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The impact of temperature on gaming productivity: evidence from online games

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The impact of temperature on gaming productivity: evidence from online games

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Abstract

This paper studies the short-run impacts of temperature on human performance in the computer-mediated environment using server logs of a popular online game in China. Taking advantage of the quasi-experiment of winter central heating policy in China, we distinguish the impacts of outdoor and indoor temperature and find that low temperatures below 5 °C decrease game performance significantly. Non-experienced players suffered larger performance drop than experienced ones. Access to central heating attenuates negative impacts of low outdoor temperatures on gamers' performance. High temperatures above 21 °C also lead to drops in game performance. We conclude that expanding the current central heating zone will bring an increase in human performance by approximately 4% in Shanghai and surrounding provinces in the winter. While often perceived as a leisure activity, online gaming requires intense engagement and the deployment of cognitive, social, and motor skills, which are also key skills for productive activities. Our results draw attention to potential damages of extreme temperature on human performance in the modern computer-mediated environment.

Keywords Temperature · Human performance · Online game · Heating

JEL codes: Q54 · J22 · J24 · D03

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1 Introduction

In the past 50 years, the earth has experienced more extreme temperature events and larger temperature fluctuations (Peterson et al. 2013; Grotjahn et al. 2016; Jiang et al. 2016). Many studies have examined the impacts of temperature changes on agriculture, health, productivity, social conflict, and economic growth (Niemelä et al. 2002; Federspiel et al. 2004; Schlenker and Roberts 2009; Schlenker and Lobell 2010; Feng et al. 2010; Hsiang 2010; Fisher et al. 2012; Deschênes and Greenstone 2012; Heal and Park 2013; Dell et al. 2014; Heutel et al. 2017; Barreca et al. 2015; Burke et al. 2015; Graff Zivin et al. 2018). The question to what extent temperatures affect human capital formation and productivity is highly relevant for quantifying the economic impacts of weather changes. Following this line of research, we explore the short-run impacts of temperature on two aspects of human capital: productivity and time allocation. More specifically, we target gamers' performance and time allocation in a special online game, which is computer based and involves perceptual, cognitive, social, and motor skills. Our study helps to understand the short-run impacts of weather on human performance in the modern computer-mediated environment.

Human performance tends to be affected negatively by exposure to extremely high and low temperatures. By raising the skin and possibly the core temperature, heat increases the burden on the heart to pump blood and the brain to process heat (Gaoua et al. 2012; Simmons et al. 2008). Additionally, cold primarily impairs hand dexterity, tactile sensitivity, psychological stress, and cognitive ability (Schiefer et al. 1984; Heus et al. 1995; Parsons 2014; Graff Zivin et al. 2018; Cai et al. 2018). Many ergonomics studies have shown that extremely high and low temperatures affect the performance of a wide range of human cognitive-related tasks such as reasoning, learning, memory, attention, reaction, and mathematical processing (Fox 1967; Pilcher et al. 2002; Lan et al. 2014; Parsons 2014; Hygge 2015). However, by focusing on different types of human skills, these studies have reached different conclusions about the exact threshold for extreme temperature from which the performance starts to drop. This makes it difficult to extend the conclusions to other types of activities and other regions.

This paper explores the impacts of temperature on human performance in online games. Unlike pure passive leisure activities such as watching TV, online gaming involves intensive human engagement and requires the input of a complex set of skills such as attention, strategic planning, hand movement, fast reaction, and learning ability (Granic et al. 2014; Stafford and Dewar 2014). These skills generally correspond to skills that are required in the contemporary computer-mediated working environment or digital workplaces (Sourmelis et al. 2017). Furthermore, online gaming provides incentives to gamers to perform at their best through rewards (cloth, pets, mounts, etc.), level upgrading, and gears/mounts/pets/weapons transaction schemes. Therefore, studying gaming productivity can shed light on productivity in the computer-mediated environment. We use a unique server log dataset of an online game, which included 62,249 active game accounts in March 2011.[1] After matching gamers' IP address to

[1] The temperature in our sample ranges from a minimum temperature of −22.1 °C to a maximum temperature of 26 °C.

their local prefectures, we analyze the impacts of daily weather on individuals' game performance and game time.

Using a truncated panel Tobit model (Honoré 1992), we find that extreme outdoor temperature increases game time and decreases gaming productivity significantly. On average, players tend to increase their game time by approximately 8 min for each one-degree decrease when the outdoor temperature is below 5 °C and increase their game time by 3.5 min for each one-degree increase when the outdoor temperature is above 21 °C. Game productivity decreases significantly in both low-temperature (below 5 °C) and high-temperature (above 21 °C) conditions. On average, gaming productivity decreases by 2.1% per each one-degree drop in low-temperature conditions.[2]

One key feature of our study is that we distinguish between the impacts of outdoor temperature and those of indoor exposure temperature by taking advantage of the quasi-experiment involving China's central heating policy in the winter. Although outdoor temperature is frequently used to proxy the exposure temperature (Graff Zivin et al. 2018), individuals' behaviors in adopting heating or cooling facilities can cause a mismatch between outdoor temperature and exposure temperature. In China, however, heating access has been strictly regulated by the government through the central heating policy since the 1950s. The policy restricts access to central heating in northern China according to an explicit heating line and regulates different heating periods in northern regions (Almond et al. 2009). Therefore, outdoor temperature and indoor temperature would be highly correlated in unheated regions only.[3] The relationship between outdoor temperature and individual performance would be close to the real relationship between exposure temperature and performance in the unheated south. We find that access to heating attenuates the negative impacts of low temperature on game performance. It implies that heating is an effective adaptation approach in response to short-run temperature drops. Nevertheless, game time increases in both the heated north and unheated south in response to extreme temperatures, because individuals' time allocation involves the switch between indoor and outdoor activities. In addition, the impacts of temperature show significant cross-player and spatial heterogeneities. Overall, inexperienced gamers who are relatively new to the game suffer a greater loss in gaming productivity when temperature is low. When we divide all the gamers into quartiles according to their game level at the beginning of the study period, the negative impact of low temperature on gaming productivity for inexperienced gamers is around twice the impact on experienced gamers. From the spatial heterogeneity perspective, we find that the farther a prefecture is away from the heating line in the south, the more the gaming productivity drops. One potential reason is the existence of private heaters. Because we only consider central heating and that households in the unheated south might turn on their private heaters occasionally, the actual game performance would be higher than the performance in the 'perfect no-heating' scenario. As a result, our current estimates of low temperature's impacts on gaming productivity might be

[2] The missions in this game are mostly homogeneous. Even though gamers' level in the game would rise based on rewards after accomplished missions, the difficulty level of missions would not escalate.

[3] Even though households would sparsely use air conditioners or small heaters in the unheated southern region, the usage rate is much lower in March than in other colder months. According to Wang et al. (2008), less than 5% of households use any heating facility during March in southern provinces. The ratio is above 60% in January.

underestimated. Regions that are directly located to the south of the heating line tend to have a higher adoption rate of private heaters. It leads to a smaller impact of low temperature on gaming productivity. In addition, our estimates of the impacts of low temperature on game time and performance are robust to other model specifications and including other natural elements such as air pressure, cloud cover, and ambient air pollution. Since our data are a balanced panel, and we include all gamers in our sample for 31 days consecutively, our results are not prone to sample selection which involves the change of gamer groups.

This study has direct policy implications for heating provision. There have been numerous debates regarding whether China should expand the central heating zone.[4] Enlarging the central heating zone would bring additional costs in infrastructure construction and renovation. Our study points to one potential benefit of heating zone expansion in terms of productivity gains. Assuming that gaming productivity can generally reflect human performance, especially human performance in the computer-mediated environment, a simple back-of-the-envelope calculation shows that productivity would increase if heating service were provided to raise the average exposure temperature above 5 °C in southern China. After taking into account variations in population size and weather conditions in local regions, the gain in productivity ranges from 5.69% in the Jiangsu province to 0.02% in the Guangdong province in the winter. In addition, we also find evidence of negative impacts on human performance due to a high temperature above 21 °C. It draws attention to the potential damage of extreme heat.

The rest of the paper is organized as follows: Sect. 2 presents evidence of temperature's effect on time allocation and physiological and ergonomics evidence of temperature's impacts on human performance. Section 3 introduces the data. Section 4 describes the methodology. Section 5 presents the main results and policy implications. Section 6 concludes.

2 Temperature, productivity, and online gaming

This section generally introduces the connection between temperature and human performance and provides a rationale for why online game performance can reflect human performance in the computer-mediated environment.

2.1 Temperature and productivity

It has been generally agreed in the literature that there is an optimal temperature range or a plateau zone in which temperature has no significant effect on productivity (Federspiel et al. 2004; Graff Zivin et al. 2018). However, the range of the plateau zone differs a great deal among studies. Federspiel et al. (2004) state that a 'comfortable temperature range' for office work ranges from 21 to 25 °C. Within this range, the efficiency of office work does not change much. A similar plateau is reported for the impacts of temperature on cognitive abilities. Graff Zivin et al. (2018) conclude that

[4] Ho, Louise. 'Time to abolish the great divide for central heating'. *Global Times*. November 23, 2014. http://www.globaltimes.cn/content/893200.shtml

there are no significant changes in math test results when students are exposed to temperatures between 15 and 25 °C. In contrast, an extreme temperature outside the optimal zone would diminish productivity. Cai et al. (2018) find that any maximum temperature out of the range of 23–27 °C decreases manufacturing productivity in China.

2.1.1 High temperature and productivity

High temperatures tend to impair human functions. The rise in skin temperature would increase the burden on the heart to pump blood when sweating, causing thermal discomfort. Additionally, the rise in core temperature causes cardiovascular strain and increases the workload of processing heat in the brain, which has been identified as the main factor that limits performance (Marino 2002; Simmons et al. 2008; Gaoua et al. 2012). This is also the main physiological channel through which heat affects cognitive abilities. Graff Zivin et al. (2018) conclude that a high temperature above 25 °C reduces the speed and accuracy of students' ability to solve math questions, although its impact on verbal and reading questions is nonsignificant. Laboratory experiments with a strictly controlled indoor temperature also support the negative impacts of a high temperature on productivity. The speed of students' problem solving decreases by 5.7% when the indoor temperature increases from 22.5 to 26 °C (Wargocki and Wyon 2006).

