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ABSTRACT

Extreme temperatures threaten agriculture and exacerbate global food insecurity, yet their direct impact on dietary choices remains poorly understood. We provide novel evidence of how short-term exposures to extreme temperatures affect macronutrient intake in China. We show that both hot and cold weather elevate high-fat diet risks. In particular, hot weather reduces carbohydrate and protein consumption but not fat intake, while cold weather increases all nutrient intake, particularly fats. Temperature-induced dietary changes are shaped primarily by physiological responses to thermal stress, whereas physical activities demonstrate little effect. Technologies that improve indoor thermal comfort (via fans, air conditioners, and heating systems) substantially mitigate high-fat diet risks. Socioeconomic disparities are evident, with rural and poor individuals more likely to adopt high-fat diets under hot or cold weather. Projections indicate that more extreme temperatures due to climate change may increase the prevalence of high-fat diets nationally, while substantial regional heterogeneity emerges, with declines in northeast China and increases in southern China. These results highlight a crucial but overlooked pathway linking climate change to dietary health inequality.

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1. Introduction

Climate change threatens human nutrition by reducing the availability, diversity and quality of food (WHO, 2023). As a result, understanding dietary behaviors and nutritional intake has become increasingly important, given their role as fundamental components of health capital formation that directly influence productivity, healthcare costs, and overall welfare (Grossman, 1972). Specifically, the composition of macronutrient intake, such as fat, carbohydrates, and proteins, significantly affects health outcomes and the incidence of non-communicable diseases (NCDs), such as obesity, diabetes, and cardiovascular diseases, with profound implications for public health expenditures and productivity (Kivimäki et al., 2022; Ng et al., 2025). As extreme temperatures become more frequent under climate change, understanding their impact on nutritional behavior is essential for accurately estimating temperature-induced welfare losses and designing effective public policies to mitigate these consequences.

In this paper, we provide the causal evidence linking short-term exposure to temperature deviations from comfort to shifts in individual dietary choices, using data from the China Health and Nutrition Survey (CHNS). This individual-level panel dataset covers 28,941 individuals from 7,057 households across diverse geographic regions in China, spanning a period of two decades (1991-2011), thus allowing us to exploit substantial variation in dietary responses induced by temperature fluctuations.

A key empirical challenge is that temperature can influence nutrition through agricultural production, since shifts in yields and food availability may confound the demand-side effects. Our design leverages short-term weather fluctuations, which directly alter dietary demand but are unlikely to trigger significant adjustments in production, market supply, or food prices. We control for potential confounders using a rich set of fixed effects at the individual, province-month, and year-month levels, which absorb time-invariant personal characteristics, local seasonal differences, and national trends. After these controls, the remaining within-county, short-term fluctuations in temperature are plausibly random. As a result, our estimates can be interpreted as causal effects of temperature on dietary demand in a partial equilibrium setting.

Our analysis reveals that high temperatures significantly reduce the intake of carbohydrates and proteins but leave fat consumption relatively unaffected, thereby increasing the dietary share of fats. Conversely, low temperatures elevate overall caloric intake, particularly fats. Both hot and cold temperatures consequently shift individuals toward high-fat diets, which can foster obesity (Hariri and

Thibault, 2010), promote insulin resistance (Kumar et al., 2021), accelerate atherosclerosis (Lavillegrand et al., 2024), and even contribute to cancer progression (Chen et al., 2024). Hot temperatures mainly suppress low-fat foods such as cereals, while cold temperatures boost consumption of fat-rich foods like milk, eggs, nuts, and oil. These disaggregated patterns explain why both heat and cold stress ultimately raise the dietary share of fat. Given that dietary health is closely linked to productivity and healthcare expenditures, these shifts imply substantial but previously unquantified welfare loss and economic costs associated with climate change in the long term.

We further discuss the mechanisms underlying these dietary responses. Consistent with physiological pathways documented in the biomedical literature, the observed patterns align with appetite suppression under heat and elevated energy demand under cold exposure. Moreover, our analysis indicates that temperature-induced dietary changes are unlikely to be explained by shifts in individuals' working hours or physical activity levels in the short term. Turning to adaptation, we find that temperature-adjustment technologies—particularly air conditioners, fans, and heating systems—effectively mitigate the dietary impacts of both hot and cold weather by improving indoor thermal comfort. In contrast, enhanced food storage through refrigerators plays a limited role.

In addition to the average effects, our analysis identifies significant socioeconomic disparities in dietary responses. Rural and poor households are disproportionately sensitive to temperature-induced dietary changes, and their nutritional choices are more shaped by environmental constraints than their urban or richer counterparts. Such dietary changes not only affect immediate health but also have long-term implications for human capital development, productivity, and economic inequality (Maluccio et al., 2009; Almond et al., 2015; Chong et al., 2016; Hjort et al., 2017; Coffey et al., 2018). These findings point to the importance of targeted adaptation policies—such as reliable electricity for cooling and heating, resilient food storage and supply chains, and nutrition-focused safety nets—to mitigate temperature-induced nutritional inequities.

Finally, we project future dietary impacts under two climate scenarios (RCP4.5 and RCP8.5). The projections reveal that while the national average likelihood of high-fat diets will rise, the regional patterns are heterogeneous—southern China faces notable increases, whereas northeast China experiences declines. This contrast highlights the complex ways in which climate change reshapes nutrition. Based on our mechanism analysis, we further show that temperature-control technologies such as air conditioners, fans, and heating systems function as effective adaptive tools. Relative to current adoption levels, universal access to these technologies could offset roughly half of the projected nationwide increase in high-fat diets.

This study contributes to literature in three ways. First, we provide the first individual-level causal evidence that climate shocks directly affect nutrition through food demand. Extreme temperature is widely recognized as a major threat to global food production, raising concerns about whether it will trigger a nutritional crisis. Nutrition is a central determinant of human health, yet the direct impacts of climate on dietary intake remain poorly understood. By showing that extreme temperatures systematically shift individuals toward high-fat diets, our study highlights a demand-side mechanism that links climate shocks to nutritional outcomes, complementing the well-documented supply-side effects on agricultural productivity (Deschênes and Greenstone, 2007; Burke and Emerick, 2016; Aragón et al., 2021) and household nutrition (Stainier et al., 2025).[1]

Second, we uncover a novel health mechanism of extreme temperature. A large body of research has documented the wide-ranging health damages of extreme temperatures, including higher mortality and greater disease incidence (Deschênes and Greenstone, 2011; Gasparrini et al., 2015; Agarwal et al., 2021; Ebi et al., 2021), yet the dietary pathway has received little attention. Our results show that both extreme heat and cold trigger a shift toward energy-dense diets, adding a previously overlooked behavioral channel to the climate–health nexus. Relatedly, Huang and Hong (2024) find that rising temperatures increase obesity rates globally, while Churchill and Srivastava (2025) show that short-term temperature deviations in the United States alter diet quality and weight-management efforts. We advance this literature by providing the first individual-level causal evidence from a developing-country context that extreme temperatures directly shift nutritional demand toward high-fat diets, thereby documenting a complementary pathway that operates independently of agricultural production. Given the global burden of obesity—projected to reduce global GDP by 2.9% by 2035 (Ng et al., 2025) and significantly increase healthcare costs, especially in countries like China (Wang et al., 2021)—understanding this behavioral channel is crucial for public health policy.

Third, we contribute to the emerging literature on environmental determinants of diet. Recent studies show that air pollution alters food purchases by shifting spending away from unhealthy products toward healthier ones (Agarwal et al., 2025; Huang et al., 2025). We extend this line of research by demonstrating

[1] For more details on the literature focusing on temperature-induced reductions in crop output and agricultural TFP, see Table A1.

that temperature, another major environmental stressor, systematically reshapes dietary patterns with important consequences for nutrition, public health, and economic welfare. Since the pace of warming is geographically uneven, these demand-side adjustments may further reinforce both cross-country and within-country disparities in nutrition, health, and human capital accumulation.

The remainder of this paper is structured as follows. Sections 2 and 3 describe the data and methods, respectively. Section 4 presents the baseline results and robustness checks, mechanism tests, adaptation strategy tests, heterogeneous analysis, and long-term projections. Finally, Section 5 provides concluding remarks.

2. Data

Our analysis draws on three primary data sources: household survey data, high-resolution historical weather information, and climate projections. These data enable us to examine how short-term exposure to off-comfort temperatures influences individual diet patterns in China.

