Supplementary Information for Urban residents adapt to extreme heat through food delivery service in China

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Supplementary Notes

S1 Data description

In our study, we use two large-scale datasets accessed from a prominent online food delivery platform in China. The first dataset comprises aggregated information on food delivery order volumes, detailing the daily trends in the number of food delivery orders placed within distinct geographic units. The second dataset is individual-level and documents detailed order information for approximately one million platform users. Both datasets are integrated with Global Surface Summary of the Day (GSOD)[1] meteorological records. Here we provide a comprehensive overview of our data processing and alignment procedures.

S1.1 Aggregated food delivery order data

The raw order data includes the following details for each delivery order: order placement timestamp, user payment for the meal, user payment for delivery service (delivery fee), order category, and the Geohash-7 grid (approximately 76m × 76m) representing the recipient's address location. Leveraging this spatial information, we aggregate the raw order data into two distinct geographic levels: city-level and neighborhood-level. In this context, cities correspond to prefectural cities in China, further subdivided into Geohash-5 neighborhoods, each covering an area of approximately 4.9km × 4.9km. For each geographic unit, we calculate its order volume, total payment, and total delivery fee for the entire day, during the lunch peak hours (10:30-13:30), and during the evening peak hours (17:00-20:00). To ensure data accuracy, we filter out any irrelevant delivery orders, such as those for "drugs" and "flowers", exclusively retaining orders categorized as "food" and "beverages". Among all orders, 34.7% are placed during lunchtime, and 24.5% are placed during dinner hours.

Our data collection period spans from January 1st, 2017, to August 20th, 2023. Recognizing the potential influence of the COVID-19 epidemic on food delivery behaviours, we exclude data from January 2020 to December 2022. Our primary focus is on the 100 cities with the highest order volumes, collectively constituting 78.5% of the total orders within mainland China. Table S1 lists the names of these cities. Figure S1 illustrates the spatial coverage of these 100 cities and their corresponding share of order volume. Among them, four first-tier cities, *i.e.*, Beijing, Shanghai, Shenzhen, and Guangzhou, account for the most substantial food delivery order volumes, comprising 17.4% of the nationwide orders. To ensure data reliability, we filter out neighborhoods with food delivery order records spanning less than 1,000 days during the 1,327-day data collection period, ultimately retaining daily food delivery order information for 9,638 neighborhoods.

S1.2 Individual-level food delivery order data

In addition to aggregated geographic unit-level datasets, we also collect an individual-level dataset to analyze users' micro-level behaviours and assess their health benefits. We randomly sample one million platform users and retrieve their food delivery order records from January 1st, 2017, to August 20th, 2023. We process the raw order records to extract the following information: order placement timestamp, meal cost, delivery fee, delivery origin (restaurant location), and delivery destination (user location). Order distance is calculated as the geodesic distance between the origin and the destination.

The food delivery platform provides demographic profiles, including gender, income level, and age, for a subset of users. To ensure user privacy, income levels are simply categorized as "high-income" or "low-income". Similarly, age groups are classified into "below 25", "25 to 40", and "over 40". The demographic distribution among the sampled users is presented in Table S22. Leveraging both order location information and user profiles, we further process city-level daily order datasets for different demographic groups. For instance, this allows us to examine the daily food delivery order volume for female users in each city.

S1.3 Weather data

To construct the panel datasets required for our analysis of the weather's impact on food delivery orders, we link geographic units with daily ground station-level meteorological records. We use R package "GSODR"[2] to source data from Global Surface Summary of the Day (GSOD)[1] provided by the US National Centers for Environmental Information (NCEI). GSOD offers climate records collected from 402 ground stations in China, depicted as triangular markers in Figure S1. Following the methodology outlined in ref.[3], we first link each city and neighbourhood with all climate stations located within a 100km buffer, centered at their respective administrative center (for cities) or geographic center (for neighborhoods). For each geographic unit, we calculate the daily weather conditions by averaging the weather indicators from all matched stations. The weather indicators for individual order records are determined based on the neighborhood in which the user is located. These collected indicators encompass the maximum temperature, precipitation, and relative humidity index.

S2 Regression analysis

By combining the aforementioned datasets, we obtain panel datasets that document the daily fluctuation in online food delivery orders and weather indicators across two geographical unit levels. We use fixed-effect regression analysis on these panel datasets to study the impact of daily maximum temperature, especially the range of extreme heat, on users' food delivery order behaviours.

S2.1 Geographic unit-level analysis

We first study the impact of daily maximum temperature on a city's food delivery order behaviours by fitting the following regression with the ordinary least squares method:

$$\ln(Y_{ct}+1) = f(\text{temp}_{ct}, \beta) + \alpha Z_{ct} + \mu_c + \lambda_t + \varepsilon_{ct}, \tag{1}$$

where c indexes the city and t indexes calendar date. Y_{ct} is the dependent variable for c at date t. In our study, we focus on the food delivery order volume in the entire day, during lunch peak, and during dinner peak, as well as the food delivery fee per lunch peak delivery order. We control for the effects of other climate indicators in the term αZ_{ct}. Z_{ct} consists the binned precipitation and relative humidity level of city c at date t. Daily precipitation is segmented at 0.1, 10, 25, and 50 millimeters, corresponding to the division of precipitation levels defined by the China Meteorological Administration. The relative humidity is cut into 10% bins from 0% to 100% following ref.[4]. μ_c and λ_t are, respectively, vectors for city effects and date effects. μ_c accounts for spatial variations in the prevalence of the food delivery service as illustrated in Fig. S1. λ_t captures seasonal trends and the natural expansion of the food delivery platform. For instance, people tend to purchase more orders on weekends than on workdays. The standard error term ε_{ct} is clustered on both city and day to nonparameterically adjust for arbitrary within-unit autocorrelation[5].

At the neighbourhood level, we estimate the following regression using the ordinary least squares method:

$$\ln(Y_{ict}+1) = f(\text{temp}_{it}, \beta) + \alpha Z_{it} + \mu_i + \theta_{dow} + \gamma_{holiday} + \lambda_{cm} + \varepsilon_{ict}, \tag{2}$$

where i indexes a neighbourhood, c indexes the city it is located, m indexes the month, and t indexes calendar date. Y_{ict} is the dependent variable for i at date t. αZ_{it} consists of the binned level of precipitation and relative humidity of i at t. μ_i represents the neighbourhood fixed effects. Since there are thousands of neighbourhoods, we do not assume identical fixed date effects for all neighbourhoods. We introduce θ_{dow} and $\gamma_{holiday}$, the day-of-week fixed effects and holiday fixed effects, respectively, controlling for the weekly seasonal variation factors and order fluctuation during holidays. As well as the λ_{cm} represents city-by-month fixed effects accounting for seasonal variation in cities. The standard error term ε_{ict} is clustered on neighbourhood, city, and date levels.

Our main independent variables, temp_{ct} and temp_{it}, represent the daily maximum temperature for a geographic unit at date t. Our relationship of interest is the temperature response function $f(\text{temp}_t, \beta)$ of temp_{ct} or temp_{it}. For all results in the Main Text, $f(\text{temp}_t, \beta)$ provides separate indicator variables for each temperature bin. This allows for flexible estimation of the non-linear relationship between temperature and food delivery order behaviours. For the results shown in Figure 1 and Figure 2d in the Main Text, daily maximum temperature temp_t is divided into 1°C bins from 0°C to 40°C, plus the interval lower than 0°C and the interval higher than 40°C. In this case, 19-20°C indicator is the relative baseline. For results shown in Figure 2a-c in the Main Text, daily maximum temperature temp_t is divided into 5°C bins from 0°C to 35°C, plus the interval lower than 0°C and the interval higher than 35°C (representing heat days). We take 15-20°C indicator as the relative baseline in this case. For the estimation of future food delivery demands in Figure 4 in the Main Text, temp_t is divided into 1°C bins from -10°C to 40°C and 19-20°C indicator as the baseline. Since we take $\ln(Y_{ict}+1)$ as the dependent variable, the regression coefficients β for a temperature bin can be translated to $e^{\beta}-1$ as the percentage change in Y at that temperature relative to the baseline.

S2.2 Supplementary results

We estimate regressions on different Y's, (*e.g.*, all-day food delivery order volume, lunch peak order volume, and lunch peak per order delivery fee, etc.), and different time spans (2017, 2018, 2019, 2023, and four years combined). Since we focus on urban residents' adaptation to extreme heat, only the estimated relative increases of temperature bins over 20°C are shown in the figures in the Main Text. Figure S2 shows the increase relative to the baseline temperature of all temperature bins. During extremely cold weather conditions, the volume of food delivery orders also increases by approximately 10%. This increase is not as intense during extreme hot weather conditions. In addition, the increases in different dining periods do not exhibit significant gaps, indicating a relatively similar adaptation in the entire day. The regression coefficients on geographic unit-level food delivery order volumes are shown in Table S2 to Table S5. The regression coefficients on geographic unit-level lunch peak delivery fees are shown in Table S20 and Table S21.

To investigate the varying responses to heat stress among different demographic groups, we employ equation 1 on separate city-level panels generated from individual order records. We show the relative increase in lunch peak order volume of temperatures bin above 35°C compared with the temperatures bin from 15°C to 20°C in Figure 2 in the Main Text as the demographic group's response to extreme heat. Figure S4 illustrates the response in all-day order volumes. The regression coefficients for various demographic groups and dependent variables are shown in Table S6 to Table S19.

Some previous works studying behavioural adaptation to climate change consider the intertemporal substitution effect, that is, a lag in the response behaviour than the climate fluctuation. In ref.[6], lag models are employed to study the effect of air pollution on food delivery order behaviour in future days. In our study, the utilization of online food delivery service is an instant response to the extreme ambient temperature, unlike the perception on historical pollution condition. Therefore, we do not take historical temperature indicators into consideration.

S3 Heat exposure quantification

We evaluate the benefits of the food delivery service by quantifying the reduction in heat exposure achieved by each delivery order. When customers order food for delivery, it replaces the need for them to travel to the restaurant in person. Therefore, we approximate the value of mitigated exposure as the exposure users would encounter if they were to make a round trip to the restaurant themselves. We adopt the approach outlined in ref.[7], which defines heat exposure as the product of activity intensity, activity duration, and the National Weather Service (NWS) heat index above 27°C. The calculation of the mitigated heat exposure for each order consists of the following three steps: transportation mode assignment, activity intensity evaluation, and the final accounting of heat exposure.

S3.1 Transportation mode assignment

Since users taking different transportation modes to the restaurant may experience different heat exposure, we first assign the probability of the user taking each of the transportation modes based on the order distance d. Prior studies in the transportation literature have developed effective models for characterizing transportation mode choices[8,9]. The probability density function of travel distance for a specific transportation mode $P(d|\text{mode})$ is often represented by a Gamma distribution[10–12]:

$$P(d|\text{mode}) = \frac{1}{\Gamma(k_{\text{mode}})\theta_{\text{mode}}^{k_{\text{mode}}}} d^{k_{\text{mode}}-1} e^{-\frac{d}{\theta_{\text{mode}}}}, \tag{3}$$

where k_{mode} is the shape parameter and θ_{mode} is the scale parameter associated with the transportation mode. This distribution has an expectation of $k_{\text{mode}}\theta_{\text{mode}}$ and a variance of $k_{\text{mode}}\theta_{\text{mode}}^2$.

In our study, we consider four transportation modes, *i.e.*, walking, cycling, driving, and public transit, for the sake of computational simplicity. We adopt the parameters for these modes as provided in ref.[13], which are derived from extensive observations of travel behaviour among Chinese citizens. The parameters are shown in Table S23. Combining annual transportation reports in several major Chinese cities, we set the overall distribution of transportation modes $P(\text{mode})$ comprising 30% for walking, 12% for cycling, 28% for driving, and 30% for public transit. Given these assumptions, the transportation mode distribution for an order with distance d is computed using the Bayes' theorem:

$$P(\text{mode} = m|d) = \frac{P(d|\text{mode} = m)P(\text{mode} = m)}{\sum_{m'} P(d|\text{mode} = m')P(\text{mode} = m')}, \tag{4}$$

where m' is summed over four transportation modes. Figure S5(a) illustrates the transportation mode distribution $P(\text{mode} = m|d)$ for order distances within 10 kilometers, which is often regarded as the maximum delivery range for food delivery services.

S3.2 Activity intensity evaluation

The intensity of an activity type is characterized in the metabolic equivalent of task (MET)[14], with one MET representing the energy expended when lying or sitting quietly, equivalent to a metabolic rate of consuming 3.5mL O_2/kg/minute. For instance, the intensity of walking is 2.5 MET[15]. Based on the probability of the user taking each of the transportation modes to the restaurant, we further compute the expectation of activity intensity for the round trip, which is the multiplication of the MET for the transportation mode and the travel time.

According to the Compendium of Physical Activities[15], the intensity I_m for walking, cycling, driving, and taking public transit are 2.5, 4.0, 2.5, and 1.3 MET, respectively. Drawing from transportation reports in Chinese cities, we set the average travel speeds v_m for walking, cycling, driving, and public transit as 4.8, 9.7, 30, and 15 km/h, respectively. Consequently, for an order with a distance d, we calculate its expected heat exposure per °C as:

$$\text{Heat exposure}(d) = \sum_m P(\text{mode} = m|d) \times I_m \times \frac{2d}{v_m} \times (\text{NWS heat index} - 27C), \tag{5}$$

where m corresponds to one of the transportation modes. Figure S5(b) illustrates Heat exposure(d) for order distances within 10 kilometers. Notice that the curve grows slower when the distance is above 2km because of the higher probability of driving or taking public transit for longer travel distances. All relevant parameters are summarized in Table S23.

S3.3 Accounting mitigated heat exposure

Following ref.[7], we finally multiple Heat exposure(d) with the heat index exceeding 27°C when the order is placed to obtain the mitigated heat exposure, with a dimension of MET·minute·°C. The NWS heat index quantifies the outdoor ambient temperature incorporating both temperature T and humidity RH with the following formula[16]:

$$\begin{aligned}\text{Heat index}(T, RH) = & -8.78469475556 + 1.61139411T + 2.33854883889RH - 0.14611605T \cdot RH - 0.012308094T^2 \\ & -0.0164248277778RH^2 + 2.211732 \times 10^{-3}T^2RH + 7.2546 \times 10^{-4}T \cdot RH^2 - 3.582 \times 10^{-6}T^2RH^2.\end{aligned} \quad (6)$$

NWS recommends precautionary measures when the heat index exceeds 27°C. Therefore, for each order placed during the lunch peak period (10:30-13:30), we compute its corresponding heat index based on the daily maximum temperature and relative humidity of the neighbourhood in which it is located. To put it into perspective, the average heat index for T =35°C is 49.4°. For an order with a distance of 1 kilometer under this 49.4°heat index condition, its expected mitigate exposure is $\text{Heat exposure}(d) \times (\text{Heat index} - 27) = 50.4 \times 22.4 \approx 1129$ MET·minute·°C.

Based on the mitigated heat exposure for each food delivery order, we assess the effect of heat exposure mitigation for different user groups, in different provinces, and on different days. Figure 3 in the Main text illustrates the temporal shift and demographic differences in heat exposure mitigation. Figure S6 illustrates the spatial variance in heat exposure mitigation.