There is also evidence of the impacts of heat on human productivity, which requires multiple human functions simultaneously such as cognition, movement, and attention. Seppanen et al. (2004) find that each one-degree increase in temperature leads to a 2% decrease in office work performance. Several studies find that the typing speed of call center employees decreases significantly by approximately 1.8–2.2% for each one-degree increase above 25 °C (Niemelä et al. 2002; Federspiel et al. 2004). Somanathan (2015) explores productivity in Indian manufacturing plants in which workers were exposed to different humidity-adjusted temperatures[5] and concludes that productivity decreased by approximately 3% for each one-degree increase above 20°C. Cai et al. (2018) find that workers' productivity in a paper-cup manufacturing firm in China drops by 8.5% when the maximum daily temperature increases from 27 to 35 °C. Other evidence includes decreased productivity among construction workers in Thailand and bankers in Tokyo when the temperature is above 25 °C (Srinavin and Mohamed 2003; Lee et al. 2014). Overall, studies using both strictly controlled laboratory experiments and observational data show decreases in productivity in association with high temperature, although the identified ranges of high temperature are slightly different.

2.1.2 Low temperature and productivity

Low temperature typically affects the human body initially by cooling the extremities such as the hands, head, and feet. As a result, it causes impairments in hand dexterity,

[5] Somanathan (2015) uses WetBulb Globe Temperature, which is adjusted for heat and humidity for overall average temperature.

tactile sensitivity, psychological stress, and cognitive ability (Schiefer et al. 1984; Heus et al. 1995; Parsons 2014; Graff Zivin et al. 2018). As opposed to heat, which can activate the body's evaporative system by controlling the core temperature, the body has less physiological defense against cold. Humans rely mainly on external options, such as clothing, housing, and heating to defend against cold.

Low temperature also significantly decreases productivity in the short run. Schiefer et al. (1984) find that hand dexterity, measured by typing speed, decreases by approximately 5–15% when the temperature drops from 24 to 18 °C. Low temperature can also decrease cognitive abilities. Graff Zivin et al. (2018) find a significant drop in math test scores in association with low temperatures below 15 °C. Cai et al. (2018) find a significant drop of worker productivity by 11% when the daily maximum temperature drops from 23 to 15 °C. However, there are few papers on extremely low temperatures below 5 °C. Extreme cold is important for regions that are constantly exposed to low temperatures and that have limited access to heating. Our study fills in the gap in the literature on the impacts of low temperature on human performance.

2.2 Temperature and time allocation

In addition to the impacts on human performance, temperature also affects individuals' time allocation. The most relevant type of time allocation is switching between indoor and outdoor activities.

When the weather is unfavorable for outdoor activities, people tend to switch from outdoor activities to indoor activities. Connolly (2008) finds that men shifted approximately 30 min from outdoor leisure to indoor labor on rainy days in the USA using the American Time Use Survey data from 2003 to 2004. In addition, both high temperatures and low temperatures can restrict outdoor activities. Eisenberg and Okeke (2009) explain that people substitute indoor exercises for outdoor exercises when the temperature exceeds 27 °C. Graff Zivin and Neidell (2014) also find that a high temperature above 30 °C decreases the time spent on labor and outdoor leisure and increases the time spent on indoor leisure. The substitution of indoor for outdoor activities and leisure for work in high temperatures is also supported by evidence in Germany and India (Kruger and Neugart 2015; Somanathan 2015).

2.3 Online gaming and human performance

The measurement of human performance is key to evaluating the impacts of temperature quantitatively. Most previous studies focus on traditional work such as working in call centers (Seppanen et al. 2004; Niemelä et al. 2002), typing (Schiefer et al. 1984), and solving math problems (Graff Zivin et al. 2018). However, in the modern social and work environment, computer-aided activities are expanding fast (Zuboff 1982; Freeman 2002; Colbert et al. 2016). The skills required in the computer-mediated environment are significantly different from those required in the traditional environment (Acemoglu 2012). In addition to analytical and reasoning skills, computer-mediated activities require the inputs of intellectual skills on abstract thinking, explicit inferential reasoning, procedural logic, and systematic understanding (Zuboff 1982).

Although often perceived as a leisure activity, playing online games demands a comprehensive set of skills such as attention, patience, hand dexterity, strategic planning, learning, cooperation, and fast decision-making (Adachi and Willoughby 2013; Granic et al. 2014; Kowert and Quandt 2015; Fan et al. 2017). These skills are often the key inputs that are required in computer-mediated workplaces. Gamer productivity reflects the condition of human functioning on these skills. Unlike regular passive leisure activities such as watching TV, online gaming requires active engagement which is a key factor affecting subjective well-being and cognitive consequences after games (Bavelier et al. 2011; Kuykendall et al. 2015). The reward and transaction system of online games provide incentives for gamers to perform at their best.

3 Data

3.1 The online game

We obtain a unique dataset of players' daily records for a popular online computer game, *Dragon Nest*, from March 1 to March 31, 2011. It is a 3D action massive multiplayer online role-playing game (MMORPG) and has been promoted with free downloads in China since 2009.[6] In the game, each player can choose one or more characters with seven occupations including warrior, archer, cleric, sorceress, academic, Kali,[7] and assassin. Players have full control of the movement of their chosen characters in the game. Players can act alone or team up with other players to accomplish missions by defeating monsters. The reward for accomplishing a mission is usually game coins, clothing for characters, and an upgraded game level. Any gamer can reach a maximum level of 40 in the game. The game is composed of many tasks with a main storyline running throughout the whole game. Not only can the players play against monsters in each task, but they can also play against other characters that are controlled by their peers. The key skills that are required in the game include alertness, quick reaction, strategic planning, and virtual world communication skills with other players.[8] There are two important features of the game that are essential to our study. First, unlike other online games in which players can purchase 'weapons' or 'cloth' to enhance their performance in the game, the purchased 'cloth' in this game is only for decoration and visual effects. Therefore, it relies on players' skills to accomplish missions. Second, the difficulty levels of missions are not cumulative.[9] Missions in

[6] Players are encouraged to purchase game coins to enjoy more game features such as getting more game clothes, pets, etc. Those items make the character more attractive in the visual effects, but they would not help the players in respect of skills or power.

[7] Kali is an occupation in the game. The character is usually shown as a female dancer with certain combat skills.

[8] High-level players usually complete more missions and play longer, but are not necessarily more skilled players. It is common to see a low-level player defeat a high-level player. Here we measure the performance using the number of missions accomplished by a player, which is considered as comparable output by the players.

[9] This is unlike the classic platform video game Super Mario Brothers, in which missions become more difficult as players complete more missions.

this game are designed to attract players' interest in the game for as long as possible.[10] Even though missions have various settings and underlying stories, the difficulty levels of the missions are mostly homogeneous. This distinguishes the online games of our study to some other MMORPG online games such as Blizzard's World of Warcraft.[11] In fact, this distinguishes most Chinese online games with Blizzard's games. As a result, the number of missions that are completed in a day can generally reflect how well a gamer performs.

In all, there were 4,811,925 game accounts in March 2011. Most gamers play the game occasionally. To capture relatively frequent players, we retain game accounts that either log into the game more than 60 times, or reach 30 or more total hours of log-in time in March. After filtering, our analysis includes 62,249 active game accounts. We follow these game accounts for 31 days consecutively to rule out sample selection problems. As this game is computer based, all game accounts can be linked to their corresponding prefecture according to their unique IP address.[12] Game log records include the game ID, IP address, log-in time, and the number of missions completed each day. Figure 1 shows the geographic concentration of gamers across China. The top three regions or provinces with respect to the number of game players are Jiangsu, Zhejiang, and Hong Kong. Players spent 102 min playing this game each day on average, as shown in Table 1. The average game time conditional upon a gamer being logged into the game is 148 min. Game time shows a clear weekly cycle, as shown in Fig. 2. The average game time is much longer on weekends than on weekdays (95 min on weekdays and 127 min on weekends), as shown in Fig. 3. On average, a player completes 1.8 missions each day. The log file only recorded the level information of players with the level above 2. So daily level information is available for 41,112 accounts and the average level is around 25 for players with level records.

3.2 Weather data

We obtain outdoor weather information, including the daily average land-surface temperature, precipitation, and wind speed, for 757 inland weather stations from the China Meteorological Weather Center. Weather records in Hong Kong and Macau are obtained from the Hong Kong Observatory and Macao Meteorological and Geophysical Bureau separately. Because game players are identified at the prefecture level geographically, we track prefectures to their nearest weather station based on the straight-line distance between each weather station and the geographic centroids of prefectures. In order to control the impacts of pollution on gamers, we also extract daily pollution records on PM_{10} and API (Air Pollution Index) for large cities from the Ministry of Environmental Protection in China.

[10] Players typically are attracted to the game by obtaining decorative equipment, cloth, pets, etc., by playing the game using repetition, iteration, and escalation in different stages.

[11] Blizzard Entertainment Inc. is the most influential video game developer based in Irvine, California. Some of the most famous games created by Blizzard includes StarCraft, Warcraft III: The Frozen Throne and World of Warcraft series.

[12] Prefecture is the lowest administrative level which the IP address can be matched.

