Ambient Temperature and Food Behavior of Consumer: A Case Study of China

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ABSTRACT: Human behaviors are believed to be sensitive to environmental conditions. However, little is known about the role of temperature in individual daily behaviors. We examine the links between temperature and food intake using nearly one million purchasing records from China. The results show that a 1°C increase in temperature would cause a 0.11% decrease in food intake, which amounts to USD 4.2 million of daily food expenditures nationwide. Moreover, females appear to be more sensitive to the temperature in their food intake than males. In addition, we observe a U-shaped relationship between the temperature and the willingness to order a takeout online, and this observation is robust under multiple alternative estimations. Our results indicate that a higher temperature would reduce energy demand for body thermoregulation, resulting in less food intake. Both extreme high and low temperatures can cause disutility. Therefore, the consumers who still want to satisfy their needs for food intake feel compelled to alter their willingness to pay under the extreme temperature events. The quantitative analysis can provide helpful references for modeling the climate–consumer relationship in integrated assessment models. Thus, it is an interesting avenue for future research to bridge the climate and consumers to identify welfare loss and inequality due to climate change.

SIGNIFICANCE STATEMENT: The role of weather conditions in human behaviors is gaining popularity as extreme temperature occurs more frequently due to an ever-warming planet. Our study aims to understand which weather condition matters to consumer behaviors and how we could adapt to their impacts. We find that a 1°C increase in temperature would cause a 0.11% decrease in food intake, which amounts to USD 4.2 million of daily food expenditures nationwide. Temperature effect on food intake indicates that weather induced consumer behavior is a promising field of consumer research. More attention should be paid to the role of climate change in the consumer side.

KEYWORDS: Climate change; Temperature; Economic value; Societal impacts

1. Introduction

The role of climate conditions in consumer behaviors has been a classic topic in modern economics. The IPCC Fifth Assessment Report (Pachauri et al. 2014) suggests global surface average temperature is expected to rise due to ongoing climate change, which will bring about more climatic extremes. The challenges arising from global warming have captured the notice of scholars seeking to identify the socioeconomic outcomes of the rising temperature. Traditional wisdom tends to investigate the influence on sectoral output (Deschênes and Greenstone 2012; Burke et al. 2015), labor productivity (Graff Zivin and Neidell 2014), and health welfare (Hsiang et al. 2013; Burke et al. 2018). However, little is known about the impact on consumer behaviors.

Nowadays, an increasing number of extreme climatic events emphasize the environmental impact on individual behaviors and mental states. Scientific evidence shows that individual performances are sensitive to environmental conditions via several interrelated channels. Psychological studies show that the environment could exercise its effects on human mental states and behavioral patterns in terms of physical perception, psychological perception, and value judgment (DellaVigna 2009). In physical terms, the temperature could alter human behaviors (Bowler and Tirri 1974; Schiff and Somjen 1985; Yablonskiy et al. 2000). For example, the brain can respond to a changing temperature by releasing certain brain chemicals, displaying different electrical properties, and functioning at various capacity levels. Physical or mental discomfort due to high temperature may well impair our memory performance. Those tasks entailing memorization are heavily reliant on the ability to memorize during the multistep process. Graff Zivin et al. (2020) argued that a 1° increase in temperature would bring down the academic performance in score by 0.32% in China. Heyes and Saberian (2019) found that a 10°F (5.5°C) rise in outdoor temperature made it less likely by 1.075% for the immigration court to render a judgment favorable to the applicant. These studies prove that temperature can affect the cognitive abilities essential to one's career, breadwinning capabilities, and even the crossroads of life. Zhang et al. (2018) found that the temperature shows an inverted U-shaped relationship with the total factor productivity. This nonlinear connection turns out to dominate the temperature-output effect. Ambient temperature could alter the individual emotion states, indirectly affecting its consumption choices and even its

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perceptions of happiness (Currie et al. 2009; Heyes et al. 2016; Zhang et al. 2017).

Weather is vital and closely connected to human society. Unlike the classical economic theory, the response in consumer behavior to weather fluctuation is not assumed in the economic man hypothesis. Some studies validated that the weather could impact consumer decisions (Gardner 1985; Hirshleifer and Shumway 2003; Hong and Sun 2012; Li et al. 2017; Baker et al. 2018). The link between the weather and psychology is the primary channel for determining one's behaviors (Spangenberg et al. 1996). For example, Buchheim and Kolaska (2017) found that the weather at the purchasing time, albeit less relevant for deciding whether to visit the theater next time, could significantly influence whether a customer will purchase a theater ticket in the meanwhile. Murray et al. (2010) argued that temperature, humidity, snowfall, and sunlight could indeed affect retail sales. Busse et al. (2015) found that one more snowy or rainy day could boost the sales of convertibles or a car with 4-wheel drive. The results appear to be inconsistent under the classical utility theory but cannot turn down the role of weather in the decision-making for consumers.

