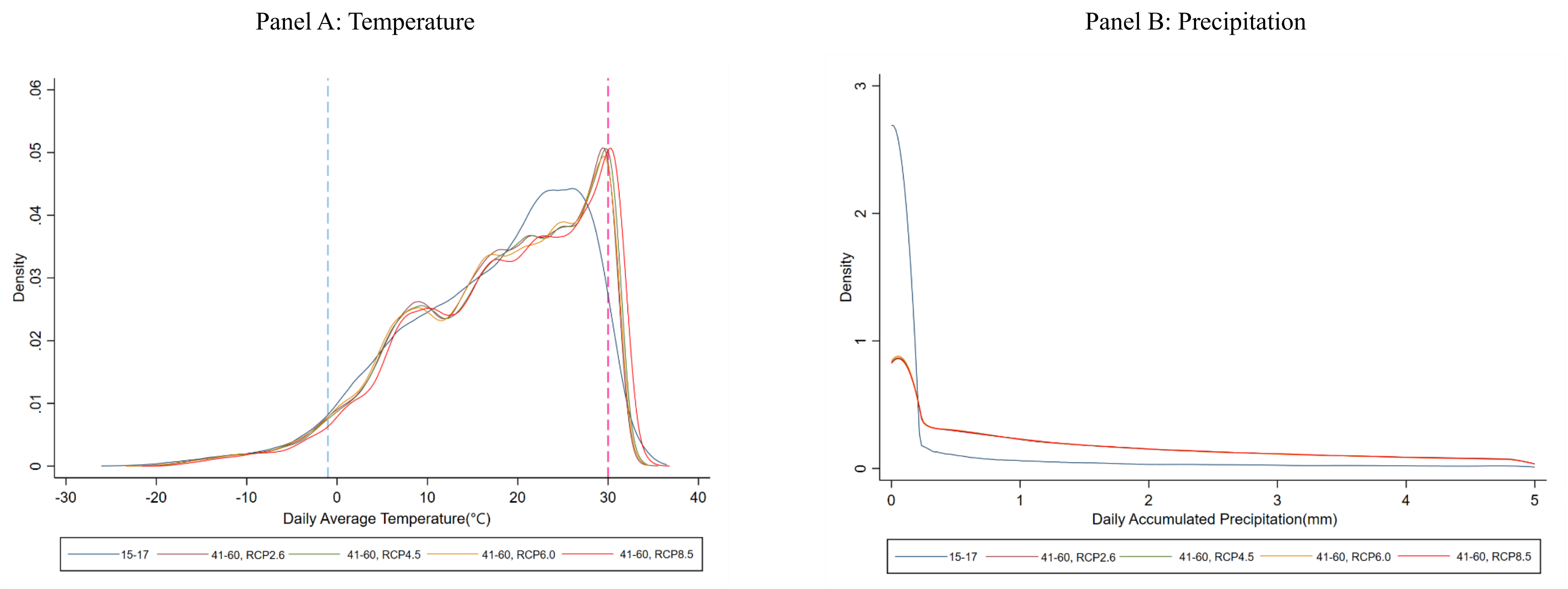


Figure 11 Distribution of the daily average temperature and daily accumulated precipitation of 49 cities in the sample period (15-17) and the medium-term future (41-60).

Notes: Daily average temperature and daily accumulated precipitation under each RCP are the averages of five GCMs. The blue and red vertical lines in Panel A present the cutoff point of extremely high temperatures (-1℃) and extremely low temperatures (30℃). In panel B, we truncate the daily accumulated precipitation at 5mm, considering the right-skewed distribution. The kernel to estimate the density function is the Epanechnikov kernel.

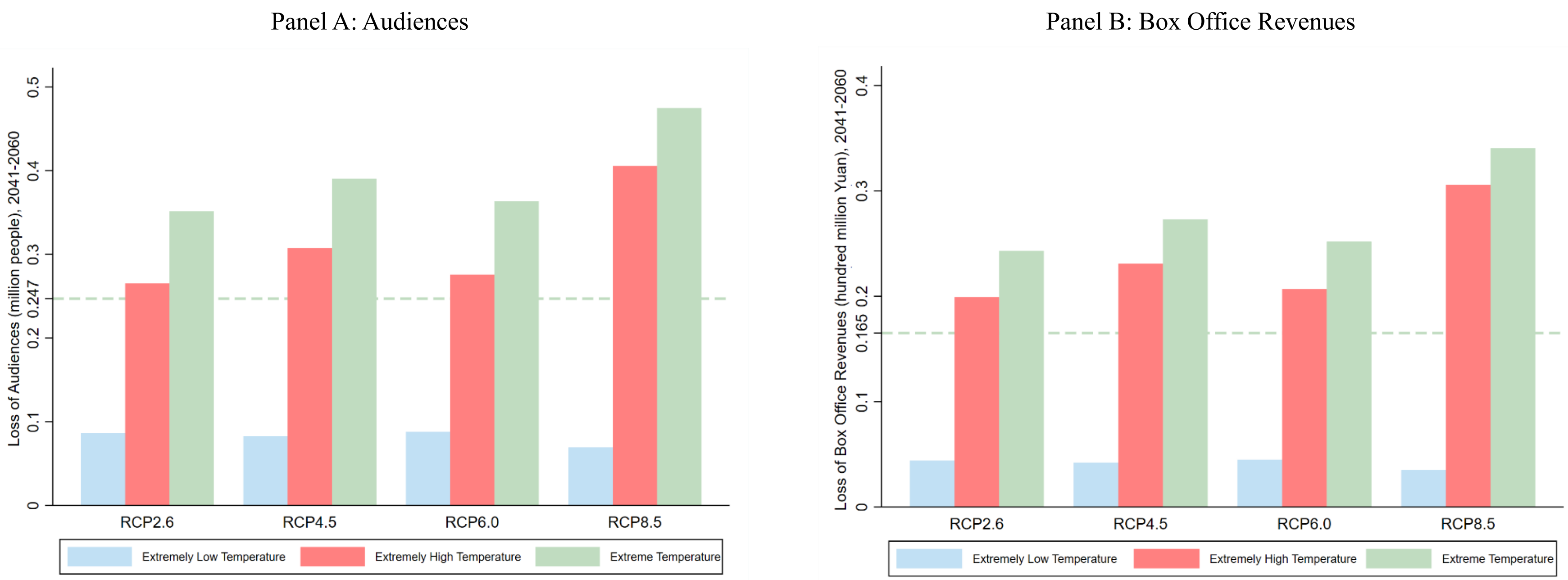


Figure 12 The predicted annual loss of audiences and box office revenues of 49 cities induced by extreme temperatures in the medium-term future (41-60).
Notes: The calculation is implemented at the sample level. The impact of extreme temperatures on movie-goings under each RCP is the average by five GCMs. The green dotted line in Panel A and Panel B represents the annual loss of audiences and box office revenues caused by extreme temperatures in the sample period (15-17) at the sample level.