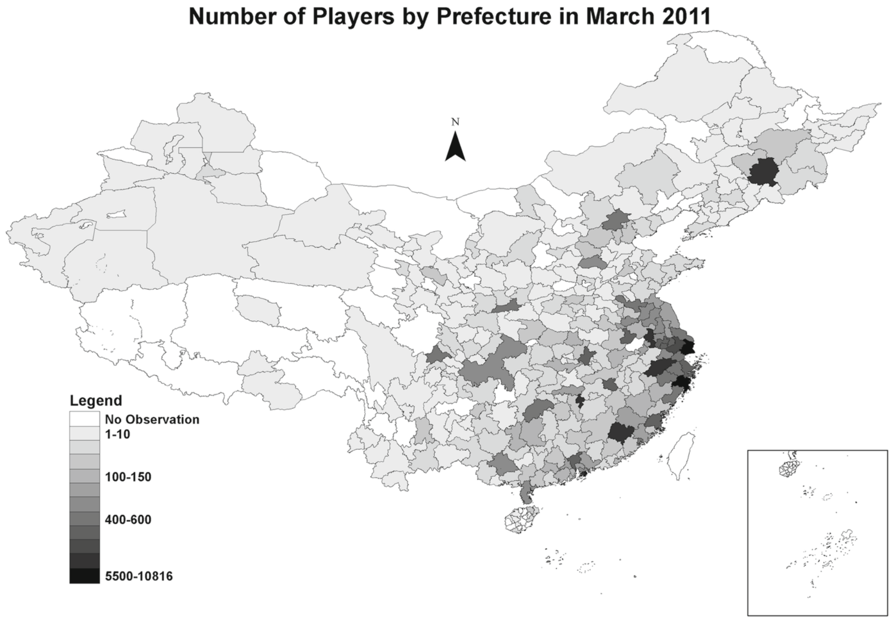

Fig. 1 Players by prefecture in March 2011

Table 1 Summary statistics

Variables	Units	Obs	Mean	SD	Min	Max
Game time	Minutes per day	1,929,719	102.7	129.0	0	1440
Missions	Number per day	1,929,719	1.8	4.8	0	91
Game level		1,274,472	25	9.9	2	40
Daily precipitation	mm	1,929,719	1.3	4.2	0	46
Daily average temperature	Celsius degree	1,929,719	9.6	5.7	− 22.1	26
Daily average wind speed	m/s	1,929,719	2.8	1.8	0	14.1
Dummy for heating		1,929,719	0.1	0.3	0	1
Daily average API*		1,312,002	72.7	19.0	15	415

*Daily API (Air Pollution Index) was not reported by many small prefectures in March 2011

Table 1 shows the variation in temperature and precipitation during the study period. Daily temperature varies from − 22.1 to 26 °C. Therefore, even though the duration of our study period is only 31 days, the geographic and temporal variations in temperature are large. As our study period is in March, which is a relatively cool month in China, we have abundant observations with low temperatures and very few observations with high temperatures above 21 °C. In contrast, most literature on temperature's impacts focuses on the social and economic impacts of high temperature driven by concerns about climate change (Schlenker and Roberts 2009; Graff Zivin et al. 2018).

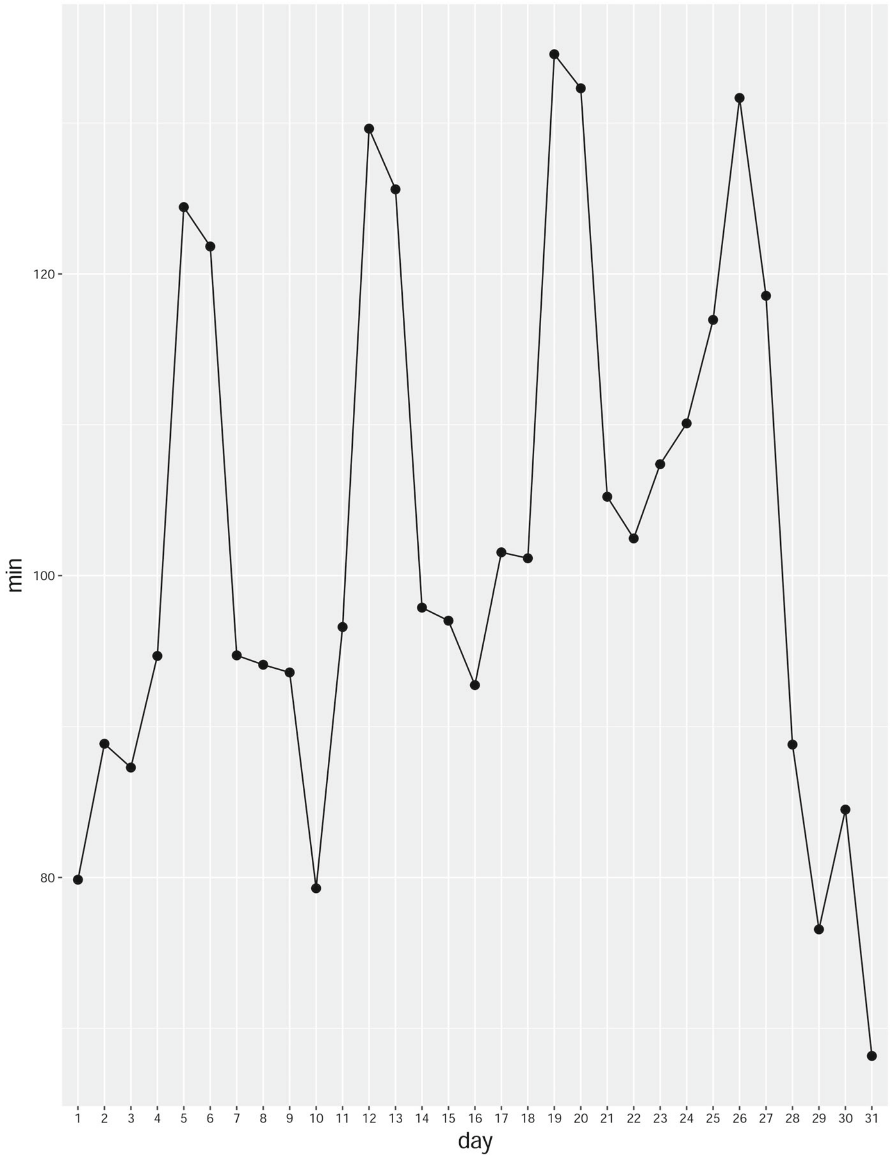

Fig. 2 Average game time every day in March 2011

4 Empirical approach

We employ the generalized panel Tobit model proposed by Honoré (1992) to estimate the impacts of temperature. Because our data come from a panel of individuals over a short time period and the outcome variables of game time and missions accomplished

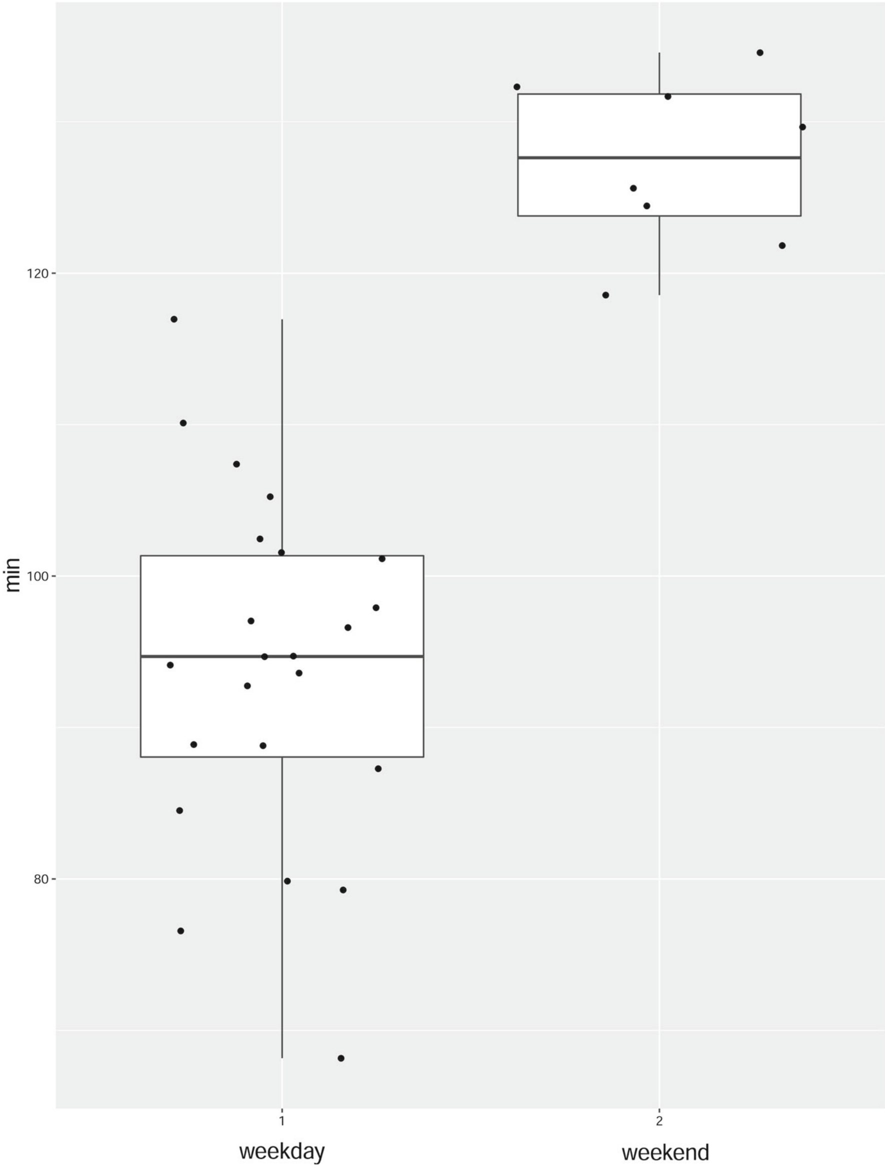

Fig. 3 Average game time in weekdays and weekends

are zero-truncated on the left side, the estimators from the traditional panel data model with fixed effects will be biased. We briefly introduce the model in the following subsection.

4.1 Panel Tobit model

The panel Tobit estimator is a trimmed least absolute deviation (LAD) estimator that is robust to nonparametric error term distributions with arbitrary dependence structures among individuals. We control for the cross-sectional dependence due to the nature of the multiplayer online game, as it is an interactive playing environment. If the spillover effects of unobserved random errors across individuals are not considered, the estimated effect will be confounded. This estimator has desired properties such as consistency and asymptotic normality and works well, especially in settings similar to our data, that is panel data with big N and small T (Hsiao 2014). The estimation model is:

$$
\begin{aligned}
y_{it} &= \begin{cases} 0 & y^*_{it} \leq 0 \\ y^*_{it} & y^*_{it} > 0 \end{cases} \\
y^*_{it} &= f(\text{temp}_{ct}) + \rho \mathrm{W}_{ct} + \eta_i + \mu_t + \epsilon_{it},
\end{aligned} \tag{1}
$$

where y_{it} is the dependent variable of game time or missions accomplished for individual i on day t. The variable temp_{ct} is the outdoor temperature of prefecture c. W_{ct} is a vector of other weather control variables, including precipitation, average wind speed, and Air Pollution Index on day t. The variable of interest in our study is temperature, which is exogenous to the structural equation. We include individual fixed effects η_i to control for any time-invariant variations at the individual level, such as age, gender, education, and income.[13] We include daily fixed effects μ_t, to control for factors that do not vary among individuals such as weekend and weekday effects. As the outdoor temperature is exogenous, the estimated coefficients have implications for the causal effect of temperature changes.