Food intake is a fundamental means for individuals, regardless of their gender, age, and race, to ensure adequate energy for nutrition and thermoregulation. Besides, food intake is more of an instinct behavior in our daily life (Wansink and Sobal 2007; Stroebe et al. 2013). Typically, there are four stimuli for food demand: individual factors, social environment, physical environment, and macroenvironment (Story et al. 2008). Individual factors include self-efficacy, outcome expectations, and motivations (Higgs 2008). Social environment refers to partners with whom to have the meal, such as family or friends (Hetherington et al. 2006). Physical environment stands for the dining site, such as campus, workplace, or home (Wansink 2004). Macroenvironment reflects the societal and cultural norms and values. The decision of food intake is proved to be irrational since the environment could exert substantive effects on the food intake behavior (Stroebele and De Castro 2004). For example, Wansink (2004) shows by experiment that if served with bigger food-loading plates, there is a tendency for customers to eat more food. However, 21% of the interviewees were unaware of and denied consuming more, and 75% of interviewees attributed excess intake to starvation. A mere 4% recognized the true reason beneath. Zheng et al. (2019) found in a field experiment that high temperatures could lead to a loss of appetite at lunchtime. Shorten et al. (2009) found that employees would ingest fewer calories from a meal after a physical exercise if the ambient temperature is higher than normal. That is to say, there ought to be less demand for calories in a hotter environment, leading to reduced food intake for the thermic effect.

Two notable features are perceived recently: digitalization and mobilization. The development of the internet industry provides various choices for consumers. As a consequence, the takeaway platform alters the time allocation and individual's lifestyle drastically. In recent years, the rise of mobile applications offers multiple choices for consumers who want to order a takeout order online. In statistical terms, there will be 20% more takeout orders in days of heavy rain or snow. An explanation for this latest trend is that both extremely high and low temperatures would cause disutility. Whoever wants to satisfy their needs for food intake may turn to different means of dining under the extreme temperature events. However, little is known about the willingness to pay under the temperature extremes for consumers.

Several issues are left untouched in previous studies on temperature and consumer behavior. Most studies are based on limited samples or cases in developed countries. In contrast, little is known about the developing world. Besides, the proposed models tend to omit several key variables and ignore individual heterogeneity. Therefore, relatively few studies articulate the links between temperature and food intake from the lens of both gender and economic level differences. Because of the limitations mentioned above, we investigate the temperature effects on the food demand to uncover the following questions using our microlevel data: (i) To what extent will temperature affect the consumer expenditure? (ii) Is there a nonlinear response in consumer behavior to temperature changes? (iii) How would temperature affect the individual willingness for the takeout order? (iv) How could the temperature affect consumer behavior in different gender, wealth, and seasonal groups?

The remainder of the paper is organized as follows: The following section describes the data sources. The model is introduced in section 3, and section 4 reports the results. Section 5 discusses the results, and section 6 concludes the paper.

2. Data

In this section, we describe the data used for the empirical analyses in the following sections. Our data consist of two groups.

a. Purchasing records

From the authorized administrative department at Beijing Institute of Technology, we obtained the student identification cards' purchasing records of nearly 28 000 students in the Haidian District, Beijing, China, within an entire academic year from October 2018 to June 2019. Eight thousand students were randomly selected as observations out of all students within the university. We extract the purchasing records at all restaurants on campus by filtering personal confidential information. Each record includes information about monetary transaction values, time, the purchasing counter's code, and a unique identification code for the cardholder. In addition, we have access to details of the gender and the educational level of the cardholders. Statistics show that 54.5% of the whole sample are male, and 72.6% are undergraduates.

We briefly introduce the daily life patterns of students in the surveyed campus here. Every student in the university shares a four- or six-person dormitory and individually owns a personal student card. They can do all shopping with the card on campus. They have to stay on campus to attend courses, leaving them insufficient time to go outside for personal affairs generally. The winter or summer vacation usually falls between January and February or between July and August, when the students leave the campus. For all restaurant owners on campus, they receive subsidies intended for lowering operating costs from the Ministry of Education. Therefore, food supplied in the restaurants on campus is more competitively advantaged to those outside the campus. Our target group is adults aged 19–29 who are in good health conditions and can determine their food consumption preferences. Thus, purchasing records can reflect their demand for food in a generally clear manner.

b. Weather data

We collected the weather data from the National Climatic Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA; available at https://www.ncei.noaa.gov/data/global-hourly/). The data contain global station-level weather records per 3 h, including temperature, precipitation, dewpoint temperature, visibility, and wind speed. The relative humidity is not reported in the NCDC data but instead is constructed using a standard meteorological formula combining temperature and dewpoint temperature. However, only two weather stations, the distances of which to campus are 27.5 and 50.1 km, could provide hourly records for weather variables. Additionally, air quality data are from Beijing Municipal Ecological and Environmental Monitoring Center (available at http://www.bjmemc.com.cn/). We select the two nearest monitoring stations to calculate the campus air quality, with a respective distance of 7.5 and 10 km to the campus. To calculate the weather and air quality variables, we adapt an inverse-distance-weight method (Barreca et al. 2016; Zhang et al. 2018) to approximate these values for the campus.

