Weather, Climate Change, and Movie Recreation Demand in China

Chen Xi Wei Xie Xiaoguang Chen Pan He*

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Abstract: Accurately assessing the impacts of climate change on each economic sector is essential for designing effective climate policies. Existing studies focus on climate effects on agricultural and industrial production, and exploration of impacts on demand in the service sector remains limited, 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 to moderate temperatures, one additional extremely hot day (daily average temperature ≥30°C) leads to a 3.27%, 5.94%, and 0.86% reduction in audiences, box office revenues, and attendance rate, respectively. Effects of extreme cold (daily average temperature <-1°C) are magnitude close to extreme heat but are estimated less precisely. The magnitude of precipitation effects is slightly small compared to temperatures. We examine the impact of extreme temperatures on movie supply, and confirm the bias induced by the supply side does not shake the demand side estimation. The negative impacts of extreme temperatures are most pronounced in the 3-7 days after a movie premiere, with movies screened in high-tier cities and on Fridays more likely to suffer, while demand for high-quality movies suffers less under temperature shocks. Our results suggest weather shocks have caused considerable losses to the film industry in China during the sample period, and moviegoing losses due to climate change are predicted to increase by 20%-60% from the current stage in the medium-term future (years 2041-2060).

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 this century. Comprehensively assessing 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). However, the literature on the economic impacts of climate change mainly focuses on the agricultural sector (Deschênes and Greenstone, 2007; Schlenker et al., 2009; Chen et al., 2016; Zhang et al., 2017) and the industrial sector (Dell et al., 2012; Zhang et al., 2018; Chen et al., 2019; Somanathan et al., 2021). Studies identifying the climatic impacts on the service sector using high-frequency micro-level data are very limited.

Two attributes of the service sector raise challenges in examining how consumers' demand is affected by weather variations, both from the data resolution and the identification strategy. First, consumers' demand for agricultural and industrial products is stable over a long period, on a quarterly or yearly scale, while demand for service goods can be affected by immediate environmental changes. Using high-frequency bank card transition data, Lai et al.(2022) find food consumption responds less to daily temperature fluctuations, but entertainment spending responds significantly to temperature. This feature calls for finer data resolution when estimating the impact of weather on the service sector from the demand side, and the coarse time-aggregated data may cause over-smoothing of idiosyncratic responses. Second, the simultaneous effects of weather on the demand and supply of the service sector are intertwined, causing difficulty in separating a single effect alone. For example, on rainy days, customers' demand for taxis increases dramatically. However, precipitation also encourages drivers to turn leisure into work (Connolly, 2008), which increases the availability of taxi services (Brodeur and Nield, 2018). The omission of supply-side-related variables may lead to biased estimation in assessing the impact of weather on the service sector from the demand side, and the bias still exists even after controlling for abundant fixed effects, considering demand and supply are associated with the weather with the same frequency. This feature is a reminder that the bias caused by the simultaneous supply-side factors needs to be rigorously clarified when evaluating weather impacts on service demands, and the one-side-based identification strategy widely adopted in evaluating effects on agricultural or industrial production may be misleading (Deschênes and Greenstone, 2007; Somanathan et al., 2021).

In this paper, we exploit high-frequency movie-viewing data of 49 cities in China between 2015 to 2017 to examine the impact of weather variations- mainly temperature and precipitation, on moviegoing. Focusing on the film industry has unique advantages in deepening our understanding of how weather affects service demands. First, the movie box office data is the basis for the movie producer, distributor, and theaters to share dividends, and is accurately and electronically recorded and made public to audiences as a signal of a movie's popularity,[2] which guarantees the reliability of moviegoing variables and away us from measurement error. Second, during our sample period, the film industry was one of the fastest developing industries in the service sector in China. 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%, and 22.0%, respectively (Figure 1). China is one of the largest movie markets worldwide, and the preference of audiences in China even affects Hollywood casting (Hermosilla et al., 2018).[3] Estimating the weather-movie demands relationship also helps to understand how the service sector in the transition of merging economies can be affected by future climate change. Third, the fine-grained data allow us to examine the causal effect of short-term weather fluctuation on movie demand, and also help to clarify the biased direction caused by potential omissions of supply-side variables.

We obtain theater-level movie viewing records of 49 cities in China between 2015-2017 from an online box office statistics website, and aggregate theater-level data to the movie-city-day level to conduct the econometric analysis. To accurately describe

[2] One can easily find out the box office of a movie from online ticketing sites, such as Maoyan: https://piaofang.maoyan.com/dashboard, or Taopiaopiao: https://dianying.taobao.com/.

[3] 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.

movies' characteristics, we obtain variables including the overall rating, movie language, runtime, and production countries of 1,273 non-rescreened movies from Douban.com, a popular movie consumer review website in China. Meteorological and air quality data are obtained from the China Meteorological Administration and the Ministry of Ecology and Environment of China, respectively, and are aggregated to the city-day level to merge with the movie viewing data. Finally, approximately 721 thousand observations are used in the analysis.

We use the semi-parametric weather bins approach and control for the abundant movie, spatial, and temporal level fixed effects to identify the impact of weather on movie demand. The temperature distribution is split into 18 bins with 2°C as the interval, and the zone the body feels most comfortable, [20,22)°C, is dropped as the reference group. We find that, compared with the reference group, extreme heat day with a daily average temperature over 30°C significantly leads to a 4.15%, 6.17%, and 1.25% reduction in audiences, box office revenues, and attendance rate. The negative effects of extreme cold with a daily average temperature below -2°C are similar in magnitude to extreme heat but only marginally statistically significant. The daily cumulative precipitation has a significant and linearly negative effect on moviegoing, but the magnitude is relatively small compared to the effects of extreme temperatures. Our baseline results are stable under a series of robustness checks, such as expanding the interval of the reference bin, controlling for stricter city-by-month fixed effects, replacing the cluster level of standard errors, and altering the selection of the analysis sample. We further find moviegoing mainly responds to contemporary extreme temperature shock, with weak evidence of lagging effects. The effect of temperature on movie demand has a substantial heterogeneity, including movies' quality, movie life cycle, city tiers, and day-of-week heterogeneities.

In identifying the effect of weather on movie demand, a major concern is omitting contemporaneous movie supply variables may bias estimates. We develop a framework at the city-day level to examine whether movie supply is associated with weather variations. The results show that after controlling for the city and seasonal patterns, movie supply behaviors are related to weather fluctuations. From the extensive margin, the number of movies premiered increases with more extremely hot days. And from the intensive margin, more movies are screened on extremely cold days. Combining the baseline finding that extreme temperatures negatively affect movie demand, the supply-side results indicate that the potential bias only underestimates negative effects, and the specification gives a conservative interpretation.

Our findings have clear policy implications. We translate the estimates of audience responses into monetization losses. The back-of-the-envelope calculation suggests that extreme temperatures (precipitations) in 2017 led to 4.93 (0.13) million losses in moviegoers and a 292.74 (7.24) million Chinese Yuan loss in box office revenues across 49 cities in China. The single-year calculation implies that short-term weather variations caused sizeable economic losses to the film industry in China. Moreover, we project our baseline results to the medium-term future (2041-2060) under different representative concentration paths (RCPs) to investigate the role of climate change on movie demands in China.[4] Moviegoing losses (audiences and box office revenues) caused by extreme temperatures will be 1.4-2 times that of the current stage, and the largest losses are under the severest climate scenario- RCP8.5. Accumulated precipitation is predicted to decrease in the future, partly offsetting the negative effect caused by extreme temperatures. When precipitation and temperature are considered together, movie demand losses in the medium-term future in China are predicted to increase by 20-60% from the current stage due to climate change.

He et al. (2022) examine the impact of air pollution on moviegoing, and weather conditions are also considered. However, our paper is distinguished from He et al. (2022) in the following aspects. First, we use more recent moviegoing data, from 2015-2017, and more movie samples, 1,273 non-rescreened movies. He et al. (2022) use the viewing data of 829 movies during 2012-2014. Second, besides the audience scale used by He et al.(2022), we also adopt two other variables, box office revenues and attendance rates, to describe consumers' movie demand. Third, from the identification

[4] In executing the prediction, we assume that China's film market will remain consistent with the current period in the medium-term future, which helps to isolate the effect of climate factors. One may doubt the reliability of the assumption. However, we clarify that the assumption is not this paper's main concern and does not shake the policy implications. We provide a more detailed discussion in Section 5.2 and Section 6.

strategy, we rigorously examine how the demand-side-focused estimate can be biased by the movie supply-weather association. Though He et al. (2022) mention that air pollution may be a consideration for the movie release, they argue that it is hard to forecast air quality weeks in advance, and the air quality is plausible exogenous after release once controlling for many fixed effects. Our study suggests that the nature of this exogenous should be treated cautiously. We find that both the extensive and intensive margins of movie supply are associated with ambient environmental factors. Even if the release decision made by the movie distributor is not affected by air pollution, theaters may adjust the arrangement for a movie that has been released based on real-time air quality. The adjustment at the intensive margin can affect availability for the specific movie and thus lead to a biased demand-side estimate. At last, as a by-product, we take a step forward by using thermal inversion as the instrumental variable for air pollution. 2SLS estimates show that air pollution has no significant effect on moviegoing during our sample period.[5]

This paper is connected to a series of literature and highlights its contribution from at least three aspects. First, to the best of our knowledge, it is the first study to causally identify how demands for a fast-growing industry in the service sector of an emerging economy are affected by weather variations and project the short-term weather estimations to the medium-term future to inform climate policy implications. Moreover, we develop an empirical framework to clarify the biased direction caused by supply-side responses in evaluating weather impacts from the demand side. This consideration is essential for analyzing the demand-supply intertwined service activities, such as the behavior of taxi drivers (Brodeur and Nield, 2018), couriers (Wang et al.,2022), and take-away riders.