We explore several forms of $f(\text{temp}_{it})$ to estimate the nonlinear effects of temperature on game time and gaming productivity. First, following Schlenker and Roberts (2009), we use two types of degree days: heating degree days below 5 °C and cooling degree days above 21 °C, to capture the impacts of extreme low temperature and extreme high temperature. They reflect additional degrees to be heated or cooled to reach certain thresholds[14]. We choose the threshold of low temperature at 5 °C according to China's current heating policy, which recommends central heating being provided in regions with an average monthly temperature below 5 °C. We choose the threshold of high temperature at 21 °C, following Graff Zivin et al. (2018). Our results on the nonlinear impacts of temperature also show that there is an obvious change in both game time and gaming productivity when temperature exceeds 21 °C .

We use two additional functions of temperature to verify the nonlinearity of temperature's impacts: a polynomial function and a group of dummy variables for temperature

[13] As our study period only covers 31 days in March, we assume that individuals' income does not change during this period.

[14] Here, hdd(5) $= 5 -$ temp if temp$<$ 5 and 0 otherwise. Similarly, cdd(21) $=$ temp $-$ 21 if temp$>$ 21 and 0 otherwise.

bins. A fifth-degree polynomial function[15] of daily average temperature is included in the right-hand side of Eq. 1 to calculate the predictive means of the dependent variable at any temperature level. We also estimate the marginal impacts of temperature by including a group of dummy variables for every 2-degree bin, used as a 'step function,' which has been used by Schlenker and Roberts (2009) and Graff Zivin and Neidell (2014) to capture the nonlinear effects of temperature. The default temperature group is 10–12 °C, which falls in the temperature neutral zone identified by other studies (Graff Zivin and Neidell 2014; Kruger and Neugart 2015). It is also the temperature range in which the temperature neutral zone starts. Therefore, estimated coefficients of other temperature bins will be the difference in game outcomes in other temperature ranges compared to the default group.

4.2 Quasi-experiment: heating policy in China

Distinguishing outdoor and indoor temperature is key to estimating the direct impacts of temperature on human performance. Given that gamers in this study are all PC gamers, they primarily play the game indoors. Their exposure temperature might be different from the outdoor temperature, especially in regions with heating services.[16] Whereas outdoor temperature is highly correlated with indoor temperature when there are no heating or cooling services, their correlation is much lower in regions with heating services.[17] By comparing gamers' performance with and without heating in the same outdoor temperature, we can directly measure the impacts of temperature on game performance and evaluate the effect of heating access on human performance.

The previous argument relies on the exogeneity of heating access from daily temperature variations. If individuals turn heating on and off in response to outdoor temperature, we then cannot interpret the difference between unheated and heated samples as the net effects of heating. The unique heating regulation in China provides an opportunity to address this issue.

China's current central heating policy, which dates back to the 1950s, is distinctive in both geographic and temporal features. From a geographic perspective, the central heating zone is framed by a south–north heating line. It specifies that buildings in the north of the Qin Mountain and the Huai River, known as the Qinling Huaihe line, should be equipped with central heating facilities (Almond et al. 2009; Chen et al. 2013),[18] whereas regions located to the south of the line are not, even though some southern cities might reach freezing temperatures in the winter. From a temporal perspective, there are local variations regarding the heating period. Provinces typically regulate their own heating periods each year. Figure 4 plots the accessibility to heating services for Chinese prefectures in March 2011. Beijing and the surrounding northern

15 The shape of the nonlinear curves of temperature and both dependent variables are stable, even for higher-order polynomials.

16 Because we only cover gaming records in March, which is a cold month in China, cooling is rare.

17 The correlation without heating or cooling is above 0.9 and approximately 0.2 if there is heating (Nguyen et al. 2014).

18 In fact, the *Standard for Heating, Ventilation, and Air Adjustment Design* specifically indicates the indoor temperature to be maintained under heating. The central heating service should maintain an indoor temperature around 16–22 °C (MOHURD 2012).

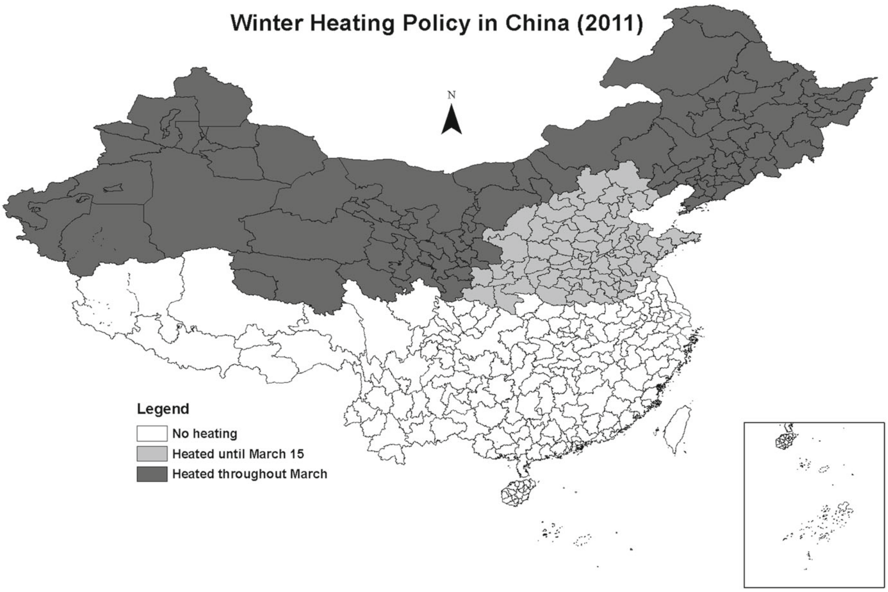

Fig. 4 Winter Heating Policy of China in 2011. *Note* The winter heating in Beijing, Hebei, Shanxi, Shandong, Shaanxi, Tianjin, and Henan ended on March 15, and the heating in Heilongjiang, Jilin, Liaoning, and Inner Mongolia ended on April 15, 2011

provinces such as Hebei, Shanxi, Shandong, Shaanxi, and Tianjin are often heated from November 15 to March 15 every year.[19] Northeast provinces, such as Heilongjiang, Jilin, Liaoning, and Inner Mongolia, are heated until April 15. Therefore, not only we can compare outcome variables in heated and non-heated regions, but also we can compare those with and without heating access in the heated regions.

5 Results

5.1 Temperature and game performance

Gamers accomplish fewer missions in both high and low temperatures outside the comfort zone. Given that gamers' performance can also be affected by playing time, we control game time to isolate the direct impacts of temperature on gamers' performance. Column 1 in Table 2 shows that gamers accomplish fewer missions in low temperatures, as shown by the negative coefficient of heating degree days below 5 °C. The number of missions drops by 0.14 for each one-degree drop below 5 °C. The result is robust to adding higher-order polynomials of game time, as shown in column 2. The estimate of low temperature is also robust to adjusting the threshold of low temperature to

[19] The period might be extended if the average temperature dropped below 5 °C for five consecutive days or if extremely cold days were expected after March 15. Source: Beijing Heating Administration Method (No. 216 of the Beijing Municipal Government).

Table 2 Temperature and mission

Variables	(1) Mission	(2) Mission	(3) Mission	(4) Mission	(5) Mission	(6) 1(Mission > 0)
cdd(21)	−0.31***	−0.41***	−0.47***	−0.015	0.48***	0.078***
	(0.11)	(0.13)	(0.13)	(0.18)	(0.17)	(0.017)
hdd(5)	−0.14***	−0.19***		−0.16***	−0.12***	−0.030***
	(0.019)	(0.023)		(0.025)	(0.026)	(0.0020)
hdd(10)			−0.13***			
			(0.016)			
Precipitation	−0.0033	−0.0071	−0.0023	−0.0075	−0.0036	−0.000094
	(0.0043)	(0.0050)	(0.0051)	(0.0062)	(0.0062)	(0.00063)
Wind speed	0.25***	0.25***	0.24***	0.13***	0.14***	0.039***
	(0.016)	(0.019)	(0.019)	(0.027)	(0.023)	(0.0022)
Game time	0.050***	0.15***	0.15***	0.14***	0.15***	0.029***
	(0.00030)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.000076)
Game time square		−0.00031***	−0.00031***	−0.00028***	−0.00031***	−0.000061***
		(6.9e−06)	(6.9e−06)	(6.4e−06)	(6.9e−06)	(2.8e−07)
Game time cubic		2.1e−07***	2.1e−07***	1.9e−07***	2.1e−07***	3.7e−08***
		(7.3e−09)	(7.3e−09)	(6.7e−09)	(7.3e−09)	(2.7e−10)
API				0.00019		
				(0.0013)		
W*cdd(21)					108***	
					(10.4)	
W*hdd(5)					2.78***	
					(0.39)	
Player FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y
Observations	1,929,719	1,929,719	1,929,719	1,312,002	1,929,147	1,927,828
Number of players	62,249	62,249	62,249	42,338		62,188

This table shows regression results for game missions accomplished. Columns 1–5 present coefficients using the panel Tobit model in Eq. 1. Column 6 shows coefficients from a panel logit model, as the dependent variable taking 1 if mission accomplished is positive and 0 otherwise. The number of observations in column 4 is smaller due to missing data on API in local cities. All regressions include player and date fixed effects. Standard errors are in parentheses. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

10 °C, controlling Air Pollution Index (API) as shown in columns 3 and 4.[20] Because gamers may form teams to accomplish missions, the impacts of temperature might be spilled over to other team members. Column 5 controls the weather variables (including temperature, precipitation, and wind) of other prefectures. It shows that the impacts of low temperature remain robust. Given that there are a lot of zeros in the observation of game missions, we also check the gamers' success rate in terms of completing any positive mission. Column 6 lists the results using the panel logit

[20] Because there are several cities with missing API data, the observation for column 4 while controlling for API is smaller than that in column 3.