Tables

Table 1 Summary statistics.

Variable	Mean	SD	Min	Max	Count
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	65490.2	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	1,193
Number of ratings (Persons)	50884.74	115337.1	0	1071835	1,361
Runtime (minutes)	99.68	13.99	64	192	1,361
Panel C: Meteorological and air quality variables					
Temperature (℃)	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 4 times in a day, 0 = otherwise)	0.34	0.48	0	1	53,704
Panel D: Meteorological prediction variables (2041-2060)					
Temperature- RCP2.6 (℃)	17.60	10.30	-29.52	41.25	357,945
Temperature- RCP4.5 (℃)	17.85	10.35	-30.04	41.98	357,945
Temperature- RCP6.0 (℃)	17.60	10.36	-29.44	41.26	357,945
Temperature- RCP8.5 (℃)	18.52	10.30	-28.16	41.74	357,945
Precipitation- RCP2.6 (mm)	3.27	8.24	0	289.03	357,945
Precipitation- RCP4.5 (mm)	3.23	8.23	0	333.96	357,945
Precipitation- RCP6.0 (mm)	3.05	7.85	0	394.10	357,945
Precipitation- RCP8.5 (mm)	3.13	8.17	0	367.66	357,945

Notes: The observations in Panel A are viewing records for each movie at the city-day level. The average number of audiences per screen is defined as the total number of audiences divided by the number of screenings for the specific movie within a day. The average box office revenues per screen are defined as total revenues divided by the number of screenings for the specific movie within a day. The average attendance rate for the specific movie is given by the total number of audiences divided by the number of seats available. In Panel B, Douban ratings for 163 movies are missing because of too few reviews. In Panel C, daily temperature and precipitation prediction data under each scenario for 49 cities during 2041-2060 are calculated by averaging five climate models.

Table 2 Effects of temperature fluctuations and extreme temperatures on movie-goings.

	Panel A: Quadratic temperatures			*Panel B*: Extreme temperatures		
	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature^2	-0.0001***	-0.0001**	-0.0030***			
	(0.0000)	(0.0000)	(0.0005)			
Temperature	0.0032***	0.0053***	0.0843***			
	(0.0011)	(0.0017)	(0.0218)			
Extremely hot days				-0.0327***	-0.0594***	-0.8633***
				(0.0111)	(0.0168)	(0.2492)
Extremely cold days				-0.0273*	-0.0333	-0.9925***
				(0.0147)	(0.0228)	(0.2792)
Precipitation	-0.0005***	-0.0007***	-0.0066***	-0.0006***	-0.0009***	-0.0066***
	(0.0001)	(0.0002)	(0.0023)	(0.0001)	(0.0002)	(0.0023)
Pressure	0.0007	0.0007	0.0593***	0.0002	-0.0007	0.0603***
	(0.0009)	(0.0014)	(0.0157)	(0.0007)	(0.0013)	(0.0131)
Relative humidity	0.0010***	0.0014***	0.0115***	0.0009***	0.0011***	0.0106***
	(0.0002)	(0.0003)	(0.0034)	(0.0002)	(0.0003)	(0.0033)
Wind speed	-0.0034*	-0.0064**	-0.0431	-0.0033*	-0.0065**	-0.0323
	(0.0019)	(0.0032)	(0.0319)	(0.0019)	(0.0032)	(0.0319)
Cloud cover	-0.0001	0.0001	-0.0054**	-0.0001	0.0001	-0.0035
	(0.0001)	(0.0002)	(0.0026)	(0.0001)	(0.0002)	(0.0025)
AQI	0.0003***	0.0003***	0.0048***	0.0003***	0.0003***	0.0041***
	(0.0001)	(0.0001)	(0.0009)	(0.0001)	(0.0001)	(0.0009)

Ticket price	-0.0051***	0.0074***	-0.0378***	-0.0051***	0.0075***	-0.0377***
	(0.0004)	(0.0008)	(0.0091)	(0.0004)	(0.0008)	(0.0091)
Screenings	0.0028***	0.0054***	-0.0028	0.0028***	0.0054***	-0.0028
	(0.0001)	(0.0003)	(0.0018)	(0.0001)	(0.0003)	(0.0018)
Inflection temperature(°C)	20.04	26.18	14.09			
Mean of explained variables in the reference group				17.02	643.85	15.37
Movie FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
DsP FE	YES	YES	YES	YES	YES	YES
Observations	721,308	721,308	721,308	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2043	0.2957	0.2937	0.2042

Notes: Each panel contains three separate regressions, using the logarithmic average number of audiences per screen, the logarithmic average number of box office revenues per screen, and the average attendance rate as explained variables respectively. In panel A, the quadratic term of temperatures is used to portray its non-linear impacts. Inflection temperatures are calculated based on coefficients of *Temperature* and $Temperature^2$. In panel B, temperature measures are two dummy variables-extreme hots and extreme colds. References are observations with temperatures falling into (-1,30) °C. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3 Effects of extreme temperatures on movie-goings: city tiers heterogeneity

	Panel A: Extreme temperatures			*Panel B*: Extremely high temperatures			*Panel C*: Extremely low temperatures		
	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Extreme temperatures×1st-tier cities	-0.0436**	-0.0796***	-1.1273***	-0.1112***	-0.1978***	-1.9990***	0.0979***	0.1650***	0.7617
	(0.0182)	(0.0293)	(0.3958)	(0.0221)	(0.0336)	(0.5474)	(0.0329)	(0.0607)	(0.5108)
Extreme temperatures×New-1st-tier cities	-0.0539***	-0.1132***	-1.1788***	-0.0495***	-0.1171***	-1.4156***	-0.0573***	-0.1052***	-0.7504**
	(0.0121)	(0.0203)	(0.2722)	(0.0168)	(0.0270)	(0.3991)	(0.0166)	(0.0293)	(0.3172)
Extreme temperatures×2nd-tier cities	-0.0128	0.0005	-0.7370***	0.0062	0.0281	-0.0850	-0.0315	-0.0276	-1.3821***
	(0.0133)	(0.0202)	(0.2500)	(0.0158)	(0.0244)	(0.3102)	(0.0205)	(0.0309)	(0.3882)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2042	0.2958	0.2938	0.2043	0.2958	0.2938	0.2043

Notes: Columns (1)-(3) are estimated by three separate regressions. Column (4) and (7), column (5) and (8), column (6) and (9) are estimated together, respectively. Control variables contain weather variables, the AQI, and the city-date-movie level variables. Fixed effects include Movie fixed effects, city fixed effects, date fixed effects, and days-since-premiered fixed effects. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 Effects of extreme temperatures on movie-goings: day-of-week heterogeneity