Second, this paper is also an extension of the previous weather-recreation demand literature in the context of one of the largest recreation demand markets worldwide.

[5] We are not suggesting that the results of He et al. (2022) are misleading by omitting movie-supply considerations. We note the watershed of the two studies is 2014- the tricky year when China started to roll out the real-time quality monitoring system, and the difference in results may reflect the effect of more transparent air information (Barwick et al., 2019). We provide a more detailed discussion in Section 4.2, but note that it is still hard to fully explain the contradiction. Reanalysis using data spanning years before and after the real-time monitoring system was established may be a solution.

Previous studies evaluate weather impacts on recreational activities, but focus on non-market-based activities in the context of developed economies, such as Dundas and von Haefen (2020), Chan and Wichman (2020). Since these activities are non-market-based, that brings challenges in assessing the welfare consequences of climate change.[6] This paper focuses on a market-based recreation activity, and welfare changes are thus calculated explicitly leveraging the price signal. Moreover, since the value standard of market-based recreation is clear, outputs of these activities can be classified into the service sector output and be a component of aggregate national output. Therefore, market-based recreation is at least as essential as non-market-based recreation in assessing the socio-economic impacts of climate change. This paper also enriches the literature that explores weather impacts on recreation from the aggregated level, such as Graff Zivin and Neidell (2014), Lai et al. (2022).

Third, this paper also dialogues with studies exploring network externalities and learning effects on movie consumption, in which plausible exogenous weather shocks are instrumented for abnormal moviegoing, such as Moretti (2011) and Gilchrist and Sands (2016).[7] This paper finds temperature effects on moviegoing are contemporaneous and not homogeneous across days after the movie premiere but concentrated in the 3-7 days after the premiere. This pattern suggests the role of ex-ante priors and ex-post information in shaping weather effects and also deepens our understanding of the validity of instruments in aforecited studies.

2. Data

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

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

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

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 China Business Network, a leading financial media group in China.[8] 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 China's film market.[9] 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 movie-city-day 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's 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.[10] Based on the premiere date information, we calculate the number of days since the movie premiered.

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

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

[9] 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.

[10] For instance, the rating interface of *Wolf Warriors* 2 on Douban.com is https://movie.douban.com/subject/26363254/.

Center, an official institution under the jurisdiction of the China Meteorological Administration.[11] 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).[12] In addition to weather conditions, ambient air quality is another relevant factor in moviegoers' decision-making (He et al., 2022). We include the air quality index (AQI) obtained from the Ministry of Ecology and Environment of China as a control variable.[13] 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.[14] 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 $0.5° \times 0.5°$. The prediction data is assigned 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.[15]

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[11] More details about the meteorological data can be found at http://data.cma.cn/en.
[12] We also choose 150km and 200km as the radii for robustness checks, and the results are robust.
[13] 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: https://air.cnemc.cn:18007/.
[14] For a more detailed introduction about the ISI-MPI, see https://www.isimip.org/.
[15] 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.

3. Empirical strategy

3.1 *Baseline specification*

We focus on 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 (HDFE) model, Eq.(1) is proposed to assess the influence of short-run weather variations:

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

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.[16] $f(Temp_{cd})$ 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,

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

which signal movies' popularity and may affect moviegoers' interest and admission chances.

Taking advantage of the high-frequency data, we then control for abundant fixed effects making weather variations plausibly exogenous to time-variant unobservables to identify the causal effects of weather variations on moviegoing. The movie fixed effect θ_i captures observable time-invariant movie characteristics, such as movie quality and runtime, and all other time-invariant 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 the summer holidays and the Spring Festival. There may be a non-linear relationship between the scale of moviegoers and the days since the movie premiered, which is flexibly captured by DsP (days-since-premiered) fixed effects. In the baseline analysis, we cluster standard errors at the movie level, allowing demands for the same movie over time to be serially correlated and the contemporaneous correlation of demands for the same movie across cities

3.2 *Definition of temperature measures*

Ongoing literature reveals the profound impact of extreme temperatures on human behaviors from multiple perspectives, including time allocation (Graff 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.[17] Eq.(1) thus can be explicitly written as:

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

To ensure that the number of bins is large enough to depict the movie viewing-temperature relationship accurately and that the number of observations in each bin is comparable, we divide temperatures into 18 bins with a 2°C interval[18]. $TempBin_{cd}^j$ contains a series of dummy variables, which equal one if city c's daily average temperature falls into the 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, similar to Karlsson and Ziebarth (2018) and Chan and Wichman (2020). We indicate a day with an average temperature over 30°C as an *extremely hot day* and an 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:

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

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

[18] 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.

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 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*

The above specifications tend to detect the causal effect of extreme temperatures on movie demand, whereas the omission of supply-side factors, which influence the availability of the specific movie and are associated with temperatures, can bias demand-side estimates. Temperatures may be associated with movie availability, not only from the extensive margins- the timing of a movie premiere, but also intensive margins- screening frequency after a movie has premiered.

Though fewer empirical studies examine the relationship between temperatures and movie premiere decisions directly, theoretical analysis suggests optimal premiere strategies vary across movie quality.[19] In a signaling model, King et al. (2017) demonstrate that high-quality movies are suitable for release in a high demand and high quality elastic period, and a low demand and less quality-sensitive period is better for low-quality movies to premiere. Since temperatures across a year are closely related to audiences' movie demand periods, this finding reveals the potential linkage between temperatures and movie release timing. Our data provide a more detailed description for this link. In Panel A of Figure 2, movie premieres are dominantly concentrated on Friday, and one reasonable explanation is that a release on Friday can attract audiences from Friday night to Sunday, contributing to a higher early-period box office. In Panel B of Figure 2, two hotspot periods, July to September and November to December, account for a large percentage of movie premieres within a year, corresponding to the summer period and the Spring Festival, respectively. Our findings are consistent with Einav (2010), who documents that movie release dates are densely clustered around

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

weekends and holidays. In addition, we pick up the top 22 days with the most movie premieres in 2015-2017 (Table A2) and find all the popular days are Fridays, echoing the pattern presented in Figure 2.

The most plausible explanation for these pieces of evidence is that the movie premiere decision is made by the producer and distributor in pursuit of high box office and word-of-mouth, indicating the relationship between temperatures and premiere timing is correlated but not causal. Generally, a movie's premiere date is decided a few months ahead, and information is available to audiences through news reports or websites.[20] While short-term temperatures can be predicted from the weather forecast, it is quite challenging to precisely predict weather conditions months ahead.

In empirical practice, the correlation between temperatures and movie supply at extensive margins is not a major obstacle. Since the correlation varies monthly or seasonal, it can be captured by controlling for month-of-year fixed effects. However, the effect of temperatures on movie supply at the intensive margin is trickier. After a movie is released, theater owners have the flexibility to adjust screening schedules based on their expectations for movie performances, reflected in screening frequency changes and showtime of a specific movie across a day, in which nuanced real-time weather conditions can be essential factors. The interference from the movie supply side can dramatically affect estimates of temperatures on movie demand, and it is hard to role out by controlling for fixed effects, considering it also varies at the city-day level as fluctuations of movie demand and weather.

We implement the following specification at the city-day level to examine whether movie supply is associated with extreme temperatures, after controlling for spatial-and-seasonal trends. And if so, we clarify the biased direction in temperature-movie demand estimates induced by omitting supply-side factors.

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

[20] 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.

S_{cd} denotes movie supply behaviors, with the extensive margin proxied by the number of movies premiering on date d in city c and a dummy for at least one movie premiered, and the intensive margin is indexed by the number of movies screened. City-specific time-invariant characteristics are absorbed by the city fixed effects τ_c. We include year fixed effects σ_{year}, month-of-year fixed effects λ_{MoY}, and day-of-week fixed effects π_{DoW} to capture time trends described in Figure 2. The setting of weather and air quality variables in Eq.(4) is the same as that in Eq.(2).