3. Method

From the obtained data, a multivariable econometric model is introduced to investigate the temperature effect on personal food expenditures:

$$C_{i,k,d} = f(T_{k,d}) + W + \alpha_k + \gamma_i + \varepsilon, \tag{1}$$

where i refers to an individual, k refers to one of three meals—breakfast, lunch, and dinner—d denotes individual day, and C is the dependent variable. The dependent variable in logarithmic form can eliminate the bias due to the heteroscedasticity as well as the inconsistent orders of magnitude between the expenditures and the daily temperature. Additionally, the estimated coefficients can be interpreted as a semielasticity about the percentage changes in expenditure when outdoor temperature increases by 1°C.

Our variable of interest is the outdoor temperature. The empirical evidence supports that a potentially nonlinear effect of temperature would exist in psychological and behavioral economics. Therefore, we consider a flexible specification of temperature function $f(T_{k,d})$ in splines or higher-degree polynomials.

To our knowledge, consumer expenditure is usually associated with several factors apart from temperature. Among them, the air quality and other meteorological variables (i.e., rainfall, wind, and sunshine) may also influence expenditures via individual's recognitions and perceptions of the environment. We realize that some weather variables are also vital in estimating the temperature–expenditure relationship. Sunshine duration and cloud are associated with rainfall since a thicker layer of clouds often accompanies heavier rain, reducing the sunshine duration. Besides, wind speed is negatively related to air pressure, or equivalently, barometric pressure (Burton et al. 2011; Ambach and Schmid 2017). If sunshine, cloud, and air pressure are added to the model together with temperature, rainfall, wind speed, and humidity, the estimation would be biased due to the collinearity. Thus, we only include temperature, rainfall, wind speed, and humidity in the model. Furthermore, air pollution is likely to induce overweight or even obesity (Deschenes et al. 2020), which calls for the need to control the daily mean $PM_{2.5}$ density in the model.

On the other hand, the seasonal food preferences—which means high-calorie dishes are more welcome in winter while cold dishes or foods that are easier to digest are more prevalent in summer—determine the variation of individual expenditures as a seasonal cycle. Similarly, food expenditures are dependent on the price level of the restaurant, and marginal consumption propensity changes due to holidays and festivals.

As a consequence, the control variable W includes a series of factors that may influence expenditures, namely $PM_{2.5}$ density (log) at the purchasing time, daily precipitation in log form, daily mean wind speed, daily mean relative humidity, a dummy variable of vacation, the month of the year fixed effect, and restaurant-specific fixed effect. The dummy variable vacation is equal to 1 when the day is a weekend day, summer/winter vacation, or public holiday and otherwise is equal to 0.

Our observation contains the detailed consumption information of each meal by day and individual. To control the underlying factors varying with individuals and periods, the individual fixed-effect γ_i is added to the model to absorb the unobserved factors invariant to individuals (i.e., health condition and budget limitation). The meal fixed effect α_k is expected to absorb the unobserved factors invariant in a day, that is, food choices in the restaurant for breakfast, lunch, and dinner. We assume that food purchasing is only influenced by physical conditions and ambient environment at the time rather than projected plans for the following days. Therefore, we exclude weather variables with lagged items in the model.

There is no available information about the food descriptions for every record to calculate the calorie intake. Therefore, we also assume that a higher expenditure for food intake reflects a higher amount of caloric intake (Allen 2017). Although the hypothesis may not necessarily be true, we provide several specifications to safeguard the hypothesis. Healthy food is typically expensive in commercial restaurants outside the campus. Unlike them, the restaurants on campus are generally subsidized by the National Ministry of Education (http://www.moe.gov.cn/srcsite/A03/s3013/200801/t20080108_76840.html), ensuring lower food expenditures for the students. Thus, there is no significant variation of food prices on campus, which avoids the student's adverse selection of food. However, we hasten to note that there are many styles of food served by the restaurants on campus, leading to the heterogeneity in purchasing amounts. Consequently, we introduce a dummy variable of the restaurants to absorb the effect of restaurant-varied food style preference on the expenditures.