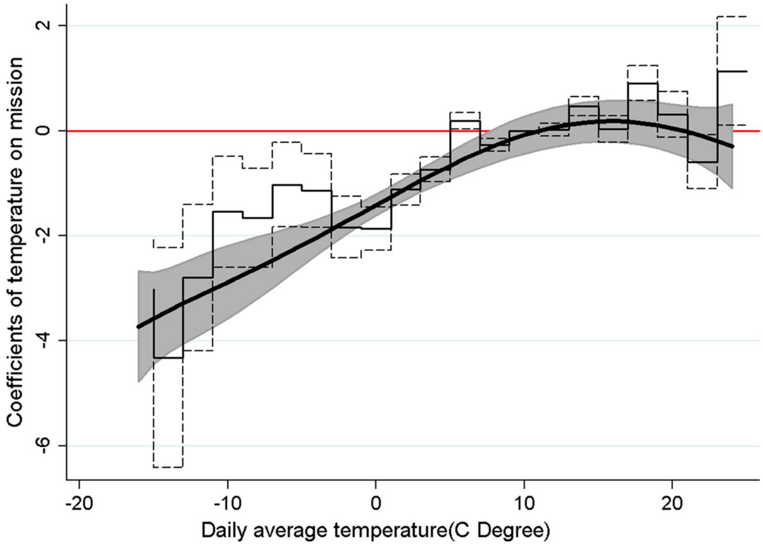

Fig. 5 Nonlinear impacts of temperature on game mission. *Notes*: The smooth curve represents temperature impacts on mission using a fifth-degree polynomial regression model. The stair-step curve plots coefficients of temperature bins with an interval of 2 Celsius degrees. Solid lines are estimates, and the shaded area represents 95% CI. Panel Tobit models are used to estimate these coefficients. Both regression models control precipitation and wind speed. Player and date fixed effects are included.

model. The likelihood of players completing missions drops in low temperatures. This is consistent with the decreased performance in cold shown in columns 1–5. In addition to low temperatures, gamers also accomplish fewer missions in high temperatures above 21 °C. In contrast to the impacts of low temperature, the reduction in gamers' performance at high temperatures is almost twice that at low temperatures. It indicates that gamers' productivity is more vulnerable to heat than to cold.

We obtain similar results in the impacts of high temperature and low temperature using nonlinear functions of temperature. First, we fit a panel Tobit model while including the fifth-degree polynomial function of temperature. Figure 5 plots predictive means and confidence intervals of missions corresponding to different temperatures. It shows that there is a wide plateau range between 5 and 20 °C, within which the temperature has no significant impact on game performance. The number of missions is significantly smaller when the temperature is below 5 °C, which is also the reason we set the threshold of low temperature at 5 °C. Second, we use a 'step function' by including a series of dummy variables for every 2-degree bin. Figure 5 plots the estimated coefficients and their confidence intervals for all the temperature bins, as shown in the stair-step curves. Low temperature is associated with significant decreases in game performance, and gamers' performance is not significantly different when temperature is between 10 and 20 °C. This is consistent with the idea of 'comfortable temperature range' described in previous studies (Federspiel et al. 2004; Graff Zivin et al. 2018).

Table 3 Impacts of temperature on mission per hour

Variables	(1) Mission/h	(2) Mission/h	(3) ln (mission/h)	(4) ln (mission/h)
Game time		– 0.026***		– 0.0031***
		(0.0021)		(0.000040)
cdd(21)	– 0.80***	– 0.87***	– 0.084	– 0.076
	(0.17)	(0.22)	(0.072)	(0.063)
hdd(5)	– 0.39***	– 0.51***	– 0.023***	– 0.020***
	(0.052)	(0.058)	(0.0077)	(0.0075)
Observations	1,332,210	1,332,210	548,584	548,584
R-squared			0.335	0.428
Player FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y

Columns 1 and 2 are using panel Tobit models, and columns 3 and 4 are using OLS regression models. All regressions control precipitation and wind speed. Player and date fixed effects are included. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

In addition to temperature, game time is positively correlated with the number of missions completed. Longer game time leads to higher game performance. The negative coefficients of extreme temperatures after controlling game time indicate that the negative productivity drop exceeds the positive impacts of longer game time induced by extreme temperatures. This is confirmed by analysis on gaming productivity per unit hour (as shown in Table 3). Neither precipitation nor pollution significantly affects game performance. This again confirms that online game performance as an indoor activity is not affected by outdoor factors directly. However, outdoor temperature can affect gamers' performance through changes in the indoor temperature.

5.2 Temperature and game time

Overall, gamers tend to spend more time gaming on both hot and cold days. Column 1 of Table 4 shows that players spend 7.96 additional minutes on the game for each one-degree drop in the daily average temperature below 5 °C. This pattern is robust to raising the threshold of low temperature to 10 °C, as shown in column 2. However, the coefficient of hdd(10) is slightly smaller than that of hdd(5), which indicates that the response in game time is larger in the lower temperature range. Column 3 shows that the odds of gameplay increases when the temperature is below 5 °C. As a result, players are more likely to stay indoors and play the game on cold days.

High temperatures are also positively correlated with game time. Players spend an average of 3.49 more minutes for each one-degree increase in temperature when it is above 21 °C. The response is smaller than that associated with a low temperature. For other weather elements, we observe that players tend to play the game longer on windy days, as shown in columns 1–4 of Table 4. It is consistent with the intuition that players tend to spend more time on indoor activities when the outdoor environment is less welcoming. More rainfall is associated with decreases in both game time and the

Table 4 Temperature and game time

Variables	(1) Time	(2) Time	(3) Time	(4) 1(Time>0)
cdd(21)	3.49***	5.23***	− 5.72***	0.12***
	(0.87)	(0.86)	(1.74)	(0.014)
hdd(5)	7.96***		9.33***	0.12***
	(0.11)		(0.12)	(0.0012)
hdd(10)		5.53***		
		(0.12)		
Precipitation	− 0.89***	− 1.08***	− 1.24***	− 0.0040***
	(0.034)	(0.035)	(0.053)	(0.00057)
Wind speed	3.56***	3.59***	5.07***	0.089***
	(0.12)	(0.12)	(0.22)	(0.0019)
API			0.0092	
			(0.012)	
Player FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Observations	1,929,719	1,929,719	1,312,002	1,768,798
Number of players	62,249	62,249	42,338	57,058

This table shows regression results for game time. Columns 1–3 present coefficients of main weather variables using the panel Tobit model in Eq. 1. Column 4 shows coefficients from a panel logit model, as the dependent variable taking 1 if game time is positive and 0 otherwise. The number of observations in column 3 is smaller due to missing data on API in local cities. All regressions include player and date fixed effects. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, * $p < 0.1$

odds ratio of gameplay. Although rainfall typically causes a switch from outdoor to indoor activities, heavy rainfall and lightning may cause a power outage and a reduction in the use of electrical appliances. In addition, we did not find a significant impact of the Air Pollution Index on game time, as shown in column 4.[21] The coefficients of high temperature, cdd(21), on game are not robust. One possible reason is that we do not have a sufficient number of observations in high temperatures during the study period.[22]

Similar patterns of impacts of temperature on game time are revealed in the nonlinear model specifications. Figure 6 plots the predictive means and confidence intervals of game time for each temperature range using [10–12) °C as the reference temperature group. It shows that there is a wide plateau range between 10 and 20 °C, within which temperature has no significant impacts on game time. When the temperature increases or decreases at both ends, game time is longer. Game time is significantly higher when the temperature is either above 21 °C, or below 5 °C. We observe a similar pattern of

[21] Because the Air Pollution Index is only available in most large prefectures or cities, the number of observations drops by around 32%.

[22] Schlenker and Roberts (2009) found a detrimental impact on crop yields when the temperature exceeds 28 °C.

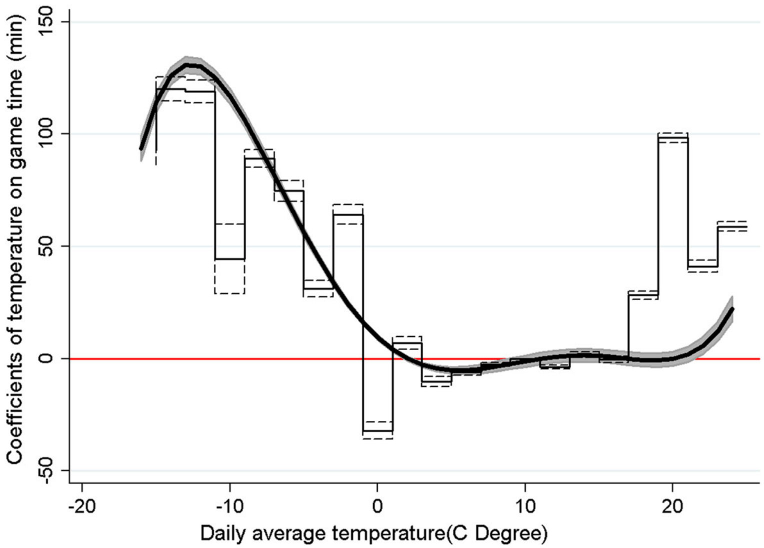

Fig. 6 Nonlinear impacts of temperature on game time. *Notes*: The smooth curve represents temperature impacts on game time using a fifth-degree polynomial regression model. The stair-step curve plots coefficients of temperature bins with an interval of 2 Celsius degrees. Solid lines are estimates, and the shaded area represents 95% CI. Panel Tobit models are used to estimate these coefficients. Both regression models control precipitation and wind speed. Player and date fixed effects are included

nonlinearity while controlling for a series of dummy variables for every 2-degree bin, as shown in the stair-step curve in Fig. 6.

5.3 Result on heating policy

Given that heating would reduce variations in the indoor exposure temperature, we expect to observe a much smaller impact of temperature on gamers' performance for heated samples. Table 5 shows the regression coefficients including heating service access and interactions of heating service and temperature. In column 1, the positive coefficient of the interaction term between heating status and hdd(5) indicates that gamers with heating access shift more time toward game playing when the outdoor temperature is below 5 °C. As heating typically provides a relatively comfortable indoor environment in cold weather, players tend to stay indoors longer and spend more time on game playing. Comparing to those in unheated regions, players in heated regions shift 6.4 more minutes toward game playing for the same temperature drop below 5 °C. For game performance, heating decreases the negative impacts of low temperatures on mission performance significantly, as shown in column 2. The positive coefficient of the interaction term shows that heating can reduce the negative impacts of low temperature. This again confirms that gamers' performance is affected by the unobserved indoor temperature, which is stable in heated regions. Because the number of missions can be counted, we adopt a panel Poisson model with individual fixed effects to examine the robustness of results. Column 3 presents the coefficients of

Table 5 Temperature, central heating, and online game

Variables	(1) Game time	(2) Mission	(3) Mission Poisson
cdd(21)	3.52***	− 0.41***	− 0.054***
	(0.87)	(0.13)	(0.0052)
hdd(5)	1.71***	− 0.42***	-0.048***
	(0.47)	(0.054)	(0.0018)
hdd(5)*1(heating)	6.40***	0.28***	0.037***
	(0.47)	(0.055)	(0.0019)
1(heating)	− 12.2***	− 0.26	− 0.031***
	(2.21)	(0.16)	(0.0042)
Player FE	Y	Y	Y
Day FE	Y	Y	Y
Observations	1,929,719	1,929,719	1,929,719
Number of players	62,249	62,249	62,249

Columns 1 and 2 show results for game time and mission using panel Tobit model. 1(Heating) is an indicator variable for access to central heating in local prefectures. All regressions control precipitation and wind speed. The regression in column 2 controls a polynomial function of game time to the third degree. Player and date fixed effects are included. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

high temperature and low temperature on the logarithm count of missions. It confirms that heating improves overall game performance in cold temperatures.