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.[21] 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 insignificant or weakly significant, suggesting the impact of temperature on moviegoing is mainly driven by extreme temperatures and only weakly affected by moderate temperatures.[22] An extremely hot day with a 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 an average temperature lower than -2°C, equivalent to a

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

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

0.72 reduction in audiences and 60.29 Chinese Yuan revenue losses. These results indicate that moviegoers are sensitive to both extremely high and low temperatures, though estimations for extreme cold are less precise. Moreover, we find that the daily cumulative precipitation, another indicator commonly adopted to reflect climate change, has a significant negative impact on moviegoing but is small in magnitude. We further confirm this approximately linear effect of precipitation by using the quadratic precipitation setting and the precipitation-bins model, detailed in Table A4.

We also compare our baseline results with previous representative studies, which use micro-level data and adopt the temperature-bins model to investigate the effects of temperature fluctuation on the service sector or recreational activities.[23] The only study we are aware of that uses micro-level data to examine the impact of weather variations on the service sector is He et al. (2019), which uses financial records of hotels in the US between 2016 to 2018. They find the profit rate of hotels is broadly affected by temperatures, and once the temperature deviates from the reference interval, 18-20°C, the negative effects of temperatures appear, which presents a different effect pattern than this paper. Compared to the reference temperature interval, extreme heat with an *average temperature* falling to 30-32°C leads to a 12.7% reduction in revenue per occupied room, and the negative effect extends to 30.5% when the temperature exceeds 32°C. For extreme cold with temperature below -2°C, the negative effect is estimated as 9.6% (column 5 of Table S2 of He et al. (2019)). We note that the magnitude of the extreme heat effect on revenues estimated by He et al. (2019) is 2-5 times ours, but the magnitude of extreme cold effects is comparable between the two studies. This paper also links to studies focusing on outdoor recreation demands, though these activities are mainly non-market-based. Dundas and von Haefen (2020) use individual-level data and structurally estimate how participation in shoreline marine recreational fishing can be affected by weather conditions in the US during 2004-2009, and they find that the effects of extreme cold and extreme heat are asymmetric. Relative to the reference group, 70-75°F (21.1-23.9°C), an additional extreme heat day with a *maximum*

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[23] Because the magnitude of the precipitation effect is relatively small in our study, and precipitation measurement varies in the external literature, we omit the comparison of precipitation results here.

temperature over 85°F (29.4°C) is associated with a nearly 0.9% reduction in the likelihood of going for recreational fishing,[24] which is slightly smaller than our estimates for the movie audience scale (Model 3 of Table 2 of Dundas and von Haefen (2020), the preferred specification). However, the negative effect of extreme cold is found to be disproportionately larger compared to our moviegoing findings. Extreme cold below 30°F (-1.1°C) causes a 22.1% marginal loss of participation in recreational fishing, which is twice the magnitude of movie audiences reduction. Using data from over 27 million bike-share trips on weekends during 2010-2017, Chan and Wichman (2020) explore the impact of weather on outdoor recreational cycling in North American cities. The deterioration of temperature on cycling is concentrated in extreme cold, and the effect of extreme heat is consistently found to be insignificant. Compared to 60-70°F (15.6-21.1°C), extreme cold with a daily *average temperature* below 30°F (-1.1°C) leads to a 75%-80% reduction in both the quantity and duration of trips (column 6 of Tables 2 and 3 of Chan and Wichman (2020)),[25] which is a far greater effect than our moviegoing estimation. Some studies also examine the impact of weather on recreation but do not focus on specific activities, allowing us to compare our results with existing findings at a higher aggregated level. Graff Zivin and Neidell (2014) use American Time Use Survey (ATUS), a nationally representative survey, to examine the impact of temperature on time allocation between labor, outdoor leisure, and indoor leisure. Outdoor leisure decreases by roughly 55 minutes under the extreme cold with a daily *average temperature* below 30°F (-1.1°C) compare to the reference group 70-75°F (21.1-23.9°C) (outdoor leisure estimates for all individuals in Table A2 of Graff Zivin and Neidell (2014)), a reduction 1.25 times the sample mean of outdoor leisure (Table 1 of Graff Zivin and Neidell (2014)).[26] However, outdoor leisure is

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[24] We use the estimated results for three temperature bins (85-90, 90-95, and >95°F) and take the average to obtain the extreme heat effect, which ensures the definition of extreme heat is consistent with this paper. (-0.006-0.004-0.018)/3=-0.0093.

[25] Coefficients of temperature bins in Tables 2 and 3 are translated into marginal effects in percent following the formula in footnote 14 in Chan and Wichman (2020).

[26] Though Graff Zivin and Neidell (2014) mainly focus on the effects of *maximum temperature* in their paper, we describe *average temperature*-based findings here because their choice of reference group under average temperature is close to us and feasible for comparing results. The effects of temperature on time allocation are very close, whether the temperature is average or maximum measured, see Table A1 and A2 in Graff Zivin and Neidell (2014).

under-responsive to extreme heat, and the estimate (*average temperature* over 85°F) is statistically insignificant. In a recent study focusing on China, Lai et al.(2022) use the 2013-2018 UnionPay bank card transaction data to examine the effects of temperature on various types of aggregated consumption. Specific to the entertainment category, results show that extreme cold with the *average daily temperature past ten days* below 30°F (-1.1°C) reduces entertainment consumption per card by 0.808 Yuan (11.8% of the sample mean) compared to that in the moderate temperature interval 70-75°F (21.1-23.9°C) (column 3 of Supplementary Table 4 of Lai et al. (2022)), which is very close to the effect of extreme cold on box office revenues we estimated above.[27] In contrast to this paper and previous studies, Lai et al. (2022) find extreme heat increases entertainment consumption. Once interday temperature deviates from 70-75°F (21.1-23.9°C) to over 85°F (29.4°C), entertainment consumption per card jumps 0.234 Yuan or 3.4% of the sample mean (column 3 of Supplementary Table 4 of Lai et al. (2022))[28]. However, since entertainment consumption captured by bank card transaction data is the sum of indoor and recreational spending, it is hard to isolate the effect of temperature on outdoor recreation demands alone. In summary, previous studies consistently find negative effects of extreme cold on the service industry and recreation. Our estimate is comparable in magnitude to some of these studies, though with less precision. However, the patterns of extreme heat are highly inconsistent. Either the negative effect is disproportionately large, or it attenuated to zero. We find a negative effect of extreme heat with a moderate magnitude in the context of movie viewing in China, further enriching the literature.

The fact that moviegoing responds less to temperature bins except in extreme cases

[27] Two important notes here. First, the temperature measurement of Lai et al.(2022) is different from ours and the literature cited in this section. Lai et al. (2022) use the average daily temperature past ten days to allow interday consumption substitution. However, Section 4.4 shows that moviegoing response to contemporaneous temperature shocks only and lagged effects up to ten days are insignificant. We compare our results with Lai et al. (2022) to examine the external validity because it is the only study that analyzes the temperature-recreation relationship using comprehensive micro-data and focusing on China. Second, we do not use the reference temperature, 40-45°F, in Lai et al.(2022), but 70-75°F to intuitively compare results. The extreme cold effect (-11.8%) is calculated as follows. We first take the mean of the coefficients for bins with temperatures below 30°F, that is, (-0.922-0.574-0.523-0.404-0.757)/5=-0.636 (column 3 of Supplementary Table 4 of Lai et al. (2022)). Then, combined with the coefficient of 70-75°F (0.172, column 3 of Supplementary Table 4) and the sample mean of entertainment consumption per card (6.84Yuan, Supplementary Table 2), the extreme effect is obtained by (-0.636-0.172)/6.84=-11.8%.

[28] The extreme heat effect is (0.406-0.172)/6.84=3.4%.

encourages us to extend the reference interval, thus directly estimating the impact of extreme temperatures rather than temperature fluctuations on movie viewings. Estimation results based on Eq.(3) are presented in Panel B of Table 2. Temperature extremes are days when the average temperature is below 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 of 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.

Notably, air pollution is estimated to be positively associated with moviegoing under the HDFE specification and assuming air quality fluctuations are exogenous and random, which seems in contrast to He et al. (2022). The relationship is still robust under the air quality-bins setting or using PM2.5/ PM10 as alternative air quality indicators.[29] We discuss the result from two aspects. First, the sampling period of our study and He et al. (2022) is different. The watershed is 2014,[30] 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 fishing and outdoor dining, it also offers shelter from damages from particulate matters for the duration of the activity. That is to say, entering the theater for a movie is an avoidance choice for short-time pollution, given the audience is located outdoors during severe air pollution. The real-time air quality information reinforces the avoidance behavior after 2014, the period covered by our

[29] Detailed results are provided in Table A5.

[30] 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.

sample. 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, the lack of information on the whereabouts of audiences (indoors or outdoors) when they decide to see a movie limits in-depth exploration of this question. Second, air quality may be endogenous, as found in the literature, leading to biased air pollution estimates. Therefore, results from the HDFE specification should be interpreted cautiously.