2.1 Household data

We use the individual-level data from the China Health and Nutrition Survey (CHNS). It encompasses 28,941 individuals from 7,057 households in 9 provinces from 1991 to 2011 (see Figure A1(a)).[2] This dataset has three advantages for studying the effects of off-comfort temperatures on nutrition intake. First, it provides detailed individual-level information on nutrition. Such data are rarely available: purchase records do not reveal actual consumption, and large-scale longitudinal surveys with dietary intake measures are uncommon. The CHNS overcomes this limitation by offering repeated, precise records of food and nutrient intake, enabling us to directly observe what people consume rather than inferring it indirectly (for more details about the questionnaire on food consumption, see Figure A2). In addition, it contains information on demographics, socioeconomic status, and health outcomes, which further enriches our analysis. Second, encompassing nine provinces across China, this dataset spans diverse climatic zones, permitting a robust exploration of temperature variation. Finally, the timing of the CHNS

[2] Although the CHNS has continued beyond 2011, its detailed food consumption and nutrient intake data are only available up to 2011, with no subsequent updates. Therefore, our analysis is limited to this period. We provide more details on data construction in Appendix A1. Food Consumption. Considering that extreme temperatures have become more frequent in the past fifteen years under climate change, our identified effects are likely conservative estimates.

surveys, primarily conducted between September and November (see Figure A1(b)), offers distinct empirical advantages. On the one hand, temperatures during these months are relatively moderate yet still sufficiently variable, providing an ideal setting to observe sudden hot or cold shocks rather than prolonged, stable extreme temperatures. On the other hand, this period largely avoids major agricultural growing seasons. Thus, the potential confounding effects of fluctuations in crop growth can be substantially mitigated, further strengthening the causal interpretation of our household-side estimates.

Following the guidance of *Chinese Dietary Reference Intakes—Macronutrient (WS/T 578.1-2017)*, we calculate the energy intake in calories based on the amount of carbohydrates, protein, and fat intake. According to the guidance, different macronutrients provide different calories: 1g protein or 1g carbohydrate both provide 4 kcal energy, and 1g fat provides 9 kcal energy. Therefore, if the intake of carbohydrates and protein decreases by 1%, while fat intake remains unchanged, the percentage decrease in calorie intake will be less than 1%. For more details about the data cleaning process, see Appendix A.

2.2 Meteorological data

The meteorological data comes from the China Meteorological Data Sharing Service (CMDSS) system. It includes daily average temperature, wind speed, accumulated rainfall, relative humidity, and sunshine hours from more than 2000 weather stations in China. We construct the daily county-level weather variables by taking an inverse-distance weighted average of all the stations located within a 50-mile radius of the county centroid, using the distance between the centroid and stations as weights.

Because dietary intake in the CHNS is measured over three consecutive days, we construct temperature exposure within the same three-day window. To capture the intensity of heat and cold during this period, we use cumulative cooling degree days (CDD) and heating degree days (HDD). This approach provides a more precise characterization of short-term thermal exposure than conventional temperature bins, because they measure not only whether daily average temperature crosses a threshold but also by how much it exceeds or falls short of it. In light of the distribution of average daily temperature experienced by the respondents (in Figure A1(c)), we choose 25°C and 5°C as the thresholds, which may not appear particularly extreme at first glance but are intended to capture meaningful deviations from the thermal comfort range. For example, if the average temperature for three consecutive days is 23°C, 25°C, and 27°C, the CDD for these three days is 0°C, 0°C, and 2°C, and the 3-day CDD for these three days is 2°C. These two cutoffs are also applied in the *Uniform standard for the design of civil buildings (GB 50352- 2019)*, which suggests that the number of days with annual average daily temperatures below 5°C and above 25 °C can be used as an auxiliary indicator when dividing the temperature zones (for more details and the original version in Chinese, see Figure A3).

Figure A4 further demonstrates that when the daily average temperature reaches 5°C or 25°C, the corresponding minimum or maximum daily temperatures are already significantly lower or higher, respectively, indicating actual exposure to relatively cold or hot conditions even at these seemingly moderate average temperature levels. This supports the validity of our temperature thresholds in capturing meaningful cold and heat exposure episodes for our empirical analysis.

2.3 Climate projections

We use the climate projection data provided by the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) to predict the impacts of climate change on food consumption and macronutrient intake by the end of this century (2080-2099). The NEX-GDDP dataset includes downscaled projections for four Representative Concentration Pathways (RCPS) from 21 models conducted under the Coupled Model Inter-comparison Project Phase 5, developed to support the Fifth IPCC report. We use RCP4.5 (an emissions stabilization scenario) and RCP8.5 (a scenario with intensive growth in fossil fuel emissions, namely "business-as-usual") in line with the literature (Li et al., 2019; Carleton et al., 2022; Lai et al., 2022). The dataset contains daily maximum and minimum temperatures at a spatial resolution of 0.25 degrees. Our projection is based on the median projected temperature and climate from the 21 models and aggregates the original dataset to the city level daily temperature.

2.4 Summary statistics

Table A2 shows the summary statistics of the variables used in this paper, providing two important messages. First, the overall 3-day energy intake for the entire sample was approximately 6398 kcal, with a protein intake of around 195 g. According to the *Chinese dietary reference intakes - Macronutrient (WS/T 578.1-2017)*, adults' recommended daily energy intake ranges from approximately 2100 to 3200 kcal, while the reference protein intake is about 55-65 g/day. Considering the inclusion of children in the sample, the average values for the entire sample may exhibit slight deviations from those of the population aged 18 years and older. Consequently, the observed energy and protein intakes can be considered within the normal range. Figure A5 highlights two notable trends regarding dietary fat consumption from 1991 to 2011 in our sample. The percentage of individuals consuming a high-fat diet (defined as more than 30%

of dietary energy coming from fat) (Wang et al., 2020) exhibited a rapid increase from 22.44% in 1991 to 56.95% in 2011. Meanwhile, the average percentage of total dietary energy derived from fats also steadily increased from 22.06% in 1991 to 32.38% in 2011. This upward trajectory underscores a clear dietary shift in China toward greater fat consumption during the study period, reflecting both nutritional transition and increasing risk factors associated with obesity and other non-communicable diseases.

Second, the distributions of 3-day CDD and HDD are broadly comparable, with mean values of 0.668°C and 0.504°C, respectively. This is largely shaped by survey timing: as shown in Figure A1(b), most CHNS surveys were conducted between September and November. Consequently, respondents were typically exposed to average temperatures between 5 and 25°C, with relatively few observations below 0°C or above 30°C (see Figure A1(c)). The chosen cutoffs of 5°C and 25°C are approximately at the 5th and 95th percentiles of the 3-day average temperature.

3. Empirical Strategies

To investigate the effects of off-comfort temperatures on diet, we employ an ordinary least squares (OLS) framework. Because short-term temperature fluctuations are beyond individual control, they can be regarded as quasi-random once rich sets of fixed effects are included. Moreover, the CHNS dietary surveys were conducted at varying dates within each year, creating additional quasi-random variation in temperature exposure even among individuals living in the same county. Based on this strategy, we estimate the following regression:

$$Y_{icymd} = \alpha + f(temp_{cymd}) + \beta W_{cymd} + \lambda_{ym} + \gamma_{pm} + \sigma_i + \epsilon_{icymd} \quad (1)$$

where Y_{icymd} represent the outcome variables which we are interested in over the past three days for individual i in county c, year y, month m, and day d. First, we consider overall food consumption and total energy intake. Second, we examine the intake of three macronutrients: carbohydrates, proteins, and fats. Third, we focus on dietary composition, measured by the proportion of energy from fat and the high-fat diet index. We use the logarithmic form of total consumption, energy, carbohydrates, proteins, and fat to explore the changes in growth rates due to heat and cold stress. For the proportion of energy from the fat and high-fat diet index, we use the actual value as it is already measured in percentage.

The key independent variable is $temp_{cymd}$, which denotes the daily average temperature. Its functional form, $f(temp_{cymd})$, captures the flexible measure of temperature. In our baseline specification, we employ the cumulative CDD (above 25°C) and HDD (below 5°C) over the past three days to measure short-term exposure to high and low temperatures, respectively. To ensure the robustness of our findings, we also explore alternative definitions of temperature exposure in the robustness checks. W_{cymd} is a vector of the 3-day average meteorological variables other than temperature, including precipitation, relative humidity, wind speed, and sunshine hours.

To address potential confounding factors, we incorporate a rich set of fixed effects at multiple levels. Year-month fixed effects (λ_{ym}) control for nationwide changes, such as economic development that expands food availability and quality, and climate trends. Province-month fixed effects (γ_{pm}) capture seasonal and regional differences in food supply and consumption habits. For instance, local harvest cycles and dietary traditions vary across provinces, and typical seasonal temperatures also differ systematically between the north and the south. With these fixed effects, we exploit only deviations from the usual seasonal climate within the same province. Individual fixed effects (σ_i) absorb all time-invariant personal characteristics, such as baseline health status, inherent dietary preferences, or cultural eating habits that do not change across survey waves. Taken together, these fixed effects purge systematic variation from both the temperature and dietary sides, leaving short-term fluctuations in temperature plausibly random. This design allows our OLS estimates to be interpreted as causal effects. The error term (ϵ_{icymd}) is clustered at the individual level to account for within-person correlation over time.