S4 Food delivery order projection

S4.1 Climate models

To estimate the potential impact of future climate change on food delivery demands, we employ a set of 16 climate projection ensemble datasets sourced from Coupled Model Intercomparison Project Phase 5 (CMIP-5) as listed in Table S24. These datasets are projected under the RCP8.5 "business as usual" emission scenario with an ensemble member of r1i1p1. The RCP8.5 scenario suggests that emissions continue to rise throughout the 21st century. Given that these datasets provide grid-level estimations of daily maximum surface temperatures, we extract the projected temperature for the grid corresponding to the central point of each city from 2019 to 2050. The temperature provided by a CMIP-5 model for city c in year y and date d is denoted as $\text{Temp}_{c,y,d}^{CMIP5}$.

To calibrate the projected temperatures, we adopt the subsequent procedure. For each city, we add the difference in its monthly average maximum temperatures between CMIP5 model projections in 2019 and real recorded daily maximum temperature sourced from GSOD in 2019 $\text{Temp}_{c,y,d}^{GSOD}$ to future projections[17]:

$$\widehat{\text{Temp}}_{c,y,d}^{CMIP5} = \text{Temp}_{c,y,d}^{CMIP5} + (\overline{\text{Temp}}_{c,2019,m}^{GSOD} - \overline{\text{Temp}}_{c,2019,m}^{CMIP5}), \quad (7)$$

where c denotes the city, y, m, and d are the respective year, month, and date. $\overline{\text{Temp}}_{c,2019,m}^{CMIP5}$ represent the monthly average over all CMIP-5 models for city c. Figure 4a in the Main Text contrasts the calibrated temperature projection in 2035 and 2050 with the temperature recorded in 2019, illustrating a discernible global warming trend in the absence of emission control measures.

S4.2 Forecasting future food delivery demands

We combine the city-level projections of daily maximum temperature with historical estimates of the impact of daily maximum temperature on lunch peak food delivery order volume, as described in equation 1. Here we use a non-linear model that divides maximum temperatures into 1°C bins from -10°C to 40°C and regress on the four-year panels (2017, 2018, 2019, and 2023) encompassing the entire population as well as various demographic groups. For each regression model, we first compute the estimated daily food delivery order volume in 2019 in each city $\hat{Y}_{ct,2019}$ with $\text{Temp}_{ct,2019}$ as the baseline order volume. Then we replace $\text{Temp}_{ct,2019}$ with $\widehat{\text{Temp}}_{ct,y}$, the adjusted temperature projection for the same day of a future year y, to forecast the future food delivery order volume on that day $\hat{Y}_{ct,y}$ for each CMIP5 model.

With the above process, we can obtain the projected order volume in each city for each CMIP-5 model in a future day. We compare the average of $\hat{Y}_{ct,y}$ over all models and compare it with the baseline order volume in 2019 to assess the impact of future climate change. This comparison can be further conducted on all demographic groups based on the city-level panels constructed from the individual-level order record dataset. We focus on the monthly and annual relative increase in order volume across different demographic groups as well as different cities. Figure 4 in the Main Text demonstrates the heterogeneous change in different months and compares the annual change from 2024 to 2050 across demographic groups. We show the spatial variation in the change of 2050 food delivery demands in Figure S7 with six cities with relative increase higher than 3% marked. Cities in Southern and Central China are expected to experience more substantial demand increases than cities in cooler Northern China.

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Supplementary Figures

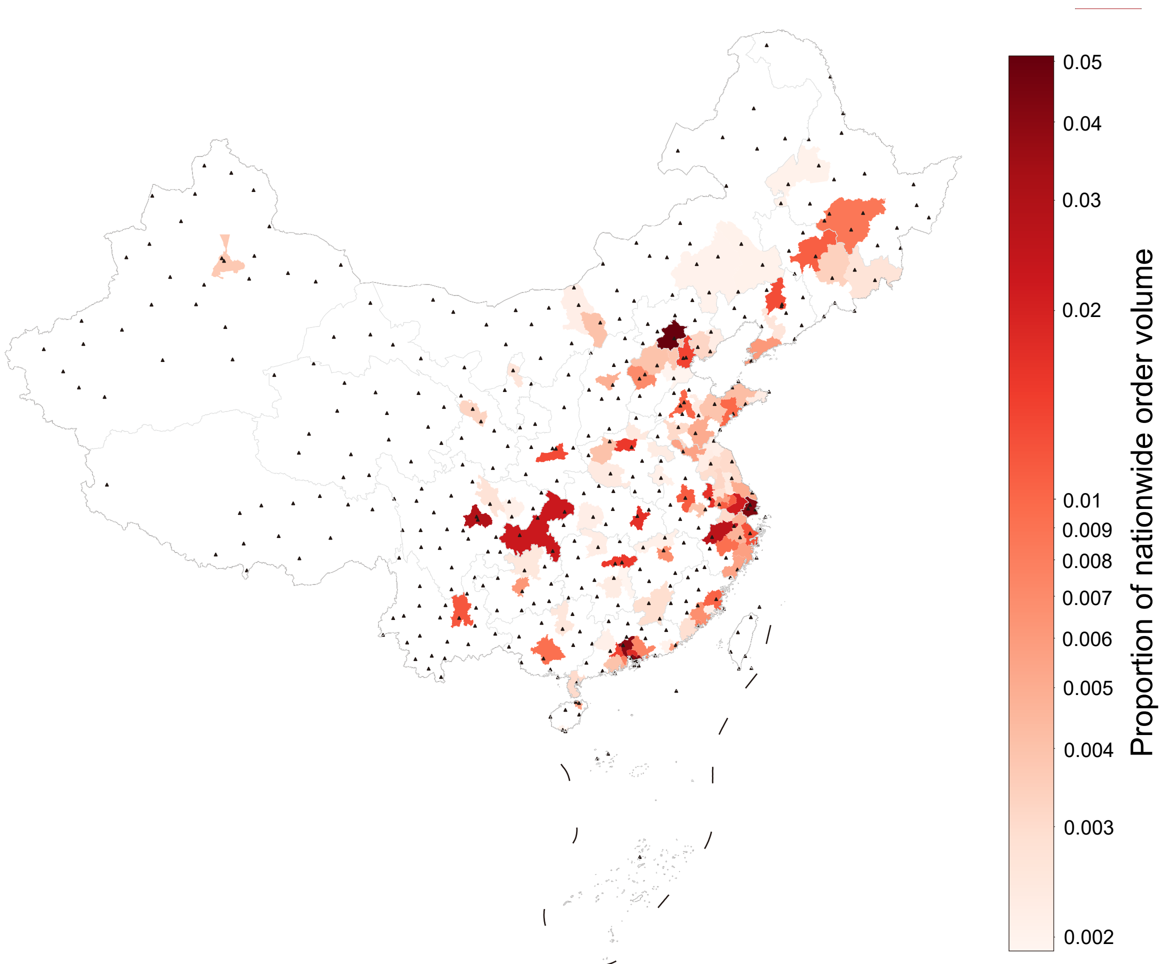

Figure S1. Spatial distribution of prefectural 100 cities with highest order volumes. Colours denote the ratio of the city's order volume to the nationwide order volume. Black markers represent ground stations with meteorological data.

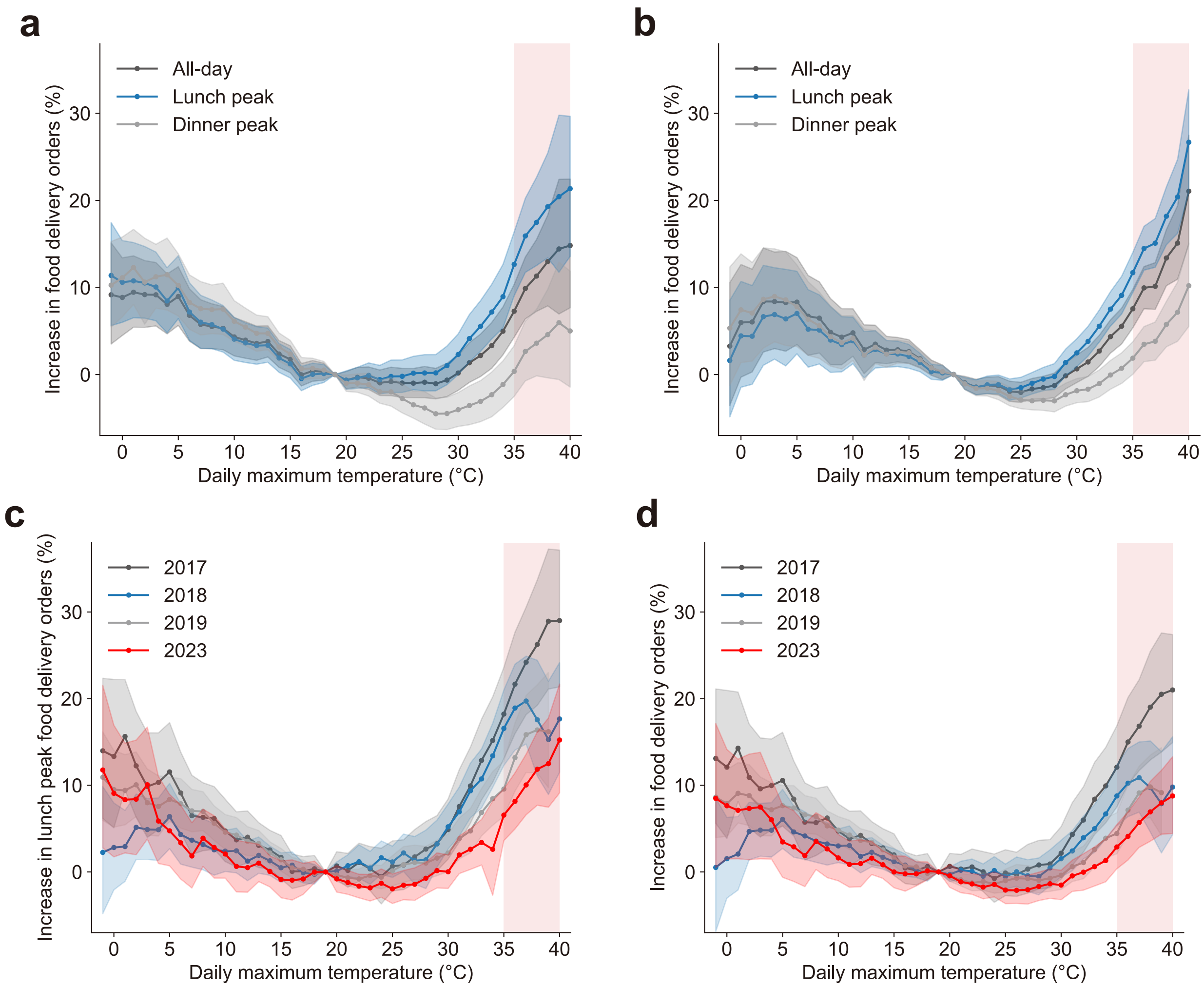

Figure S2. **a, b** The estimated effect of daily maximum temperature on the number of all-day, lunch peak, and dinner peak food delivery orders over 100 Chinese cities (**a**) and 9,638 urban neighbourhoods (**b**). **c,d** The estimated effect of daily maximum temperature on lunch peak (**c**) and all-day (**d**) food delivery orders over 100 Chinese cities in four separate years. Shaded areas represent 95% confidence intervals. The light red colour denotes the temperature range of heat events. All temperature bins are illustrated.

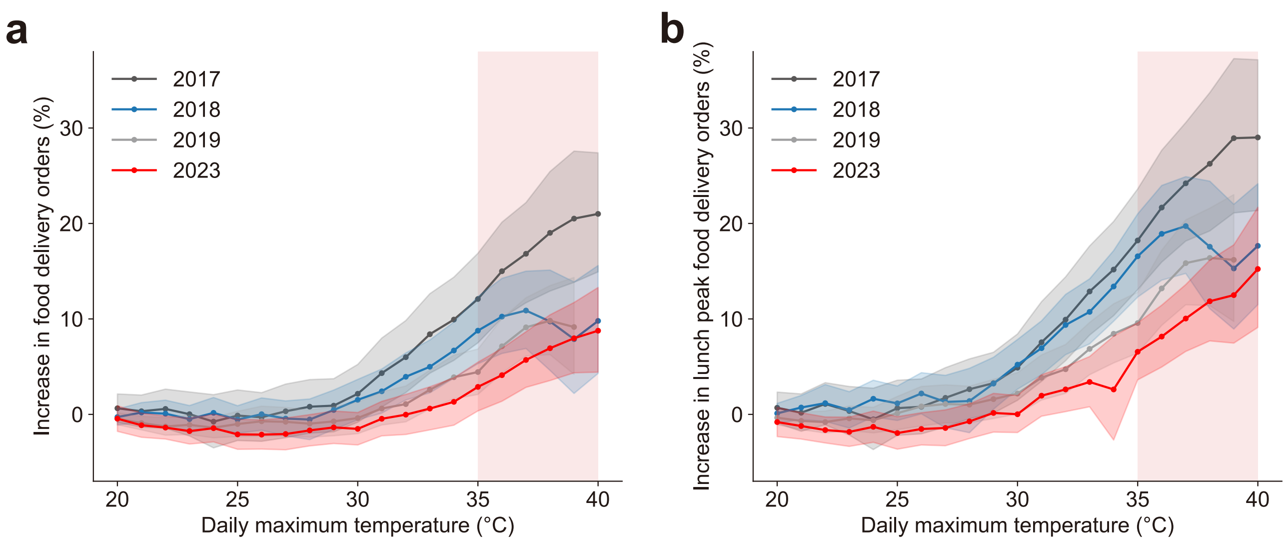

Figure S3. The estimated effect of daily maximum temperature on all-day (**a**) and lunch peak (**b**) food delivery orders over 100 Chinese cities in 2017, 2018, 2019, and 2023, respectively.

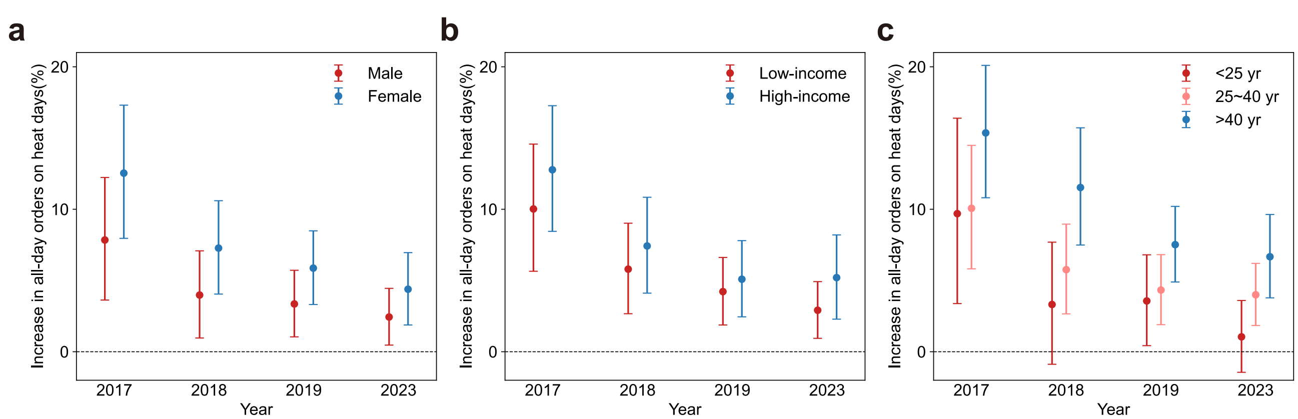

Figure S4. Relative increase in food delivery orders on heat days across gender (**a**), income (**b**), and age (**c**) groups in four separate years.