4.2 *Robustness checks*

In this section, we conduct various attempts to check the robustness of our baseline findings. We first extend the baseline specification above. In the baseline model, we control for abundant fixed effects to isolate weather variations with unobservables. Besides fixed effects that have been controlled for, we further include the city-by-month fixed effects, which absorb the normal weather status varies across months in a given city. However, the role of controlling for the city-by-month fixed effects is ambiguous. On the one hand, the city-by-month fixed effects help capture local time trends in moviegoing demands and weather conditions, resulting in residual shocks that are plausible random deviations from the local norms. On the other hand, considering that explanatory variables vary at the city-day level, stricter control for the city-by-month fixed effects may reduce available variations for identifying the effect of weather variations and cause attenuation bias (Fisher et al., 2012). As shown in Figure 4, after controlling for stricter city-by-month fixed effects, the negative impacts of extreme temperatures on movie-goings are estimated to be slightly smaller than baseline results but still statistically significant.[31] Moreover, we replace the standard error clustering from the movie level to the city level, allowing for serial correlation of movie attendance within a city and audiences' contemporaneous choosing across multiple movies. The city-level clustering specification leads to less precise estimations of extreme temperatures- confidence intervals become wider compared to baseline results, but statistical significance is still maintained.

[31] We also examine the robustness of extremely high and low temperature effects, as illustrated in Figures A1 and A2.

Beyond modifying the baseline specification, we also apply other robustness checks. First, in the baseline analysis, 88 movies rescreened during 2015-2017 are excluded considering that audiences' differential preferences for rescreened versus newly released movies may cause an ambiguous effect on the results. We now use all 1,361 movies (including rescreened movie samples) and rerun the analysis.[32] Second, the cloud cover variable has a large number of missing observations, as shown in the descriptive statistics. We drop the variable in this part to examine the robustness. Third, we exclude observations with the movie ticket price below 1% or above 95% quantile of the price distribution. The cutoff point is 22.42 Chinese Yuan and 65 Chinese Yuan, respectively. Forth, the abnormal screening behavior of theaters may cause unexpected results. Therefore, we exclude movie samples screened for fewer than seven days between 2015-2017 within each city. In addition, Movies have experienced big success at the box office and have had word-of-mouth may be postponed to go offline, thus having screening days far exceeding other movies.[33] To avoid results being biased by these blockbuster movies, movie samples screened for more than 80 days in each city are also excluded. Figure 4 indicates that extreme temperatures have negative and stable effects on moviegoing under each specification, reflecting that the baseline results are robust. Again, the negative impact of extreme temperatures is mainly driven by extreme heat, and estimates of extreme cold are systematically insignificant (Figures A1 and A2).

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 results inconsistent 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 temperatures. We use thermal inversion as an instrumental variable (IV) for air quality,

[32] When using all movie samples for analysis, control for the days-since-premiered (DsP) fixed effects is no longer available.

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

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).[34] The thermal inversion condition of each city is identified based on its geographic center. 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 the 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, it equals zero. HDFE-2SLS estimation results are reported in Table A6. The Cragg-Donald Wald F-statistic 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 temperature estimates, as findings in Table A6 are close to the pattern presented in Figure 3.

4.3 *Bias induced by temperature effects on movie supply*

We examine the association between extreme temperatures and movie supply from both extensive and intensive margins exploiting the framework proposed in Section 3.3, and clarify the biased direction caused by omitting supply-side factors in estimating temperature effects on movie demand. Panel A and B of Figure 5 illustrate the correlation between temperature and movie supply at extensive margins, i.e., premiere frequency and decision. Panel A of Figure 5 indicates temperatures below the reference zone are almost not significantly correlated with premiere frequency, once controlling for abundant spatial-and-seasonal fixed effects. When the explanatory variable is alternated by at least one movie premiered, the significant positive correlation between temperatures over the reference zone and movie supply disappears, as presented in Panel B of Figure 5[35]. These findings are consistent with movie premiere features. The

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[34] 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.

[35] We still use the OLS approach in estimating the relationship for explanation convenience. Panel B of Figure 5

premiere timing is determined by the movie producer and distributor months ahead before the release to seek the highest possible box office returns. Therefore, movie premieres are associated with temperatures at the monthly level, which is absorbed by controlling for fixed effects, suggesting movie supply at the extensive margin does not introduce essential bias in movie demand estimates.

However, bias induced by movie supply at the intensive margin is more problematic since real-time weather conditions can affect theater owners' schedules for a specific movie and is infeasible to be addressed by controlling for fixed effects. Panel C of Figure 5 confirms this speculation, which shows that temperatures below 20°C are systematically and significantly associated with movie screenings. Fortunately, lower temperatures actually come with higher movie availability, considering extreme cold reduces moviegoing found in Figure 3, which indicates that omitting variables related to movie supply at the intensive margin only underestimates the damage of extreme cold on movie demand. Overall, our findings inform that omitting movie-supply factors, if any, leads to conservative estimates of extreme temperatures on moviegoing, and baseline results should be explained as the lower bound on the impact of extreme temperatures.

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 for up to 10 days to investigate potential intertemporal effects.[36] The model to examine the lagging effect of extreme heat/cold is the following:

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

presents the result under a linear probability model (LPM).

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

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 extreme heat and extreme cold 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.[37] 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 for $\eta = 0$, but almost insignificant for any $\eta > 0$. This finding confirms that audiences' movie-viewing demand responds strongly to contemporaneous temperature shocks and is less sensitive to extreme temperature exposure in the recent past.

4.5 *Heterogeneity*

4.5.1 Movie's life cycle

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.[38]

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

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

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

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.[39] 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 insignificant, 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 expectations, especially for audiences with 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

[39] 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.

movie also smoothly declines, as shown in the tails of the exponential fitting curve in Figure 7. The insignificant 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,[40] 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 groups according to their classification by the China Business Network. Similarly, we interact city tier indicators with extreme temperatures and investigate the estimation results of interaction terms.

[40] This relationship is not surprising because a city's economic development level is one of the main factors considered by the China Business Network 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.

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., it 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.[41] 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 viewing is flexible, the external weather conditions are nudging factors in their decision-making process. On weekends, crowds of audiences flood into theaters

[41] 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).

because of ample 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 weather shocks, 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 a higher rating indicates a higher quality movie. 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.[42] 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 inelastic response to extreme temperatures is caused by 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 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

[42] 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.

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').[43] 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 are produced by China alone (951 movies), 17.91% of them are produced by countries other than China (228 movies), and 7.38% of them are 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 developed 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 '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 film projection unit.[44] Under these regulations, it is difficult for imported movies to enter China, which explains why movie distributors mainly import high-quality movies to maximize profits.

[43] 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.
[44] Article 45 of the Regulations. See: http://www.asianlii.org/cn/legis/cen/laws/roaof382/

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.[45] Since the statistics on audiences and box office revenues for each city are unavailable for 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)

[45] 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.

and Eq.(9) to calculate losses in audiences and box office revenues induced by extreme temperatures across 49 cities in 2017:

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

and

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

$\mathbf{1}(ExtreHighTemp_{cd})$ denotes whether date d in city c was an extremely hot day with a daily average temperature above 30°C, while $\mathbf{1}(ExtreLowTemp_{cd})$ denotes whether date d in city c was an extremely cold day with a daily average temperature below -1°C. 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 the sample level to the 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.[46] Precipitation

[46] 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

is another main variable that reflects the effects of climate change. Its economic impacts on moviegoing are monetized in a slightly different way.[47] 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 the 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 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

effect of extreme temperatures.

[47] 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.

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 applies 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 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 heat waves 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 the IPCC (2014) pointed out 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.[48] 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 at the city-day level by assuming that future movie-viewing demands in each city do not deviate sharply from the current state. We first obtain the city-day level observations for moviegoers and box office revenues by aggregating the original movie-city-day

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

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 city, 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 compared to the current period, mainly due to more frequent extreme heat.[49] The

[49] The predicted annual loss of audiences and movie ticket revenues induced by extreme temperatures shown in

predicted reduction in audiences and box office revenues is strongest for RCP8.5, 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 steady at 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, 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 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 robust finding 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 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

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Figure 12 is the average of the loss calculated by the five GCMs. For predictions by each GCM, see Table A10.

intuitively understanding the economic cost of climate change on the demand-driven film industry and even the service sector, which has positive implications for formulating policies to address future climate change challenges.

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 outdoor recreation, especially focusing on a market-based activity with clear financial indicators. For we aim to identify the effect of weather on movie demands, a formal framework is built to clarify potential biases caused by supply-side factors. This problem is especially serious when both the demand and supply behaviors of one activity are simultaneously affected by high-frequency weather changes. We contribute to the literature by providing a referential empirical framework. It is encouraging to clarify the market correlation theoretically and characterize such behaviors through structural estimates in the future.

There are still some limitations of this 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 perceives as comfortable, [20,22)°C, two confounding mechanisms lead to the movie viewing pattern observed. If the audience is indoors, deterioration of the outdoor temperature may prevent the 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 movie performance depends on the proportion of potential audiences located indoors or outdoors. These two effects offset each other, aggregate at the theater level, and are 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 significantly damage 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 insignificant 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 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 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.