	Panel A: Extreme temperatures			*Panel B*: Extremely high temperatures			*Panel C*: Extremely low temperatures		
	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Extreme temperatures×Monday	-0.0332**	-0.0433*	-1.0887***	-0.0156	-0.0389	-0.6368*	-0.0480**	-0.0454	-1.4878***
	(0.0135)	(0.0223)	(0.2543)	(0.0185)	(0.0302)	(0.3722)	(0.0200)	(0.0330)	(0.3487)
Extreme temperatures×Tuesday	-0.0299**	-0.0440*	-0.8784***	-0.0265	-0.0317	-0.7368**	-0.0326	-0.0530	-1.0128***
	(0.0142)	(0.0235)	(0.2426)	(0.0198)	(0.0320)	(0.3411)	(0.0205)	(0.0348)	(0.3385)
Extreme temperatures×Wednesday	-0.0558***	-0.0787***	-1.4558***	-0.0319*	-0.0475	-1.0056***	-0.0739***	-0.1007***	-1.8127***
	(0.0137)	(0.0232)	(0.2474)	(0.0189)	(0.0314)	(0.3826)	(0.0193)	(0.0330)	(0.3221)
Extreme temperatures×Thursday	-0.0199	-0.0346	-0.7467***	-0.0104	-0.0418	-0.3582	-0.0264	-0.0273	-1.0416***
	(0.0135)	(0.0233)	(0.2451)	(0.0183)	(0.0303)	(0.3652)	(0.0195)	(0.0342)	(0.3380)
Extreme temperatures×Friday	-0.0618***	-0.0946***	-1.4183***	-0.0811***	-0.1409***	-1.7458***	-0.0439*	-0.0507	-1.1293***
	(0.0157)	(0.0264)	(0.3123)	(0.0197)	(0.0334)	(0.4275)	(0.0234)	(0.0395)	(0.4238)
Extreme temperatures×Saturday	-0.0102	-0.0162	-0.6820**	-0.0453**	-0.0764***	-1.0659**	0.0217	0.0396	-0.3447
	(0.0145)	(0.0230)	(0.3160)	(0.0189)	(0.0296)	(0.4529)	(0.0212)	(0.0346)	(0.4151)
Extreme temperatures×Sunday	0.0013	-0.0123	-0.2275	-0.0158	-0.0377	-0.4466	0.0157	0.0105	-0.0573
	(0.0137)	(0.0227)	(0.2919)	(0.0186)	(0.0311)	(0.4019)	(0.0198)	(0.0329)	(0.3958)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2043	0.2958	0.2937	0.2043	0.2958	0.2937	0.2043

Notes: Columns (1)-(3) are estimated by three separate regressions. Column (4) and (7), column (5) and (8), column (6) and (9) are estimated together, respectively. Control variables contain weather variables, the AQI, and the city-date-movie level variables. Fixed effects include Movie fixed effects, city fixed effects, date fixed effects, and days-since-premiered fixed effects. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Figures

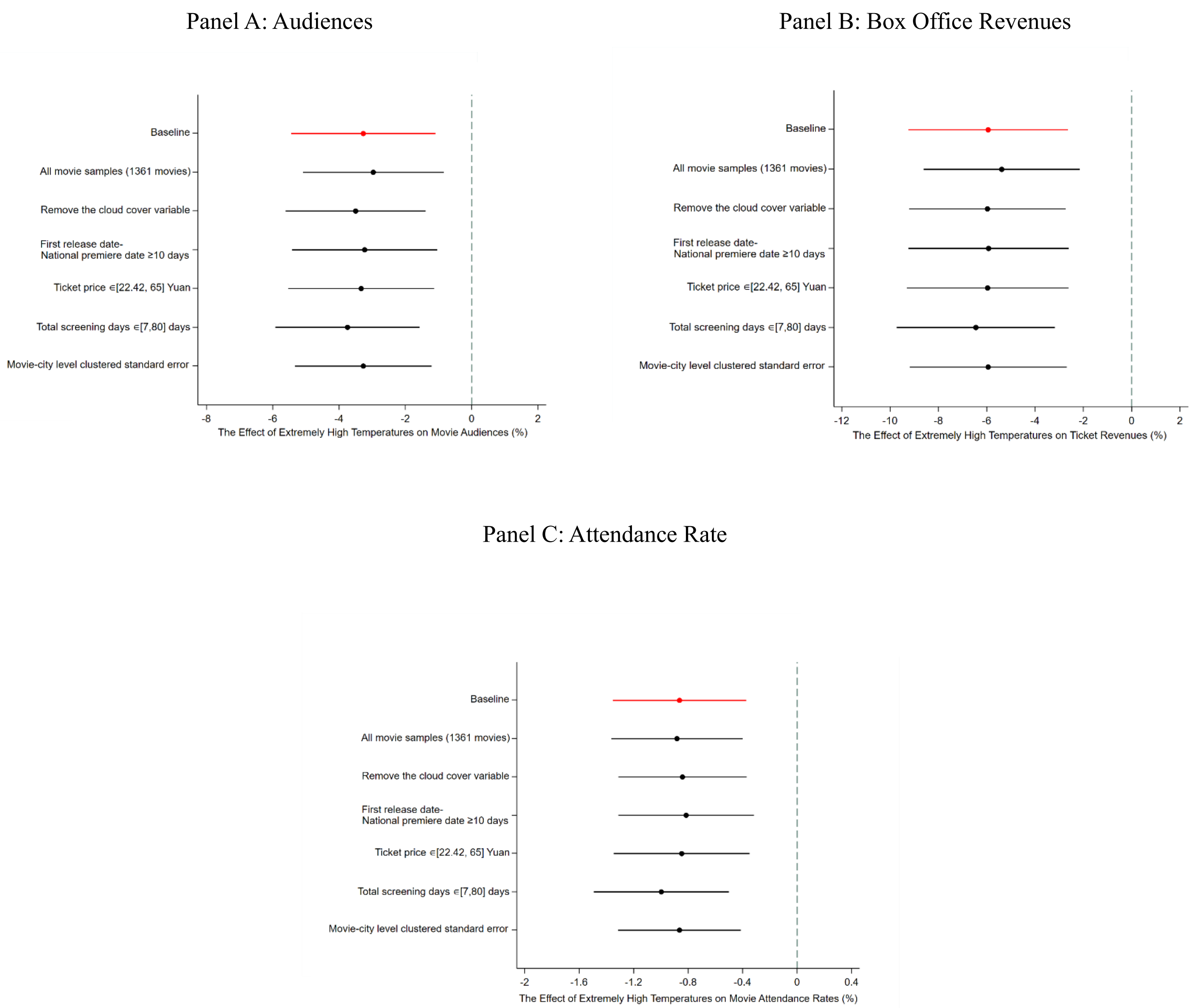
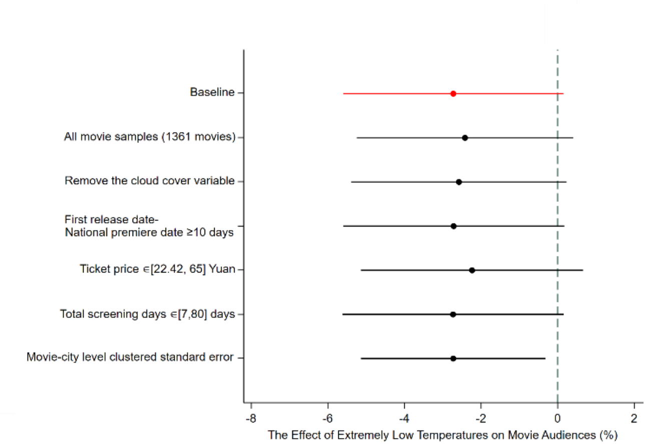
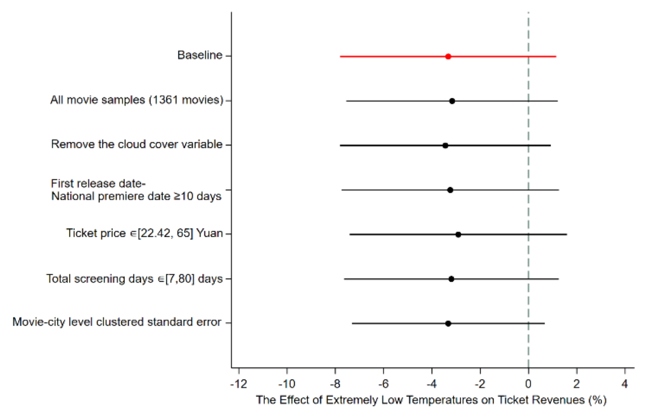