4. Results

We proceed in this section as follows. First, we assess how heat and cold affect macronutrient intake and the shifts in dietary patterns. Second, we discuss the potential mechanisms that may underly these dietary changes, including physiological appetite regulation and physical activities. Third, we test two potential adaptation strategies, i.e., thermal comfort, and food storage accessibility. Fourth, we uncover significant heterogeneity in dietary responses, with rural and poor populations more prone to high-fat diets, highlighting a potential source of temperature-induced health inequality. Finally, we project the proportion of energy from fat and the probability of high-fat diets by the end of the century under different adaptation scenarios. These projections underscore the need for targeted policies to mitigate temperature-induced dietary risks.

4.1 Baseline results

Figure 1(a) (and Table A3) shows the effects of short-term temperature fluctuations on food consumption and macronutrient intake estimated by equation (1). Heat significantly reduces both food consumption and energy intake, while cold has the opposite effect. For every 1°C above 25°C over the past three days, food consumption decreases by 0.267%, and energy intake declines by 0.292%. In contrast, for every 1°C below 5°C, food consumption increases by 0.152%, and energy intake rises by 0.148%. These findings align with the common sense that heat suppresses appetite, whereas people need to increase food intake to maintain body temperature during cold days.

The distinct impacts of food and energy extend to macronutrient composition, including carbohydrates, proteins, and fat intake. From column (5) to (10) in Figure 1(a), each 1°C above 25°C decreases the intake of carbohydrates by -0.388% and the intake of proteins by -0.590%, but slightly increases the intake of fat by 0.029%. Conversely, each 1°C below 5°C increases the intake of carbohydrates, proteins, and fat intake by 0.101%, 0.152%, and 0.335%, respectively. In a word, heat reduces carbohydrate and protein intake but leaves fat intake relatively stable, resulting in a smaller calorie decline. Cold increases fat intake more than carbohydrates and proteins, driving higher energy intake.

Although heat and cold have opposite effects on food consumption, both lead to higher fat intake. To directly examine these effects on dietary health, we focus on two indices: the proportion of energy from fat and the likelihood of a high-fat diet. Regression results in columns (11) to (14) show that temperatures deviating from comfort increase both the proportion of energy from fat and the probability of high-fat diets. Specifically, each 1°C above 25°C raises the proportion of energy from fat by 0.091% and the likelihood of a high-fat diet by 0.464%. Each 1°C below 5°C increases the proportion of energy from fat by 0.031% and the likelihood of a high-fat diet by 0.179%. The coefficients for CDD are both economically larger and statistically more significant than those for HDD, suggesting that hot weather has stronger dietary impacts than cold weather.

These results suggest that temperatures significantly alter dietary patterns. For example, consider a 3-day heat wave with an average daily temperature of 30°C (corresponding to a CDD of 15°C). This heat wave increases the proportion of dietary energy derived from fat by 1.365% (5.02% of the sample mean, 11.9% of the standard deviation) and raises the probability of adopting a high-fat diet by 6.96% (17.6% of the mean, 14.2% of the standard deviation). In comparison, a 3-day cold wave averaging 0°C (HDD of 15°C) produces smaller but still statistically meaningful effects, increasing the proportion of energy from fat by 0.465% (1.71% of the mean, 4.04% of the standard deviation) and the likelihood of a high-fat diet by 2.685% (6.80% of the mean, 5.49% of the standard deviation).

These dietary patterns pose serious health risks, particularly obesity, which directly enables severe diseases like cardiovascular conditions, diabetes, and cancers (Sung et al., 2019; Soerjomataram and Bray, 2021; Ng et al., 2025). Excess calories convert into body fat when not burned. Even stable calorie intake with a higher fat proportion elevates obesity risk. We use the OLS approach to reveal the correlation of Body Mass Index (BMI) with energy intake and dietary structure (for more details about the regression model, see Appendix B). Table A4 shows the regression results and reveals three messages. Both calorie intake and fat proportion are positively and statistically associated with BMI. While calorie intake often receives more attention, the high-fat diets highlighted in this study pose a hidden yet critical health threat. Our paper shows that heat and cold stress may increase obesity and NCD risks through long-term diet changes.

We validate our findings through multiple robustness checks (see Appendix C for details of the method and Table A5 to Table A7 for regression results). First, we cluster standard errors at both individual levels and household-year levels to account for within-household and temporal correlations. Second, we incorporate province-specific linear wave trends to control for heterogeneous provincial trends in economic development. Third, we restrict the sample to individuals with complete dietary survey records to ensure data quality. Fourth, we use the original levels of food consumption and macronutrient intake as alternative outcomes. Finally, we test alternative definitions of temperature variables, including varying thresholds and nonparametric models. All checks yield consistent estimates, supporting the robustness of our main findings.

4.2 Different food groups and condiments

We track dietary structure changes through 12 types of food and 3 types of condiments. We simplify these items into six aggregated groups for clearer pattern identification. Each group of food and condiments has zero values (see Table A2) and is small. Thus, we use the real consumption value for each group as the outcome variable instead of the logarithm form after adding one. Temperature-driven consumption changes for each group are presented in Figure 1(b) and Table A8.

Two clear patterns emerge. First, heat primarily reduces the intake of cereals and meats, while milk, vegetables, fruits, eggs, nuts, and oils remain largely unaffected. Heat reduces the consumption of cereals and meats, while milk, vegetables, fruits, eggs, nuts, and oil show no significant changes. According to China's Nutrition of Main Foods (Chinese Center for Disease Control and Prevention, 2018), we roughly calculate the proportions of three macronutrients supplied by the four major food groups (see Figure A6). Cereals, tubers, and dried legumes are low in fat (nearly 5g per 100g), while milk, eggs, and nuts have more fat (about 26g per 100g), and oils are the most fat-dense. Notably, edible oil accounts for 50% of total fat intake in China (Wang et al., 2020). As a result, hot weather suppresses the consumption of low-fat staples but leaves high-fat items stable, which raises the dietary fat share.

Second, cold exposure induces broad-based increases across most food groups, with the largest gains observed in vegetables, fruits, milk, eggs, nuts, and oils. In contrast, cereals and meat show little response. Because the strongest increases come from high-fat sources such as nuts and oil, cold weather also pushes diets toward higher fat intake, although the per-degree effect is smaller than under heat stress.

Taken together, these results show that the main drivers of temperature-induced high-fat diets differ across contexts. Heat reduces low-fat staples while leaving high-fat items unchanged, whereas cold stimulates demand for fat-rich items. Both hot and cold stress, therefore, shift individuals toward high-fat diets, with important implications for future food demand and nutrition under climate change.

4.3 Mechanisms

Several potential mechanisms may explain how off-comfort temperatures influence food consumption and macronutrient intake. First, Physiological responses to thermal stress offer a plausible mechanism. Cold exposure activates sympathetic thermogenesis, including shivering and brown adipose tissue (BAT) activation, which substantially increases energy expenditure and relies heavily on fatty-acid oxidation (Virtanen et al., 2009). These processes heighten caloric needs and can increase demand for energy-dense foods such as fats. In contrast, hot ambient conditions suppress appetite and reduce energy intake (Institute of Medicine, 1993). Because carbohydrates and proteins entail higher diet-induced thermogenesis than fats (Westerterp, 2004), heat is more likely to suppress their intake.

Second, heat and cold might influence dietary behavior by changing individuals' time allocation or physical activity. For instance, heat and cold could alter working hours and, consequently, nutritional demands. Similarly, individuals may adjust their leisure activities, such as outdoor exercises (Graff Zivin and Neidell, 2014), thereby indirectly influencing energy and macronutrient requirements. Due to data constraints within the CHNS dataset, we first control for respondents' occupation types and physical activity preferences (for details about these variables, see Appendix A). Table A9 illustrates that, after accounting for these variables, the estimated coefficients of CDD and HDD for each outcome remain consistent with our baseline findings. Additionally, we examine whether temperature fluctuations influence respondents' working hours by analyzing reported hours worked during the previous week and corresponding temperature exposure. As presented in Table A10, neither CDD nor HDD from the previous week significantly affect working hours. Taken together, results from both Table A9 and A10 suggest that the effects of temperature on dietary behavior and nutritional intake observed in our analysis are unlikely to be mediated through changes in work time or physical activity.

4.4 Adaptation strategies

Here we consider two potential adaptation strategies. First, the presence of cooling and heating technologies, such as air conditioners, fans, and heating systems, directly affects individuals' thermal comfort. By modifying temperature perception and improving indoor comfort, these technologies may help individuals maintain their normal dietary habits despite outdoor temperature fluctuations. Second, refrigerators allow households to extend the food storage period, reducing the frequency of grocery shopping during episodes of off-comfort temperatures. Thus, refrigerators potentially mitigate temperature impacts by enhancing food availability at home.