The last, as Graff Zivin and Neidell (2014) suggested, extreme temperatures may move leisure activities from outdoors to indoors. The negative effect of extreme temperatures on outdoor moviegoing may benefit online movie-viewing demands or other indoor activities. This paper fails to quantify the general equilibrium effect of climate change and is still for future research.

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Figures and tables in the text

Figures

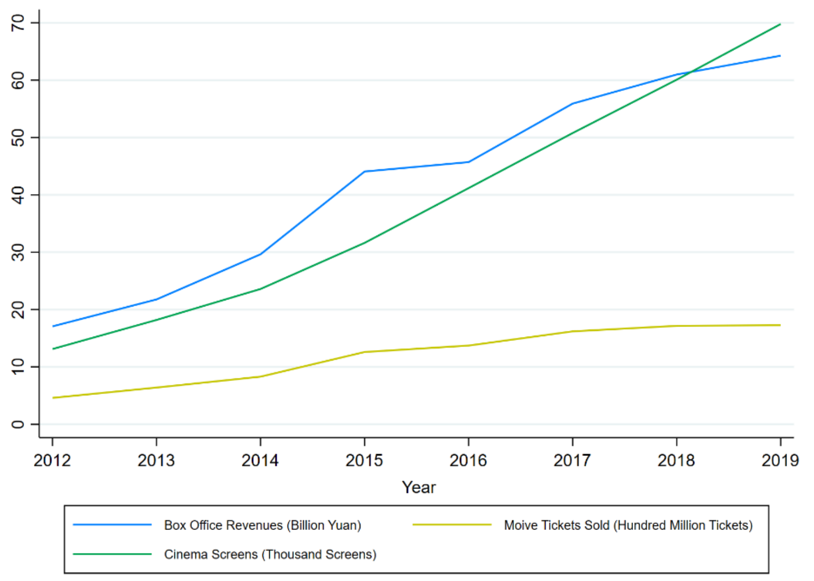
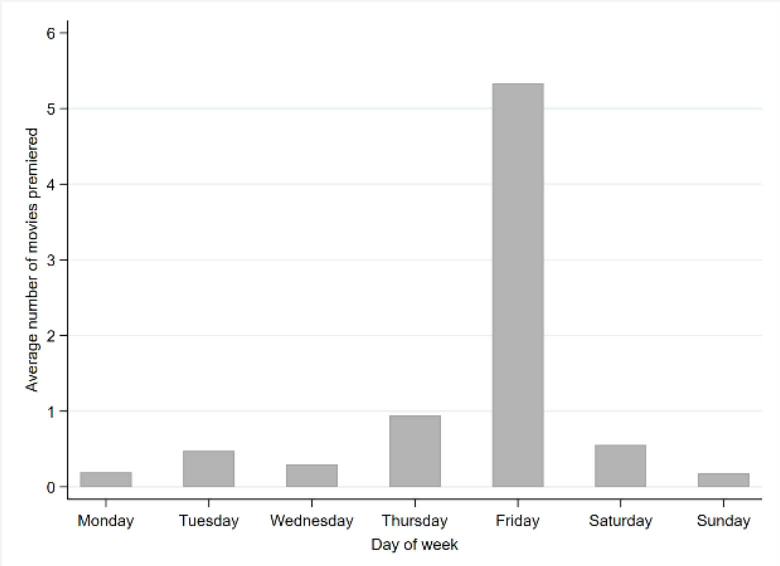


Figure 1 Development of China's film industry: 2012-2019.

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

Panel A: By day-of-week



Panel B: By month-of-year

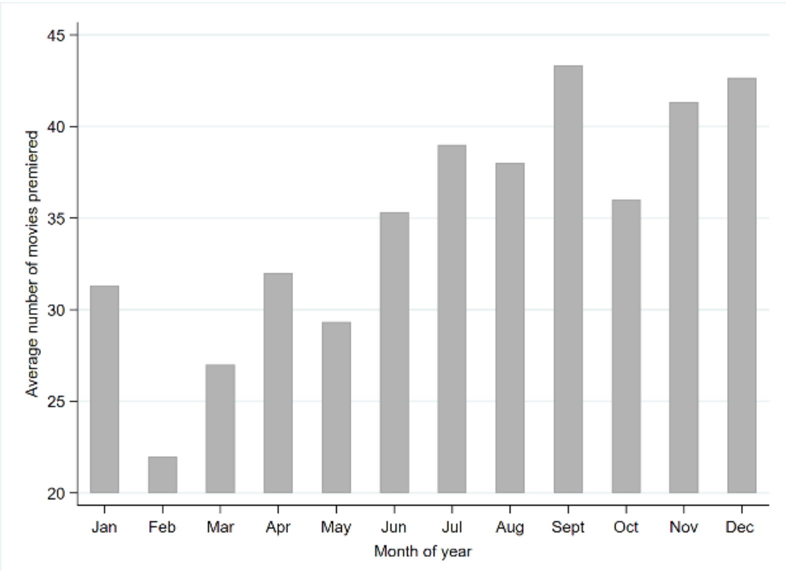
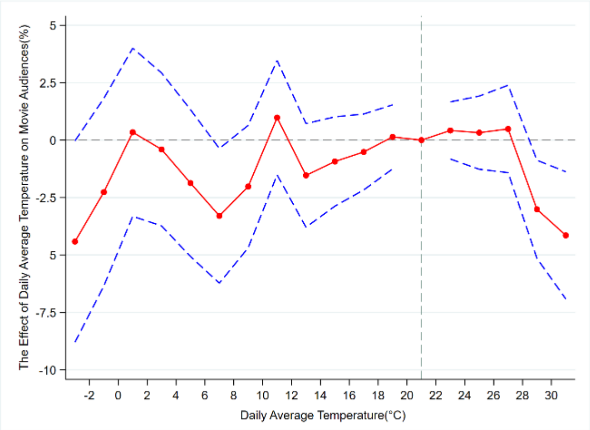
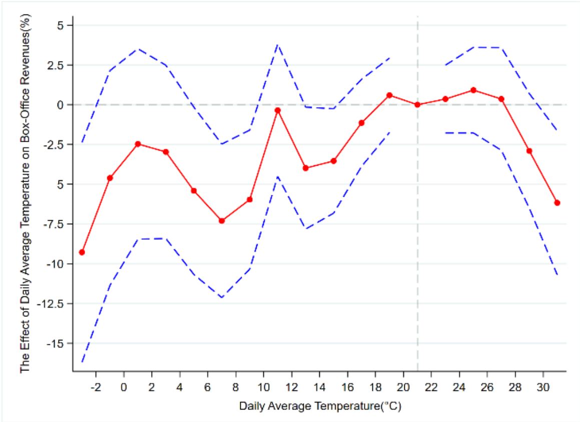


Figure 2 The average number of movies premiered by day-of-week and month-of-day in 2015-2017.
Notes: The premiere date of non-rescreened movies comes from the movie-rating database. In 1273 non-rescreened movie samples, 21 movies are excluded when plotting the figure since their premiere year is 2014.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

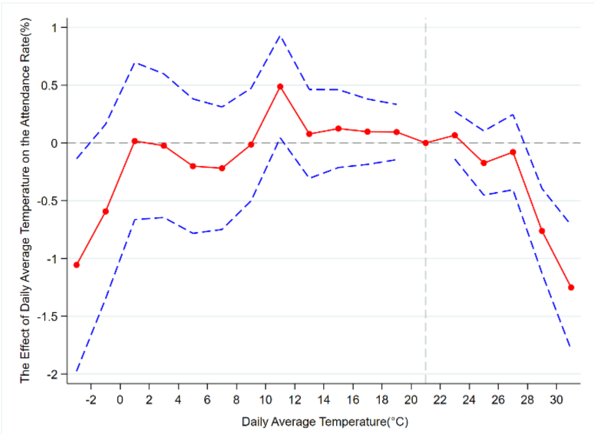
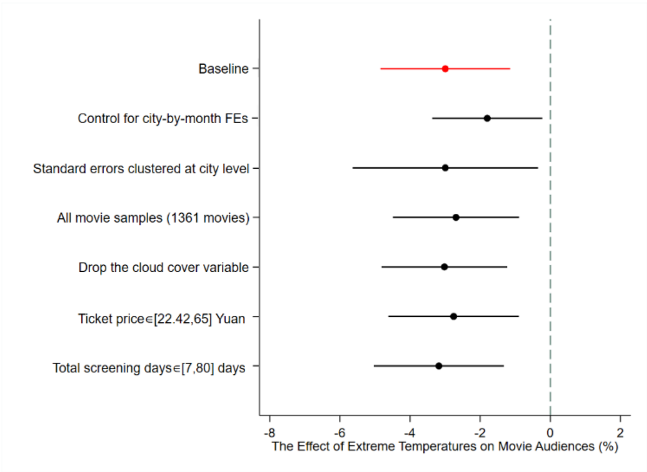
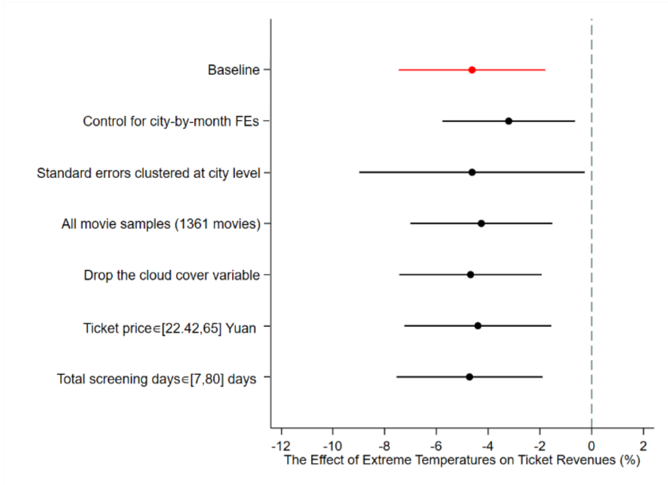