Figure A1 Effects of extremely high temperatures on movie-goings: robustness checks.
Notes: The figure illustrates the effect of extremely high temperatures on movie-goings under various robustness check settings. Points represent the point estimation results, and horizontal solid lines indicate the 95% confidence interval.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

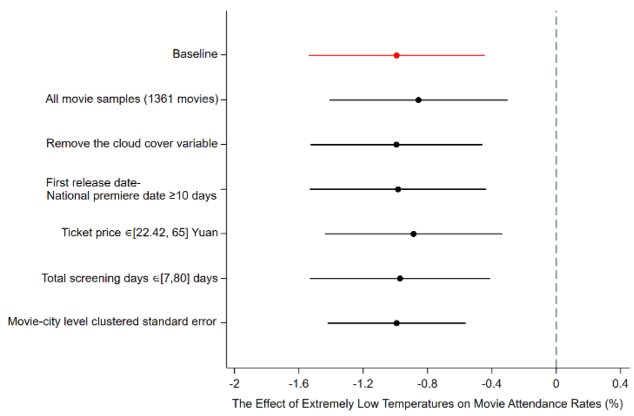


Figure A2 Effects of extremely low temperatures on movie-goings: robustness checks.

Notes: The figure illustrates the effect of extremely low temperatures on movie-goings under various robustness check settings. Points represent the point estimation results, and horizontal solid lines indicate the 95% confidence interval.

Panel A: Audiences

Panel B: Box Office Revenues

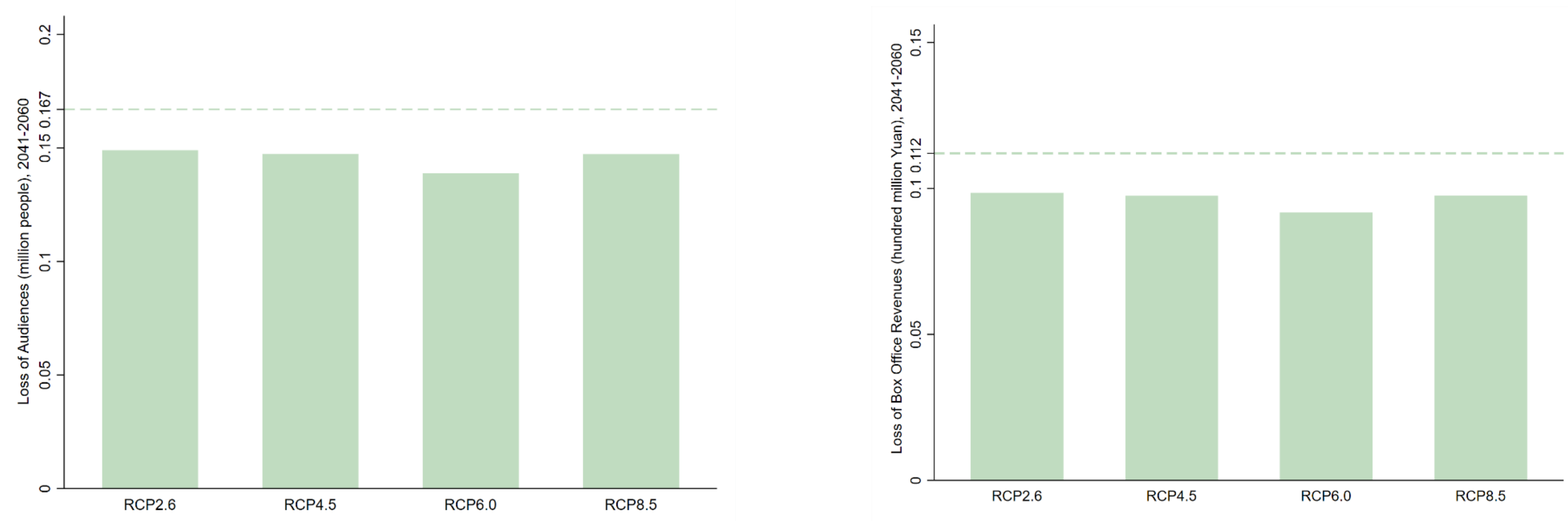


Figure A3 The predicted annual loss of audiences and box office revenues of 49 cities induced by precipitations in the medium-term future (41-60).

Notes: The calculation is implemented at the sample level. The impact of precipitations on movie-goings under each RCP is the average by five GCMs. The green dotted line in Panel A and Panel B represents the annual loss of audiences and box office revenues caused by precipitations in the sample period (15-17) at the sample level.

Tables

Table A1 Movie box office revenues and audiences of 49 cities in 2017.