TABLE 1. Summary statistics. The study period is from October 2018 to June 2019. Temp refers to the hourly temperature. Cash refers to the expenditure per meal and per person. Pre, $PM_{2.5}$, and RH refer to daily cumulative rainfall, mean daily $PM_{2.5}$ density, and mean daily relative humidity.

Variable (unit)	Obs	Mean	Std error	Min	Max
Temp (°C)	1 647 933	11.77	11.00	−11.2	35.8
Cash (CNY)	1 647 933	10.21	5.94	2	36
Pre (mm)	1 647 933	7.61	37.99	0	367
$PM_{2.5}$ (μg m^{-3})	1 647 933	47.52	46.60	1	527.7
RH (%)	1 647 933	41.2	24.3	10.5	85.4

The endogenous problems are explained as follows. First, our measure of temperature exposure is likely to suffer from measurement errors. These arise from the fact that weather stations are distributed far away from the campus. Because of the heat island effect, the temperature might be higher than that measured in the weather station. To this end, we conduct several alternative estimations by using daily mean, maximum, and minimum temperature to replace hourly temperature. Meanwhile, as for the differences between indoor and outdoor weather and air quality, we realize that our data only capture the outside conditions, and there would be a bias in measuring the indoor conditions. The temperature differences may partly arise from the indoor cooling or heating devices in summer or winter, and indoor air quality variations may to some extent be attributed to air purifying devices. The air quality is much related to the seasonal cycle, as the air pollution tends to worsen in winter. Because the indoor heating and cooling devices are seasonally and interchangeably operating in winter and summer, we add a month fixed-effect to the model to control the seasonal effect.

Second, food intake relies on individual energy consumption. We recognize that students may work out less regularly when exposed to high and low temperatures. Unfortunately, we have no access to information on individual daily time allocation. The exercise frequency varies by season and personal preference. Since students have a limited time for part-time jobs, their budgets count heavily on allowances from parents and salaries from mentors (typically only for postgraduates). The preference for food and the marginal consumption propensity is also vital to expenditures. However, these financial situations and preference features are confidential and are unknown to us. We, therefore, add two fixed effects into the model: individual fixed effect and month of the year fixed effect to absorb the effect of the exercise frequency and other unobserved factors varying with individual and season on the dependent variable.

Third, for concerns that one student may purchase several sets of meals on behalf of other students, unfortunately, we have no clue about their purchasing behaviors on behalf of others from the data. As a remedy, we delete the observations in which the expenditure exceeds the 99th percentile in samples. Meanwhile, we add the individual fixed effect to account for the unexpected and abrupt increase in the expenditure due to purchasing meals for their classmates or roommates. As an additional benefit, this specification could take into account a sudden and rare decrease in expenditure due to fever or stomach issues.

Last, consumption patterns are also associated with the period of staying on campus and academic cycles (for which they are allowed to leave the campus). Whether they are on campus will directly influence whether they will dine inside. Consequently, the binary variables—vacation and month of year fixed effect—are controlled in the model to rule out the bias due to students' stay on campus.

Whoever stays indoors would make a choice between dining at the school restaurants or place a takeout online (where students or any other customers can order food on applications on the phone that will be sent directly to assigned destinations in about an hour; for simplicity, we refer to it as online food order hereinafter). Considering the outdoor weather may alter one's willingness to pay under the temperature extremes, we build a binary probit model to explore the link between temperature and the demand for takeout order:

$$\mathrm{Probit}(P_{i,d}) = \ln\left(\frac{P_{i,d}}{1 - P_{i,d}}\right) = \beta_0 + f(T_{i,d}) + W_{i,d} + \varepsilon \qquad (2)$$

where $P_{i,d}$ is equal to 1 when the individual has no records of either lunch or dinner on weekdays and 0 otherwise. Takeout services provided by restaurants usually start at 1030 local

TABLE 2. Estimation of the temperature–expenditure relationship. The dependent variables are the logarithm of expenditure (log cash). Hourly temperature, daily rainfall, daily $PM_{2.5}$ density, daily wind speed, daily relative humidity, and a dummy variable of vacation day (binary) are controlled in the model. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at levels $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.