Figure 3 The impact of temperature fluctuations on movie-goings by the temperature-bins model. *Notes:* The red points represent the impact of temperatures falling into corresponding bins on movie-goings, compared with the reference group [20,22)°C. The blue dashed lines indicate the 95% confidence interval.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

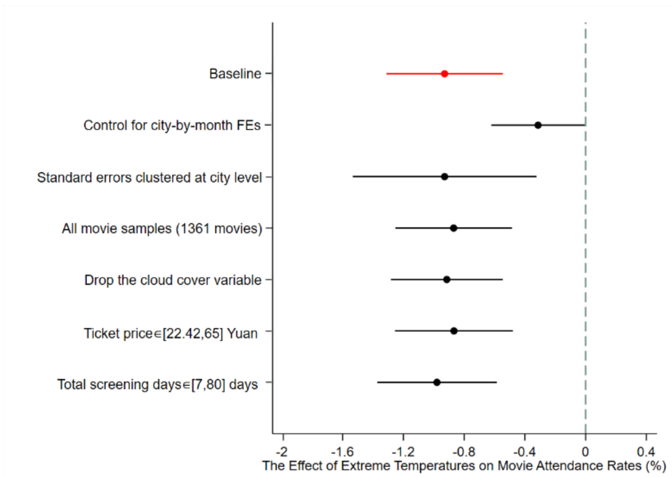
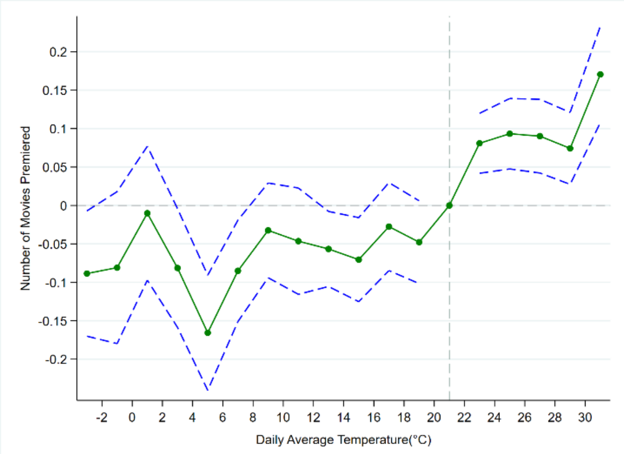


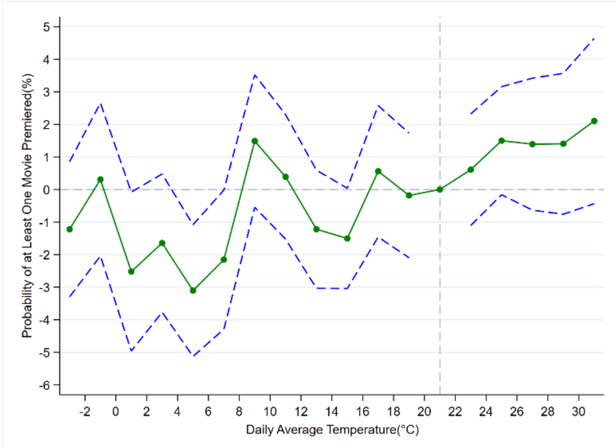
Figure 4 Effects of extreme temperatures on movie-goings: robustness checks.

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 Premiered



Panel B: At Least One Movie Premiered



Panel C: The Number of Movies Screened

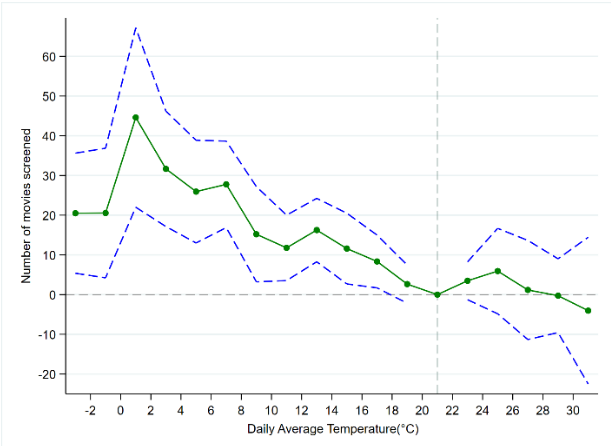


Figure 5 Correlation between temperatures and movie supply.

Notes: The green points represent the change in the number of movie premieres, screenings, and the probability of at least one movie premiering on the day the temperature falls into corresponding bins, compared with that in the reference group [20,22)°C. The blue dashed lines indicate the 95% confidence interval.

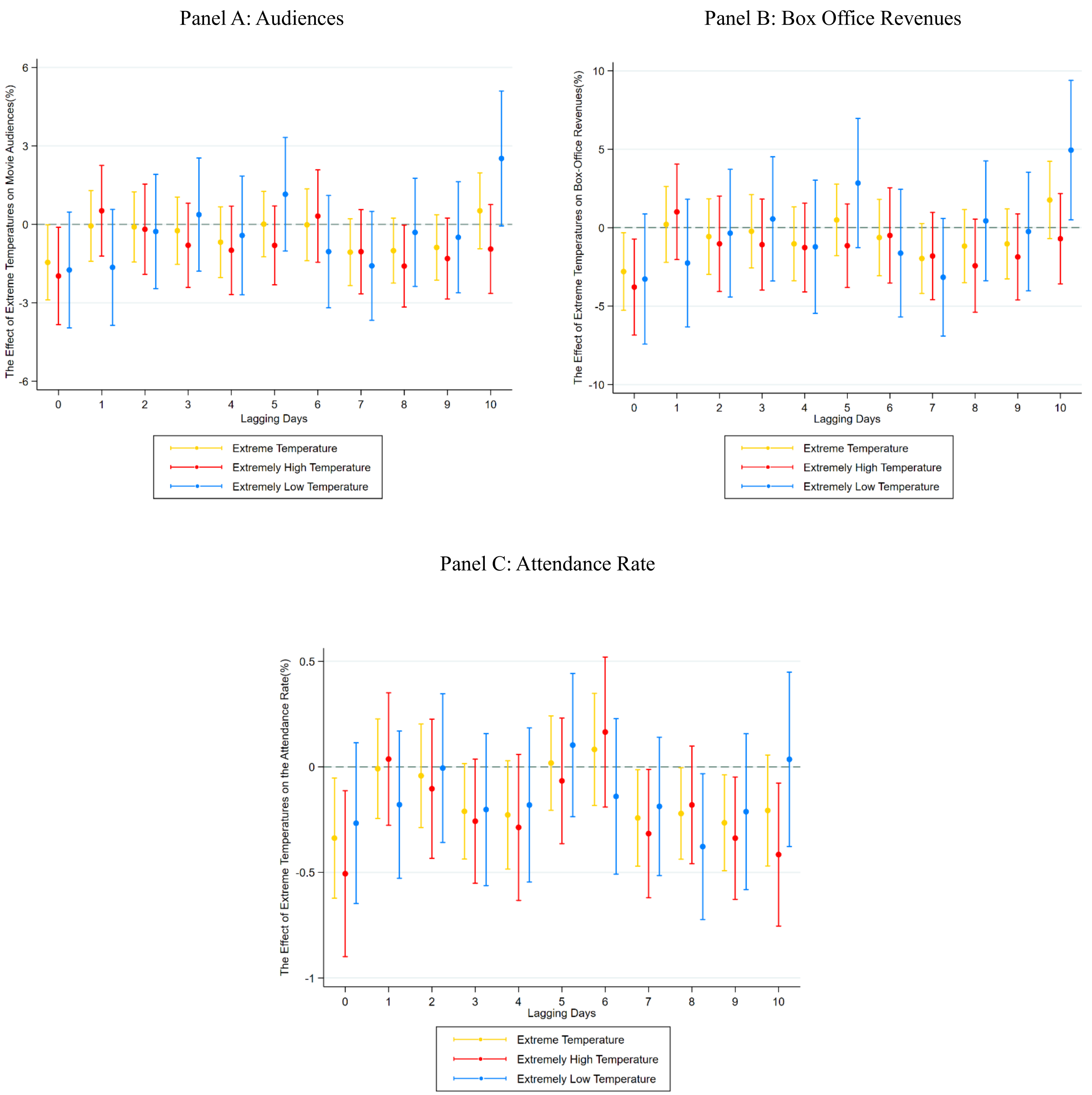


Figure 6 The lagging effects of extreme temperatures on movie-goings up to 10 days.