We simultaneously take all the appliances (i.e., fans, air conditioners, heating systems, and refrigerators) into consideration by adding their interactions with temperature (for more details about the method, see Appendix D).[3] Results are shown in Figure 2 and Table A11. In rows (3) and (4) of each subfigure, fans and air conditioners mitigate the effects of heat. Notably, our data only indicates appliance ownership rather than actual usage, which does not affect the validity of our discussion. If these appliances were

[3] Air conditioner is widely seen as the main appliance for mitigating the effects of high temperatures (Davis and Gertler, 2015; Barreca et al., 2016; Mullins and White, 2019; Randazzo et al., 2023). However, in our dataset, the ownership of air conditioners is lower than 20%. By contrast, more than 50% of individuals have at least one fan in their household. These ratios appear reasonable given that fans are less expensive than air conditioners. Thus, solely considering air conditioners would underestimate the overall effect. Therefore, we consider the roles of both fans and air conditioners.

owned but not actively used, our estimated effects of the appliances would represent a lower bound; actual usage would presumably yield even stronger benefits. Empirical results show that fans significantly mitigate the decline in food consumption (by 0.637%), energy intake (by 0.532%), carbohydrate intake (by 0.787%), and protein intake (by 0.807%) during hot weather. Meanwhile, air conditioners significantly reduce fat intake (by 0.523%). Taken together, these cooling technologies alleviate the impact of heat on the proportion of dietary energy from fat and reduce the likelihood of adopting a high-fat diet. In contrast, heating systems mitigate cold exposure by warming indoor temperatures. In row (5) of each subfigure, they reduce food (-1.176%) and nutrient intake (-1.210%). The marginal effect on fat (-1.471%) is larger than on carbohydrates (-1.313%) and protein (-0.758%). As a result, heating systems slightly reduce the likelihood of high-fat diets.

Unlike temperature adjustment technologies, refrigerators mitigate temperature effects by improving food storage and accessibility. However, while refrigerators increase the intake of food (0.300%) and carbohydrate (0.227%) during heat, their impact on fat intake is minimal (see rows (6) and (7) of each subfigure).

Combined with the mechanism analysis, these findings highlight that dietary shifts may be driven more by biological factors, such as appetite regulation or self-preservation during off-comfort temperatures. From a policy perspective, promoting access to affordable and effective household appliances could serve as a climate adaptation strategy to mitigate undesirable dietary shifts.

4.5 Heterogeneous analysis

The analysis above proves that both heat and cold significantly affect diet structure and enhance the probability of having a high-fat diet. However, such impacts may differ based on individual characteristics. Understanding how climatic variability influences dietary behaviors across different population subgroups is essential for designing targeted nutritional and climate policies. Figure 3 (and Table A12) presents heterogeneities for the two diet-related variables, leading to three key findings.

First, we focus on age and gender. In the first section of Figure 3, off-comfort temperatures affect older adults less than other age groups, possibly because reduced appetite buffers their physiological responses. As for children, they appear more vulnerable to cold than to heat. Early-life macronutrient intake of children significantly influences health outcomes and the accumulation of human capital

(Maluccio et al., 2009; Almond et al., 2015; Chong et al., 2016; Hjort et al., 2017; Coffey et al., 2018). Gender differences remain minimal in dietary responses. Men and women exhibit similar temperature sensitivity (see the second section of Figure 3).

Second, we compare people living in urban and rural areas. In the third section of Figure 3, rural populations are more sensitive to temperature compared to urban residents. Rural residents exhibit stronger temperature-driven increases in the proportion of energy from fat and a higher propensity for high-fat diets under heat and cold stress. This urban-rural disparity stems from structural inequities in China. Rural areas face compounded vulnerabilities from inadequate food storage infrastructure, limited market access, and higher transportation costs (Liu et al., 2014). Thermal technology adoption also lags in rural households (Yu et al., 2019) (in our sample, see summary statistics in Table A13). These systemic gaps, rooted in socioeconomic constraints and differential health literacy, concentrate climate risks more in rural communities.

Third, we explore how household wealth differs in their dietary responses to temperatures. We divide the sample into two groups, "poor" and "rich," depending on the median household income of each survey year as the threshold. As shown in the fourth section of Figure 3, individuals from poorer households are notably more vulnerable to off-comfort temperatures compared to their richer counterparts. Both hot and cold temperature shocks drive larger increases in the proportion of energy from fats and a higher likelihood of adopting high-fat diets among lower-income groups. Wealthier households, benefiting from better economic resources, can more effectively buffer the adverse dietary impacts of heat and cold. In contrast, people with lower wealth levels have less adaptation capacity, such as having less access to fans, air conditioners, and refrigerators (see Table A13), amplifying their climate-nutrition risks through both behavioral and socioeconomic constraints. Such socioeconomic gaps underscore the importance of policy measures targeting economically disadvantaged populations to mitigate potential temperature-induced nutritional inequalities.

4.6 End-of-century projections

Climate projections predict that the global climate will experience more extremely hot days and fewer extremely cold days by the end of this century (see Figure 4(b)). In this context, we focus on two climate scenarios, RCP4.5 and RCP8.5: the former is a medium stabilization pathway assuming some global action to reduce emissions, while the latter is a high-concentration pathway assuming little effort to mitigate climate change (van Vuuren et al., 2011). Under these two scenarios, we project end-of-century temperature-induced changes in the proportion of energy from fat and the probability of adopting a high-fat diet, based on empirical relationships from equations (1) and (3) (for more projection details, see Appendix D). These two equations correspond to two adaptation strategies: (1) the current level, where adaptation remains at the status quo, and (2) complete adaptation, where complete adaptation is achieved. While economic growth will likely increase the adoption of fans, air conditioners, and other heating products, complete saturation remains implausible. Our projections thus establish upper (baseline) and lower (complete adaptation) bounds for climate-driven dietary impacts.

The results shown in Figure 4(a) have three observations (for the projection results of other variables, see Figure A7). First, people in more than half of the areas are likely to consume excess fat and have a high-fat diet because of global warming. These effects are stronger under the scenario RCP8.5 than under RCP4.5. On average, climate change will increase the proportion of energy from fat by 0.05 (0.22) percentage points under RCP4.5 (8.5), and the probability of a high-fat diet by 0.21 (1.04). Second, while the average effects of temperature are not substantial, spatial heterogeneity indicates a large difference between different cities. For example, the effect of temperature on the probability of having a high-fat diet varies from -1.31 to 2.35 (-1.60 to 3.96) percentage points under RCP4.5 (8.5) across different cities. Overall, there are increased vulnerabilities in southern China, where individuals are more prone to high-fat diets. In the Northeast, people are less likely to have a high-fat diet, and this result is likely driven by a decrease in cold weather and an increase in relatively warm (rather than hot) weather. Third, adaptation technologies significantly mitigate the effects of temperatures, especially for the probability of having a high-fat diet. On average, with adaptation, climate change will increase the proportion of energy from fat by 0.03 (0.10) percentage points under RCP4.5 (8.5), and the probability of a high-fat diet by 0.09 (0.56). Thus, adaptation strategies offset almost half of the effects of climate change. This result highlights the importance of adaptive behavior in improving individual dietary health.

5. Conclusion

Climate change has resulted in increasing extreme weather conditions globally. Using detailed longitudinal survey data on individual-level dietary intake combined with high-resolution weather records, we identify the causal impact of temperature fluctuations on dietary composition. We find that heat reduces carbohydrate and protein intake without significantly affecting fat intake, whereas cold weather significantly increases the intake of all three macronutrients. Consequently, people tend to derive more energy from fat and adopt high-fat diets when experiencing both hot and cold temperatures.

Indoor temperature adjustment technologies, such as air conditioners, fans, and heating systems, play a critical role in adapting temperature-induced dietary shifts, whereas improved food accessibility through refrigerators exhibit limited effects. There would be potentially enlarged disparities under future climate change scenarios, as rural and poor residents seem more sensitive to off-comfort temperatures than their counterparts. End-of-century projections show that people in South and East China tend to consume more fat compared to people living in Northeast China, and thermal regulation systems could partially mitigate the prevalence of high-fat diets across these regions. Given China's large geographic span and wide temperature range, these regional differences may also foreshadow heterogeneous global responses. Warmer southern regions are likely to bear greater public health costs, although direct evidence at the global scale remains to be established and awaits future research.

Overall, this paper contributes new evidence on how temperature fluctuation shapes human dietary behaviors. The key message of these results is that off-comfort temperatures have an obvious effect on fat consumption proportion and high-fat diet, which varies by rural, urban, and wealth, and could be moderated by thermal regulation systems. Therefore, policymakers need to pay more attention to the impacts of short-term off-comfort temperatures on nutritional intake. This not only requires ample provisions of food, but also protective measures like air conditioners and heating systems. Besides, heterogeneity effects mean that governments need to pay more attention to vulnerable groups who are at higher risk in the face of climate change.