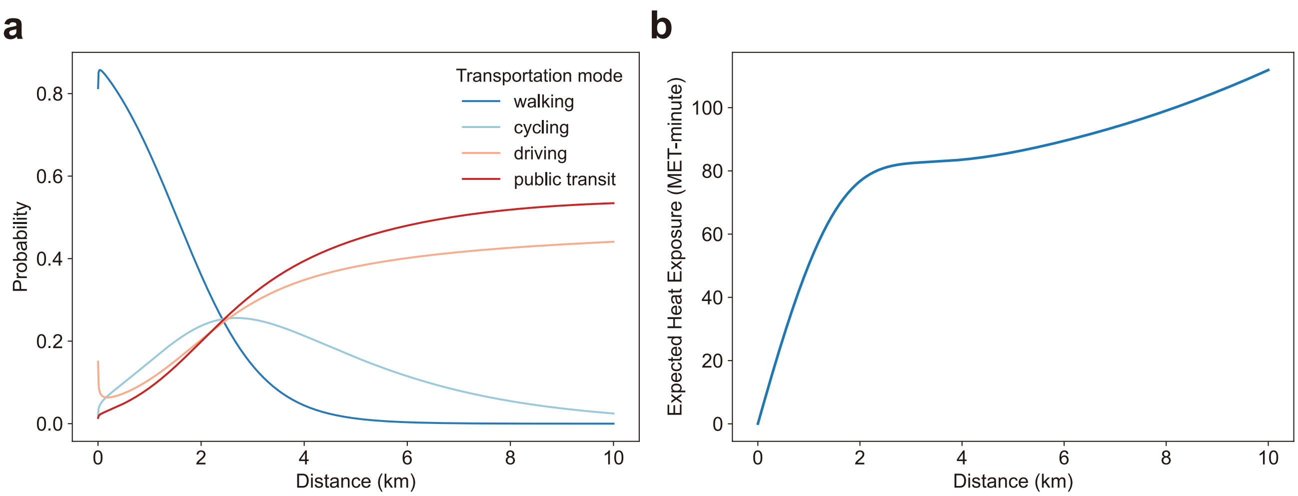

Figure S5. Information to calculate mitigated heat exposure of each food delivery order. (**a**) The probability of choosing each of the transportation modes of orders within a 10km range. (**b**) Expected heat exposure per °C of orders within a 10km range.

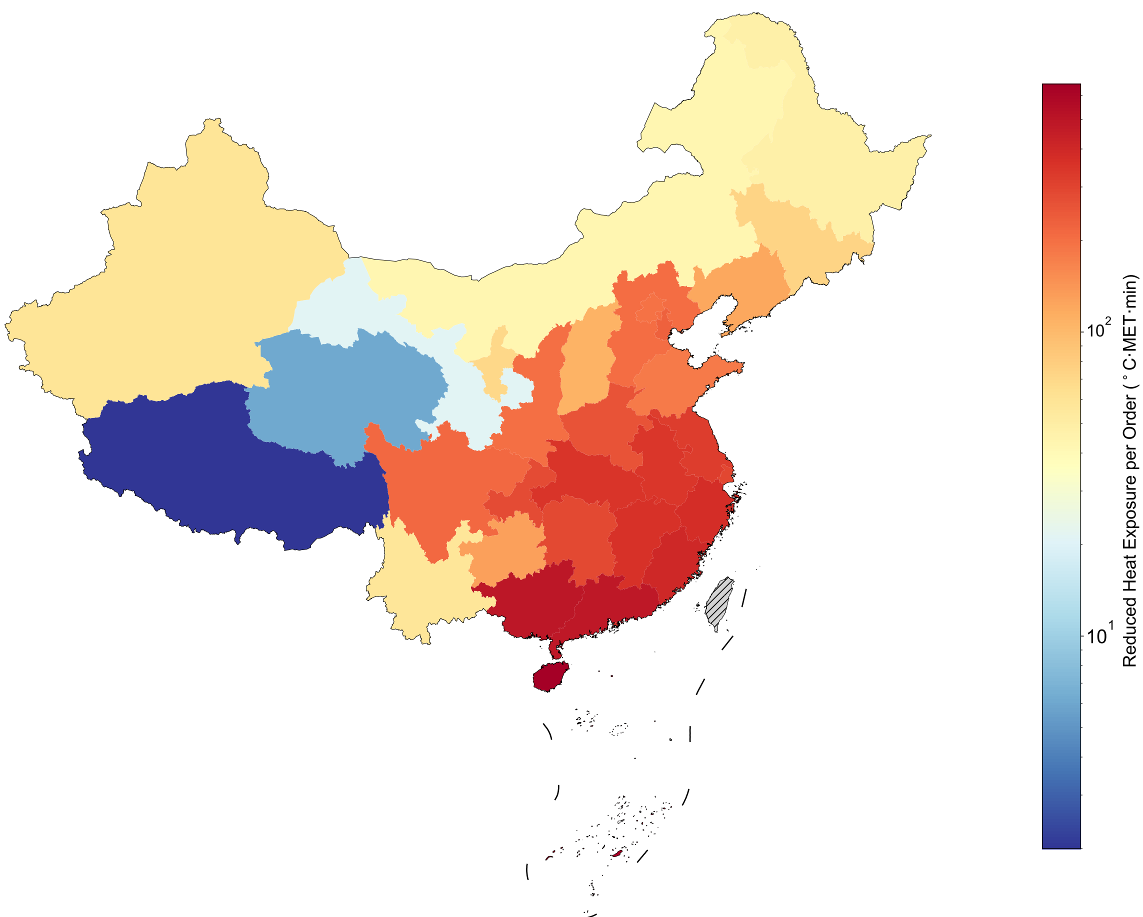

Figure S6. Mitigated heat exposure per lunch peak food delivery order across Chinese provinces.

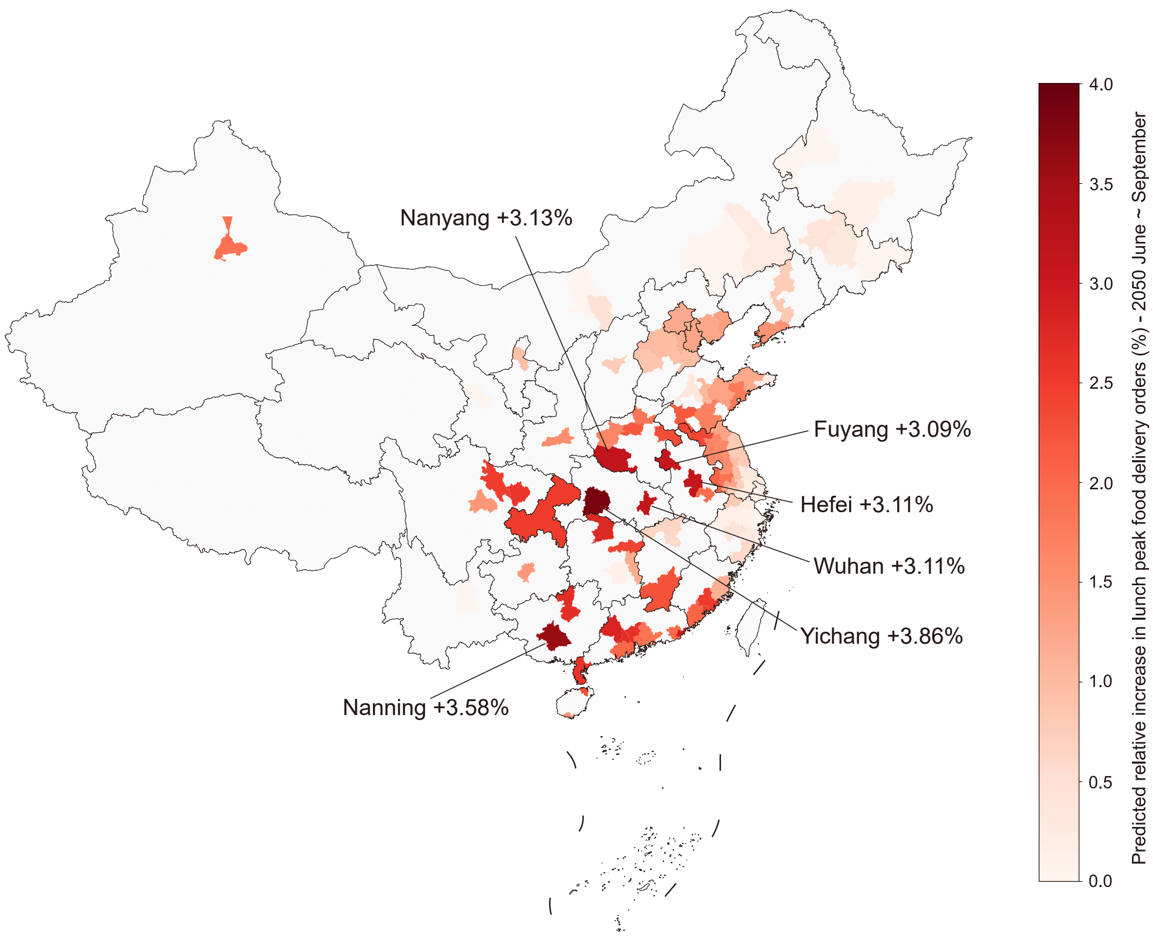

Figure S7. City-level predicted relative change in lunch peak food delivery orders in June to September for the impact of climate change by 2050. Six cities with a relative increase above 3% are highlighted.

Supplementary Tables

Table S1. List of 100 cities with highest order volumes.

Rank	City	Province	Rank	City	Province	Rank	City	Province
1	Beijing	Beijing	35	Guiyang	Guizhou	68	Zhenjiang	Jiangsu
2	Shanghai	Shanghai	36	Dalian	Liaoning	69	Zhangzhou	Fujian
3	Shenzhen	Guangdong	37	Shantou	Guangdong	70	Mianyang	Sichuan
4	Guangzhou	Guangdong	38	Changzhou	Jiangsu	71	Yanbian	Jilin
5	Chengdu	Sichuan	39	Taizhou	Zhejiang	72	Yinchuan	Ningxia
6	Hangzhou	Zhejiang	40	Haikou	Hainan	73	Anshan	Liaoning
7	Chongiqng	Chongiqng	41	Xuzhou	Jiangsu	74	Liuzhou	Guangxi
8	Suzhou	Jiangsu	42	Wenzhou	Zhejiang	75	Zunyi	Guizhou
9	Dongguan	Guangdong	43	Linyi	Shandong	76	Xinxiang	Henan
10	Wuhan	Hubei	44	Nantong	Jiangsu	77	Nanyang	Henan
11	Nanjing	Jiangsu	45	Taiyuan	Shanxi	78	Zibo	Shandong
12	Zhengzhou	Henan	46	Jiaxing	Zhejiang	79	Taizhou	Jiangsu
13	Changsha	Hunan	47	Shaoxing	Zhejiang	80	Hengyang	Hunan
14	Foshan	Guangdong	48	Zhuhai	Guangdong	81	Shangqiu	Henan
15	Tianjin	Tianjin	49	Yantai	Shandong	82	Weihai	Shandong
16	Xi'an	Shaanxi	50	Luoyang	Henan	83	Qinhuangdao	Hebei
17	Shenyang	Liaoning	51	Hohhot	Nei Mongol	84	Suqian	Jiangsu
18	Ningbo	Zhejiang	52	Baoding	Hebei	85	Changde	Hunan
19	Kunming	Yunan	53	Wuhu	Anhui	86	Yichang	Hubei
20	Hefei	Anhui	54	Jiangmen	Guangdong	87	Baotou	Nei Mongol
21	Wuxi	Jiangsu	55	Weifang	Shandong	88	Putian	Fujian
22	Changchun	Jilin	56	Langfang	Hebei	89	Lianyungang	Jiangsu
23	Fuzhou	Fujian	57	Urumqi	Xinjiang	90	Jiujiang	Jiangxi
24	Jinan	Shandong	58	Jilin	Jilin	91	Fuyang	Anhui
25	Qingdao	Shandong	59	Lanzhou	Gansu	92	Nanchong	Sichuan
26	Jinhua	Zhejiang	60	Tangshan	Hebei	93	Zhaoqing	Guangdong
27	Nanning	Guangxi	61	Yangzhou	Jiangsu	94	Qiqihar	Heilongjiang
28	Harbin	Heilongjiang	62	Jining	Shandong	95	Sanya	Hainan
29	Zhongshan	Guangdong	63	Huzhou	Zhejiang	96	Tongliao	Nei Mongol
30	Xiamen	Fujian	64	Yancheng	Jiangsu	97	Jieyang	Guangdong
31	Huizhou	Guangdong	65	Zhanjiang	Guangdong	98	Chifeng	Nei Mongol
32	Shijiazhuang	Hebei	66	Huaian	Jiangsu	99	Cangzhou	Hebei
33	Quanzhou	Fujian	67	Ganzhou	Jiangxi	100	Zhuzhou	Hunan
34	Nanchang	Jiangxi						

Table S2. Regression coefficients of city-level food delivery order volume on meteorological conditions. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable:		
	all-day orders	lunch peak orders	dinner peak orders
cut_maxtemp(-Inf,0]	0.088*** (0.027)	0.108*** (0.027)	0.098*** (0.022)
cut_maxtemp(0,1]	0.085*** (0.021)	0.101*** (0.021)	0.105*** (0.021)
cut_maxtemp(1,2]	0.090*** (0.019)	0.102*** (0.020)	0.116*** (0.019)
cut_maxtemp(2,3]	0.088*** (0.018)	0.100*** (0.019)	0.101*** (0.022)
cut_maxtemp(3,4]	0.088*** (0.017)	0.096*** (0.018)	0.106*** (0.017)
cut_maxtemp(4,5]	0.078*** (0.016)	0.081*** (0.017)	0.109*** (0.019)
cut_maxtemp(5,6]	0.086*** (0.016)	0.095*** (0.017)	0.097*** (0.016)