	1) Log cash	2) Log cash	3) Log cash	4) Log cash
Temperature	−0.0073*** (0.000)	−0.0063*** (0.000)	−0.0018*** (0.000)	−0.0011*** (0.000)
Log precipitation	0.0155*** (0.002)	−0.0315*** (0.002)	0.0030* (0.001)	0.0079*** (0.001)
Log $PM_{2.5}$		−0.1052*** (0.001)	0.0033** (0.001)	0.0027** (0.001)
Average wind speed		−0.0013*** (0.000)	0.0001 (0.000)	0.0001 (0.000)
Relative humidity		0.4565*** (0.002)	−0.0107*** (0.002)	−0.0129*** (0.002)
Vacation		0.0629*** (0.002)	−0.0010 (0.002)	0.0054*** (0.002)
Restaurant fixed effect	No	No	Yes	Yes
Meal fixed effect	No	No	Yes	Yes
Month fixed effect	No	No	Yes	Yes
Individual fixed effect	No	No	No	Yes
N	1 647 933	1 647 933	1 647 933	1 647 933

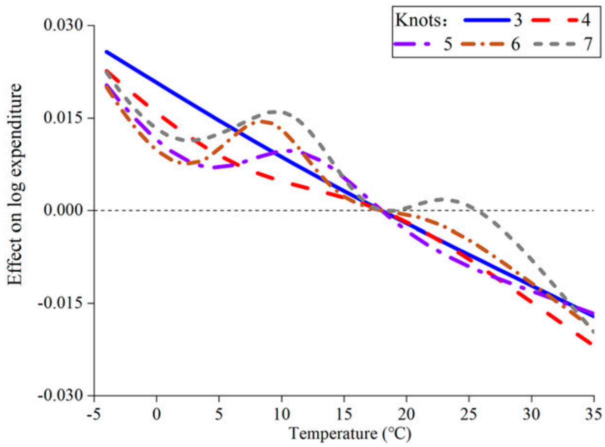

FIG. 1. Splines estimation of weather–expenditure relationship. The curves are generated by estimation from the model of Eq. (1), where the response function of temperature is set as a restricted cubic spline with a number of knots from 3 to 7.

time. Thus, there is no option for breakfast takeout. We define the occurrence of a takeout order when one has no purchasing record during the lunch or dinner time of the day. Different from Eq. (1), T is the average temperature of that day. The control variables W contain relative humidity, wind speed, $PM_{2.5}$ density (log), daily precipitation in log form, the month-of-year fixed effect, and day-of-the-week fixed effect. The coefficients of $f(T_{i,d})$ suggest the percentage change in odd rate $[P/(1 - P)]$ due to a 1°C increase in the daily temperature.

Table 1 reports the statistics of key variables in the model. The mean value of expenditure per person for a meal is about CNY 10.2, while the mean value of daily temperature in the period is equal to 11.8°C in our sample of observations.

4. Result

a. Links between temperature and food intake

Table 2 reports the result about the estimation of Eq. (1). With the log form of expenditure as the dependent variable, there is a significantly negative link between temperature and expenditure when the control variables and individual fixed effects are introduced in the model from columns 1 to 4. In column 4, a 1°C increase in ambient temperature would cause a 0.11% decrease in expenditure. That makes sense because higher temperature lowers the demand for energy needed to maintain the body's thermal balance and therefore decreases the food intake. The coefficients of temperature support our first hypothesis. Additionally, we explore the potentially nonlinear effect of temperature on food intake in Fig. 1. A restricted cubic spline estimation proves with confidence that the temperature and food intake relationship is essentially linear, showing that ambient temperature is linearly associated with the body's thermal balance.

Our results also determine a negative effect of temperature on food intake. According to data from the National Bureau of Statistics of China, the annual food spending per capita is CNY 6084 at the 2019 price. A 1° increase in temperature would lead to a total CNY 25.6 million decrease in daily food spending nationwide.

Table 3 reports the links between temperature and food intake by meals. The estimations are conducted separately in subgroups of breakfast, lunch, and dinner. The results show that a 1°C increase in the ambient temperature would lead to a 0.33% decrease in food intake at breakfast, a 0.05% decrease in lunch, and a 0.06% decrease in dinner. We conduct a Chow test to examine the differences in temperature effect among these three groups. The differences in temperature effect are significant at the 1% level. The greater effect on breakfast indicates the body is more sensitive to the environment in the morning than at noon and in the evening.

Table 4 reports the links between temperature and food intake among different subgroups. Females are more sensitive to the environment than males. The results in columns 1 and 2 indicate a 1°C in the ambient temperature would lead to a 0.09% decrease in food intake for males and a 0.14% decrease for females. The gap in effect between the gender groups is still significant at the 5% level.

As mentioned in section 2, postgraduates have more disposable income than undergraduates. Thus, they have more flexible choices for food intake. The results in Columns 3 and 4 show that a 1°C in temperature would lead to a 0.07% decrease

TABLE 3. Weather–expenditure relationship across period in a day. The dependent variables are the logarithm of expenditure (log cash). Hourly temperature, daily rainfall, daily $PM_{2.5}$ density, daily wind speed, daily relative humidity, and a dummy variable of vacation day (binary) are controlled in the model. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at levels $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.