This study has some caveats and limitations, though none fundamentally undermine our findings. First, the impacts we document are essentially partial equilibrium effects, as we do not explicitly analyze or disentangle the responses of food producers. Second, while we do not account for variations in individuals' optimal nutritional levels—so losses or gains in nutrition intake should not be interpreted as deviations from the optimum—this limitation does not affect the validity of our estimates of temperature-induced shifts in diet. Third, food availability and dietary patterns in China have evolved considerably over the past decades, but our empirical strategy with fixed effects ensures that these structural changes are unlikely to drive the short-term effects we identify. Fourth, our results capture short-term responses to temperature fluctuations rather than long-term adjustments under climate change, and the long-term dietary impacts of climate change remain to be explored. Finally, while the 3-day recall method used to collect food consumption data may involve recall biases, the rich detail of the CHNS dataset and our robustness checks suggest that any such errors are unlikely to overturn our main conclusions.

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Figures

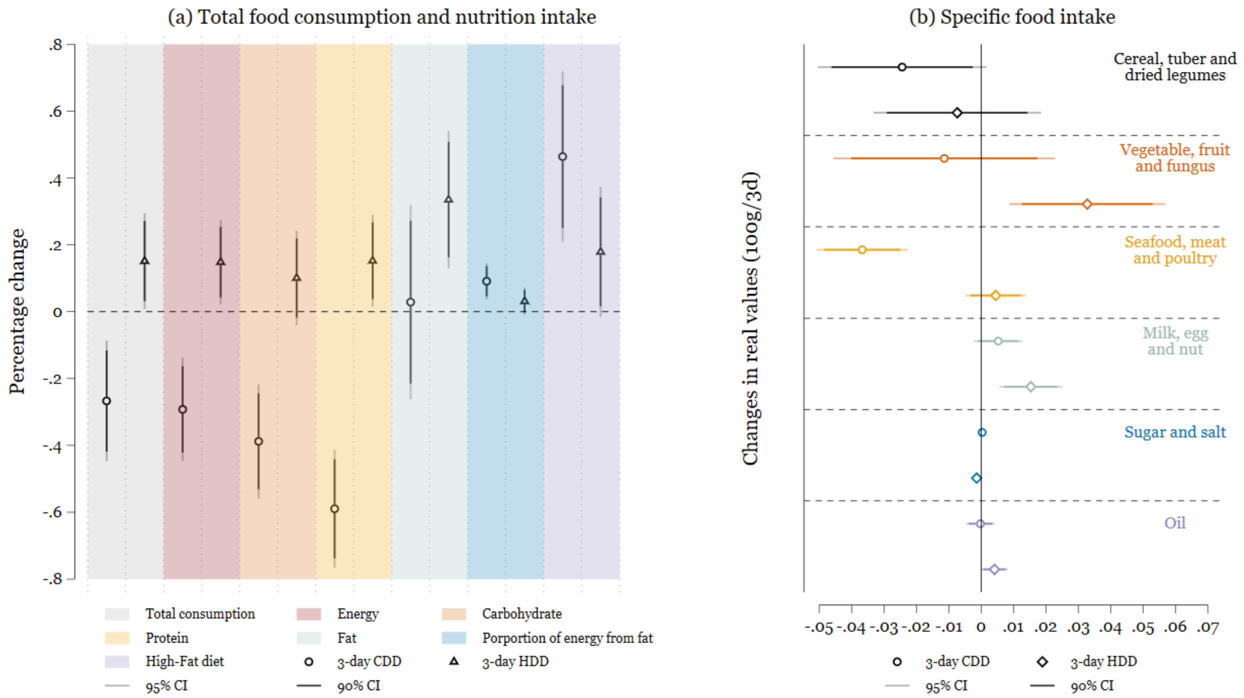

Figure 1. Temperature affects food consumption and macronutrient intake.

Notes: These figures illustrate the effects of temperature on 3-day food consumption, macronutrient intake, the proportion of energy from fat, and the probability of high-fat diets (in (a)) and the intake of six groups of food and condiments (in (b)). The foods include cereals, tubers, dried legumes, vegetables, fruits, fungus, seafood, meat, poultry, milk, eggs, and nuts, while the condiments include sugar, salt, and oils. Total consumption is calculated by summing up all the food consumed by the individual, excluding the condiments, which are only usable after 1997. In Figure (a), the outcome variables are the logarithmic form of the value of food consumption or macronutrient intake and the original levels of the proportion of energy from fat and high-fat diets. For ease of interpretation, we multiply the coefficients and CIs in Table A3 by 100 so that the results can be interpreted as a change in percentage. In Figure (b), the outcome variables are the original levels of the intake of each group of food and condiments. As shown in equation (1), the regression model includes individual fixed effects, year-month fixed effects, and province-month fixed effects. The regression results are reported in Table A3 and Table A8. The circles and triangles represent the regression coefficients, and the dark (light) lines represent 90% (95%) confidence intervals. Standard errors are clustered at the individual level.

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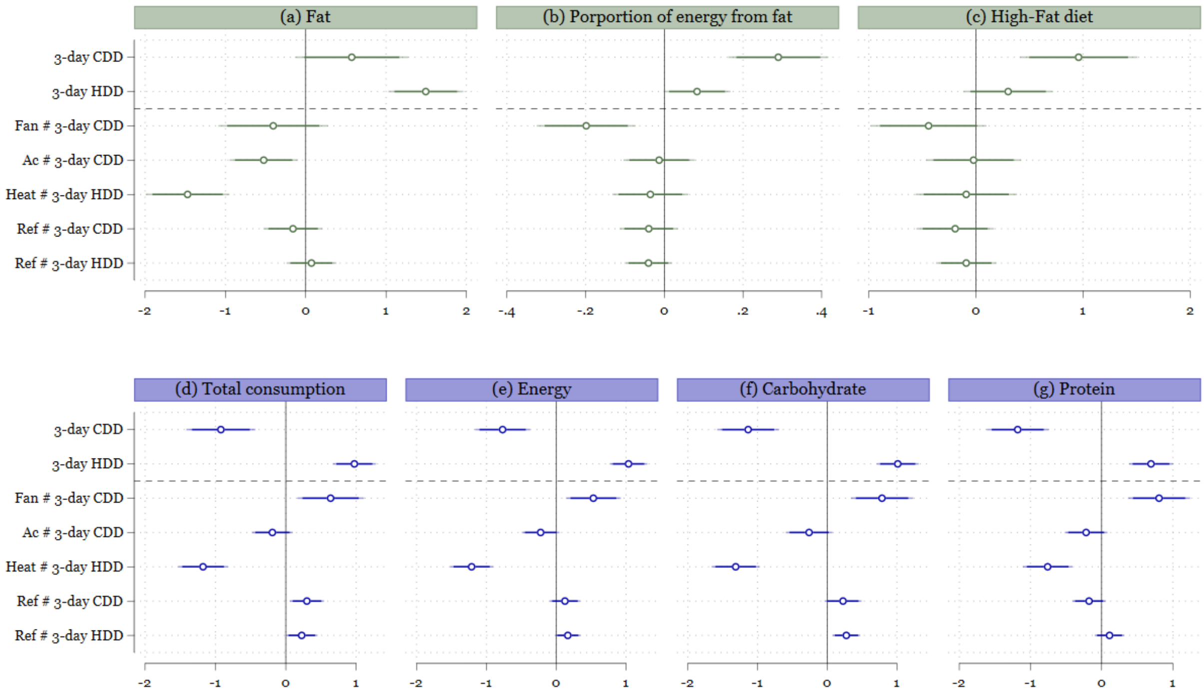

Figure 2. Adaptation effects of fans, air conditioners, heating systems, and refrigerators.

Notes: These figures demonstrate the adaptation effects of home appliances on 3-day food consumption, macronutrient intake, proportion of energy from fat, and high-fat diet index. The outcome variables are the logarithmic form of the value of food consumption or macronutrient intake and the original levels of the proportion of energy from fat and high-fat diets. As shown in equation (3), the regression model includes individual fixed effects, year-month fixed effects, and province-month fixed effects. The regression results are documented in Table A11. The circles represent the regression coefficients, and the dark (light) lines represent 90% (95%) confidence intervals. For ease of interpretation, we multiply the coefficients and CIs in Table A11 by 100 so that the result can be interpreted as a change in percentage. Standard errors are clustered at the individual level.