cut_maxtemp(6,7]	0.066*** (0.014)	0.069*** (0.016)	0.080*** (0.015)
cut_maxtemp(7,8]	0.056*** (0.013)	0.058*** (0.014)	0.073*** (0.014)
cut_maxtemp(8,9]	0.054*** (0.012)	0.056*** (0.013)	0.072*** (0.013)
cut_maxtemp(9,10]	0.052*** (0.012)	0.051*** (0.013)	0.072*** (0.014)
cut_maxtemp(10,11]	0.042*** (0.011)	0.040*** (0.012)	0.059*** (0.011)
cut_maxtemp(11,12]	0.039*** (0.010)	0.036*** (0.011)	0.053*** (0.010)
cut_maxtemp(12,13]	0.035*** (0.010)	0.033*** (0.011)	0.046*** (0.010)
cut_maxtemp(13,14]	0.037*** (0.009)	0.033*** (0.010)	0.046*** (0.009)
cut_maxtemp(14,15]	0.023*** (0.008)	0.019** (0.008)	0.031*** (0.008)
cut_maxtemp(15,16]	0.017** (0.008)	0.012 (0.008)	0.023*** (0.008)
cut_maxtemp(16,17]	-0.000 (0.006)	-0.005 (0.007)	0.007 (0.006)
cut_maxtemp(17,18]	0.004 (0.006)	0.000 (0.006)	0.007 (0.006)
cut_maxtemp(18,19]	0.003 (0.005)	0.001 (0.005)	0.005 (0.005)
cut_maxtemp(20,21]	-0.006 (0.005)	-0.006 (0.005)	-0.010** (0.005)
cut_maxtemp(21,22]	-0.003 (0.006)	-0.004 (0.006)	-0.010* (0.005)
cut_maxtemp(22,23]	-0.004 (0.007)	-0.001 (0.007)	-0.012* (0.007)
cut_maxtemp(23,24]	-0.010 (0.007)	-0.006 (0.008)	-0.020*** (0.007)
cut_maxtemp(24,25]	-0.008 (0.008)	-0.002 (0.009)	-0.020** (0.009)
cut_maxtemp(25,26]	-0.010 (0.009)	-0.002 (0.009)	-0.028*** (0.009)
cut_maxtemp(26,27]	-0.010 (0.009)	0.002 (0.010)	-0.035*** (0.008)
cut_maxtemp(27,28]	-0.009 (0.009)	0.002 (0.010)	-0.039*** (0.010)
cut_maxtemp(28,29]	-0.011 (0.009)	0.002 (0.010)	-0.046*** (0.009)
cut_maxtemp(29,30]	-0.006 (0.010)	0.010 (0.011)	-0.046*** (0.010)
cut_maxtemp(30,31]	0.002 (0.010)	0.023* (0.012)	-0.041*** (0.010)
cut_maxtemp(31,32]	0.013 (0.011)	0.041*** (0.013)	-0.036*** (0.012)
cut_maxtemp(32,33]	0.022* (0.012)	0.054*** (0.014)	-0.031** (0.012)
cut_maxtemp(33,34]	0.033** (0.013)	0.069*** (0.015)	-0.023* (0.013)
cut_maxtemp(34,35]	0.049*** (0.013)	0.086*** (0.017)	-0.011 (0.014)
cut_maxtemp(35,36]	0.070*** (0.014)	0.119*** (0.016)	0.004 (0.015)
cut_maxtemp(36,37]	0.094*** (0.016)	0.148*** (0.019)	0.026 (0.017)
cut_maxtemp(37,38]	0.107*** (0.019)	0.161*** (0.022)	0.035* (0.019)
cut_maxtemp(38,39]	0.122*** (0.023)	0.176*** (0.025)	0.045* (0.025)
cut_maxtemp(39,40]	0.135*** (0.034)	0.186*** (0.038)	0.058* (0.032)
cut_maxtemp(40, Inf]	0.138*** (0.032)	0.194*** (0.033)	0.049 (0.032)
cut_precp(0.1,10]	0.013*** (0.003)	0.006* (0.003)	0.018*** (0.003)
cut_precp(10,25]	0.047*** (0.005)	0.030*** (0.005)	0.065*** (0.005)
cut_precp(25,50]	0.055*** (0.009)	0.026* (0.013)	0.080*** (0.013)
cut_precp(50, Inf]	0.039** (0.018)	-0.021 (0.034)	0.058 (0.036)
cut_humid(10,20]	0.066 (0.044)	0.057 (0.041)	0.068 (0.045)
cut_humid(20,30]	0.058 (0.045)	0.046 (0.043)	0.067 (0.047)
cut_humid(30,40]	0.047 (0.046)	0.032 (0.044)	0.055 (0.048)
cut_humid(40,50]	0.027 (0.047)	0.013 (0.045)	0.032 (0.049)
cut_humid(50,60]	0.017 (0.048)	0.003 (0.045)	0.019 (0.049)
cut_humid(60,70]	0.018 (0.048)	0.006 (0.045)	0.021 (0.049)
cut_humid(70,80]	0.017 (0.049)	0.005 (0.046)	0.023 (0.050)
cut_humid(80,90]	0.032 (0.050)	0.016 (0.047)	0.042 (0.051)
cut_humid(90, Inf]	0.072 (0.050)	0.057 (0.047)	0.073 (0.051)
City Fixed Effect	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes
Observations	129,760	129,760	129,760
Adjusted R^2	0.976	0.969	0.964

Note: Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Data coverage time: Jan. 1st 2017 to Dec. 31st 2019, Jan. 1st 2023 to Aug. 20th 2023

Table S3. Regression coefficients of urban neighbourhood-level food delivery order volume on meteorological conditions. Relative increases are interpreted as $e^{\beta}-1$.

	Dependent variable:		
	all-day orders	lunch peak orders	dinner peak orders
cut_maxtemp(-Inf,0]	0.032 (0.035)	0.016 (0.034)	0.052 (0.033)
cut_maxtemp(0,1]	0.058^{*} (0.031)	0.043 (0.030)	0.072^{**} (0.030)
cut_maxtemp(1,2]	0.059^{**} (0.028)	0.043 (0.028)	0.068^{**} (0.027)
cut_maxtemp(2,3]	0.081^{***} (0.028)	0.064^{**} (0.027)	0.083^{***} (0.027)
cut_maxtemp(3,4]	0.081^{***} (0.026)	0.067^{***} (0.025)	0.086^{***} (0.025)
cut_maxtemp(4,5]	0.079^{***} (0.027)	0.062^{**} (0.027)	0.082^{***} (0.025)
cut_maxtemp(5,6]	0.080^{***} (0.024)	0.068^{***} (0.023)	0.075^{***} (0.022)
cut_maxtemp(6,7]	0.065^{***} (0.022)	0.051^{**} (0.022)	0.062^{***} (0.020)
cut_maxtemp(7,8]	0.063^{***} (0.020)	0.050^{***} (0.019)	0.054^{***} (0.018)
cut_maxtemp(8,9]	0.047^{**} (0.018)	0.039^{**} (0.019)	0.043^{**} (0.017)
cut_maxtemp(9,10]	0.042^{***} (0.016)	0.034^{**} (0.016)	0.036^{**} (0.015)
cut_maxtemp(10,11]	0.047^{***} (0.013)	0.038^{***} (0.013)	0.041^{***} (0.013)
cut_maxtemp(11,12]	0.028^{**} (0.014)	0.022^{*} (0.013)	0.022 (0.015)
cut_maxtemp(12,13]	0.034^{***} (0.011)	0.028^{***} (0.011)	0.031^{***} (0.009)
cut_maxtemp(13,14]	0.028^{***} (0.008)	0.023^{***} (0.008)	0.023^{***} (0.008)
cut_maxtemp(14,15]	0.028^{***} (0.007)	0.023^{***} (0.007)	0.026^{***} (0.007)
cut_maxtemp(15,16]	0.026^{***} (0.007)	0.021^{***} (0.007)	0.025^{***} (0.006)
cut_maxtemp(16,17]	0.018^{***} (0.005)	0.014^{**} (0.005)	0.017^{***} (0.005)
cut_maxtemp(17,18]	0.008^{*} (0.004)	0.003 (0.004)	0.008^{*} (0.004)
cut_maxtemp(18,19]	0.002 (0.004)	0.002 (0.004)	0.003 (0.004)
cut_maxtemp(20,21]	-0.010^{**} (0.004)	-0.010^{***} (0.004)	-0.011^{***} (0.003)
cut_maxtemp(21,22]	-0.014^{***} (0.005)	-0.015^{***} (0.004)	-0.016^{***} (0.004)
cut_maxtemp(22,23]	-0.013^{**} (0.005)	-0.012^{**} (0.005)	-0.016^{***} (0.005)
cut_maxtemp(23,24]	-0.013^{**} (0.005)	-0.011^{**} (0.006)	-0.019^{***} (0.005)
cut_maxtemp(24,25]	-0.020^{***} (0.006)	-0.018^{***} (0.006)	-0.025^{***} (0.006)
cut_maxtemp(25,26]	-0.021^{***} (0.006)	-0.015^{**} (0.006)	-0.030^{***} (0.005)
cut_maxtemp(26,27]	-0.017^{***} (0.006)	-0.010 (0.006)	-0.031^{***} (0.005)
cut_maxtemp(27,28]	-0.015^{**} (0.007)	-0.005 (0.007)	-0.030^{***} (0.006)
cut_maxtemp(28,29]	-0.013^{*} (0.007)	-0.002 (0.008)	-0.031^{***} (0.007)
cut_maxtemp(29,30]	-0.001 (0.008)	0.014^{*} (0.008)	-0.023^{***} (0.007)
cut_maxtemp(30,31]	0.007 (0.008)	0.025^{***} (0.008)	-0.019^{***} (0.007)
cut_maxtemp(31,32]	0.014^{*} (0.008)	0.037^{***} (0.008)	-0.017^{**} (0.007)
cut_maxtemp(32,33]	0.027^{***} (0.009)	0.054^{***} (0.009)	-0.010 (0.008)
cut_maxtemp(33,34]	0.043^{***} (0.009)	0.072^{***} (0.009)	-0.001 (0.008)
cut_maxtemp(34,35]	0.054^{***} (0.010)	0.087^{***} (0.010)	0.007 (0.009)
cut_maxtemp(35,36]	0.073^{***} (0.010)	0.111^{***} (0.010)	0.019^{**} (0.009)
cut_maxtemp(36,37]	0.095^{***} (0.011)	0.135^{***} (0.011)	0.034^{***} (0.010)
cut_maxtemp(37,38]	0.097^{***} (0.012)	0.141^{***} (0.012)	0.037^{***} (0.011)
cut_maxtemp(38,39]	0.126^{***} (0.015)	0.167^{***} (0.014)	0.056^{***} (0.013)
cut_maxtemp(39,40]	0.141^{***} (0.019)	0.186^{***} (0.018)	0.069^{***} (0.016)
cut_maxtemp(40, Inf]	0.191^{***} (0.026)	0.237^{***} (0.024)	0.097^{***} (0.022)
cut_precp(0.1,10]	0.010^{***} (0.003)	0.005 (0.003)	0.015^{***} (0.004)
cut_precp(10,25]	0.045^{***} (0.005)	0.030^{***} (0.005)	0.057^{***} (0.005)
cut_precp(25,50]	0.054^{***} (0.006)	0.032^{***} (0.007)	0.069^{***} (0.007)
cut_precp(50, Inf]	0.039^{**} (0.017)	0.002 (0.024)	0.054^{**} (0.022)
cut_humid(10,20]	0.027 (0.029)	0.015 (0.025)	0.013 (0.026)
cut_humid(20,30]	0.024 (0.030)	0.010 (0.026)	0.012 (0.028)
cut_humid(30,40]	0.020 (0.030)	0.004 (0.026)	0.009 (0.028)

cut_humid(40,50]	0.016 (0.031)	0.001 (0.027)	0.005 (0.028)
cut_humid(50,60]	0.018 (0.032)	0.004 (0.028)	0.005 (0.029)
cut_humid(60,70]	0.020 (0.033)	0.008 (0.029)	0.006 (0.030)
cut_humid(70,80]	0.030 (0.033)	0.017 (0.029)	0.014 (0.030)
cut_humid(80,90]	0.041 (0.034)	0.023 (0.030)	0.029 (0.031)
cut_humid(90, Inf]	0.090*** (0.035)	0.071** (0.031)	0.071** (0.032)
is_holiday	-0.085** (0.034)	-0.096*** (0.031)	-0.115*** (0.036)
is_spring_festival	-0.520*** (0.061)	-0.485*** (0.058)	-0.500*** (0.062)
weekday_Tue	0.011 (0.014)	0.005 (0.014)	0.017 (0.014)
weekday_Wed	0.017 (0.013)	0.012 (0.013)	0.025* (0.013)
weekday_Thu	0.021 (0.014)	0.016 (0.012)	0.025 (0.015)
weekday_Fri	0.039*** (0.014)	0.023* (0.013)	0.041*** (0.015)
weekday_Sat	0.107*** (0.016)	0.099*** (0.014)	0.065*** (0.017)
weekday_Sun	0.117*** (0.015)	0.114*** (0.014)	0.077*** (0.015)
Neighbourhood Fixed Effect	Yes	Yes	Yes
City-month Fixed Effect	Yes	Yes	Yes
Observations	12,487,350	12,487,350	12,487,350
Adjusted R^2	0.915	0.925	0.923
Note:	Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		
Data coverage time:	Jan. 1st 2017 to Dec. 31st 2019, Jan. 1st 2023 to Aug. 20th 2023		

Table S4. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Lunch peak order volume			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.131*** (0.036)	0.022 (0.036)	0.104*** (0.023)	0.111*** (0.042)
cut_maxtemp(0,1]	0.125*** (0.038)	0.028 (0.025)	0.091*** (0.020)	0.087** (0.035)
cut_maxtemp(1,2]	0.145*** (0.028)	0.029 (0.020)	0.090*** (0.019)	0.080*** (0.029)
cut_maxtemp(2,3]	0.116*** (0.027)	0.050*** (0.018)	0.096*** (0.017)	0.081** (0.031)
cut_maxtemp(3,4]	0.094*** (0.028)	0.048*** (0.017)	0.077*** (0.018)	0.096*** (0.030)
cut_maxtemp(4,5]	0.098*** (0.025)	0.048*** (0.017)	0.073*** (0.016)	0.057** (0.024)
cut_maxtemp(5,6]	0.109*** (0.025)	0.062*** (0.018)	0.080*** (0.012)	0.046** (0.020)
cut_maxtemp(6,7]	0.087*** (0.021)	0.042** (0.017)	0.076*** (0.013)	0.033 (0.021)
cut_maxtemp(7,8]	0.063*** (0.022)	0.036** (0.015)	0.068*** (0.012)	0.018 (0.019)
cut_maxtemp(8,9]	0.061*** (0.019)	0.031** (0.014)	0.068*** (0.011)	0.038** (0.016)
cut_maxtemp(9,10]	0.060*** (0.017)	0.025* (0.015)	0.055*** (0.010)	0.028 (0.018)
cut_maxtemp(10,11]	0.046*** (0.017)	0.024** (0.012)	0.045*** (0.010)	0.021 (0.014)
cut_maxtemp(11,12]	0.036** (0.015)	0.024* (0.013)	0.042*** (0.010)	0.006 (0.015)
cut_maxtemp(12,13]	0.039*** (0.014)	0.012 (0.011)	0.035*** (0.008)	0.005 (0.014)
cut_maxtemp(13,14]	0.030** (0.013)	0.019* (0.010)	0.032*** (0.007)	0.010 (0.011)
cut_maxtemp(14,15]	0.025** (0.011)	0.013 (0.008)	0.022*** (0.006)	0.001 (0.009)
cut_maxtemp(15,16]	0.017 (0.012)	0.005 (0.009)	0.014** (0.007)	-0.009 (0.011)
cut_maxtemp(16,17]	0.001 (0.010)	0.008 (0.008)	0.005 (0.006)	-0.010 (0.012)
cut_maxtemp(17,18]	0.001 (0.009)	-0.001 (0.006)	0.003 (0.005)	-0.008 (0.009)
cut_maxtemp(18,19]	0.004 (0.008)	-0.003 (0.006)	-0.002 (0.005)	-0.000 (0.006)
cut_maxtemp(20,21]	0.007 (0.008)	0.001 (0.005)	-0.003 (0.004)	-0.008 (0.008)
cut_maxtemp(21,22]	0.002 (0.010)	0.007 (0.006)	-0.007 (0.005)	-0.012* (0.007)
cut_maxtemp(22,23]	0.011 (0.011)	0.012 (0.010)	-0.008 (0.006)	-0.017** (0.007)
cut_maxtemp(23,24]	0.003 (0.013)	0.005 (0.010)	-0.004 (0.006)	-0.018** (0.008)