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.

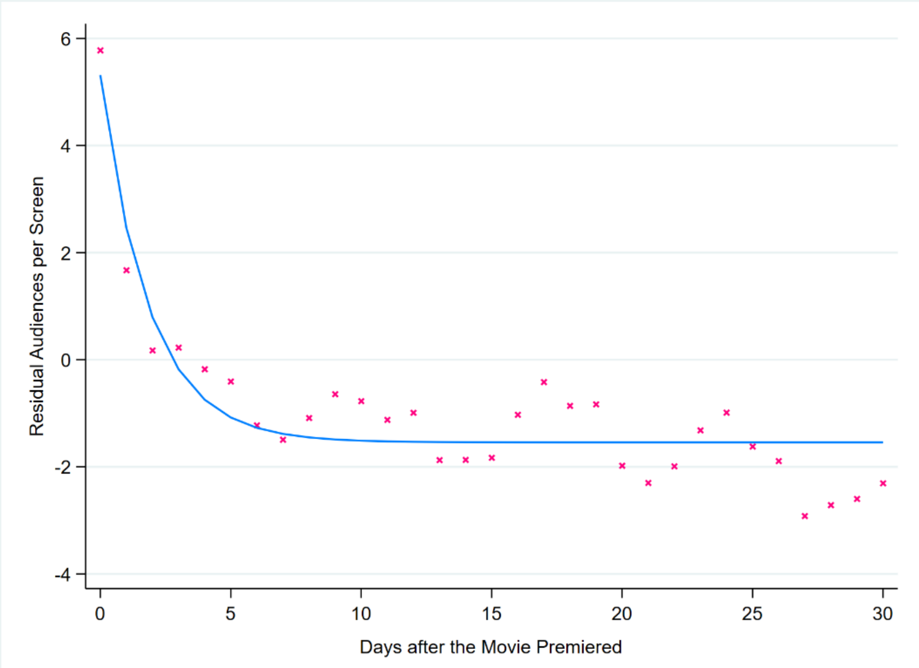
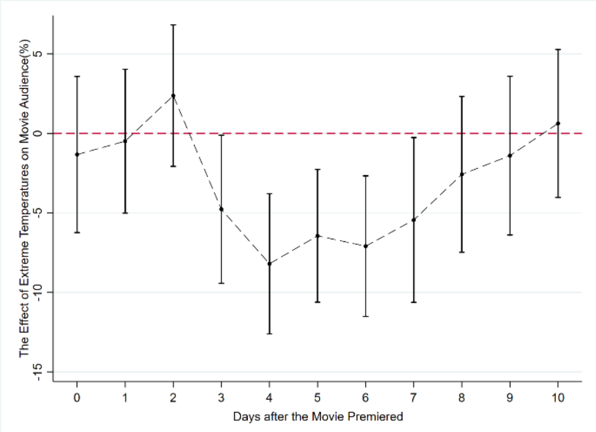
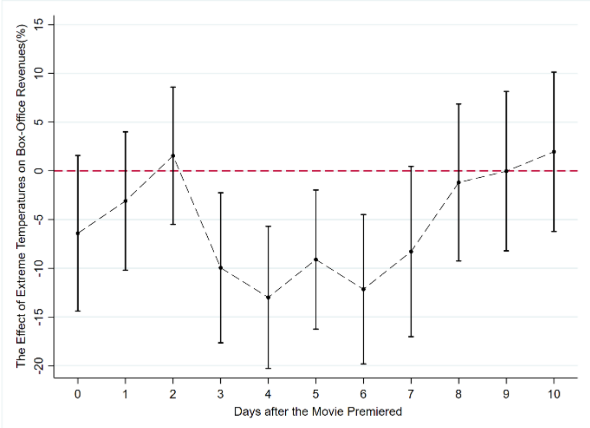


Figure 7 The relationship between audiences per screen and days after the movie premiered.
Notes: Red points denote the audiences per screen after removing day-of-week fixed effects and city fixed effects. The blue curve is an exponential fitting with three parameters.

Panel A: Audiences



Panel B: Box Office Revenues



Panel C: Attendance Rate

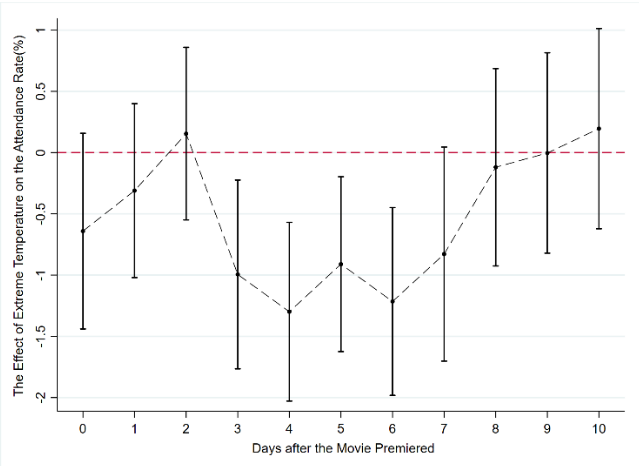


Figure 8 Heterogeneous effects of extreme temperatures on movie-goings on different days after the movie premiered.

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

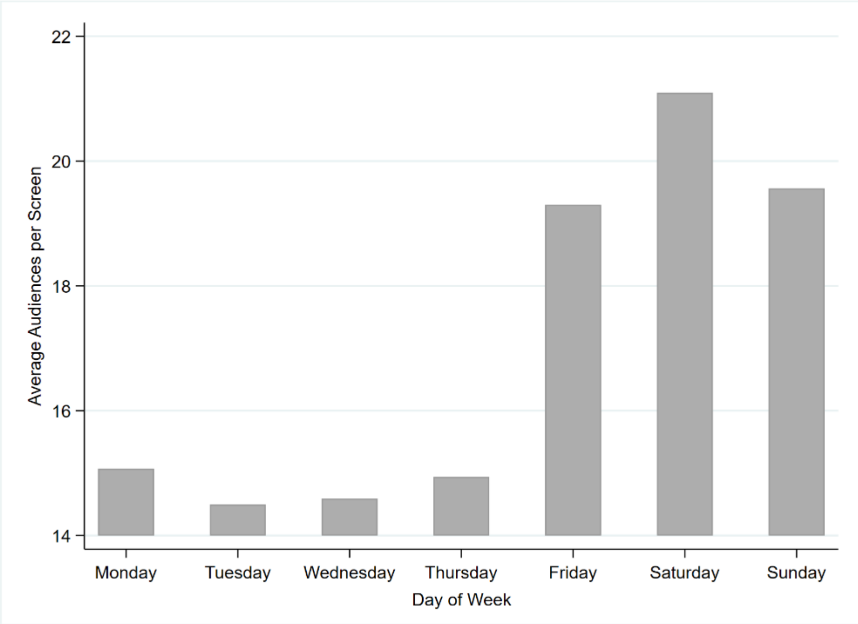
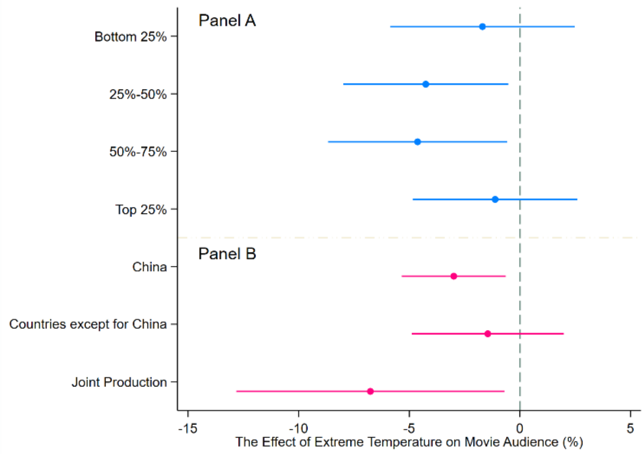


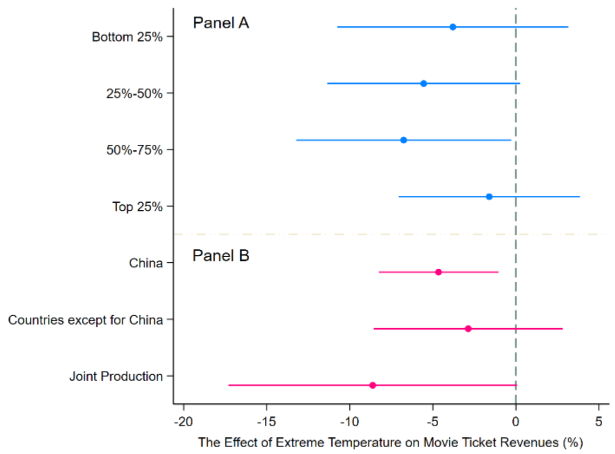
Figure 9 Average audiences per screen by day-of-week.