In addition to the average impact, there might be regional heterogeneities in the effects of heating on gamers. Because China follows an explicit heating line, we group all observations into five categories based on the relative geographic distance from the heating line to the local prefectures. From north to south, the five groups are those that are located more than 500 km north of the heating line, within 500 km north of the heating line, within 200 km south of the heating line, 200–400 km south of the heating line, and more than 400 km south of the heating line. Figure 7 plots the coefficients of low temperature, measured by degrees below 5 °C in each distance group. It shows that low temperature barely affects gamers' performance in heated regions. The coefficients in both groups north of the heating line are insignificant. In all three groups located south of the heating line, low temperature lowers down gamers' performance significantly. This confirms the results in Table 5 which shows that heating service reduces the negative impacts of temperature significantly. However, the marginal impact of low temperature is the largest in the group located 200–400 km south of the heating line. We only observe a small negative impact of low temperature on game performance for those that are located immediately south of the heating line. The potential reason might be that private heaters may be occasionally used in those regions, while it is not accounted for in our analysis. Therefore, our estimates of the low temperature in the group located 0–200 km south of the heating line would be a combination of impacts from low temperature and impacts from private heating services.

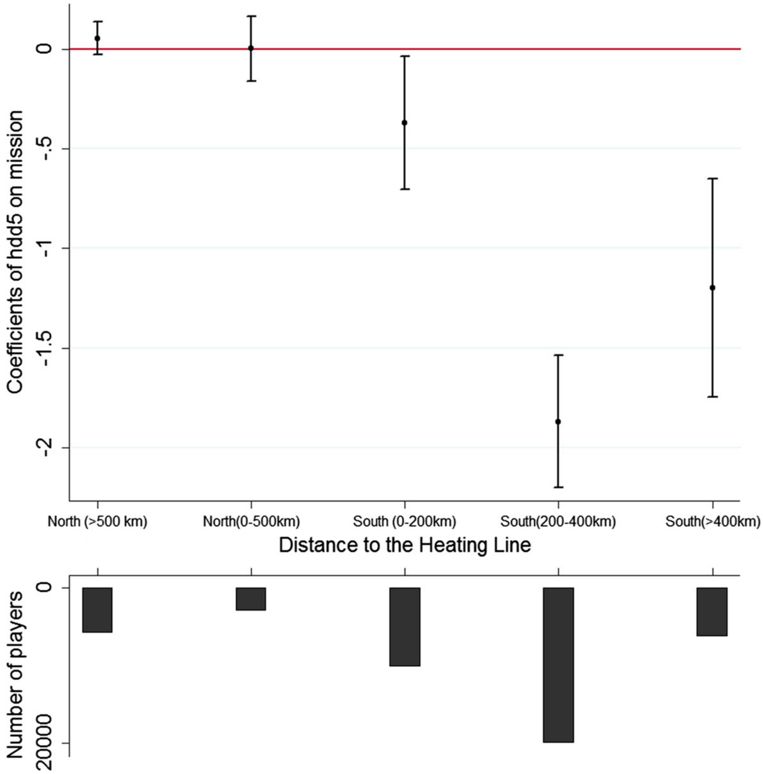

Fig. 7 Temperature impacts on game mission by distance to heating line. *Notes*: This graph plots coefficients and 95% CIs of hdd(5) on game missions for gamers grouped by distances between their prefectures and the heating line. From left to right, the gamer groups are those located more than 500 km north of the heating line, within 500 km north of the heating line, within 200 km south of the heating line, 200–400 km south of the heating line, and more than 400km south of the heating line. The lower panel of the figure plots out the number of players included in each distance group. Panel Tobit models are used to estimate these coefficients. All regressions control precipitation and wind speed. Player and date fixed effects are included

5.4 Heterogeneities of temperature's impacts

Gamers can be affected by extreme temperature differently. We explore how experienced and non-experienced gamers differ in their response to extreme temperatures. Because gamers are granted to a certain level based on their performance in the past, we use their level information at the first day of March to indicate how experienced a gamer is. The higher level indicates that the player has accomplished more missions in the past. To explore their differences, we divide all the gamers into four quartiles based on their level in the first day and estimate the impacts of temperature on game time and game performance separately for each group.

Figure 8 plots the coefficients and 95% confidence intervals of low temperature and high temperature on game performance for each gamer group. The left graph of Fig. 8 reveals that game performance drops significantly at low temperatures below 5 °C. The performance drop is larger for inexperienced gamers. It indicates that experience

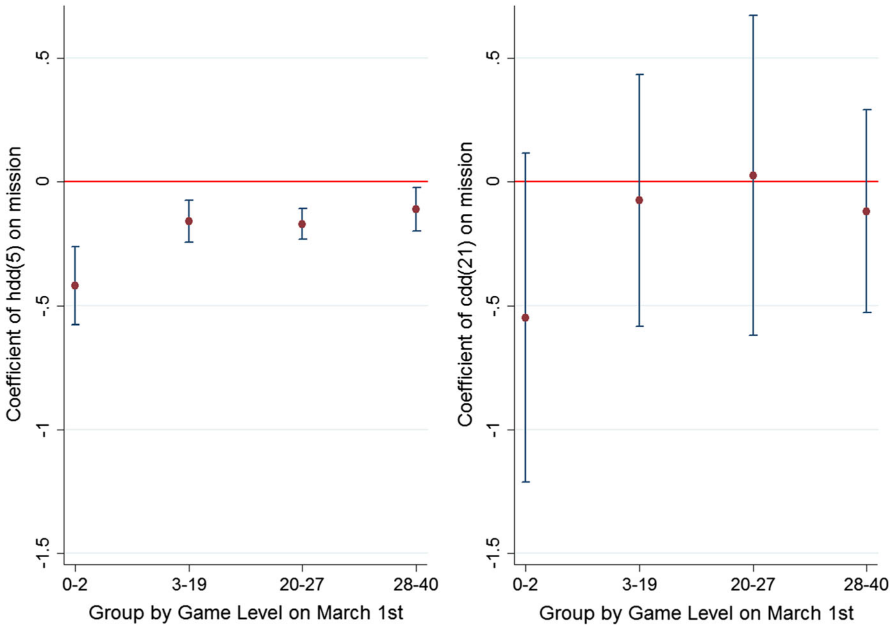

Fig. 8 Temperature impacts on gaming productivity by gamer groups. *Notes*: This graph plots coefficients and 95% CIs of hdd(5) and cdd(21) on game missions for separate gamer groups. Gamers are divided into 4 groups according their game level at the first day of March. From left to right, each group represents the lowest quartile (0–25%), second quartile (25–50%), third quartile (50–75%), and the highest quartile (75–100%). Panel Tobit models are used to estimate these coefficients. All regressions control precipitation and wind speed. Player and date fixed effects are included

or practice would attenuate the negative impacts of low temperature. The right graph plots impacts of high temperature on game performance. Consistent with the impacts of low temperature, gaming productivity of inexperienced gamers dropped more in high temperatures. Experienced player are barely affected by high temperature in their gaming productivity.

Different from gaming productivity, game time is affected by extreme temperature in different patterns among the four player groups. Figure 9 plots the coefficients of extreme temperatures on game time for each group separately. The left graph reveals that game time increases at low temperatures below 5 °C. The game time of extremely experienced and new players is not affected by low temperature. In contrast, only medium-level players allocate more time to gameplay in response to temperature decreases below 5 °C. This is consistent with the intuition that both new gamers and dedicated gamers tend to be attracted by a game with game time less sensitive to weather changes. Because medium-level players already played the game with their curiosity to the game partially filled, their game time is affected by low temperature more. The right graph plots the impacts of high temperature above 21 °C on game time. The pattern is exactly the opposite to that for low temperature. The game time of players in the first and fourth quantiles increases significantly in high temperature, while game time of medium-level players decreased. This might be caused by the

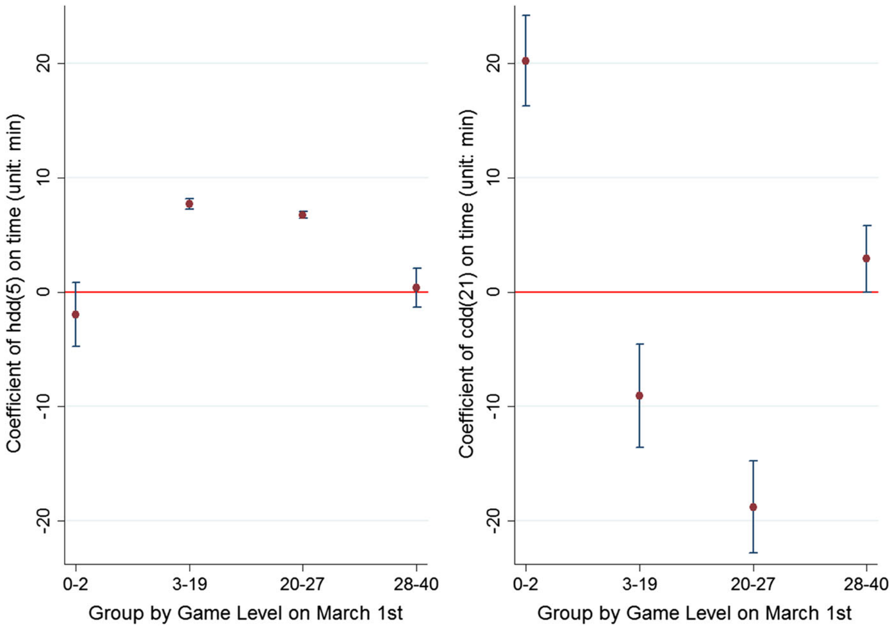

Fig. 9 Temperature impacts on game time by gamer groups. *Notes*: This graph plots coefficients and 95% CIs of hdd(5) and cdd(21) on game time for separate gamer groups. Gamers are divided into 4 groups according their game level at the first day of March. From left to right, each group represents the lowest quartile (0–25%), second quartile (25–50%), third quartile (50–75%), and the highest quartile (75–100%). Panel Tobit models are used to estimate these coefficients. All regressions control precipitation and wind speed. Player and date fixed effects are included

discomfort due to temperature increase in both indoor and outdoor environments. The inconsistency of results may also be driven by the limitation of our data that we do not have many observations with high temperature above 21 °C.