cut_maxtemp(24,25]	-0.005 (0.016)	0.016* (0.010)	-0.006 (0.007)	-0.013 (0.008)
cut_maxtemp(25,26]	0.007 (0.014)	0.011 (0.009)	0.001 (0.009)	-0.020** (0.009)
cut_maxtemp(26,27]	0.008 (0.014)	0.022** (0.011)	0.008 (0.010)	-0.015* (0.009)
cut_maxtemp(27,28]	0.017 (0.015)	0.013 (0.014)	0.011 (0.010)	-0.014 (0.010)
cut_maxtemp(28,29]	0.026* (0.015)	0.014 (0.017)	0.010 (0.010)	-0.007 (0.009)
cut_maxtemp(29,30]	0.032** (0.016)	0.032** (0.013)	0.016 (0.010)	0.002 (0.010)
cut_maxtemp(30,31]	0.048*** (0.017)	0.051*** (0.012)	0.022** (0.011)	0.000 (0.010)
cut_maxtemp(31,32]	0.073*** (0.020)	0.067*** (0.013)	0.038*** (0.011)	0.019* (0.011)
cut_maxtemp(32,33]	0.095*** (0.020)	0.090*** (0.015)	0.046*** (0.012)	0.026** (0.012)
cut_maxtemp(33,34]	0.121*** (0.021)	0.102*** (0.015)	0.066*** (0.013)	0.033** (0.013)
cut_maxtemp(34,35]	0.141*** (0.022)	0.126*** (0.016)	0.081*** (0.014)	0.026 (0.027)
cut_maxtemp(35,36]	0.167*** (0.022)	0.153*** (0.019)	0.091*** (0.015)	0.064*** (0.014)
cut_maxtemp(36,37]	0.196*** (0.024)	0.173*** (0.021)	0.124*** (0.018)	0.078*** (0.015)
cut_maxtemp(37,38]	0.217*** (0.025)	0.180*** (0.021)	0.147*** (0.019)	0.096*** (0.016)
cut_maxtemp(38,39]	0.233*** (0.029)	0.162*** (0.029)	0.152*** (0.022)	0.112*** (0.019)
cut_maxtemp(39,40]	0.254*** (0.032)	0.142*** (0.029)	0.150*** (0.029)	0.118*** (0.023)
cut_maxtemp(40, Inf]	0.255*** (0.031)	0.163*** (0.027)	0.005* (0.003)	0.142*** (0.027)
cut_precp(0.1,10]	0.011** (0.004)	0.004 (0.004)	0.025*** (0.005)	0.009*** (0.003)
cut_precp(10,25]	0.036*** (0.008)	0.018*** (0.006)	0.045*** (0.006)	0.038*** (0.007)
cut_precp(25,50]	0.040*** (0.014)	-0.002 (0.038)	0.040*** (0.012)	0.047*** (0.009)
cut_precp(50, Inf]	0.043** (0.019)	-0.045 (0.069)	-0.009 (0.014)	-0.130 (0.163)
cut_humid(20,30]	-0.024* (0.012)	-0.050 (0.032)	-0.035** (0.014)	0.012 (0.012)
cut_humid(30,40]	-0.036** (0.016)	-0.055 (0.040)	-0.052*** (0.015)	0.005 (0.011)
cut_humid(40,50]	-0.057*** (0.016)	-0.081* (0.043)	-0.069*** (0.015)	-0.015 (0.013)
cut_humid(50,60]	-0.070*** (0.018)	-0.098** (0.044)	-0.080*** (0.016)	-0.032*** (0.012)
cut_humid(60,70]	-0.070*** (0.020)	-0.106** (0.044)	-0.086*** (0.016)	-0.037*** (0.013)
cut_humid(70,80]	-0.077*** (0.023)	-0.109** (0.045)	-0.091*** (0.017)	-0.021* (0.012)
cut_humid(80,90]	-0.069*** (0.024)	-0.105** (0.046)	-0.093*** (0.018)	-0.009 (0.013)
cut_humid(90, Inf]	-0.008 (0.023)	-0.090* (0.047)	-0.056*** (0.020)	-0.002 (0.013)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.975	0.967	0.989	0.976
Note:		Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01		

Table S5. Annual regression coefficients of city-level all-day food delivery order volume on meteorological conditions. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Daily order volume			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.123*** (0.035)	0.005 (0.039)	0.083*** (0.022)	0.082** (0.039)
cut_maxtemp(0,1]	0.114*** (0.038)	0.015 (0.023)	0.076*** (0.018)	0.074** (0.030)
cut_maxtemp(1,2]	0.133*** (0.028)	0.020 (0.021)	0.087*** (0.016)	0.069** (0.027)
cut_maxtemp(2,3]	0.104*** (0.027)	0.046*** (0.016)	0.084*** (0.016)	0.071** (0.029)
cut_maxtemp(3,4]	0.092*** (0.026)	0.047*** (0.015)	0.073*** (0.016)	0.072** (0.029)
cut_maxtemp(4,5]	0.095*** (0.024)	0.047*** (0.015)	0.069*** (0.014)	0.058*** (0.022)
cut_maxtemp(5,6]	0.100*** (0.025)	0.059*** (0.016)	0.074*** (0.011)	0.034* (0.020)
cut_maxtemp(6,7]	0.081*** (0.020)	0.045*** (0.014)	0.071*** (0.012)	0.029 (0.020)
cut_maxtemp(7,8]	0.056*** (0.021)	0.041*** (0.013)	0.064*** (0.010)	0.019 (0.018)
cut_maxtemp(8,9]	0.055*** (0.018)	0.035*** (0.012)	0.062*** (0.010)	0.035** (0.016)

cut_maxtemp(9,10]	0.060*** (0.017)	0.032*** (0.012)	0.052*** (0.008)	0.026 (0.017)
cut_maxtemp(10,11]	0.046*** (0.015)	0.030*** (0.010)	0.047*** (0.007)	0.016 (0.013)
cut_maxtemp(11,12]	0.038** (0.015)	0.030*** (0.011)	0.042*** (0.008)	0.009 (0.013)
cut_maxtemp(12,13]	0.041*** (0.013)	0.018* (0.010)	0.036*** (0.007)	0.010 (0.014)
cut_maxtemp(13,14]	0.032*** (0.012)	0.022*** (0.008)	0.034*** (0.006)	0.016* (0.009)
cut_maxtemp(14,15]	0.027** (0.011)	0.017** (0.007)	0.025*** (0.005)	0.008 (0.008)
cut_maxtemp(15,16]	0.020 (0.012)	0.012 (0.007)	0.017*** (0.005)	-0.000 (0.009)
cut_maxtemp(16,17]	0.005 (0.009)	0.008 (0.006)	0.007 (0.004)	-0.002 (0.010)
cut_maxtemp(17,18]	0.002 (0.009)	0.002 (0.005)	0.006 (0.004)	-0.002 (0.007)
cut_maxtemp(18,19]	0.006 (0.007)	-0.001 (0.005)	-0.002 (0.004)	0.001 (0.005)
cut_maxtemp(20,21]	0.006 (0.007)	-0.003 (0.004)	-0.005 (0.003)	-0.004 (0.007)
cut_maxtemp(21,22]	0.003 (0.008)	0.002 (0.005)	-0.009** (0.004)	-0.011* (0.006)
cut_maxtemp(22,23]	0.006 (0.010)	0.001 (0.007)	-0.013*** (0.005)	-0.014** (0.006)
cut_maxtemp(23,24]	0.000 (0.012)	-0.005 (0.007)	-0.011** (0.005)	-0.018** (0.007)
cut_maxtemp(24,25]	-0.008 (0.014)	0.002 (0.008)	-0.014** (0.005)	-0.015* (0.007)
cut_maxtemp(25,26]	-0.001 (0.013)	-0.005 (0.007)	-0.010 (0.007)	-0.021** (0.008)
cut_maxtemp(26,27]	-0.003 (0.013)	0.000 (0.009)	-0.007 (0.008)	-0.021*** (0.008)
cut_maxtemp(27,28]	0.003 (0.014)	-0.004 (0.009)	-0.008 (0.008)	-0.021** (0.009)
cut_maxtemp(28,29]	0.008 (0.014)	-0.005 (0.011)	-0.010 (0.007)	-0.017** (0.008)
cut_maxtemp(29,30]	0.009 (0.014)	0.005 (0.010)	-0.007 (0.008)	-0.014 (0.009)
cut_maxtemp(30,31]	0.021 (0.015)	0.015 (0.010)	-0.004 (0.008)	-0.015* (0.009)
cut_maxtemp(31,32]	0.042** (0.017)	0.024** (0.011)	0.006 (0.009)	-0.005 (0.009)
cut_maxtemp(32,33]	0.058*** (0.018)	0.039*** (0.012)	0.011 (0.009)	-0.000 (0.011)
cut_maxtemp(33,34]	0.081*** (0.019)	0.049*** (0.013)	0.025** (0.010)	0.006 (0.011)
cut_maxtemp(34,35]	0.095*** (0.020)	0.065*** (0.014)	0.038*** (0.011)	0.013 (0.012)
cut_maxtemp(35,36]	0.114*** (0.021)	0.084*** (0.016)	0.043*** (0.011)	0.028** (0.013)
cut_maxtemp(36,37]	0.140*** (0.022)	0.098*** (0.018)	0.069*** (0.013)	0.040*** (0.013)
cut_maxtemp(37,38]	0.156*** (0.023)	0.103*** (0.018)	0.087*** (0.014)	0.055*** (0.014)
cut_maxtemp(38,39]	0.174*** (0.026)	0.093*** (0.024)	0.094*** (0.017)	0.067*** (0.016)
cut_maxtemp(39,40]	0.187*** (0.029)	0.076*** (0.027)	0.088*** (0.023)	0.077*** (0.017)
cut_maxtemp(40, Inf]	0.191*** (0.026)	0.093*** (0.026)	0.010*** (0.002)	0.084*** (0.021)
cut_precp(0.1,10]	0.017*** (0.004)	0.011*** (0.004)	0.040*** (0.004)	0.017*** (0.003)
cut_precp(10,25]	0.057*** (0.008)	0.033*** (0.005)	0.063*** (0.005)	0.049*** (0.004)
cut_precp(25,50]	0.065*** (0.014)	0.038** (0.019)	0.065*** (0.013)	0.064*** (0.007)
cut_precp(50, Inf]	0.075*** (0.019)	0.011 (0.043)	0.013* (0.007)	0.032 (0.029)
cut_humid(20,30]	-0.023* (0.012)	-0.048 (0.037)	-0.006 (0.006)	0.027* (0.016)
cut_humid(30,40]	-0.035** (0.015)	-0.050 (0.046)	-0.019*** (0.007)	0.020 (0.014)
cut_humid(40,50]	-0.059*** (0.016)	-0.074 (0.049)	-0.034*** (0.007)	0.005 (0.014)
cut_humid(50,60]	-0.072*** (0.019)	-0.093* (0.050)	-0.043*** (0.008)	-0.014 (0.015)
cut_humid(60,70]	-0.074*** (0.021)	-0.104** (0.051)	-0.047*** (0.009)	-0.020 (0.016)
cut_humid(70,80]	-0.081*** (0.024)	-0.110** (0.052)	-0.051*** (0.010)	-0.006 (0.015)
cut_humid(80,90]	-0.073*** (0.026)	-0.107** (0.054)	-0.047*** (0.012)	0.007 (0.016)
cut_humid(90, Inf]	-0.011 (0.025)	-0.089 (0.055)	-0.013 (0.014)	0.019 (0.016)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.978	0.980	0.992	0.990
Note:	Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

Table S6. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions for female users. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Lunch peak order volume - female users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.101*** (0.033)	0.019 (0.033)	0.019 (0.033)	0.087** (0.040)
cut_maxtemp(0,5]	0.083*** (0.025)	0.042*** (0.016)	0.042*** (0.016)	0.058** (0.026)
cut_maxtemp(5,10]	0.059*** (0.016)	0.045*** (0.013)	0.045*** (0.013)	0.032** (0.014)
cut_maxtemp(10,15]	0.037*** (0.010)	0.030*** (0.008)	0.030*** (0.008)	0.020** (0.010)
cut_maxtemp(20,25]	-0.001 (0.012)	-0.002 (0.008)	-0.002 (0.008)	0.001 (0.007)
cut_maxtemp(25,30]	0.009 (0.015)	0.001 (0.010)	0.001 (0.010)	-0.003 (0.009)
cut_maxtemp(30,35]	0.078*** (0.019)	0.050*** (0.012)	0.050*** (0.012)	0.027*** (0.009)
cut_maxtemp(35, Inf]	0.165*** (0.023)	0.116*** (0.017)	0.116*** (0.017)	0.080*** (0.012)
cut_precp(0.1,10]	0.009* (0.005)	0.001 (0.005)	0.001 (0.005)	0.008** (0.004)
cut_precp(10,25]	0.026*** (0.009)	0.009 (0.006)	0.009 (0.006)	0.026*** (0.007)
cut_precp(25,50]	0.023 (0.016)	-0.003 (0.024)	-0.003 (0.024)	0.034*** (0.009)
cut_precp(50, Inf]	0.023 (0.022)	-0.064 (0.063)	-0.064 (0.063)	-0.088 (0.101)
cut_humid(20,30]	-0.015 (0.025)	-0.160** (0.062)	-0.160** (0.062)	-0.036 (0.053)
cut_humid(30,40]	-0.018 (0.028)	-0.187*** (0.064)	-0.187*** (0.064)	-0.043 (0.051)
cut_humid(40,50]	-0.033 (0.028)	-0.216*** (0.066)	-0.216*** (0.066)	-0.065 (0.050)
cut_humid(50,60]	-0.041 (0.030)	-0.223*** (0.068)	-0.223*** (0.068)	-0.085* (0.050)
cut_humid(60,70]	-0.042 (0.030)	-0.230*** (0.068)	-0.230*** (0.068)	-0.086* (0.050)
cut_humid(70,80]	-0.054* (0.032)	-0.233*** (0.069)	-0.233*** (0.069)	-0.074 (0.050)
cut_humid(80,90]	-0.049 (0.033)	-0.228*** (0.070)	-0.228*** (0.070)	-0.066 (0.050)
cut_humid(90, Inf]	0.006 (0.033)	-0.221*** (0.070)	-0.221*** (0.070)	-0.057 (0.050)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.951	0.958	0.976	0.974
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S7. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions for male users. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Lunch peak order volume - male users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.095*** (0.031)	0.028 (0.032)	0.028 (0.032)	0.127*** (0.039)
cut_maxtemp(0,5]	0.101*** (0.023)	0.027 (0.016)	0.027 (0.016)	0.075*** (0.021)
cut_maxtemp(5,10]	0.051*** (0.017)	0.022* (0.012)	0.022* (0.012)	0.055*** (0.013)
cut_maxtemp(10,15]	0.036*** (0.010)	0.016** (0.007)	0.016** (0.007)	0.025*** (0.009)
cut_maxtemp(20,25]	0.007 (0.010)	-0.002 (0.008)	-0.002 (0.008)	-0.008 (0.007)
cut_maxtemp(25,30]	0.016 (0.013)	0.002 (0.009)	0.002 (0.009)	-0.012 (0.009)
cut_maxtemp(30,35]	0.063*** (0.018)	0.044*** (0.012)	0.044*** (0.012)	0.014 (0.011)
cut_maxtemp(35, Inf]	0.136*** (0.024)	0.093*** (0.017)	0.093*** (0.017)	0.056*** (0.014)
cut_precp(0.1,10]	0.006 (0.005)	-0.002 (0.005)	-0.002 (0.005)	0.010** (0.004)
cut_precp(10,25]	0.028*** (0.009)	0.011 (0.007)	0.011 (0.007)	0.040*** (0.006)
cut_precp(25,50]	0.033** (0.014)	0.006 (0.021)	0.006 (0.021)	0.037*** (0.009)
cut_precp(50, Inf]	0.039* (0.020)	-0.058 (0.061)	-0.058 (0.061)	-0.029 (0.087)

cut_humid(20,30]	-0.036* (0.022)	-0.025 (0.089)	-0.025 (0.089)	0.053 (0.120)
cut_humid(30,40]	-0.040 (0.024)	-0.040 (0.091)	-0.040 (0.091)	0.056 (0.119)
cut_humid(40,50]	-0.067*** (0.025)	-0.068 (0.093)	-0.068 (0.093)	0.036 (0.119)
cut_humid(50,60]	-0.080*** (0.025)	-0.078 (0.094)	-0.078 (0.094)	0.017 (0.119)
cut_humid(60,70]	-0.083*** (0.026)	-0.089 (0.093)	-0.089 (0.093)	0.017 (0.120)
cut_humid(70,80]	-0.085*** (0.027)	-0.092 (0.093)	-0.092 (0.093)	0.027 (0.119)
cut_humid(80,90]	-0.084*** (0.030)	-0.083 (0.094)	-0.083 (0.094)	0.034 (0.119)
cut_humid(90, Inf]	-0.031 (0.029)	-0.081 (0.095)	-0.081 (0.095)	0.038 (0.119)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.943	0.956	0.974	0.977
Note:		Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01		

Table S8. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions for high-income users. Relative increases are interpreted as $e^{\beta}-1$.