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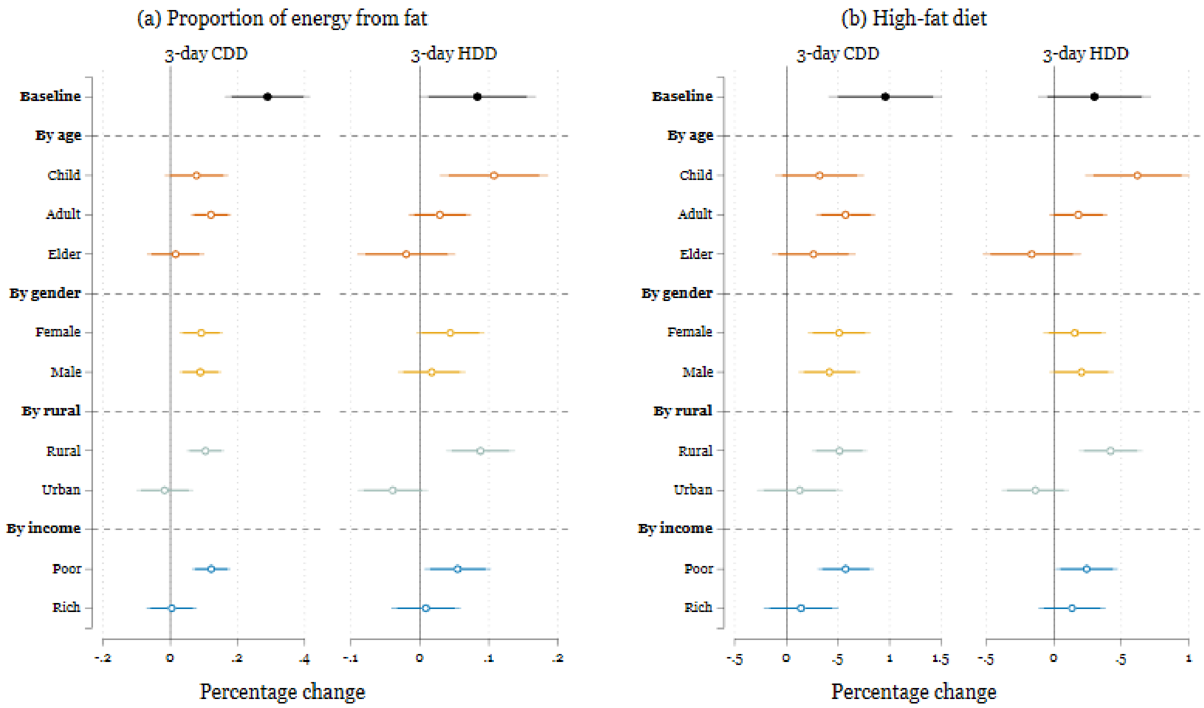

Figure 3. Heterogeneous effects of temperature on the proportion of energy from fat and high-fat diets.

Notes: These figures show the heterogeneity of the effect of off-comfort temperatures on the proportion of energy from fat and the probability of having a high-fat diet. The outcome variables are the original levels. The regression model includes individual fixed effects, year-month fixed effects, and province-month fixed effects. The regression results are reported in Table A12. The circles represent the regression coefficients, and the dark (light) lines represent 90% (95%) confidence intervals. For ease of interpretation, we multiply the coefficients and CIs in Table A12 by 100 so that the result can be interpreted as a change in percentage. Standard errors are clustered at the individual level.

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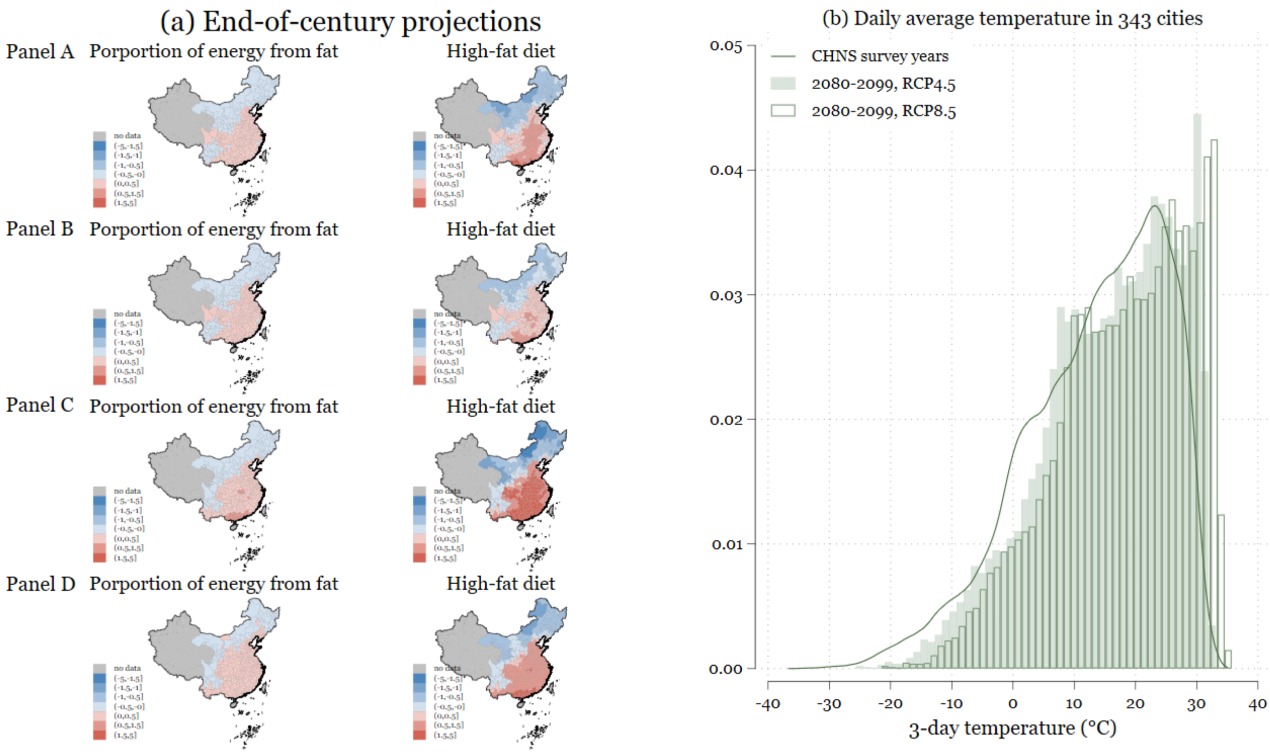

Figure 4. End-of-century projections and distribution of daily average temperature in 343 cities. *Notes:* Figure (a) shows the predicted impact of climate change on the proportion of energy from fat and the probability of a high-fat diet for each city in 2080-2099 relative to CHNS survey waves. Due to the limited coverage of provinces of CHNS (see Figure A1), results based on this database may not be representative of the national average, especially in the Northwest region and the Tibetan Plateau. Therefore, we remove Qinghai, Tibet, and Xinjiang provinces from the forecast. Panel A and Panel C show the projection results based on equation (4) under the climate scenarios RCP4.5 and RCP8.5, respectively. Panel B and Panel D show the projection results based on equation (5), which considers the adaptation effects of the fans, air conditioners, heating systems, and refrigerators under the climate scenarios RCP4.5 and RCP8.5. All the scales in subgraphs are uniform. Red indicates an increase in the proportion or probability, while blue shows the opposite effect. Figure (b) shows the distribution of daily temperature in three scenarios. The first scenario is the average daily temperature during the CHNS survey years, which are 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011. The second scenario is the projected average daily temperature in RCP4.5, and the third is RCP8.5. We average the data to the city-day level and plot the density picture.

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Appendix A: Data cleaning

A1. Food consumption

Detailed food consumption information is collected using the 24-hour recalls on 3 consecutive days, with each food item assigned a corresponding food code from the Chinese Food Composition Table (FCT). Household food consumption was measured daily by weighing all available foods at the start and end of each survey day, alongside detailed recording of purchases, home production, and food waste. Individual dietary intake data were gathered each day through interviews, capturing both at-home and away-from-home food consumption. The household and individual dietary intakes were cross-validated to ensure data quality, with trained nutritionists conducting all interviews (China Health and Nutrition Survey Data Collection).

To derive the average daily food consumption, we aggregate individual-level food consumption over the 3-day interview period and divide it by the total person-days for each type of food. Any observations with missing food codes are excluded from the analysis. For individuals with multiple records on the same day, we consider the highest number of person-days as the count. Only 1,512 of 3,040,836 observations have this problem. In the raw data, 2,075,211 observations have the records of person-days, and approximately 95.7% of them are recorded as 1. Missing values occur throughout all years, so we substitute the incorrect person-days with the value of 1. It is worth noting that while most individuals have completed 3-day records, some only have 1-day or 2-day records. We opt to drop these observations for two reasons. First, food consumption data from individuals with less than a 3-day record raises reliability concerns. Second, 1-day or 2-day records are more prone to measurement errors compared to 3-day records, which could potentially bias the estimation. We drop 27,792 of 3,040,836 observations in this step. Finally, 3,040,836 observations have 3-day records, and 94.09% of them have a person-day count of three.