	1) Breakfast	2) Lunch	3) Dinner
Temperature	−0.0033*** (0.000)	−0.0005*** (0.000)	−0.0006*** (0.000)
Log precipitation	−0.0167*** (0.003)	0.0111*** (0.002)	0.0130*** (0.002)
Log $PM_{2.5}$	−0.0058** (0.002)	0.0056*** (0.001)	0.0033* (0.002)
Avg wind speed	0.0006*** (0.000)	−0.0001 (0.000)	0.0001 (0.000)
Relative humidity	0.0729*** (0.006)	−0.0230*** (0.003)	−0.0221*** (0.003)
Vacation	0.0375*** (0.003)	−0.0077*** (0.002)	0.0068** (0.003)
Restaurant fixed effect	Yes	Yes	Yes
Meal fixed effect	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes
N	383 831	737 757	526 345

TABLE 4. Weather-expenditure relationship across gender, income level and heating policy. The dependent variables are the logarithm of expenditure (log cash). Hourly temperature, daily rainfall, daily $PM_{2.5}$ density, daily wind speed, daily relative humidity, and a dummy variable of vacation day (binary) are controlled in the model. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at levels $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.

	1) Men	2) Women	3) Undergraduate	4) Postgraduate	5) Heating	6) No heating
Temperature	−0.0009*** (0.000)	−0.0014*** (0.000)	−0.0007*** (0.000)	−0.0022*** (0.000)	−0.0019*** (0.000)	−0.0008*** (0.000)
Log precipitation	0.0066*** (0.002)	0.0102*** (0.002)	0.0077*** (0.002)	0.0090*** (0.002)	−0.0178* (0.008)	0.0105*** (0.001)
Log $PM_{2.5}$	0.0052*** (0.001)	−0.0014 (0.002)	0.0016 (0.001)	0.0040* (0.002)	0.0011 (0.002)	0.0021 (0.001)
Avg wind speed	−0.0000 (0.000)	0.0002* (0.000)	−0.0000 (0.000)	0.0003** (0.000)	−0.0001 (0.000)	0.0002* (0.000)
Relative humidity	−0.0151*** (0.003)	−0.0096** (0.004)	−0.0146*** (0.003)	−0.0041 (0.004)	0.0037 (0.005)	−0.0166*** (0.003)
Vacation	0.0036 (0.002)	0.0086** (0.003)	0.0076*** (0.002)	0.0087** (0.003)	−0.0084** (0.003)	0.0092*** (0.002)
Restaurant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Meal fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	1 005 961	641 972	1 195 882	452 051	562 615	1 085 318

in food intake for undergraduates and a 0.22% decrease for postgraduates. The differences in temperature effect between undergraduates and postgraduates are significant at the 1% level, which can be explained by the fact that postgraduates may have more flexible time, allowing them to choose an alternative food intake with a higher economic cost.

As a result of the heating policy in winter, the indoor temperature would be kept at 18°C from 15 November to 15 March. The results in column 5 show that a 1°C decrease in outdoor temperature would lead to a 0.19% increase in food intake during the heating period, although the indoor temperature is relatively stable. However, the temperature effect is comparatively weaker in the nonheating period. The results for the heating period indicate that the demand for food intake depends on the psychological perception of the outdoor environment rather than the actual indoor temperature.

b. Links between temperature and online food order

In this section, we explore the relationship between temperature and online food order. Considering the uncertainty in the form of temperature function in the probit model of Eq. (2), we conduct several nonlinear estimations using the restricted cubic splines method with 3–7 knots. Figure 2 depicts the nonlinear estimation of temperature in different numbers of knots. It is found that there is a potential U-shaped relationship between temperature and the possibility to order food online. Thereby, we set the temperature function as a quadratic polynomial in the form $f(T_{i,d}) = \beta_1 T_{i,d} + \beta_2 T_{i,d}^2$.

An examination of Table 5 reveals the links between temperature and online orders among different subgroups. Figure 3 depicts the nonlinear effect of temperature in Table 5. In general, there is a significant U-shaped relationship between temperature and online food orders. That is to say, both high and low temperatures would cause a decrease in the willingness to go outside for lunch or dinner, increasing the willingness to pay for the online food order to meet the demand of food intake. Statistically, when temperature increases from 30° to 32°C, the odd rate of choosing

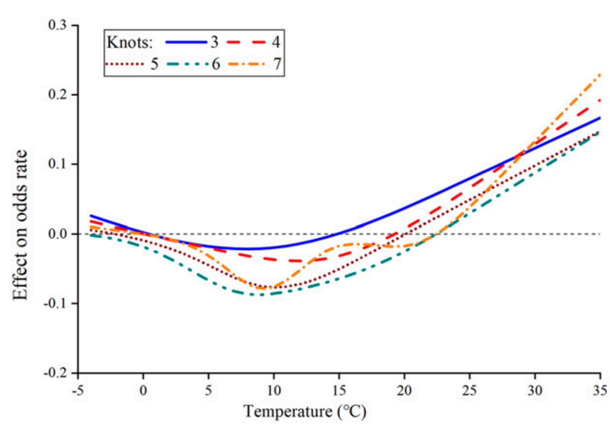

FIG. 2. Splines estimation of weather effect on the possibility of online behavior. The curves are generated by estimation from the model of Eq. (2), where the response function of temperature is set as a restricted cubic spline with a number of knots from 3 to 7.