	Dependent variable: Lunch peak order volume - high-income users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.116*** (0.033)	0.043 (0.031)	0.043 (0.031)	0.128*** (0.039)
cut_maxtemp(0,5]	0.080*** (0.022)	0.048*** (0.014)	0.048*** (0.014)	0.041* (0.023)
cut_maxtemp(5,10]	0.049*** (0.015)	0.041*** (0.013)	0.041*** (0.013)	0.031** (0.014)
cut_maxtemp(10,15]	0.024** (0.010)	0.018** (0.007)	0.018** (0.007)	0.020** (0.010)
cut_maxtemp(20,25]	0.004 (0.012)	0.005 (0.009)	0.005 (0.009)	0.002 (0.008)
cut_maxtemp(25,30]	0.024* (0.014)	0.021** (0.010)	0.021** (0.010)	0.009 (0.011)
cut_maxtemp(30,35]	0.084*** (0.018)	0.069*** (0.013)	0.069*** (0.013)	0.039*** (0.012)
cut_maxtemp(35, Inf]	0.172*** (0.025)	0.123*** (0.018)	0.123*** (0.018)	0.090*** (0.016)
cut_precp(0.1,10]	0.009* (0.005)	-0.001 (0.005)	-0.001 (0.005)	0.001 (0.005)
cut_precp(10,25]	0.026*** (0.009)	0.009 (0.008)	0.009 (0.008)	0.017** (0.007)
cut_precp(25,50]	0.038** (0.017)	0.003 (0.021)	0.003 (0.021)	0.026*** (0.010)
cut_precp(50, Inf]	0.044* (0.023)	-0.076 (0.057)	-0.076 (0.057)	-0.070 (0.076)
cut_humid(20,30]	-0.039 (0.027)	-0.314*** (0.114)	-0.314*** (0.114)	0.055 (0.034)
cut_humid(30,40]	-0.034 (0.025)	-0.348*** (0.125)	-0.348*** (0.125)	0.053 (0.032)
cut_humid(40,50]	-0.069** (0.028)	-0.364*** (0.126)	-0.364*** (0.126)	0.043 (0.029)
cut_humid(50,60]	-0.073*** (0.028)	-0.367*** (0.130)	-0.367*** (0.130)	0.020 (0.031)
cut_humid(60,70]	-0.080*** (0.027)	-0.378*** (0.128)	-0.378*** (0.128)	0.022 (0.032)
cut_humid(70,80]	-0.080*** (0.030)	-0.385*** (0.129)	-0.385*** (0.129)	0.030 (0.032)
cut_humid(80,90]	-0.082** (0.032)	-0.374*** (0.129)	-0.374*** (0.129)	0.039 (0.032)
cut_humid(90, Inf]	-0.032 (0.032)	-0.373*** (0.130)	-0.373*** (0.130)	0.045 (0.033)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.931	0.950	0.965	0.971
Note:		Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01		

Table S9. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions for low-income users. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Lunch peak order volume - low-income users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.101^{***} (0.033)	0.016 (0.033)	0.016 (0.033)	0.098^{**} (0.040)
cut_maxtemp(0,5]	0.093^{***} (0.025)	0.033^{**} (0.016)	0.033^{**} (0.016)	0.069^{***} (0.026)
cut_maxtemp(5,10]	0.057^{***} (0.016)	0.032^{**} (0.012)	0.032^{**} (0.012)	0.042^{***} (0.014)
cut_maxtemp(10,15]	0.041^{***} (0.010)	0.024^{***} (0.008)	0.024^{***} (0.008)	0.022^{**} (0.009)
cut_maxtemp(20,25]	0.000 (0.011)	-0.004 (0.008)	-0.004 (0.008)	-0.004 (0.007)
cut_maxtemp(25,30]	0.005 (0.014)	-0.002 (0.009)	-0.002 (0.009)	-0.011 (0.008)
cut_maxtemp(30,35]	0.065^{***} (0.018)	0.044^{***} (0.012)	0.044^{***} (0.012)	0.017^{*} (0.009)
cut_maxtemp(35, Inf]	0.145^{***} (0.023)	0.104^{***} (0.017)	0.104^{***} (0.017)	0.064^{***} (0.011)
cut_precp(0.1,10]	0.007 (0.005)	0.002 (0.005)	0.002 (0.005)	0.011^{***} (0.004)
cut_precp(10,25]	0.028^{***} (0.009)	0.012^{*} (0.006)	0.012^{*} (0.006)	0.037^{***} (0.006)
cut_precp(25,50]	0.022 (0.016)	-0.000 (0.024)	-0.000 (0.024)	0.039^{***} (0.009)
cut_precp(50, Inf]	0.025 (0.021)	-0.059 (0.065)	-0.059 (0.065)	-0.065 (0.103)
cut_humid(20,30]	-0.019 (0.021)	-0.076 (0.053)	-0.076 (0.053)	-0.032 (0.035)
cut_humid(30,40]	-0.027 (0.024)	-0.090 (0.057)	-0.090 (0.057)	-0.038 (0.034)
cut_humid(40,50]	-0.041^{*} (0.024)	-0.122^{**} (0.058)	-0.122^{**} (0.058)	-0.061^{*} (0.031)
cut_humid(50,60]	-0.054^{**} (0.026)	-0.132^{**} (0.059)	-0.132^{**} (0.059)	-0.078^{**} (0.033)
cut_humid(60,70]	-0.053^{*} (0.027)	-0.141^{**} (0.059)	-0.141^{**} (0.059)	-0.080^{**} (0.032)
cut_humid(70,80]	-0.064^{**} (0.029)	-0.144^{**} (0.060)	-0.144^{**} (0.060)	-0.069^{**} (0.032)
cut_humid(80,90]	-0.060^{**} (0.030)	-0.140^{**} (0.061)	-0.140^{**} (0.061)	-0.062^{*} (0.033)
cut_humid(90, Inf]	-0.005 (0.029)	-0.134^{**} (0.061)	-0.134^{**} (0.061)	-0.056^{*} (0.032)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.931	0.950	0.965	0.971
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S10. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions for users over 40. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Lunch peak order volume - users over 40			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.104^{***} (0.034)	0.063^{*} (0.033)	0.063^{*} (0.033)	0.083^{**} (0.038)
cut_maxtemp(0,5]	0.085^{***} (0.025)	0.041^{**} (0.018)	0.041^{**} (0.018)	0.045^{*} (0.025)
cut_maxtemp(5,10]	0.041^{**} (0.019)	0.030^{**} (0.013)	0.030^{**} (0.013)	0.014 (0.014)
cut_maxtemp(10,15]	0.024^{**} (0.011)	0.013 (0.009)	0.013 (0.009)	0.009 (0.009)
cut_maxtemp(20,25]	0.010 (0.012)	0.006 (0.010)	0.006 (0.010)	-0.007 (0.009)
cut_maxtemp(25,30]	0.028^{*} (0.014)	0.028^{**} (0.011)	0.028^{**} (0.011)	-0.005 (0.010)
cut_maxtemp(30,35]	0.088^{***} (0.019)	0.088^{***} (0.014)	0.088^{***} (0.014)	0.028^{**} (0.013)
cut_maxtemp(35, Inf]	0.204^{***} (0.026)	0.159^{***} (0.020)	0.159^{***} (0.020)	0.089^{***} (0.016)
cut_precp(0.1,10]	0.009 (0.007)	0.001 (0.007)	0.001 (0.007)	0.005 (0.006)
cut_precp(10,25]	0.019^{*} (0.010)	0.012 (0.009)	0.012 (0.009)	0.019^{**} (0.009)
cut_precp(25,50]	0.034^{**} (0.017)	0.010 (0.020)	0.010 (0.020)	0.030^{**} (0.013)
cut_precp(50, Inf]	0.044 (0.030)	-0.059 (0.049)	-0.059 (0.049)	-0.042 (0.071)

cut_humid(20,30]	-0.061* (0.034)	-0.084 (0.217)	-0.084 (0.217)	-0.051 (0.072)
cut_humid(30,40]	-0.056 (0.037)	-0.123 (0.210)	-0.123 (0.210)	-0.029 (0.073)
cut_humid(40,50]	-0.078** (0.034)	-0.159 (0.211)	-0.159 (0.211)	-0.055 (0.075)
cut_humid(50,60]	-0.107*** (0.035)	-0.157 (0.213)	-0.157 (0.213)	-0.073 (0.073)
cut_humid(60,70]	-0.097*** (0.035)	-0.173 (0.214)	-0.173 (0.214)	-0.072 (0.073)
cut_humid(70,80]	-0.092*** (0.035)	-0.177 (0.214)	-0.177 (0.214)	-0.064 (0.073)
cut_humid(80,90]	-0.090** (0.036)	-0.166 (0.213)	-0.166 (0.213)	-0.062 (0.072)
cut_humid(90, Inf]	-0.056 (0.037)	-0.162 (0.213)	-0.162 (0.213)	-0.048 (0.072)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.884	0.914	0.935	0.940
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S11. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions for users between 25 and 40. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Lunch peak order volume - users between 25 and 40			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.098*** (0.031)	0.009 (0.032)	0.009 (0.032)	0.096*** (0.034)
cut_maxtemp(0,5]	0.084*** (0.024)	0.032** (0.015)	0.032** (0.015)	0.061*** (0.021)
cut_maxtemp(5,10]	0.052*** (0.016)	0.033*** (0.012)	0.033*** (0.012)	0.042*** (0.012)
cut_maxtemp(10,15]	0.036*** (0.009)	0.024*** (0.007)	0.024*** (0.007)	0.020** (0.008)
cut_maxtemp(20,25]	0.000 (0.011)	-0.006 (0.008)	-0.006 (0.008)	-0.004 (0.007)
cut_maxtemp(25,30]	0.005 (0.014)	-0.002 (0.009)	-0.002 (0.009)	-0.008 (0.008)
cut_maxtemp(30,35]	0.065*** (0.018)	0.042*** (0.012)	0.042*** (0.012)	0.024** (0.009)
cut_maxtemp(35, Inf]	0.146*** (0.022)	0.103*** (0.017)	0.103*** (0.017)	0.076*** (0.012)
cut_precp(0.1,10]	0.009* (0.005)	0.001 (0.004)	0.001 (0.004)	0.008** (0.004)
cut_precp(10,25]	0.028*** (0.009)	0.011* (0.006)	0.011* (0.006)	0.030*** (0.007)
cut_precp(25,50]	0.023 (0.016)	-0.001 (0.024)	-0.001 (0.024)	0.037*** (0.009)
cut_precp(50, Inf]	0.026 (0.020)	-0.065 (0.066)	-0.065 (0.066)	-0.072 (0.094)
cut_humid(20,30]	-0.009 (0.023)	-0.105 (0.074)	-0.105 (0.074)	-0.013 (0.052)
cut_humid(30,40]	-0.015 (0.023)	-0.118 (0.080)	-0.118 (0.080)	-0.019 (0.050)
cut_humid(40,50]	-0.032 (0.024)	-0.145* (0.081)	-0.145* (0.081)	-0.038 (0.049)
cut_humid(50,60]	-0.038 (0.026)	-0.155* (0.083)	-0.155* (0.083)	-0.055 (0.050)
cut_humid(60,70]	-0.041 (0.027)	-0.164** (0.082)	-0.164** (0.082)	-0.057 (0.049)
cut_humid(70,80]	-0.050* (0.029)	-0.167** (0.083)	-0.167** (0.083)	-0.043 (0.050)
cut_humid(80,90]	-0.046 (0.030)	-0.160* (0.083)	-0.160* (0.083)	-0.034 (0.050)
cut_humid(90, Inf]	0.011 (0.029)	-0.155* (0.084)	-0.155* (0.084)	-0.028 (0.050)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.959	0.963	0.981	0.978
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S12. Annual regression coefficients of city-level lunch peak food delivery order volume on meteorological conditions for users below 25. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Lunch peak order volume - users below 25			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.076** (0.038)	0.028 (0.040)	0.028 (0.040)	0.106* (0.054)
cut_maxtemp(0,5]	0.099*** (0.031)	0.047** (0.023)	0.047** (0.023)	0.072** (0.033)
cut_maxtemp(5,10]	0.054** (0.023)	0.034* (0.020)	0.034* (0.020)	0.042** (0.019)
cut_maxtemp(10,15]	0.023 (0.014)	0.021 (0.013)	0.021 (0.013)	0.028** (0.013)
cut_maxtemp(20,25]	-0.006 (0.015)	0.017 (0.011)	0.017 (0.011)	0.004 (0.010)
cut_maxtemp(25,30]	0.029 (0.020)	0.020 (0.015)	0.020 (0.015)	-0.000 (0.012)
cut_maxtemp(30,35]	0.084*** (0.022)	0.062*** (0.021)	0.062*** (0.021)	0.016 (0.013)
cut_maxtemp(35, Inf]	0.150*** (0.031)	0.101*** (0.026)	0.101*** (0.026)	0.045*** (0.016)
cut_precp(0.1,10]	-0.002 (0.008)	0.001 (0.006)	0.001 (0.006)	0.014*** (0.004)
cut_precp(10,25]	0.028* (0.014)	0.010 (0.009)	0.010 (0.009)	0.044*** (0.007)
cut_precp(25,50]	0.043* (0.023)	0.013 (0.021)	0.013 (0.021)	0.035*** (0.009)
cut_precp(50, Inf]	0.038 (0.031)	-0.031 (0.052)	-0.031 (0.052)	-0.030 (0.091)
cut_humid(20,30]	-0.072** (0.034)	-0.273*** (0.081)	-0.273*** (0.081)	0.004 (0.067)
cut_humid(30,40]	-0.110*** (0.034)	-0.305*** (0.078)	-0.305*** (0.078)	-0.005 (0.073)
cut_humid(40,50]	-0.122*** (0.035)	-0.341*** (0.088)	-0.341*** (0.088)	-0.026 (0.077)
cut_humid(50,60]	-0.138*** (0.038)	-0.358*** (0.086)	-0.358*** (0.086)	-0.053 (0.077)
cut_humid(60,70]	-0.130*** (0.040)	-0.359*** (0.086)	-0.359*** (0.086)	-0.053 (0.076)
cut_humid(70,80]	-0.146*** (0.041)	-0.363*** (0.088)	-0.363*** (0.088)	-0.047 (0.076)
cut_humid(80,90]	-0.138*** (0.044)	-0.359*** (0.088)	-0.359*** (0.088)	-0.042 (0.077)
cut_humid(90, Inf]	-0.099** (0.042)	-0.359*** (0.090)	-0.359*** (0.090)	-0.041 (0.077)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.813	0.882	0.936	0.966
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S13. Annual regression coefficients of city-level daily food delivery order volume on meteorological conditions for female users. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Daily order volume - female users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.095*** (0.031)	0.004 (0.036)	0.004 (0.036)	0.058 (0.035)
cut_maxtemp(0,5]	0.079*** (0.023)	0.035** (0.015)	0.035** (0.015)	0.050** (0.022)
cut_maxtemp(5,10]	0.053*** (0.014)	0.042*** (0.011)	0.042*** (0.011)	0.020 (0.013)
cut_maxtemp(10,15]	0.031*** (0.008)	0.026*** (0.007)	0.026*** (0.007)	0.011 (0.008)
cut_maxtemp(20,25]	-0.003 (0.011)	-0.006 (0.007)	-0.006 (0.007)	-0.006 (0.007)
cut_maxtemp(25,30]	-0.005 (0.013)	-0.012 (0.008)	-0.012 (0.008)	-0.011 (0.009)
cut_maxtemp(30,35]	0.041** (0.016)	0.021* (0.011)	0.021* (0.011)	0.006 (0.009)
cut_maxtemp(35, Inf]	0.118*** (0.021)	0.070*** (0.015)	0.070*** (0.015)	0.043*** (0.012)
cut_precp(0.1,10]	0.016*** (0.004)	0.009** (0.004)	0.009** (0.004)	0.016*** (0.003)
cut_precp(10,25]	0.045*** (0.008)	0.027*** (0.005)	0.027*** (0.005)	0.039*** (0.005)
cut_precp(25,50]	0.052*** (0.014)	0.025 (0.019)	0.025 (0.019)	0.051*** (0.007)
cut_precp(50, Inf]	0.058*** (0.019)	-0.010 (0.048)	-0.010 (0.048)	0.006 (0.031)