During the survey periods, three versions of the FCT were available, requiring the alignment of food codes with specific species. We classify all items into 12 distinct food categories, primarily aligning them with the current version of the FCT. These 12 categories encompass cereals, tubers, dried legumes, vegetables, fungi, fruits, nuts, meats, poultry, dairy products, eggs, and seafood. To ensure the accuracy of the data, individuals displaying extreme values are excluded from the analysis. Specifically, observations are omitted if the z-score for any food category exceeds 10. Furthermore, specific categories such as infant foods, ethnic cuisine, fast food, and beverages are disregarded due to the varying classifications and definitions across different versions of the FCT. For each person, we adjust their 3-day intake based on the person-days. We sum up all the 12 types of food consumed by the individual as one variable, i.e., total food consumption. Since CHNS only provides the total consumption amount of each household for the condiments, we average the total amount for everyone who eats at home.

We drop the data from the first and final surveys in our analysis for three reasons. First, the sample size in 1989 was relatively small compared with other waves. Only people aged 1-6 and 20-45 were collected in the food consumption survey. Second, the first survey wave lasted from 1989 to 1990. Finally, the official CHNS website does not provide information on food consumption and macronutrient intake for 2015. Before using the data in empirical analysis, we exclude observations in which the key dependent variables—total food consumption, carbohydrate, protein, and fat—fall outside the 0.5th to 99.5th percentile range.

A2. BMI

When handling BMI data, we carefully review the original entries and exclude observations suspected of containing erroneous height or weight values, as well as juvenile individuals. Furthermore, observations with BMI values falling outside the 0.5th to 99.5th percentile range are removed from the analysis.

A3. Working and exercising

For working and exercising variables, most survey questions refer to annual averages, presenting challenges in accurately aligning these responses with short-term temperature fluctuations.

First, to capture exercise behaviors, we construct a variable named "sport time" by aggregating respondents' daily time spent engaging in various physical activities. These activities include martial arts, gymnastics, dancing, acrobatics, running (track and field), swimming, soccer, basketball, tennis, badminton, volleyball, and other forms of exercise such as ping pong and Tai Chi. Additionally, we create three dummy variables—"walking", "exercise", and "bodybuilding"—to represent individual preferences for these specific physical activities. Given the lack of precise time frames associated with these variables, we include them solely as control variables in our mechanism analysis.

Second, concerning work-related data, we address the timing mismatch by using responses to the survey question: "During the past week, for how many hours did you work?" This includes working hours from both primary and secondary occupations. We then match each individual's reported working hours with their corresponding temperature exposure during the preceding week, based on precise interview dates. To minimize measurement errors, evident outliers, such as weekly working hours exceeding the 99.5th percentile (e.g., 168 hours), were excluded from our analysis.

Appendix B: Correlation of BMI with energy intake and dietary structure

We use the OLS approach to reveal the correlation of BMI with energy intake and dietary structure. The regression model is as follows:

$$Y_{icymd} = \alpha + \beta_1 Cal_{icymd} + \delta Fat_{icymd} + \lambda_{ym} + \gamma_{pm} + \sigma_i + \epsilon_{icymd} \tag{2}$$

where Y_{icymd} represent the BMI of adult (age ≥ 18) i in county c, measured at year y, month m, and day d. Cal_{icymd} are the amount of calorie intake of adult i over the past three days. Fat_{icymd} represent the fat-related variables, including the real amount of fat intake, the proportion of energy from fat, or the probability of having a high-fat diet. The remaining variables and symbols are the same as those in equation (1).

Appendix C: Robustness checks

To ensure our results are convincing, we adopt a series of robustness tests. Specifically, we first estimate standard errors clustered within individuals and household-years to account for autocorrelation and household-by-year correlation of the error terms. Second, in addition to the fixed effects considered in the baseline model, we include the provincial year trend, which allows different year trends in each province. Third, we drop observations which we do not have an exact 3-day dietary intake survey. Almost 35% observations only have a household survey date instead of the clear date of each day in the 3-day dietary surveys. We do not drop them in the baseline and use the household survey date as the final date of food surveys because the sample is relatively large. Fourth, we change the outcome variables to their original levels. These regression results are shown in Table A5.

Fifth, we change several cutoffs of CDD and HDD. Although the *Uniform standard* uses 5°C and 25°C as the suggested cutoffs, we try several different divisions, such as 4-26°C, 6-24°C, and 10-20°C. Besides, we use the daily maximum and minimum temperatures to calculate the 3-day cumulative CDD and HDD. Since the distributions of maximum temperature are significantly shifted to the right compared with the average temperature (as shown in Figure A1(c)), the cutoff values are adjusted to 30°C for maximum temperature. These results, shown in Table A6, are consistent with our baseline estimates.

Finally, we consider the non-linear effect of temperature on diet, which means the form of $f(temp_{cymd})$ is $\sum_k Tbin_{cymd}^k$. $Tbin_{cymd}^k$ represents the number of days in the past three days for which the average temperature falls into the kth bin. We generate several bins to capture the non-linear effect. Depending on the distribution of 3-day average temperature, we set 7 bins which are 1°C and below, (1°C, 3°C], (3°C, 5°C], (5°C, 25°C], (25°C, 27°C], (27°C, 29°C], and 29°C and above. To avoid complete multicollinearity problems, the temperature bin (5°C, 25°C] is dropped as the reference group, which is more suitable for human health and could make it easier to observe the effects of high and low temperatures. Regression results are shown in Table A7. All checks yield consistent estimates, supporting the robustness of our main findings.

Appendix D: Adaptation

There may be some endogeneity when installing these home appliances. Extreme temperatures may affect the work time (Somanathan et al., 2021; Heyes and Saberian, 2022) and income (Carleton, 2017) of individuals, which determines the household purchasing power. Therefore, we use information on the respondents' initial per capita household income by year fixed effects to control for the impact of wealth. All the income variables are deflated by the management of CHNS, so they are comparable even though different households may enter the survey in different waves.

Since the CHNS questionnaire does not document the adoption of district heating systems in households, we use an alternative approach—whether the county respondents lived in a provided collective heating service. Specifically, households are defined as having heating systems if their county offered collective heating services (i.e., in the south of the Qinling-Huaihe line) during the survey period from November to February. The regression model employed in this section is as follows:

$$\begin{aligned} Y_{icymd} = \alpha + f\left(temp_{cymd}\right) + f\left(temp_{cymd}\right) * mod_{it} + mod_{it} \\ +\beta W_{cymd} + \lambda_{ym} + \gamma_{pm} + \sigma_i + \epsilon_{icymd} \end{aligned} \tag{3}$$

where, mod_{it} represents a vector of the technologies of individual i in year t, including whether there are fans, air conditioners, heating systems, and refrigerators in the household. If the answer is yes, the dummy variable mod_{it} is 1; otherwise, 0. Because the fans, air conditioners, and heating systems always work in summer and winter, respectively, we only interact with them with CDD (for air conditioners and fans) and HDD (for heating systems). Air conditioners may be used for both heating and cooling. However, given the early time period of our study and the overall low rate of air conditioning ownership, we argue that people used air conditioning primarily for cooling during the study period. The remaining variables and symbols are the same as the ones in the equation (1).

Appendix E: Projection method

We try to predict the overall impact of temperature changes based on our baseline regression results (in Table A3) for each city j using the model as follows:

$$\Delta Y_j(\%) = \left(\hat{\beta}_{cdd} \times \Delta CDD_j + \hat{\beta}_{hdd} \times \Delta HDD_j\right) * 3 * 100 \tag{4}$$

where $\Delta Y_j(\%)$ indicates the temperature change impacts on food consumption and macronutrient intake of individuals in city c. $\hat{\beta}_{cdd}$ and $\hat{\beta}_{hdd}$ represent the estimated coefficient for 3-day CDD and 3-day HDD in our baseline regression, respectively. ΔCDD_j and ΔHDD_j are the predicted change of yearly-average 1-day CDD and HDD in city j. Here we consider the changes between our survey waves (i.e., 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011) and 2080-2099.

We also consider the effect of adaptation strategies. This projection scenario assumes that each individual simultaneously has an air conditioner, fan, refrigerator, and heating system in the household. Not all individuals may be equipped with all adaptation methods (e.g., residents in South China may have no heating systems). Thus, the result in this scenario is a lower bar of the actual effect of off-comfort temperatures because we may overestimate the effects of adaptation behavior at the aggregate level. The model is as follows:

$$\begin{aligned}\Delta Y_j(\%) = [&\left(\hat{\beta}_{cdd} + \hat{\beta}_{cdd*ac} + \hat{\beta}_{cdd*fan} + \hat{\beta}_{cdd*ref}\right) \times \Delta CDD_j + \\ &\left(\hat{\beta}_{hdd} + \hat{\beta}_{hdd*heat} + \hat{\beta}_{hdd*ref}\right) \times \Delta HDD_j] * 3 * 100\end{aligned} \tag{5}$$

where $\hat{\beta}_{cdd*ac}$ and $\hat{\beta}_{cdd*fan}$ represents the coefficient of 3-day CDD by air conditioners and fans in Table A11. $\hat{\beta}_{cdd*ref}$ represents the coefficient of 3-day CDD by refrigerators, and $\hat{\beta}_{hdd*ref}$ means the coefficient of interaction of 3-day HDD and refrigerators. $\hat{\beta}_{hdd*heat}$ represents the coefficient of 3-day HDD by heating systems. These four coefficients capture the effects of adaptation strategies.