TABLE 5. Weather effect on the possibility of online consumption behaviors. The dependent variables are the logarithm of the probability ratio of placing a food delivering order. Hourly temperature and its square item, daily rainfall, daily $PM_{2.5}$ density, daily wind speed, and daily relative humidity are controlled in the model. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at levels $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.

	1) Total	2) Male	3) Female	4) Undergraduate	5) Postgraduate
Temperature	−0.0039*** (0.001)	−0.0032** (0.001)	−0.0050*** (0.001)	−0.0042*** (0.001)	−0.0030*** (0.002)
Temperature^2	0.0003*** (0.000)	0.0002*** (0.000)	0.0004*** (0.000)	0.0003*** (0.000)	0.0003*** (0.000)
Log precipitation	−0.0181* (0.008)	−0.0157 (0.010)	−0.0196 (0.013)	−0.0201* (0.009)	−0.0121 (0.016)
Log $PM_{2.5}$	−0.0773*** (0.005)	−0.0786*** (0.007)	−0.0785*** (0.009)	−0.0787*** (0.006)	−0.0705*** (0.010)
Avg wind speed	0.0005 (0.000)	0.0006 (0.000)	0.0002 (0.001)	0.0007 (0.000)	0.0000 (0.001)
Relative humidity	0.4124*** (0.010)	0.4330*** (0.013)	0.3788*** (0.016)	0.3969*** (0.011)	0.4567*** (0.020)
Weekday fixed effect	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes
N	397 595	242 519	155 076	296 432	101 163

an online food order would increase by 2.9%. As mentioned above, a U-shaped relationship between temperature and online orders is witnessed in both female and male groups. Besides, online orders by females appear more sensitive to high-temperature conditions than those of males since the curve of females (red dashed line) is much higher than that of males (blue line). Relative to undergraduates, postgraduates are more likely to place an online food order encountering a temperature rise, possibly because postgraduates are better off with disposable income from their mentors.

Our results could measure the willingness of consumers to pay for the hot weather. The temperature would alter the individual time allocation. The consumer would pay more to prevent himself from the disutility resulting from being exposed to the extreme weather. Our data show the daily average cost of food intake is CNY 30.6. According to the report issued by the MeiTuan,[1] a Chinese online shopping platform offering local products and retail services, the average value per food order is about CNY 40. Since the restaurants at the campus would benefit from the fiscal subsidies from the Ministry of Education, the average cost of three meals per day on campus would be lower than dining outside by CNY 90. In the sample data, 66% of students are engaged in ordering food online. Considering a temperature rise from 30° to 32°C, the possibility of online food orders would increase by 1.5%. Therefore, the expected value of payment for hot days is about CNY 2.1. Overall, there will be an additional demand for online food orders with a market value of CNY 4.6 million when considering 2.2 million college students in China. If the sellers adopt flexible promotion measures, there would be a greater chance to gain more profits and market shares. The economic cost of such a temperature rise would be CNY 2.9 billion on the consumer side in China.

Table 6 reports the robustness check in the relationship between temperature and food intake. The hourly temperature is selected as the variable of interest. Nevertheless, consumers could not know the actual temperature and may rely on the weather forecast that merely provides the maximum and minimum temperature of the day. Therefore, we use the maximum, minimum, and average daily temperature as a proxy of hourly temperature. The results in columns 1–3 are generally consistent with the baseline results in Table 2. The consistency confirms that the relationship between the temperature and food intake is robust to alternative specifications of the model.

c. Discussion

Based on analyses in the last sections, we investigate the temperature effect on consumer food intake and online food choices. Our results have several implications in the following respects.

First, the amount of food intake is associated with environmental factors. Based on our findings, people living in the high latitude area would have more intake than in the low latitude area where the mean temperature tends to be lower (Zhao et al. 2020). The potential health burden due to excess intake of calories may pose a vital challenge to global health inequality (Afshin et al. 2019; Forouhi and Unwin 2019).