City	Box office ranking	Box office revenues (ten thousand Chinese Yuan)	Proportion of the national box office revenues (%)	Audiences (ten thousand people)	Attendance rate (%)
1st-tier cities					
Shanghai	1	327956.62	6.26	8301.74	18.17
Beijing	2	321985.32	6.15	7636.86	20.10
Shenzhen	3	205046.72	3.91	5619.82	16.28
Guangzhou	4	204666.79	3.91	5421.45	17.74
new-1st-tier cities					
Chengdu	5	169368.44	3.23	5156.64	16.88
Wuhan	6	136475.84	2.61	4508.11	17.26
Chongqing	7	134698.47	2.57	4367.36	12.27
Hangzhou	8	126989.12	2.42	3816.78	14.73
Suzhou	9	106146.82	2.03	3347.83	13.89
Nanjing	10	94532.67	1.80	3006.81	18.14
Xi’an	11	90324.26	1.72	2950.80	16.26
Tianjin	12	76687.04	1.46	2414.42	13.92
Zhengzhou	13	74241.73	1.42	2449.78	15.50
Dongguan	14	72017.74	1.37	2207.51	11.62
Changsha	15	71350.57	1.36	2185.77	13.58
Ningbo	16	66004.08	1.26	2027.68	13.56
Shenyang	19	56614.40	1.08	1911.80	14.02
Dalian	22	53128.06	1.01	1726.22	16.85
Qingdao	25	48285.57	0.92	1594.98	13.59
2nd-tier cities					
Foshan	17	63745.46	1.22	2097.48	12.00
Wuxi	18	60957.90	1.16	1920.57	12.61
Hefei	20	55935.76	1.07	1821.26	12.82
Fuzhou	21	53693.22	1.03	1550.29	13.94
Haerbin	23	51441.81	0.98	1668.21	16.68
Kunming	24	51284.58	0.98	1668.21	16.68
Changchun	26	47042.00	0.90	1445.76	16.19
Xiaman	27	44150.19	0.84	1284.45	16.27
Wenzhou	28	42943.44	0.82	1256.18	11.70
Nanning	29	42571.14	0.81	1212.47	15.19
Nanchang	30	41824.44	0.80	1317.94	15.91
Jinhua	31	41421.83	0.79	1221.05	13.04
Changzhou	32	38899.76	0.74	1277.89	13.35
Nantong	33	38427.70	0.73	1380.89	12.00

Jinan	34	38330.50	0.73	1177.76	15.12
Shijiazhuang	35	35811.34	0.68	1165.20	13.01
Guiyang	36	32570.82	0.62	909.64	16.80
Quanzhou	37	32482.63	0.62	988.73	11.92
Taizhou	38	32007.88	0.61	1023.87	11.28
TaiChinese Yuan	39	31908.25	0.61	941.53	15.39
Jiaxing	40	31176.72	0.60	949.79	13.95
Shaoxing	41	30517.58	0.58	946.26	13.41
Haikou	42	29885.54	0.57	928.84	14.64
Zhongshan	43	29768.53	0.57	1027.63	11.86
Huizhou	44	28738.53	0.55	894.26	13.47
Lanzhou	45	26193.93	0.50	819.97	18.23
Wulumuqi	46	24877.95	0.47	784.81	17.18
Zhuhai	48	23601.15	0.45	715.50	18.92
Xuzhou	49	23070.37	0.44	765.13	12.20
Yantai	51	21363.01	0.41	715.74	11.09

Notes: The classification of 49 cities is fellowed the rule specified by the YiMagazine. The statistics in the table are from: https://www.askci.com/news/chanye/20180116/094421116104.shtml.

Table A2 Top 22 days movie premiered during 2015-2017.

Date	Number of movies premiered	Attribute
2017-09-22	15	Friday
2017-11-24	13	Friday
2016-11-04	12	Friday
2017-06-09	12	Friday
2017-06-16	11	Friday
2016-11-25	11	Friday
2016-12-02	10	Friday
2016-08-26	10	Friday
2015-06-26	10	Friday
2016-10-14	10	Friday
2017-12-01	10	Friday
2016-09-09	10	Friday
2017-06-30	9	Friday
2017-12-08	9	Friday
2016-08-19	9	Friday
2017-10-20	9	Friday
2017-11-17	9	Friday
2016-04-22	9	Friday
2016-05-20	9	Friday
2015-12-11	9	Friday
2016-12-09	9	Friday
2017-09-15	9	Friday

Notes: Movie released dates come from the movie-rating database. The number of movies premiered each day during 2015-2017 is calculated based on 1252 non-rescreened movie samples.

Table A3 Estimate the impact of temperatures on movie-goings by the temperature-bins model.

	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)
Temp<-2℃	-0.0442*	-0.0928**	-1.0564*
	(0.0266)	(0.0420)	(0.5584)
Temp∈[-2,0)℃	-0.0226	-0.0461	-0.5926
	(0.0248)	(0.0410)	(0.4585)
Temp∈[0,2)℃	0.0034	-0.0247	0.0166
	(0.0222)	(0.0364)	(0.4133)
Temp∈[2,4)℃	-0.0041	-0.0297	-0.0236
	(0.0202)	(0.0331)	(0.3778)
Temp∈[4,6)℃	-0.0187	-0.0541*	-0.2007
	(0.0194)	(0.0320)	(0.3534)
Temp∈[6,8)℃	-0.0330*	-0.0730**	-0.2190
	(0.0178)	(0.0293)	(0.3222)
Temp∈[8,10)℃	-0.0202	-0.0597**	-0.0137
	(0.0162)	(0.0265)	(0.2960)
Temp∈[10,12)℃	0.0098	-0.0035	0.4874*
	(0.0151)	(0.0252)	(0.2691)
Temp∈[12,14)℃	-0.0154	-0.0399*	0.0777
	(0.0137)	(0.0233)	(0.2336)
Temp∈[14,16)℃	-0.0093	-0.0354*	0.1240
	(0.0118)	(0.0200)	(0.2048)
Temp∈[16,18)℃	-0.0052	-0.0114	0.0972
	(0.0100)	(0.0166)	(0.1719)
Temp∈[18,20)℃	0.0014	0.0060	0.0944
	(0.0085)	(0.0142)	(0.1453)
Temp∈[22,24)℃	0.0042	0.0036	0.0663
	(0.0076)	(0.0129)	(0.1248)
Temp∈[24,26)℃	0.0032	0.0092	-0.1742
	(0.0097)	(0.0163)	(0.1685)
Temp∈[26,28)℃	0.0049	0.0036	-0.0796
	(0.0116)	(0.0196)	(0.1979)
Temp∈[28,30)℃	-0.0301**	-0.0290	-0.7627***
	(0.0130)	(0.0219)	(0.2232)
Temp≥30℃	-0.0415**	-0.0617**	-1.2512***
	(0.0168)	(0.0275)	(0.3276)
Mean of explained variables in the reference group	17.23	649.63	15.78
Control Variables	YES	YES	YES
Fixed effects	YES	YES	YES
Observations	721,308	721,308	721,308
R-squared	0.2958	0.2937	0.2043

Notes: The setting of control variables and fixed effects is the same as above. [20,22)℃ is omitted as the reference group. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4 Estimation of the dose-response function between precipitations and movie-goings.