5.5 Robustness check and discussion of results

We check the robustness of results by applying other regression models. Columns 1–3 in Table 6 examine temperature's impacts on game time and missions accomplished using ordinary least squares (OLS) models. Because the dependent variable is truncated at zero on the left side, the OLS estimates in column 1 will be biased. One typical solution is to perform a Box–Cox transformation of the dependent variable and calculate the logarithm value after a small shift in the variable. Column 2 shows the estimates of temperature after the Box–Cox transformation of the dependent variable after adding 1 to the value of the dependent variable. Columns 1 and 2 show that a low temperature is significantly correlated with an increase in game time and a decrease in missions. The pattern is also confirmed by the logarithm model in column 3 and panel Poisson model in column 4.

In addition to model specifications, the accuracy of weather measurements may also affect estimates of temperature on game performance. Due to the lack of temperature

Table 6 Robustness check: model specification

	Panel A: Game mission			
	(1) OLS mission	(2) ln(mission+1)	(3) ln(mission)	(4) Mission Poisson
cdd(21)	− 0.0066	0.0082	− 0.086	− 0.053***
	(0.036)	(0.0059)	(0.063)	(0.0052)
hdd(5)	− 0.094***	-0.021***	− 0.019***	− 0.016***
	(0.011)	(0.0018)	(0.0066)	(0.00084)
Player FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Observations	1,929,719	1,929,719	563,344	1,929,719
R^2	0.330	0.468	0.396	
Number of players	62,249	62,249	62,188	62,249
	Panel B: Game time			
	(1) OLS time	(2) ln(time+1)	(3) ln(time)	(4) Time Poisson
cdd(21)	4.35	0.098	0.025	0.026***
	(4.58)	(0.090)	(0.024)	(0.00064)
hdd(5)	4.69***	0.13***	0.012***	0.062***
	(0.96)	(0.029)	(0.0039)	(0.000059)
Player FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Observations	1,929,719	1,929,719	1,332,210	1,929,719
R^2	0.363	0.311	0.375	
Number of players	62,249	62,249	57,058	62,249

All regressions control precipitation and wind speed. Regressions in panel A control game time, game time square and cubic. The number of observations in column 3 is smaller because both mission and game time take the value zero in many observations. Player and date fixed effects are included. Regressions in columns 1–3 cluster errors at the prefecture level. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

information during gaming sessions for each player, we use daily average temperature for previous analysis. There are concerns that players may play games at specific hours of a day and the daily average temperature may not be exactly the outdoor temperature during the game time.[23] For instance, gamers with jobs are more likely to play the game at night, while the game time for students is more flexible. To address this issue, we use the daily minimum and maximum temperature to check the robustness of estimates, as shown in Table 7. Columns 1 and 2 show that the coefficients of hdd(5) are significantly negative for extreme cold built from minimum temperature and maximum temperature.

[23] The average diurnal temperature range, which is the difference between daily maximum temperature and minimum temperature, for Chinese prefectures in March 2011 is approximately 11 °C. However, there are huge geographic variations. The daily temperature range varies from 0.6 to 31 °C during the study period. Typically, the temperature difference is smaller in warmer days.

Table 7 Robustness check: other weather variables

	Mission			Time		
	(1) Min temp	(2) Max temp	(3) Mean temp	(4) Min temp	(5) Max temp	(6) Mean temp
cdd(21)	5.61	0.035*	0.090	− 43.3	1.89***	− 9.13***
	(5.26)	(0.019)	(0.13)	(27.1)	(0.15)	(0.99)
hdd(5)	− 0.053***	− 0.070**	− 0.14***	4.15***	12.2***	7.94***
	(0.012)	(0.028)	(0.019)	(0.086)	(0.15)	(0.11)
Pressure			0.013			0.29***
			(0.0083)			(0.068)
Humidity			− 0.0095***			− 0.39***
			(0.0021)			(0.017)
Sunshine hours			− 0.013**			1.41***
			(0.0067)			(0.053)
Precipitation	0.0028	0.0028	0.0029	-0.97***	− 0.71***	− 0.48***
	(0.0043)	(0.0044)	(0.0047)	(0.034)	(0.034)	(0.036)
Wind speed	0.25***	0.27***	0.056***	3.66***	3.65***	3.34***
	(0.016)	(0.017)	(0.019)	(0.12)	(0.12)	(0.13)
Game time	0.050***	0.050***	0.049***			
	(0.00030)	(0.00030)	(0.00030)			
Player FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y
Observations	1,929,719	1,929,719	1,814,277	1,929,719	1,929,719	1,814,277
Number of players	62,249	62,249	58,526	62,249	62,249	58,526

All regressions use panel Tobit models with player and daily fixed effects. The dependent variables for columns 1 and 2 are daily missions accomplished by players. The dependent variables for columns 3 and 4 are daily game time. The temperature variables of cdd(21) and hdd(5) in columns 1 and 3 are derived from daily minimum temperature. The temperature variables of cdd(21) and hdd(5) in columns 2 and 4 are derived from daily maximum temperature. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Gamers' performance is significantly lower in cold days using both measurements. The results for game time are also robust. Columns 4 and 5 show that gamers spend significantly more time on gaming in cold days, while both measurements are used for temperature. Overall, the impacts of low temperature under the indicator of maximum temperature are larger than those under the indicator of minimum temperature. This coincides with the previous results on nonlinear impacts of low temperature. Under the threshold of 5 °C, lower temperature causes larger negative impacts on performance and larger time switch into game playing. The results using both measurements give general lower and upper bounds of temperature impacts, which indicate that our results would not be confronted with the variations in gaming hours of a day.

Our results are also robust after accounting for potential network effect among gamers. Players can team up with up to 4 members in the game. The rewards such as gift cloth and experience value, which are used to calculate missions, will be divided among them. So while players can team up, a lot of them would also play alone. While teams are formed, they tend to form spontaneously to play a specific task. Furthermore, teams are typically composed of players who happen to be in the same game map location. So it is very rare for a player to always play with teammates from the same city. We test the robustness of our results by controlling the weather in other cities. Because we do not have the exact gaming network for each gamer, the number of gamers in a city is used to calculate the likelihood of a gamer to be teamed up with by a gamer from a different city. The more players a city has, the more likely a player from another city will be teamed up with any player from this city. The weather in other cities is a weighted-sum of weather in all other cities.[24] Column 4 of Table 6 lists the regression result while controlling for weather in other cities. The coefficient of cdd(5) in the local city remains robust and statistically significant. If a player is gaming together with someone from the same city, the positive spillover of teamwork would cause our estimated coefficients overstating the effect of temperature on gaming productivity. However, the actual effects should be only slightly lower, because all rewards and gains from accomplishing the task will be divided among all members.

We further explore the potential source of time switched into online gaming when gamers are exposed to extreme temperatures. Time reallocation may include switching time from labor to leisure and from other leisure activities to this online game. Due to a lack of individual time usage data beyond the play time variable, we are not addressing this issue in the paper. However, we can discuss several implications of time reallocation by exploring regional variations. The idea is that time reallocation to online gameplay should be lower when individuals have more leisure options such as theaters and restaurants. In China, provincial capital cities are often equipped with better facilities and greater access to leisure activities. Column 4 of Table 8 presents results on low temperature and game time while considering city status as a provincial capital city. The negative coefficient of the interaction term between low temperature and capital city status shows that time reallocation to playing the online game is smaller in capital cities than other regions in response to low temperatures. Even when we use GDP per capita as an indicator to measure how developed a local region is, column 5 shows similar results that time reallocation in response to low temperatures is lower in more developed regions.

Our results cannot be driven by sample selection concerns, because we follow a balanced panel of gamers for 31 days consecutively. The panel Tobit model with individual gamer fixed effect ensures that our results still hold for within-gamer variations of outdoor temperature and game outcomes. To ensure the elimination of sample selection concerns, we explore the impacts of temperature in relatively homogeneous gamer groups. First, we focus on experienced gamers who reached the maximum game level of 40. Columns 3 and 6 in Table 8 show the impacts of temperature on missions accomplished and game time. For these gamers who are already proficient in playing the game, a low temperature still negatively affects their game performance significantly. This confirms that the negative productivity that we observe is unlikely to be driven by variations in the quality of gamers. Second, we focus on gamers who logged

[24] The weighted weather in other cities for city i equals $\sum_{c \neq i} \lambda_c W_c$, where $\lambda_c = \frac{N_{ct}}{\sum_{c \neq i} N_{ct}}$, where N_{ct} is the number of gamers in city c on day t.