Second, females appear to be more sensitive to temperature in their food intake based on our evidence. Possible factors of gender difference in food intake include different preferences or physiological responses in gender (Rolls et al. 1991; Demarest and Allen 2000). Current data,

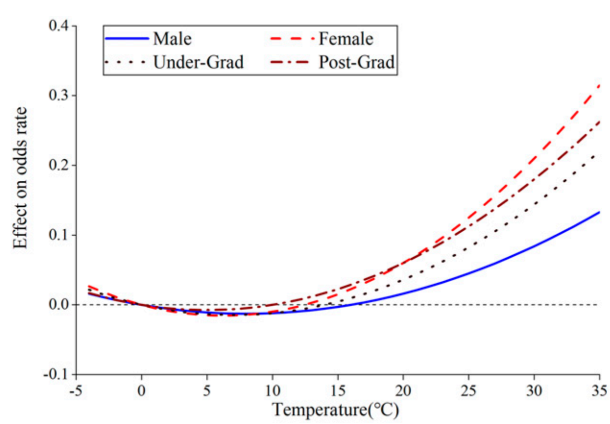

FIG. 3. Nonlinear weather effect on the possibility of online behavior. The curves are generated by estimation from the model of Eq. (2) by several subsamples. The response functions of temperature $f(T_{i,d})$ in all subsamples are equal to $\beta_1 T + \beta_2 T^2$. Other specification follows Eq. (2).

[1] The report could be found online [https://about.meituan.com/news/institute (in Chinese)].

TABLE 6. Robustness check on weather effect on food intake. The dependent variables are the logarithm of expenditure (log cash). The average, maximum, and minimum daily temperature are added respectively into the model to proxy the hourly temperature in Eq. (1). Daily rainfall, daily $PM_{2.5}$ density, daily wind speed, daily relative humidity, and a dummy variable of vacation (binary) are controlled in the model. Standard errors are in parentheses. One, two, and three asterisks indicate statistical significance at levels $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively.

	1) Log cash	2) Log cash	3) Log cash
Avg temperature	−0.0013*** (0.000)		
Max temperature		−0.0013*** (0.000)	
Min temperature			−0.0005*** (0.000)
Control	Yes	Yes	Yes
Restaurant fixed effect	Yes	Yes	Yes
Meal fixed effect	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes
N	1 647 933	1 647 933	1 647 933

unfortunately, exclude the possibility of investigating the mechanism of gender preference or response in our study. However, weather-induced behavior disparity seems to be a promising field for future consumer research.

Third, to the best of our knowledge, little empirical evidence supports climate change's role on the demand side in developing countries due to the heterogeneity of climate impact. Consequently, little was known about how climate will alter the consumer behavior associated with the household sector under any given climate scenario. Therefore, our quantified findings could provide practical implications for modeling the climate–consumer relationship in integrated assessment models (IAM). Further, more attention ought to be paid to bridging climate and consumers to identify welfare loss and inequality due to climate change.

5. Conclusions

We examine the links between the temperature and food intake using a large dataset of students purchasing records on campus. The result shows that a 10°C increase in temperature would lead to a 1.1% decrease in food intake. To put it differently, a 1°C increase in temperature would lead to a 0.11% decrease in food intake, equivalent to USD 4.2 million of daily food expenditures nationwide. The negative link is essentially linear via the flexible spline estimations. Second, we explore the willingness to pay under extreme temperature events. Our model reveals that a U-shaped relationship exists between the temperature and online food orders. Our results suggest the heat would impair body thermoregulation and therefore lower the demand for food intake. In addition, both high and low temperatures would cause disutility to individuals and increase the individual indoor time. Consequently, one is likely to pay more in food intake to shelter himself from the unfavorable outside environment.

Our analysis harbors some important implications. Our analysis suggests that females may be more sensitive to the negative links between temperature and food intake than males. Considering the gender inequality in underdeveloped regions, it is possible that temperature extremes might differentially lead to malnutrition for females, infants, and children. More attention should be paid to the Sustainable Development Goal of the United Nations—gender equality—since climate change is believed to more frequent temperature extremes in the following decades. Furthermore, our quantified findings can provide helpful implications when modeling the climate–consumer relationship in the IAM. It is an interesting avenue for future research to bridge climate and consumers to identify welfare loss and inequality due to climate change.

This paper suffers the following limitations. First, the target group is adults aged from 19 to 28 with relatively low income. The conclusion might be less representative for groups with higher levels of income. Second, the records have no information about the detailed types of food purchased in restaurants. There might be potential bias when using the monetary value to measure the amount of food intake. Third, we have no information about students' weight or weight goals, or even precisely what they eat. There is still some uncertainty to uncover in the mechanism about temperature and overall nutrition issues. Fourth, we did not account for the minor increase in the food price index, which may lead to a greater temperature effect.

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Data availability statement. Because of its proprietary nature, the supporting data cannot be made openly available. Further information about the data is available upon a reasonable request.

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