	Panel A: Quadratic precipitations			*Panel B*: Precipitation-bins		
	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation^2	0.0000**	0.0000	0.0001**			
	(0.0000)	(0.0000)	(0.0000)			
Precipitation	-0.0009***	-0.0012***	-0.0149***			
	(0.0002)	(0.0004)	(0.0042)			
Precipitation∈(0,0.8]mm				-0.0084*	-0.0126	-0.1109
				(0.0050)	(0.0088)	(0.0862)
Precipitation∈(0.8,3.5]mm				-0.0148***	-0.0203**	-0.1161
				(0.0055)	(0.0095)	(0.0974)
Precipitation∈(3.5,11.8]mm				-0.0205***	-0.0240**	-0.2636***
				(0.0058)	(0.0101)	(0.1021)
Precipitation>11.8mm				-0.0347***	-0.0473***	-0.4803***
				(0.0068)	(0.0118)	(0.1176)
Control variables	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES
Observations	721,308	721,308	721,308	721,308	721,308	721,308
R-squared	0.2958	0.2937	0.2043	0.2958	0.2937	0.2043

Notes: Each column is a separate regression. Control variables contain weather variables, the AQI, and the city-date-movie level variables. Fixed effects include Movie fixed effects, city fixed effects, date fixed effects, and days-since-premiered fixed effects. In panel B, observations are divided into four groups based on the distribution of precipitations after excluding non-zero precipitation samples. The reference group is observations with zero precipitation, accounting for 65.7% of the sample. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5 Effects of air pollution on movie-goings.

	Panel A: AQI-bins			*Panel B*: PM2.5 as the air quality index			*Panel C*: PM10 as the air quality index		
	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AQI∈(50,100]	0.0037	0.0010	0.2366***						
	(0.0044)	(0.0075)	(0.0762)						
AQI∈(100,150]	0.0148**	0.0126	0.3852***						
	(0.0070)	(0.0117)	(0.1139)						
AQI∈(150,200]	0.0320***	0.0401**	0.6283***						
	(0.0094)	(0.0162)	(0.1569)						
AQI∈(200,300]	0.0537***	0.0680***	0.8160***						
	(0.0123)	(0.0211)	(0.2016)						
AQI>300	0.0990***	0.1278***	1.5128***						
	(0.0233)	(0.0386)	(0.3717)						
PM2.5				0.0003***	0.0004***	0.0054***			
				(0.0001)	(0.0001)	(0.0010)			
PM10							0.0002***	0.0002**	0.0024***
							(0.0000)	(0.0001)	(0.0007)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2043	0.2957	0.2937	0.2043	0.2957	0.2937	0.2043

Notes: Each column is a separate regression. Control variables contain weather variables and the city-date-movie level variables. Fixed effects include Movie fixed effects, city fixed effects, date fixed effects, and days-since-premiered fixed effects. In panel A, the classification of AQI bins follows the standard enacted by the MEE. Use the air quality excellent group [0,50] as the reference. Panel B and Panel C use PM2.5 and PM10 as alternative air quality indexes, respectively. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table A6 Robustness check: use thermal inversion as IV for AQI

	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)
AQI	0.0012	0.0011	0.0233
	(0.0008)	(0.0014)	(0.0143)
Temp<2℃	-0.0615**	-0.1074**	-1.4104**
	(0.0301)	(0.0490)	(0.6086)
Temp∈[-2,0)℃	-0.0439	-0.0640	-1.0269*
	(0.0307)	(0.0518)	(0.5458)
Temp∈[0,2)℃	-0.0169	-0.0417	-0.3979
	(0.0278)	(0.0467)	(0.4997)
Temp∈[2,4)℃	-0.0204	-0.0434	-0.3572
	(0.0242)	(0.0408)	(0.4380)
Temp∈[4,6)℃	-0.0314	-0.0647*	-0.4593
	(0.0219)	(0.0370)	(0.3923)
Temp∈[6,8)℃	-0.0459**	-0.0839**	-0.4825
	(0.0206)	(0.0348)	(0.3670)
Temp∈[8,10)℃	-0.0270	-0.0653**	-0.1511
	(0.0167)	(0.0280)	(0.3043)
Temp∈[10,12)℃	0.0083	-0.0047	0.4577*
	(0.0151)	(0.0252)	(0.2683)
Temp∈[12,14)℃	-0.0145	-0.0391*	0.0962
	(0.0138)	(0.0234)	(0.2353)
Temp∈[14,16)℃	-0.0069	-0.0334	0.1733
	(0.0122)	(0.0205)	(0.2131)
Temp∈[16,18)℃	-0.0026	-0.0093	0.1493
	(0.0105)	(0.0172)	(0.1802)
Temp∈[18,20)℃	0.0025	0.0069	0.1163
	(0.0086)	(0.0143)	(0.1474)
Temp∈[22,24)℃	0.0017	0.0015	0.0153
	(0.0082)	(0.0140)	(0.1328)
Temp∈[24,26)℃	-0.0032	0.0037	-0.3058
	(0.0118)	(0.0197)	(0.1976)
Temp∈[26,28)℃	-0.0061	-0.0056	-0.3036
	(0.0159)	(0.0266)	(0.2657)
Temp∈[28,30)℃	-0.0451**	-0.0416	-1.0687***
	(0.0195)	(0.0326)	(0.3279)
Temp≥30℃	-0.0619**	-0.0788*	-1.6676***
	(0.0261)	(0.0431)	(0.4642)
Observations	721,308	721,308	721,308
R-squared	0.0064	0.0078	-0.0003

Notes: Thermal inversion is used as IV for AQI. We conduct HDFE-2SLS estimation and only report the second stage results. The first stage Cragg-Donald Wald F is 2222.174. The temperature bin [20,22)℃ is omitted as the reference group. The setting of control variables and fixed effects is the same as above. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table A7 Examine correlations between temperatures and movie screenings/premieres.

	Screened movies	Premiered movies	**1**(movie premiered)
	(1)	(2)	(3)
Temp<-2℃	20.50**	-0.09*	-0.01
	(9.01)	(0.05)	(0.01)
Temp∈[-2,0)℃	20.55**	-0.08	0.00
	(9.72)	(0.06)	(0.01)
Temp∈[0,2)℃	44.60***	-0.01	-0.03*
	(13.45)	(0.05)	(0.01)
Temp∈[2,4)℃	31.68***	-0.08*	-0.02
	(8.65)	(0.05)	(0.01)
Temp∈[4,6)℃	25.94***	-0.17***	-0.03**
	(7.71)	(0.04)	(0.01)
Temp∈[6,8)℃	27.76***	-0.09**	-0.02*
	(6.48)	(0.04)	(0.01)
Temp∈[8,10)℃	15.20**	-0.03	0.01
	(7.14)	(0.04)	(0.01)
Temp∈[10,12)℃	11.77**	-0.05	0.00
	(4.91)	(0.04)	(0.01)
Temp∈[12,14)℃	16.26***	-0.06*	-0.01
	(4.76)	(0.03)	(0.01)
Temp∈[14,16)℃	11.59**	-0.07**	-0.02
	(5.30)	(0.03)	(0.01)
Temp∈[16,18)℃	8.35**	-0.03	0.01
	(3.96)	(0.03)	(0.01)
Temp∈[18,20)℃	2.64	-0.05	-0.00
	(2.87)	(0.03)	(0.01)
Temp∈[22,24)℃	3.48	0.08***	0.01
	(2.83)	(0.02)	(0.01)
Temp∈[24,26)℃	5.93	0.09***	0.01
	(6.40)	(0.03)	(0.01)
Temp∈[26,28)℃	1.17	0.09***	0.01
	(7.43)	(0.03)	(0.01)
Temp∈[28,30)℃	-0.27	0.07**	0.01
	(5.54)	(0.03)	(0.01)
Temp≥30℃	-4.03	0.17***	0.02
	(11.01)	(0.04)	(0.02)
Control Variables	YES	YES	YES
Fixed effects	YES	YES	YES
Observations	49,222	49,222	49,222
R-squared	0.7656	0.5071	0.2587

Notes: 1252 non-rescreened movies that premiered between 2015-2017 are used for analysis. [20,22)℃ is omitted as the reference group. Control variables contain weather variables and the AQI. Fixed effects include year fixed effects, city fixed effects, day-of-week fixed effects, and month-of-year fixed effects. Standard errors in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

Table A8 Lagging effects of extreme temperatures on movie-goings up to 10 days.