Table 8 Temperature impacts and other extensions

	Mission			Time		
	(1)	(2)	(3)	(4)	(5)	(6)
hdd(5)	− 0.15***	− 0.067	− 0.17***	7.99***	9.96***	1.29
	(0.023)	(0.043)	(0.052)	(0.11)	(0.54)	(1.04)
hdd(5)*1 (capital city)	− 0.50***			− 3.18***		
	(0.076)			(0.69)		
hdd(5)* GDP/pop		− 2.0e−06***			− 0.000038***	
		(7.0e−07)			(0.000010)	
Player FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y
Observations	1,929,719	1,812,353	220,844	1,929,719	1,812,353	220,844

Panel Tobit model is used in all regressions. 1 (capital city) is an indicator variable, representing the status of capital city in local provinces. Columns 3 and 6 include results for gamers with the highest level. All regressions control precipitation and wind speed. Player and date fixed effects are included. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9 Impacts of temperature on missions accomplished: frequent gamers

Variables	Logged days in March			
	= 31	≥ 30	≥ 29	≥ 28
cdd(21)	− 0.22	− 0.12	− 0.0084	− 0.15
	(0.26)	(0.19)	(0.17)	(0.16)
hdd(5)	− 0.063	− 0.17***	− 0.19***	− 0.24***
	(0.063)	(0.053)	(0.044)	(0.040)
Observations	160,921	284,642	386,260	494,295
Players	5,191	9,182	12,460	15,945

Panel Tobit models are used to estimate these coefficients. All regressions control game time, time square, time cubic, precipitation, and wind speed. Player and date fixed effects are included. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

in the game frequently in March, particularly gamers who log in the game for at least 28 days. Column 1 in Table 9 lists the results for gamers who logged in all 31 days. It covers 5191 players. The coefficient of low temperature is negative but insignificant, potentially due to the drop in the number of players. However, when focusing on gamers who log in the game for at least 30, 29, and 28 days, as listed in columns 2–4, the coefficient of low temperature is negative and statistically significant. Their total missions drop by 0.17 for each degree drop in daily average temperature below 5 °C. This result is similar to average impacts of unit-degree temperature drop below 5 °C for the whole sample. It confirms that the main effect of low temperature on gamers' performance is not driven by the changes in gamer composition.

Table 10 Benefits of expanding central heating in south China

Province	Average hdd(5)	Days with $hdd5 > 0$	Pop (millions)	Unheated pop ratio	Productivity gain
Jiangsu	1.91	0.44	78.7	84%	5.69%
Guizhou	1.59	0.40	25.1	100%	4.66%
Hubei	1.52	0.44	57.2	100%	4.25%
Shanghai	1.34	0.42	23.0	100%	3.63%
Anhui	1.12	0.27	55.6	54%	3.31%
Zhejiang	0.98	0.36	54.4	100%	2.54%
Hunan	0.98	0.37	65.7	100%	2.50%
Jiangxi	0.80	0.35	44.6	100%	1.86%
Yunnan	0.61	0.16	38.9	100%	1.74%
Sichuan	0.51	0.28	79.5	100%	0.99%
Henan	0.15	0.03	91.8	7%	0.44%
Fujian	0.11	0.05	36.9	100%	0.23%
Chongqing	0.13	0.11	28.8	100%	0.13%
Guangxi	0.06	0.05	46.0	100%	0.09%
Guangdong	0.02	0.01	104.3	100%	0.02%

The variable of average provincial heating degree is the daily average heating degrees below 5 °C from November to March in local provinces. The total productivity was calculated using the formula of $col(2) * \beta_{1(heating)} + col(3) * \beta_{hdd5*1(heating)}$. According to the estimated coefficients in column 3 in Table 5, $\beta_{1(heating)} = -0.031$ and $\beta_{hdd5*1(heating)} = 0.037$. More details for the calculation can be found in Appendix A

5.6 Policy implications for heating regions in China

There has been an ongoing debate on whether to enlarge the heating zone in China. As China's overall living standard has improved recently, the demand for access to heating increases in southern China.[25]

Using the coefficients shown in column 3 of Table 5, we calculate the estimated benefits of expanding the heating zone. We consider a new heating policy that would provide either universal heating coverage to all regions which experience a daily average temperature below 5 °C. In addition, the indoor temperature would be maintained above 5 °C after being heated. Table 10 presents the back-of-the-envelope calculation of productivity improvements due to the additional heating in various provinces in China. The productivity gain in specific provinces ranges from 5.69% in the Jiangsu province to 0.02% in the Guangdong province, based on the weather scenario between November 15, 2010, and March 15, 2011. It is worth noting that these values are the average increase in the entire province, while we average the gain of the unheated population with the whole population in those provinces. The productivity gain for prefectures with larger unheated population would be much larger.

Furthermore, even though we have limited observations on gamers exposed to high temperature, our results also shed some light on the negative impacts of extreme heat, which has been an increasing concern in the context of climate change. For high tem-

[25] A LA Times article: http://www.latimes.com/world/asia/la-fg-china-heat-20141115-story.html

peratures, we observe an increase in game time and decrease in game performance for temperatures above 21 °C, although these results are not robust to model specification changes. The findings that a high temperature leads to longer indoor time and lower human productivity are consistent with the conclusions of Graff Zivin and Neidell (2014) and Matthews (2015). As global warming might potentially increase the occurrence of extreme heat, impaired human productivity is a key component of climate change damages.

6 Conclusion

This paper studies how temperature affects both time allocation and gaming productivity for online gamers. Using the newly available data on game records, we build a unique measure of productivity, which is the number of missions accomplished by players each day. Our results suggest that low temperature below 5 °C increases game time and decreases gamers' productivity significantly. Specifically, each one-degree drop in the outdoor temperature below 5 °C leads to 7.96 more minutes spent on the game, as well as a reduction in gaming productivity by 2.1%. High temperatures above 21 °C have similar negative impacts on game performance and positive impacts on game time.

To address the potential differences in gamers' exposure temperature and outdoor temperature, we use a quasi-experiment on heating policy in China. The results show that central heating reduces the negative impacts of temperature on gamers' productivity significantly. The negative impacts of low temperatures on productivity in the heated group are approximately half of those in the unheated group. Gamers who are located north of the heating line are barely affected by cold in terms of their game performance, whereas gamers who are located immediately south of the heating line suffer a loss in gaming productivity on cold days.

In addition, we find significant individual heterogeneities in the impacts of extreme temperatures. Experienced gamers are impacted by extreme temperatures to a lesser extent with respect to gaming productivity. New gamers with a low initial game level experience the largest drop in gaming productivity when being exposed to low or high temperature. Gamers in capital cities or richer cities, which have better facilities for leisure, switch less time to gaming in the face of low outdoor temperatures compared to gamers in other cities. Our results are robust for other model specifications such as OLS, Box–Cox, logit, and logarithm regressions models. While there might be spillover effects in performance among teammates, our results are also robust for controlling the weather variables of other cities.

Our study has direct policy implications on evaluating the potential benefits of expanding heating zone in China. If we utilize gaming productivity as a reflection of overall human performance or productivity, local regions will gain significantly in productivity if the current heating zone is expanded. If all regions with daily average temperature below 5 °C would be heated, local provinces will benefit from a productivity gain ranging from 0.05% in Henan province to 5.69% in Jiangsu province. The specific size of benefits depends upon the local weather conditions and population size. Furthermore, our results also shed some light on the negative impacts of high temperature on human performance and time allocation decision of people when the outdoor temperature is extremely high or low.

One limitation of our study is the lack of data on individual demographic, economic, and social characteristics. Further study is needed to explore the heterogeneities in the impacts of extreme temperatures using more detailed game records and individual information. In addition, as our data are from March, a study using data from a different period will be valuable to derive more robust conclusions on the impacts of high temperatures. At last, we admit that the policy implication also depends on the nexus between gaming productivity and real productivity. In the twenty-first century, the technology has fundamentally changed the skills required in common work places. More attention is needed in the future research to study human behaviors in online games.

Overall, our analysis suggests that both high temperatures and low temperatures strongly affect human time allocation and productivity. Whereas the growing attention to climate change draws more interests to the impacts of extreme heat, low temperature and extreme cold can also have strong impacts on the economic system. The issue is more concerning in regions with limited access to heating facilities. Our findings suggest that central heating in southern China can improve productivity in general.

Compliance with ethical standards

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Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Appendix A: back-of-envelope calculation

This section introduces the back-of-envelope calculation for the productivity gain from expanding central heating to south China. We assume that access to heating will be available to all regions which was exposed to daily average temperature below 5 °C. The heating period is assumed to be the same as the current heating period for most regions in north China, that is November 15 to March 15, which lasted for 121 days in 2011. Because temperature records are at the prefecture level, we calculate productivity gain for each prefecture first. Following coefficients estimated in column 3 in Table 5 using a fixed effect Poisson model, the productivity gain for a player j in day t once being heated is:

$$g_{jt} = \beta_{\text{heat}} + hdd5_{it} * \beta_{\text{interact}},$$

where g_{jt} refers to the productivity gain of individual j. β_{heat} is the estimated coefficient from the dummy of heating, 1 (heating), and β_{interact} is the estimated coefficient for the interaction term of heating and heating degree days below 5 °C. $hdd5_{it}$ refers to the heating degree below 5 °C for prefecture i where individual j is located. According to the assumption that the heating policy is the same for all individuals of a prefecture, the productivity gain for prefecture i is the same as productivity gain for any individual. So

$$g_{it} = \beta_{\text{heat}} + hdd5_{it} * \beta_{\text{interact}}.$$

The overall productivity gain for prefecture i during the heating period is the sum of productivity gain for all days with temperature below 5 °C, divided by the heating period.

$$\begin{aligned} g_i &= \frac{\sum_t [1(hdd5_{it} > 0) * (\beta_{\text{heat}} + hdd5_{it} * \beta_{\text{interact}})]}{T} \\ &= \frac{hdd5days_i * \beta_{\text{heat}} + \sum_t hdd5_{it} * \beta_{\text{interact}}}{T}, \end{aligned}$$

where $hdd5days_i$ is the number of days with temperature blow 5 °C and $\sum_t hdd5_{it}$ is the accumulated heating degree below 5 °C during the whole heating period. T is the length of the heating period.

For a province, which includes both heated and non-heated prefectures, the productivity gain during the heating period is the sum of gains of local prefectures weighted by population.

$$\begin{aligned} g_p &= \frac{\sum_i pop_{pi} * \left[hdd5days_{pi} * \beta_{\text{heat}} + \sum_t hdd5_{pit} * \beta_{\text{interact}}\right]}{T \sum_i pop_{pi}} \\ &= \frac{\sum_i pop_{pi} * hdd5days_{pi}}{T \sum_i pop_{pi}} \beta_{\text{heat}} + \frac{\sum_i pop_{pi} \sum_t hdd5_{pit}}{T \sum_i pop_{pi}} \beta_{\text{interact}}, \end{aligned}$$

where $\frac{\sum_i pop_{pi} * hdd5days_{pi}}{T \sum_i pop_{pi}}$ is the average days with hdd5 being positive, weighted by population in prefectures, and $\frac{\sum_i pop_{pi} \sum_t hdd5_{pit}}{T \sum_i pop_{pi}}$ is the population-weighted cumulative heating degree below 5 °C.

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