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

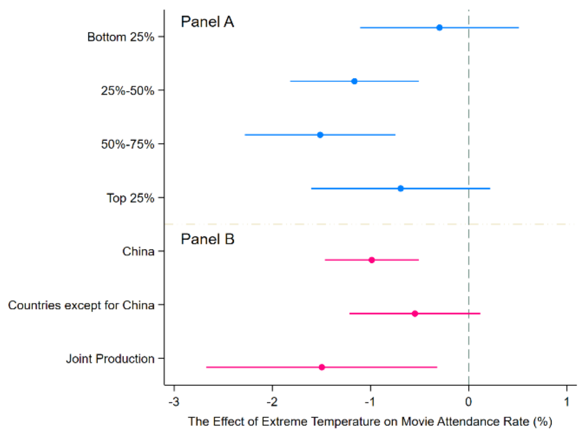


Figure 10 Effects of extreme temperatures on movie-goings: movie quality heterogeneity.

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.

Panel A: Temperature

Panel B: Precipitation

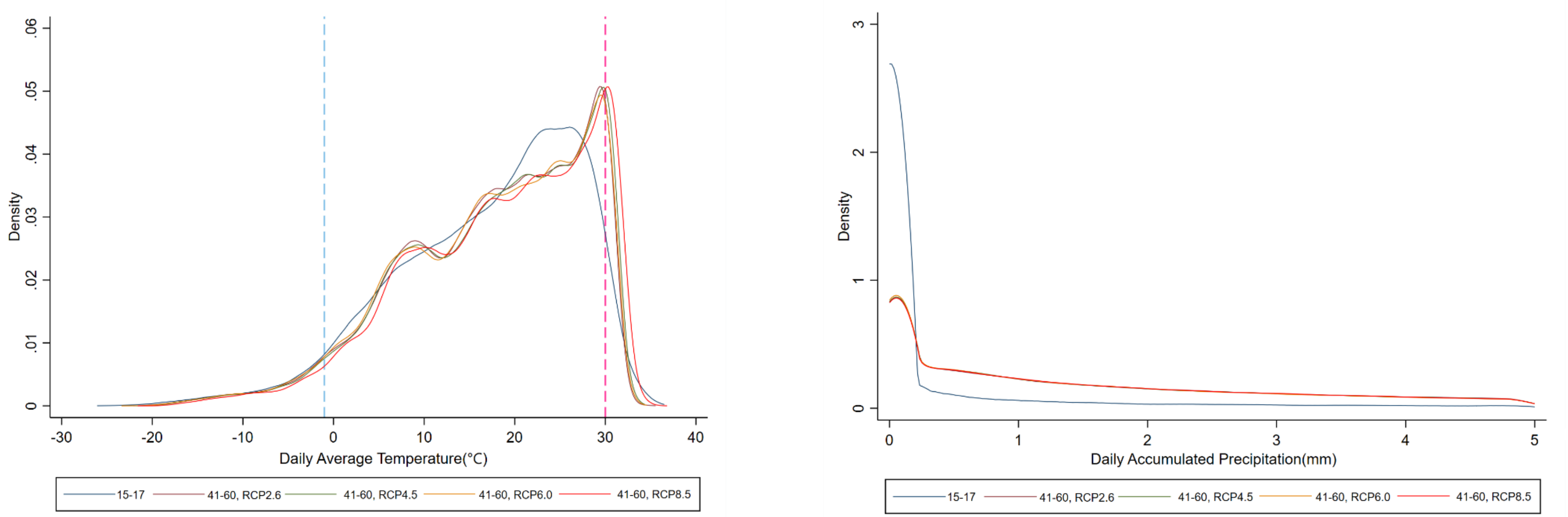


Figure 11 Density distribution of the daily average temperature and accumulated precipitation of 49 cities in the sample period (15-17) and the medium-term future (41-60).

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°C) and extremely low temperatures (30°C). The daily accumulated precipitation is truncated at 5mm in Panel B, considering its right-skewed distribution. The kernel to estimate the density function is the Epanechnikov kernel.

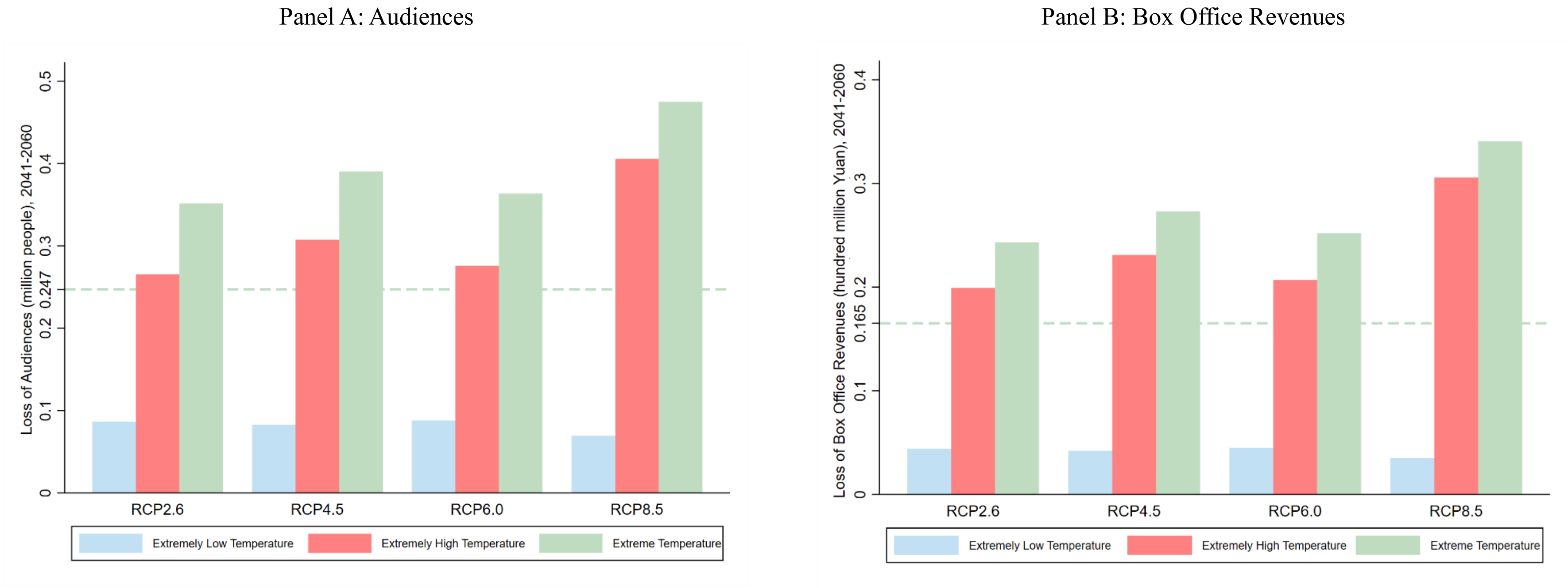


Figure 12 The predicted annual loss of audiences and box office revenues of 49 cities induced by extreme temperatures in the medium-term future (41-60).

Notes: The calculation is implemented at the sample level. The impact of extreme temperatures on movie-goings under each RCP is the average of 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 (°C)	17.10	9.97	-26.1	36.5	53,274
Precipitation (mm)	3.61	11.91	0	253	53,274
Atmospheric pressure (kPa)	99.15	4.54	80.41	104.32	53,274
Relative humidity (%)	72.02	16.84	8	100	53,274
Wind speed (m/s)	2.27	1.09	0	10.7	53,274
Cloud cover (%)	66.30	16.62	0	90	49,222
AQI	75.57	46.02	12	500	53,704
PM2.5 (μg/m^3)	47.04	39.34	0	881	53,704
PM10 (μg/m^3)	80.53	58.51	0	1398	53,704
TI (1=thermal inversion occurs more than four times in a day, 0=otherwise)	0.34	0.48	0	1	53,704
Panel D: Meteorological prediction variables (2041-2060)					
Temperature- RCP2.6 (°C)	17.60	10.30	-29.52	41.25	357,945
Temperature- RCP4.5 (°C)	17.85	10.35	-30.04	41.98	357,945
Temperature- RCP6.0 (°C)	17.60	10.36	-29.44	41.26	357,945
Temperature- RCP8.5 (°C)	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 a 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 a 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. Columns (4) and (7), columns (5) and (8), columns (6) and (9) are estimated together, respectively. Control variables contain weather variables, the AQI, and the movie-city-day 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. Columns (4) and (7), column (5) and (8), column (6) and (9) are estimated together, respectively. Control variables contain weather variables, the AQI, and the movie-city-day 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.