	Panel A: Extremely high temperatures			*Panel B*: Extremely low temperatures			*Panel C*: Extreme temperatures		
	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\eta=0$	-0.0190**	-0.0373**	-0.4691**	-0.0149	-0.0284	-0.2048	-0.0145**	-0.0280**	-0.3376**
	(0.0095)	(0.0156)	(0.2001)	(0.0113)	(0.0211)	(0.1930)	(0.0073)	(0.0126)	(0.1451)
$\eta=1$	0.0056	0.0105	0.0561	-0.0157	-0.0212	-0.1600	-0.0006	0.0021	-0.0087
	(0.0088)	(0.0155)	(0.1601)	(0.0113)	(0.0207)	(0.1778)	(0.0069)	(0.0123)	(0.1202)
$\eta=2$	-0.0015	-0.0100	-0.0861	-0.0023	-0.0028	0.0046	-0.0010	-0.0057	-0.0421
	(0.0088)	(0.0155)	(0.1676)	(0.0111)	(0.0207)	(0.1796)	(0.0069)	(0.0123)	(0.1250)
$\eta=3$	-0.0077	-0.0105	-0.2399	0.0042	0.0064	-0.1904	-0.0024	-0.0023	-0.2109*
	(0.0082)	(0.0148)	(0.1500)	(0.0110)	(0.0202)	(0.1835)	(0.0066)	(0.0119)	(0.1153)
$\eta=4$	-0.0096	-0.0124	-0.2721	-0.0037	-0.0112	-0.1664	-0.0068	-0.0103	-0.2275*
	(0.0086)	(0.0144)	(0.1764)	(0.0116)	(0.0216)	(0.1859)	(0.0069)	(0.0120)	(0.1308)
$\eta=5$	-0.0078	-0.0112	-0.0524	0.0121	0.0294	0.1167	0.0001	0.0049	0.0180
	(0.0077)	(0.0136)	(0.1519)	(0.0111)	(0.0210)	(0.1729)	(0.0064)	(0.0116)	(0.1141)
$\eta=6$	0.0035	-0.0047	0.1810	-0.0099	-0.0154	-0.1279	-0.0002	-0.0063	0.0826
	(0.0090)	(0.0155)	(0.1809)	(0.0109)	(0.0207)	(0.1877)	(0.0070)	(0.0124)	(0.1353)
$\eta=7$	-0.0101	-0.0178	-0.2989*	-0.0152	-0.0304	-0.1710	-0.0107	-0.0196*	-0.2420**
	(0.0082)	(0.0142)	(0.1547)	(0.0106)	(0.0191)	(0.1671)	(0.0065)	(0.0114)	(0.1165)
$\eta=8$	-0.0156*	-0.0240	-0.1641	-0.0025	0.0054	-0.3635**	-0.0101	-0.0117	-0.2211**
	(0.0080)	(0.0152)	(0.1423)	(0.0105)	(0.0195)	(0.1758)	(0.0063)	(0.0119)	(0.1104)
$\eta=9$	-0.0127	-0.0183	-0.3194**	-0.0044	-0.0015	-0.1984	-0.0088	-0.0103	-0.2649**
	(0.0079)	(0.0140)	(0.1478)	(0.0108)	(0.0193)	(0.1881)	(0.0064)	(0.0114)	(0.1156)
$\eta=10$	-0.0087	-0.0064	-0.3796**	0.0263**	0.0513**	0.0616	0.0052	0.0177	-0.2065
	(0.0086)	(0.0147)	(0.1723)	(0.0131)	(0.0226)	(0.2101)	(0.0074)	(0.0126)	(0.1340)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	715,734	715,734	715,734	715,734	715,734	715,734	715,734	715,734	715,734
R-squared	0.2952	0.2932	0.2048	0.2952	0.2932	0.2048	0.2952	0.2932	0.2047

Notes: Column (1) and (4), column (2) and (5), column (3) and (6) are estimated together. Columns (7)-(9) are three separate regressions. η represents the number of days lagging. Control variables contain weather variables, the AQI, and the city-date-movie level variables. Fixed effects include Movie fixed effects, city fixed effects, date fixed effects, and days-since-premiered fixed effects. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table A9 The heterogeneous impacts of extreme temperatures on movie-goings on different days after the movie premiered.