cut_humid(20,30]	-0.013 (0.023)	-0.096*** (0.022)	-0.096*** (0.022)	0.019 (0.036)
cut_humid(30,40]	-0.019 (0.025)	-0.105*** (0.020)	-0.105*** (0.020)	0.016 (0.036)
cut_humid(40,50]	-0.040 (0.026)	-0.131*** (0.023)	-0.131*** (0.023)	-0.000 (0.034)
cut_humid(50,60]	-0.049* (0.028)	-0.143*** (0.025)	-0.143*** (0.025)	-0.020 (0.034)
cut_humid(60,70]	-0.052* (0.029)	-0.152*** (0.025)	-0.152*** (0.025)	-0.023 (0.035)
cut_humid(70,80]	-0.060* (0.031)	-0.156*** (0.027)	-0.156*** (0.027)	-0.013 (0.035)
cut_humid(80,90]	-0.055* (0.033)	-0.154*** (0.030)	-0.154*** (0.030)	-0.000 (0.035)
cut_humid(90, Inf]	0.003 (0.032)	-0.141*** (0.030)	-0.141*** (0.030)	0.011 (0.035)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.967	0.972	0.986	0.986

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table S14. Annual regression coefficients of city-level daily food delivery order volume on meteorological conditions for male users. Relative increases are interpreted as $e^{\beta}-1$.

	Dependent variable: Daily order volume - male users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.085** (0.035)	0.000 (0.037)	0.000 (0.037)	0.098*** (0.034)
cut_maxtemp(0,5]	0.081*** (0.023)	0.017 (0.016)	0.017 (0.016)	0.060*** (0.018)
cut_maxtemp(5,10]	0.048*** (0.015)	0.026** (0.011)	0.026** (0.011)	0.037*** (0.012)
cut_maxtemp(10,15]	0.031*** (0.010)	0.019*** (0.006)	0.019*** (0.006)	0.019** (0.007)
cut_maxtemp(20,25]	-0.004 (0.010)	-0.009 (0.006)	-0.009 (0.006)	-0.010* (0.006)
cut_maxtemp(25,30]	-0.010 (0.012)	-0.016** (0.007)	-0.016** (0.007)	-0.021*** (0.006)
cut_maxtemp(30,35]	0.024 (0.015)	0.010 (0.010)	0.010 (0.010)	-0.004 (0.008)
cut_maxtemp(35, Inf]	0.076*** (0.020)	0.039*** (0.015)	0.039*** (0.015)	0.024** (0.010)
cut_precp(0.1,10]	0.012*** (0.004)	0.005 (0.004)	0.005 (0.004)	0.018*** (0.003)
cut_precp(10,25]	0.047*** (0.007)	0.024*** (0.006)	0.024*** (0.006)	0.048*** (0.004)
cut_precp(25,50]	0.048*** (0.013)	0.026 (0.017)	0.026 (0.017)	0.058*** (0.006)
cut_precp(50, Inf]	0.061*** (0.018)	-0.012 (0.042)	-0.012 (0.042)	0.041 (0.025)
cut_humid(20,30]	-0.030** (0.014)	-0.068 (0.068)	-0.068 (0.068)	0.002 (0.043)
cut_humid(30,40]	-0.039** (0.018)	-0.080 (0.076)	-0.080 (0.076)	-0.009 (0.043)
cut_humid(40,50]	-0.062*** (0.017)	-0.101 (0.079)	-0.101 (0.079)	-0.026 (0.044)
cut_humid(50,60]	-0.075*** (0.021)	-0.114 (0.079)	-0.114 (0.079)	-0.045 (0.044)
cut_humid(60,70]	-0.078*** (0.023)	-0.125 (0.079)	-0.125 (0.079)	-0.046 (0.044)
cut_humid(70,80]	-0.084*** (0.026)	-0.132* (0.079)	-0.132* (0.079)	-0.036 (0.043)
cut_humid(80,90]	-0.083*** (0.028)	-0.129 (0.081)	-0.129 (0.081)	-0.028 (0.043)
cut_humid(90, Inf]	-0.024 (0.027)	-0.116 (0.081)	-0.116 (0.081)	-0.018 (0.043)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.965	0.974	0.986	0.989

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table S15. Annual regression coefficients of city-level daily food delivery order volume on meteorological conditions for high-income users. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Daily order volume - high-income users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.112*** (0.033)	0.011 (0.033)	0.011 (0.033)	0.068* (0.035)
cut_maxtemp(0,5]	0.086*** (0.020)	0.027* (0.014)	0.027* (0.014)	0.026 (0.017)
cut_maxtemp(5,10]	0.051*** (0.012)	0.031*** (0.011)	0.031*** (0.011)	0.012 (0.012)
cut_maxtemp(10,15]	0.027*** (0.009)	0.015** (0.006)	0.015** (0.006)	0.010 (0.008)
cut_maxtemp(20,25]	0.004 (0.010)	-0.003 (0.007)	-0.003 (0.007)	-0.002 (0.007)
cut_maxtemp(25,30]	0.007 (0.012)	-0.002 (0.008)	-0.002 (0.008)	0.000 (0.010)
cut_maxtemp(30,35]	0.051*** (0.015)	0.032*** (0.010)	0.032*** (0.010)	0.019* (0.011)
cut_maxtemp(35, Inf]	0.120*** (0.020)	0.072*** (0.016)	0.072*** (0.016)	0.051*** (0.014)
cut_precp(0.1,10]	0.014*** (0.004)	0.007* (0.004)	0.007* (0.004)	0.009*** (0.003)
cut_precp(10,25]	0.047*** (0.007)	0.025*** (0.006)	0.025*** (0.006)	0.031*** (0.005)
cut_precp(25,50]	0.050*** (0.014)	0.019 (0.019)	0.019 (0.019)	0.041*** (0.007)
cut_precp(50, Inf]	0.060*** (0.021)	-0.019 (0.042)	-0.019 (0.042)	-0.001 (0.029)
cut_humid(20,30]	-0.013 (0.018)	-0.148 (0.124)	-0.148 (0.124)	0.023 (0.037)
cut_humid(30,40]	-0.018 (0.016)	-0.177 (0.136)	-0.177 (0.136)	0.017 (0.037)
cut_humid(40,50]	-0.042** (0.019)	-0.199 (0.139)	-0.199 (0.139)	0.004 (0.039)
cut_humid(50,60]	-0.051** (0.023)	-0.204 (0.141)	-0.204 (0.141)	-0.013 (0.038)
cut_humid(60,70]	-0.054** (0.024)	-0.222 (0.141)	-0.222 (0.141)	-0.010 (0.039)
cut_humid(70,80]	-0.059** (0.026)	-0.224 (0.141)	-0.224 (0.141)	-0.001 (0.039)
cut_humid(80,90]	-0.058** (0.028)	-0.221 (0.141)	-0.221 (0.141)	0.011 (0.040)
cut_humid(90, Inf]	-0.001 (0.027)	-0.210 (0.141)	-0.210 (0.141)	0.021 (0.040)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.962	0.974	0.984	0.987
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S16. Annual regression coefficients of city-level daily food delivery order volume on meteorological conditions for low-income users. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Daily order volume - low-income users			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.088*** (0.033)	0.001 (0.037)	0.001 (0.037)	0.077** (0.036)
cut_maxtemp(0,5]	0.076*** (0.024)	0.028* (0.016)	0.028* (0.016)	0.060*** (0.023)
cut_maxtemp(5,10]	0.049*** (0.016)	0.035*** (0.011)	0.035*** (0.011)	0.032** (0.013)
cut_maxtemp(10,15]	0.031*** (0.009)	0.025*** (0.006)	0.025*** (0.006)	0.016** (0.008)
cut_maxtemp(20,25]	-0.006 (0.010)	-0.008 (0.006)	-0.008 (0.006)	-0.010* (0.006)
cut_maxtemp(25,30]	-0.012 (0.013)	-0.015* (0.008)	-0.015* (0.008)	-0.019*** (0.007)
cut_maxtemp(30,35]	0.029* (0.016)	0.015 (0.010)	0.015 (0.010)	-0.003 (0.008)
cut_maxtemp(35, Inf]	0.095*** (0.020)	0.056*** (0.015)	0.056*** (0.015)	0.029*** (0.010)
cut_precp(0.1,10]	0.014*** (0.004)	0.009** (0.004)	0.009** (0.004)	0.019*** (0.003)
cut_precp(10,25]	0.046*** (0.008)	0.027*** (0.006)	0.027*** (0.006)	0.047*** (0.004)
cut_precp(25,50]	0.051*** (0.014)	0.029* (0.017)	0.029* (0.017)	0.058*** (0.006)
cut_precp(50, Inf]	0.060*** (0.019)	-0.011 (0.047)	-0.011 (0.047)	0.027 (0.028)

cut_humid(20,30]	-0.023 (0.019)	-0.066*** (0.017)	-0.066*** (0.017)	0.007 (0.020)
cut_humid(30,40]	-0.032 (0.021)	-0.070*** (0.020)	-0.070*** (0.020)	-0.002 (0.019)
cut_humid(40,50]	-0.054** (0.021)	-0.094*** (0.021)	-0.094*** (0.021)	-0.018 (0.019)
cut_humid(50,60]	-0.065*** (0.024)	-0.110*** (0.022)	-0.110*** (0.022)	-0.037* (0.019)
cut_humid(60,70]	-0.067** (0.026)	-0.118*** (0.023)	-0.118*** (0.023)	-0.042** (0.020)
cut_humid(70,80]	-0.074** (0.028)	-0.124*** (0.025)	-0.124*** (0.025)	-0.032 (0.019)
cut_humid(80,90]	-0.069** (0.030)	-0.122*** (0.028)	-0.122*** (0.028)	-0.022 (0.019)
cut_humid(90, Inf]	-0.011 (0.028)	-0.109*** (0.028)	-0.109*** (0.028)	-0.011 (0.019)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.968	0.972	0.987	0.988
Note:		Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01		

Table S17. Annual regression coefficients of city-level daily food delivery order volume on meteorological conditions for users over 40. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Daily order volume - users over 40			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.095** (0.036)	0.045 (0.033)	0.045 (0.033)	0.029 (0.034)
cut_maxtemp(0,5]	0.074*** (0.022)	0.044** (0.017)	0.044** (0.017)	0.029 (0.019)
cut_maxtemp(5,10]	0.036** (0.017)	0.043*** (0.012)	0.043*** (0.012)	0.002 (0.012)
cut_maxtemp(10,15]	0.020* (0.010)	0.017** (0.008)	0.017** (0.008)	0.006 (0.008)
cut_maxtemp(20,25]	-0.005 (0.010)	0.002 (0.008)	0.002 (0.008)	-0.007 (0.008)
cut_maxtemp(25,30]	-0.002 (0.012)	0.010 (0.010)	0.010 (0.010)	-0.008 (0.010)
cut_maxtemp(30,35]	0.050*** (0.015)	0.055*** (0.013)	0.055*** (0.013)	0.015 (0.011)
cut_maxtemp(35, Inf]	0.143*** (0.020)	0.109*** (0.019)	0.109*** (0.019)	0.065*** (0.014)
cut_precp(0.1,10]	0.012** (0.005)	0.008* (0.004)	0.008* (0.004)	0.012*** (0.004)
cut_precp(10,25]	0.041*** (0.008)	0.023*** (0.007)	0.023*** (0.007)	0.032*** (0.007)
cut_precp(25,50]	0.050*** (0.013)	0.029* (0.017)	0.029* (0.017)	0.047*** (0.009)
cut_precp(50, Inf]	0.081*** (0.021)	-0.003 (0.041)	-0.003 (0.041)	-0.016 (0.040)
cut_humid(20,30]	-0.054** (0.026)	-0.100 (0.164)	-0.100 (0.164)	0.093 (0.126)
cut_humid(30,40]	-0.061* (0.032)	-0.122 (0.156)	-0.122 (0.156)	0.088 (0.129)
cut_humid(40,50]	-0.094*** (0.032)	-0.150 (0.157)	-0.150 (0.157)	0.078 (0.130)
cut_humid(50,60]	-0.115*** (0.033)	-0.164 (0.159)	-0.164 (0.159)	0.065 (0.129)
cut_humid(60,70]	-0.109*** (0.034)	-0.176 (0.159)	-0.176 (0.159)	0.065 (0.128)
cut_humid(70,80]	-0.114*** (0.035)	-0.179 (0.159)	-0.179 (0.159)	0.075 (0.129)
cut_humid(80,90]	-0.109*** (0.037)	-0.175 (0.159)	-0.175 (0.159)	0.082 (0.128)
cut_humid(90, Inf]	-0.065* (0.038)	-0.161 (0.160)	-0.161 (0.160)	0.095 (0.128)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.933	0.953	0.969	0.972
Note:		Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01		