	Panel A: Extreme temperatures			*Panel B*: Extremely high temperatures			*Panel C*: Extremely low temperatures		
	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate	ln(audiences)	ln(boxoffice)	Attendance rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\omega = 0$	-0.0133	-0.0641	0.2207	-0.0637*	-0.1636***	-0.7944	0.0478	0.0540	1.4369*
	(0.0250)	(0.0407)	(0.4826)	(0.0343)	(0.0569)	(0.6762)	(0.0383)	(0.0616)	(0.7455)
$\omega = 1$	-0.0049	-0.0310	-0.3651	-0.0187	-0.0876*	-0.7014	0.0110	0.0327	0.0102
	(0.0231)	(0.0362)	(0.4664)	(0.0330)	(0.0525)	(0.7050)	(0.0334)	(0.0524)	(0.6382)
$\omega = 2$	0.0238	0.0155	-0.0516	0.0196	-0.0108	-0.2967	0.0292	0.0448	0.2216
	(0.0227)	(0.0359)	(0.4373)	(0.0328)	(0.0518)	(0.6356)	(0.0325)	(0.0524)	(0.6123)
$\omega = 3$	-0.0477**	-0.0995**	-0.6071	-0.0237	-0.0972*	-0.3664	-0.0711**	-0.1002*	-0.8475
	(0.0237)	(0.0393)	(0.4039)	(0.0349)	(0.0584)	(0.6139)	(0.0319)	(0.0532)	(0.5184)
$\omega = 4$	-0.0820***	-0.1299***	-1.2660***	-0.0357	-0.0750	-0.8222	-0.1315***	-0.1898***	-1.7428***
	(0.0225)	(0.0372)	(0.3749)	(0.0335)	(0.0552)	(0.5892)	(0.0289)	(0.0488)	(0.4631)
$\omega = 5$	-0.0644***	-0.0911**	-0.9676***	-0.0147	-0.0312	-0.3160	-0.1146***	-0.1519***	-1.6281***
	(0.0213)	(0.0364)	(0.3569)	(0.0293)	(0.0503)	(0.5362)	(0.0302)	(0.0527)	(0.4763)
$\omega = 6$	-0.0709***	-0.1216***	-1.1058***	-0.0219	-0.0629	-0.3565	-0.1203***	-0.1811***	-1.8643***
	(0.0225)	(0.0391)	(0.3607)	(0.0311)	(0.0559)	(0.5181)	(0.0322)	(0.0546)	(0.5112)
$\omega = 7$	-0.0544**	-0.0828*	-1.2468**	-0.0407	-0.0737	-1.0335	-0.0718**	-0.0979*	-1.5295**
	(0.0264)	(0.0445)	(0.5234)	(0.0387)	(0.0661)	(0.8438)	(0.0349)	(0.0594)	(0.6166)
$\omega = 8$	-0.0257	-0.0119	-1.1524**	-0.0216	-0.0059	-1.1296	-0.0311	-0.0211	-1.1953**
	(0.0250)	(0.0411)	(0.5050)	(0.0367)	(0.0588)	(0.8169)	(0.0345)	(0.0584)	(0.5999)
$\omega = 9$	-0.0140	-0.0003	-0.6962	0.0174	0.0573	-0.3259	-0.0465	-0.0603	-1.0824*
	(0.0254)	(0.0417)	(0.5066)	(0.0366)	(0.0563)	(0.8089)	(0.0346)	(0.0596)	(0.6006)
$\omega = 10$	0.0063	0.0196	-0.5139	0.0604*	0.0900	0.0258	-0.0544*	-0.0605	-1.1203**
	(0.0237)	(0.0417)	(0.4424)	(0.0327)	(0.0557)	(0.6577)	(0.0320)	(0.0592)	(0.5544)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308	721,308
R-squared	0.2957	0.2937	0.2042	0.2958	0.2937	0.2042	0.2958	0.2937	0.2042

Notes: Columns (1)-(3) are three separate regressions. Column (4) and (7), column (5) and (8), column (6) and (9) are estimated together. ω represents the number of days after the movie is released. Control variables contain weather variables, the AQI, and the city-date-movie level variables. Fixed effects include Movie fixed effects, city fixed effects, date fixed effects, and days-since-premiered fixed effects. Standard errors in parentheses are clustered at the movie level. *** p<0.01, ** p<0.05, * p<0.1.

Table A10 The predicted annual loss of audiences and box office revenues of 49 cities in the medium-term future by five GCMs under each RCP.

Panel A: GFDL-ESM2M			
		Predicted loss of audiences (million people)	Predicted loss of box office revenues (hundred million Chinese Yuan)
RCP2.6	Extremely high temperature	0.181	0.135
	Extremely low temperature	0.097	0.049
	Precipitation	0.150	0.100
RCP4.5	Extremely high temperature	0.253	0.189
	Extremely low temperature	0.083	0.042
	Precipitation	0.147	0.098
RCP6.0	Extremely high temperature	0.196	0.147
	Extremely low temperature	0.100	0.051
	Precipitation	0.140	0.093
RCP8.5	Extremely high temperature	0.330	0.249
	Extremely low temperature	0.093	0.047
	Precipitation	0.143	0.095
Panel B: HadGEM2-ES			
		Predicted loss of audiences (million people)	Predicted loss of box office revenues (hundred million Chinese Yuan)
RCP2.6	Extremely high temperature	0.357	0.269
	Extremely low temperature	0.080	0.041
	Precipitation	0.156	0.103
RCP4.5	Extremely high temperature	0.378	0.284
	Extremely low temperature	0.075	0.038
	Precipitation	0.146	0.097
RCP6.0	Extremely high temperature	0.345	0.260
	Extremely low temperature	0.082	0.042
	Precipitation	0.139	0.092
RCP8.5	Extremely high temperature	0.443	0.332
	Extremely low temperature	0.058	0.029
	Precipitation	0.156	0.103
Panel C: IPSL-CM5A-LR			
		Predicted loss of audiences (million people)	Predicted loss of box office revenues (hundred million Chinese Yuan)
RCP2.6	Extremely high temperature	0.267	0.200
	Extremely low temperature	0.086	0.044
	Precipitation	0.141	0.093
RCP4.5	Extremely high temperature	0.341	0.256
	Extremely low temperature	0.086	0.044

	Precipitation	0.149	0.099
RCP6.0	Extremely high temperature	0.284	0.212
	Extremely low temperature	0.096	0.049
	Precipitation	0.143	0.094
RCP8.5	Extremely high temperature	0.452	0.341
	Extremely low temperature	0.070	0.036
	Precipitation	0.144	0.095
Panel D: MIROC-ESM			
		Predicted loss of audiences (million people)	Predicted loss of box office revenues (hundred million Chinese Yuan)
RCP2.6	Extremely high temperature	0.306	0.230
	Extremely low temperature	0.072	0.036
	Precipitation	0.145	0.096
RCP4.5	Extremely high temperature	0.291	0.218
	Extremely low temperature	0.082	0.042
	Precipitation	0.149	0.098
RCP6.0	Extremely high temperature	0.345	0.259
	Extremely low temperature	0.076	0.039
	Precipitation	0.129	0.085
RCP8.5	Extremely high temperature	0.442	0.334
	Extremely low temperature	0.052	0.026
	Precipitation	0.141	0.094
Panel E: NorESM1-M			
		Predicted loss of audiences (million people)	Predicted loss of box office revenues (hundred million Chinese Yuan)
RCP2.6	Extremely high temperature	0.215	0.161
	Extremely low temperature	0.096	0.050
	Precipitation	0.151	0.100
RCP4.5	Extremely high temperature	0.276	0.207
	Extremely low temperature	0.087	0.044
	Precipitation	0.146	0.096
RCP6.0	Extremely high temperature	0.208	0.156
	Extremely low temperature	0.086	0.044
	Precipitation	0.142	0.094
RCP8.5	Extremely high temperature	0.361	0.272
	Extremely low temperature	0.073	0.037
	Precipitation	0.152	0.101

Notes: Calculations are implemented at the sample level. Calculations for extreme temperatures are based on Eq.(10) and Eq.(11). The annual predicted loss of audiences and box office revenues of 49 cities induced by precipitations in the medium-term future is calculated to:

$$Predicted\ loss\ in\ audience = \frac{1}{20} \times \sum_{c} \sum_{d} \overline{Audience_{c,d \in m}} \times \left[\frac{1}{2 - \exp(Precipitation_{cd} \times 0.000553)} - 1 \right]$$

and

$$Predicted\ loss\ in\ box\ office = \frac{1}{20} \times \sum_{c} \sum_{d} \overline{Boxoffice_{c,d \in m}} \times \left[\frac{1}{2 - \exp(Precipitation_{cd} \times 0.000892)} - 1 \right].$$