Table S18. Annual regression coefficients of city-level daily food delivery order volume on meteorological conditions for users between 25 and 40. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Daily order volume - users between 25 and 40			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.088^{***} (0.031)	-0.006 (0.036)	-0.006 (0.036)	0.072^{**} (0.031)
cut_maxtemp(0,5]	0.071^{***} (0.023)	0.025^{*} (0.015)	0.025^{*} (0.015)	0.053^{***} (0.019)
cut_maxtemp(5,10]	0.048^{***} (0.014)	0.033^{***} (0.011)	0.033^{***} (0.011)	0.029^{**} (0.011)
cut_maxtemp(10,15]	0.030^{***} (0.009)	0.024^{***} (0.006)	0.024^{***} (0.006)	0.014^{*} (0.007)
cut_maxtemp(20,25]	-0.003 (0.010)	-0.008 (0.006)	-0.008 (0.006)	-0.007 (0.006)
cut_maxtemp(25,30]	-0.009 (0.012)	-0.015^{**} (0.007)	-0.015^{**} (0.007)	-0.014^{*} (0.007)
cut_maxtemp(30,35]	0.030^{*} (0.016)	0.014 (0.010)	0.014 (0.010)	0.005 (0.008)
cut_maxtemp(35, Inf]	0.096^{***} (0.020)	0.056^{***} (0.015)	0.056^{***} (0.015)	0.039^{***} (0.011)
cut_precp(0.1,10]	0.014^{***} (0.004)	0.008^{**} (0.004)	0.008^{**} (0.004)	0.016^{***} (0.003)
cut_precp(10,25]	0.047^{***} (0.008)	0.027^{***} (0.005)	0.027^{***} (0.005)	0.042^{***} (0.004)
cut_precp(25,50]	0.046^{***} (0.014)	0.026 (0.018)	0.026 (0.018)	0.053^{***} (0.006)
cut_precp(50, Inf]	0.054^{***} (0.019)	-0.013 (0.047)	-0.013 (0.047)	0.016 (0.028)
cut_humid(20,30]	-0.006 (0.019)	-0.073^{***} (0.024)	-0.073^{***} (0.024)	0.001 (0.037)
cut_humid(30,40]	-0.013 (0.019)	-0.078^{**} (0.035)	-0.078^{**} (0.035)	-0.009 (0.036)
cut_humid(40,50]	-0.033 (0.020)	-0.098^{**} (0.038)	-0.098^{**} (0.038)	-0.026 (0.035)
cut_humid(50,60]	-0.040^{*} (0.024)	-0.111^{***} (0.038)	-0.111^{***} (0.038)	-0.044 (0.036)
cut_humid(60,70]	-0.044^{*} (0.025)	-0.121^{***} (0.038)	-0.121^{***} (0.038)	-0.047 (0.036)
cut_humid(70,80]	-0.050^{*} (0.028)	-0.125^{***} (0.039)	-0.125^{***} (0.039)	-0.035 (0.036)
cut_humid(80,90]	-0.046 (0.029)	-0.122^{***} (0.041)	-0.122^{***} (0.041)	-0.023 (0.037)
cut_humid(90, Inf]	0.014 (0.028)	-0.109^{**} (0.042)	-0.109^{**} (0.042)	-0.012 (0.036)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.971	0.976	0.988	0.989
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S19. Annual regression coefficients of city-level daily food delivery order volume on meteorological conditions for users below 25. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable: Daily order volume - users below 25			
	2017	2018	2019	2023
cut_maxtemp(-Inf,0]	0.085^{**} (0.042)	-0.002 (0.044)	-0.002 (0.044)	0.077 (0.047)
cut_maxtemp(0,5]	0.112^{***} (0.031)	0.020 (0.022)	0.020 (0.022)	0.055^{**} (0.026)
cut_maxtemp(5,10]	0.062^{***} (0.021)	0.028 (0.017)	0.028 (0.017)	0.028^{*} (0.016)
cut_maxtemp(10,15]	0.036^{***} (0.012)	0.017^{*} (0.010)	0.017^{*} (0.010)	0.019^{*} (0.010)
cut_maxtemp(20,25]	-0.012 (0.013)	-0.005 (0.009)	-0.005 (0.009)	-0.009 (0.008)
cut_maxtemp(25,30]	0.006 (0.018)	-0.012 (0.012)	-0.012 (0.012)	-0.018^{*} (0.010)
cut_maxtemp(30,35]	0.041^{*} (0.022)	0.014 (0.016)	0.014 (0.016)	-0.008 (0.010)
cut_maxtemp(35, Inf]	0.093^{***} (0.030)	0.033 (0.021)	0.033 (0.021)	0.010 (0.013)
cut_precp(0.1,10]	0.007 (0.006)	0.007 (0.006)	0.007 (0.006)	0.020^{***} (0.003)
cut_precp(10,25]	0.034^{***} (0.010)	0.027^{***} (0.008)	0.027^{***} (0.008)	0.050^{***} (0.005)
cut_precp(25,50]	0.075^{***} (0.020)	0.025 (0.018)	0.025 (0.018)	0.061^{***} (0.007)
cut_precp(50, Inf]	0.068^{**} (0.027)	-0.003 (0.041)	-0.003 (0.041)	0.046^{*} (0.027)

cut_humid(20,30]	-0.083*** (0.025)	-0.202** (0.097)	-0.202** (0.097)	0.019 (0.083)
cut_humid(30,40]	-0.099*** (0.029)	-0.207** (0.098)	-0.207** (0.098)	0.020 (0.089)
cut_humid(40,50]	-0.123*** (0.029)	-0.240** (0.101)	-0.240** (0.101)	0.006 (0.095)
cut_humid(50,60]	-0.142*** (0.031)	-0.257** (0.103)	-0.257** (0.103)	-0.019 (0.094)
cut_humid(60,70]	-0.134*** (0.034)	-0.268** (0.104)	-0.268** (0.104)	-0.022 (0.094)
cut_humid(70,80]	-0.144*** (0.037)	-0.276*** (0.104)	-0.276*** (0.104)	-0.014 (0.094)
cut_humid(80,90]	-0.137*** (0.040)	-0.282*** (0.106)	-0.282*** (0.106)	-0.006 (0.094)
cut_humid(90, Inf]	-0.094** (0.037)	-0.272** (0.106)	-0.272** (0.106)	0.003 (0.094)
City Fixed Effect	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes
Observations	35,827	35,666	35,601	22,666
Adjusted R^2	0.895	0.939	0.968	0.983
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01			

Table S20. Regression coefficients of city-level lunch peak food delivery fee on meteorological conditions. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable:
	lunch peak delivery fee
cut_maxtemp(-Inf,0]	0.144*** (0.009)
cut_maxtemp(0,1]	0.097*** (0.009)
cut_maxtemp(1,2]	0.084*** (0.009)
cut_maxtemp(2,3]	0.073*** (0.008)
cut_maxtemp(3,4]	0.065*** (0.008)
cut_maxtemp(4,5]	0.053*** (0.007)
cut_maxtemp(5,6]	0.045*** (0.006)
cut_maxtemp(6,7]	0.036*** (0.005)
cut_maxtemp(7,8]	0.030*** (0.005)
cut_maxtemp(8,9]	0.026*** (0.005)
cut_maxtemp(9,10]	0.017*** (0.004)
cut_maxtemp(10,11]	0.010*** (0.003)
cut_maxtemp(11,12]	0.007** (0.003)
cut_maxtemp(12,13]	0.006** (0.003)
cut_maxtemp(13,14]	0.004* (0.002)
cut_maxtemp(14,15]	0.002 (0.002)
cut_maxtemp(15,16]	0.000 (0.002)
cut_maxtemp(16,17]	-0.000 (0.001)
cut_maxtemp(17,18]	-0.000 (0.001)
cut_maxtemp(18,19]	-0.001 (0.001)
cut_maxtemp(20,21]	0.001 (0.001)
cut_maxtemp(21,22]	0.001 (0.001)
cut_maxtemp(22,23]	0.003** (0.001)
cut_maxtemp(23,24]	0.005*** (0.002)
cut_maxtemp(24,25]	0.005*** (0.002)
cut_maxtemp(25,26]	0.007*** (0.002)
cut_maxtemp(26,27]	0.011*** (0.002)
cut_maxtemp(27,28]	0.012*** (0.002)
cut_maxtemp(28,29]	0.014*** (0.003)
cut_maxtemp(29,30]	0.015*** (0.003)
cut_maxtemp(30,31]	0.018*** (0.003)

cut_maxtemp(31,32]	0.023*** (0.004)
cut_maxtemp(32,33]	0.027*** (0.004)
cut_maxtemp(33,34]	0.031*** (0.004)
cut_maxtemp(34,35]	0.034*** (0.004)
cut_maxtemp(35,36]	0.040*** (0.005)
cut_maxtemp(36,37]	0.043*** (0.005)
cut_maxtemp(37,38]	0.045*** (0.005)
cut_maxtemp(38,39]	0.051*** (0.006)
cut_maxtemp(39,40]	0.056*** (0.009)
cut_maxtemp(40, Inf]	0.056*** (0.009)
cut_precp(0.1,10]	-0.003*** (0.001)
cut_precp(10,25]	-0.001 (0.001)
cut_precp(25,50]	0.004 (0.002)
cut_precp(50, Inf]	0.006 (0.005)
cut_humid(10,20]	-0.005 (0.013)
cut_humid(20,30]	0.000 (0.014)
cut_humid(30,40]	0.002 (0.015)
cut_humid(40,50]	0.002 (0.015)
cut_humid(50,60]	0.004 (0.015)
cut_humid(60,70]	0.005 (0.015)
cut_humid(70,80]	0.006 (0.016)
cut_humid(80,90]	0.006 (0.016)
cut_humid(90, Inf]	0.014 (0.016)
City Fixed Effect	Yes
Date Fixed Effect	Yes
Observations	129,760
Adjusted R^2	0.804
Note:	*p<0.1; **p<0.05; ***p<0.01

Table S21. Regression coefficients of urban neighbourhood-level lunch peak food delivery fee on meteorological conditions. Relative increases are interpreted as $e^{\beta} - 1$.

	Dependent variable:
	lunch peak delivery fee
cut_maxtemp(-Inf,0]	0.029*** (0.007)
cut_maxtemp(0,1]	0.021*** (0.007)
cut_maxtemp(1,2]	0.022*** (0.007)
cut_maxtemp(2,3]	0.017*** (0.006)
cut_maxtemp(3,4]	0.014** (0.006)
cut_maxtemp(4,5]	0.014** (0.006)
cut_maxtemp(5,6]	0.014*** (0.005)
cut_maxtemp(6,7]	0.012** (0.005)
cut_maxtemp(7,8]	0.012*** (0.004)
cut_maxtemp(8,9]	0.011*** (0.004)
cut_maxtemp(9,10]	0.009*** (0.003)
cut_maxtemp(10,11]	0.007** (0.003)
cut_maxtemp(11,12]	0.006* (0.003)
cut_maxtemp(12,13]	0.002 (0.002)
cut_maxtemp(13,14]	0.003 (0.002)
cut_maxtemp(14,15]	0.001 (0.002)

cut_maxtemp(15,16]	-0.001 (0.002)
cut_maxtemp(16,17]	0.001 (0.001)
cut_maxtemp(17,18]	0.000 (0.001)
cut_maxtemp(18,19]	0.001 (0.001)
cut_maxtemp(20,21]	-0.000 (0.001)
cut_maxtemp(21,22]	0.001 (0.001)
cut_maxtemp(22,23]	0.001 (0.001)
cut_maxtemp(23,24]	0.001 (0.001)
cut_maxtemp(24,25]	0.001 (0.001)
cut_maxtemp(25,26]	0.003** (0.001)
cut_maxtemp(26,27]	0.005*** (0.001)
cut_maxtemp(27,28]	0.006*** (0.001)
cut_maxtemp(28,29]	0.007*** (0.001)
cut_maxtemp(29,30]	0.009*** (0.002)
cut_maxtemp(30,31]	0.012*** (0.002)
cut_maxtemp(31,32]	0.016*** (0.002)
cut_maxtemp(32,33]	0.019*** (0.002)
cut_maxtemp(33,34]	0.021*** (0.002)
cut_maxtemp(34,35]	0.026*** (0.002)
cut_maxtemp(35,36]	0.030*** (0.002)
cut_maxtemp(36,37]	0.034*** (0.002)
cut_maxtemp(37,38]	0.035*** (0.003)
cut_maxtemp(38,39]	0.037*** (0.003)
cut_maxtemp(39,40]	0.041*** (0.004)
cut_maxtemp(40, Inf]	0.048*** (0.005)
cut_precp(0.1,10]	-0.004*** (0.001)
cut_precp(10,25]	-0.006*** (0.001)
cut_precp(25,50]	-0.005*** (0.002)
cut_precp(50, Inf]	-0.009** (0.004)
cut_humid(10,20]	-0.008 (0.011)
cut_humid(20,30]	-0.015 (0.011)
cut_humid(30,40]	-0.017 (0.011)
cut_humid(40,50]	-0.018 (0.011)
cut_humid(50,60]	-0.016 (0.011)
cut_humid(60,70]	-0.015 (0.011)
cut_humid(70,80]	-0.016 (0.011)
cut_humid(80,90]	-0.018 (0.011)
cut_humid(90, Inf]	-0.014 (0.012)
is_holiday	0.010* (0.006)
is_spring_festival	0.091*** (0.013)
weekday_Tue	-0.003 (0.003)
weekday_Wed	-0.000 (0.003)
weekday_Thu	-0.000 (0.003)
weekday_Fri	-0.008*** (0.003)
weekday_Sat	0.005 (0.003)
weekday_Sun	0.010*** (0.003)
Neighbourhood Fixed Effect	Yes
City-month Fixed Effect	Yes
Observations	10,175,517
Adjusted R^2	0.243
Note:	*p<0.1; **p<0.05; ***p<0.01

Table S22. Users' demographic distribution of the individual order record dataset.

Demographic Group	No. of users
Male	388,680
Female	480,651
High-income	175,634
Low-income	702,271
<25	174,997
25∼40	625,743
>40	99,233

Table S23. Key parameters in measuring heat exposure for each order. Shape and scale parameters determine the gamma distribution of travel distance for each transportation mode. $P(\text{mode} = m)$ represents the overall mode distribution among all trips. I_m and v_m are corresponding activity intensity and expected travel speed.

Transportation mode	shape parameter k	scale parameter θ	$P(\text{mode} = m)$	I_m (MET)	v_m (km/h)
Walking	1.47	0.653	30%	2.5	4.8
Cycling	1.64	1.683	12%	4.0	9.7
Driving	1.25	7.336	28%	2.5	30
Public Transit	1.57	5.752	30%	1.3	15

Table S24. List of 16 CMIP-5 projection models used in our paper.

Model Name	Model Country
ACCESS1-0	Australia
bcc-csm1-1	China
BNU-ESM	China
CanESM2	Canada
CCSM4	United States
CESM1-BGC	United States
CSIRO-Mk3-6-0	Australia
GFDL-CM3	United States
GFDL-ESM2G	United States
GFDL-ESM2M	United States
inmcm4	Russia
IPSL-CM5A-LR	France
IPSL-CM5A-MR	France
MPI-ESM-LR	Germany
MPI-ESM-MR	Germany
NorESM1-M	Norway