Appendix Figures

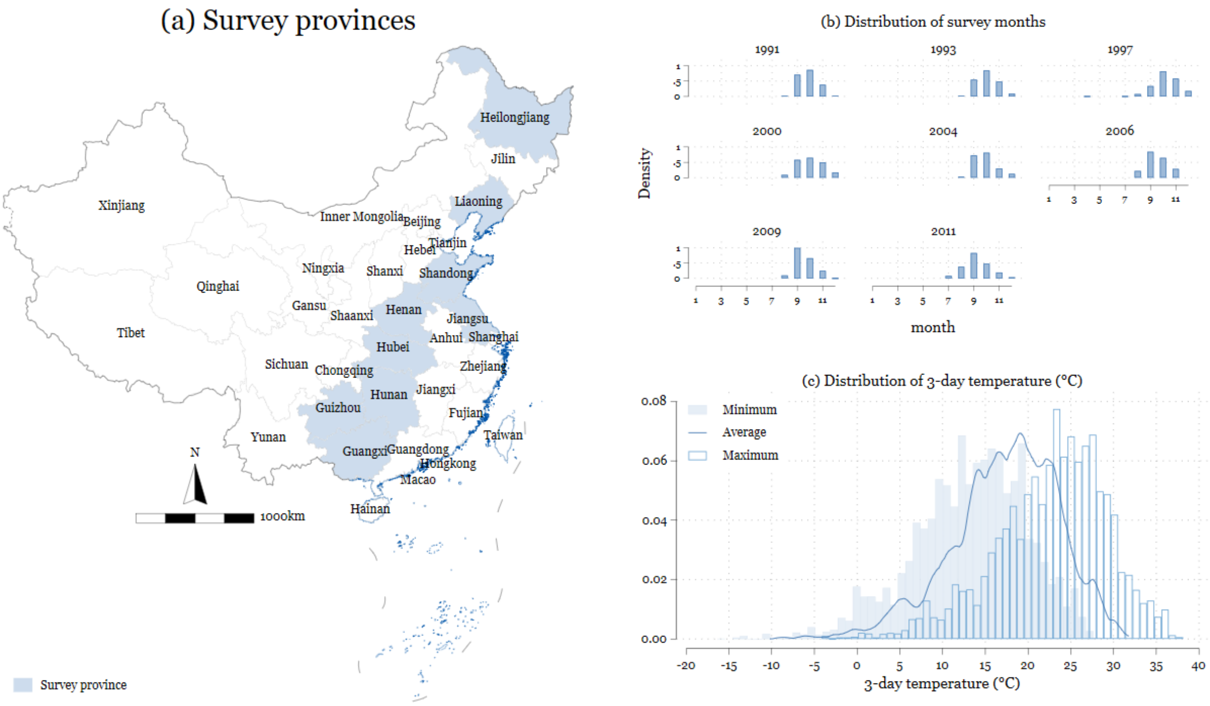

Figure A1. Survey provinces, months, and the distribution of 3-day temperature.

Notes: These figures show the survey provinces used in this paper (in (a)), the distribution of survey months in each year (in (b)), and the distribution of the 3-day temperature exposure by respondents (in (c)). The average temperatures are limited to days above 30°C and below 0°C, because the survey months mainly concentrated on September to November. The distribution patterns for maximum and minimum temperatures were similar to those of the average temperature, albeit with an overall shift in the distribution.

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Table 4. Individual Record of Daily Food

Household ID: _ _ Province (T1) _ Site (T2) _ City/County (T3) _ _ Neighborhood/Village (T4) _ _ _ HH (T5)

Name:__________ Line Number:___________ _ _ _A1

Interview Day: 1. Day 1 2. Day 2 3. Day 3 _VD

Person-Day _._V35a

Interview Date: _____Year ______Month _______Day _ _ _ _ _ _ _ _ T7

1 Item Number	2 Meal V40	3 Recipe Name	4 Ingredient Name	5 Ingredient Code V14b	6 Amount (gm) V39a	7 Edible Portion? V39b	8 Processed food? V39c	9 Meal Location V41	10 Preparation Method V42	11 Preparation Location V43
1	_			_ _ _ _ _ _	_ _ _ _	_	_	_	_	_
2	_			_ _ _ _ _ _	_ _ _ _	_	_	_	_	_
3	_			_ _ _ _ _ _	_ _ _ _	_	_	_	_	_
4	_			_ _ _ _ _ _	_ _ _ _	_	_	_	_	_

Figure A2. CHNS questionnaire: Food consumption (2011 version).

Notes: This figure shows part of the CHNS questionnaire about food consumption.

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气候区划标准》GB 50178 的建筑气候区划和《民用建筑热工设计规范》GB 50176 的建筑热工设计分区。建筑气候区划反映的是建筑与气候的关系，主要体现在各个气象基本要素的时空分布特点及其对建筑的直接作用。适用范围更广，涉及的气候参数更多。建筑气候区划以累年 1 月和 7 月平均气温、7 月平均相对湿度等作为主要指标，以年降水量、年日平均气温≤5℃和≥25℃的天数等作为辅助指标，将全国划分成 7 个 1 级区。建筑热工分区反映的是建筑热工设计与气候的关系，主要体现在气象基本要素对建筑物及围护结构的保温隔热设计的影响。考虑的因素较少、较为简单。建筑热工设计分区用累年最冷月（即 1 月）和最热月（即 7 月）平均温度作为分区主要指标，累年日平均温度≤5℃和≥25℃的天数作为辅助指标，将全国划分成 5 个区，即严寒、寒冷、夏热冬冷、夏热冬暖和温和地区，并提出相应的设计要求。由于建筑热工设计分区和建筑气候一级区划的主要分区指标一致，因此，两者的区划是相互兼容、基本一致的。建筑热工设计分区中的严寒地区，包含建筑气候区划图中的全部Ⅰ区，以及Ⅵ区中的ⅥA、ⅥB，Ⅶ区中的ⅦA、ⅦB、ⅦC；寒冷地区，包含建筑气候区划图中的全部Ⅱ区，以及Ⅵ区中的ⅥC，Ⅶ区中的ⅦD；夏热冬冷、夏热冬暖、温和地区与建筑气候区划图中的Ⅲ、Ⅳ、Ⅴ区完全一致。

由于建筑热工在建筑功能中具有重要的地位，并有形象的地区名，故将其一并对应列出。

3.4 建筑与环境

环境即包括以大气、水、土壤、植物、动物、微生物等为内容的物质因素，也包括以观念、制度、行为准则等为内容的非物质因素；既包括自然因素，也包括人文因素；既包括非生命体形式，也包括生命体形式。环境是相对于某个主体而言的，主体不同，环境的大小、内容等也就不同。狭义的环境，如环境问题中的“环境”一词，往往指向对于人类这个主体而言的一切自然环

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Climatic zoning for buildings reflects the relationship between buildings and climate, primarily demonstrated through the spatial and temporal distribution characteristics of various meteorological elements and their direct impact on buildings. This zoning is broader in scope and involves a wider range of climatic parameters. The primary indicators for climatic zoning include multi-year averages of January and July temperatures, the average relative humidity in July, and auxiliary indicators such as annual precipitation and the number of days with an average daily temperature ≤5°C or ≥25°C. Based on these indicators, the country is divided into seven zones. Thermal design zoning reflects the relationship between thermal design and climate, focusing mainly on how meteorological elements influence the insulation and heat resistance of buildings and their enclosures. The considerations in this zoning are fewer and simpler. The primary indicators for thermal design zoning include the multi-year averages of the coldest month (January) and the hottest month (July), with auxiliary indicators such as the number of days with an average daily temperature ≤5°C or ≥25°C. The country is divided into five zones: severe cold, cold, hot summer and cold winter, hot summer and warm winter, and mild regions. Corresponding design requirements are proposed for each zone. Given that the primary indicators for thermal design zoning and Level-1 climatic zoning are consistent, these two zoning systems are compatible and largely aligned.

Figure A3. Uniform standard for design of civil buildings (GB 50352- 2019), page 71.

Notes: This picture shows part of the *Uniform standard for design of civil buildings (GB 50352- 2019)*. The main information in this picture is that “when zoning the climate region, we usually use the annual average temperature in January and July and the average relative humidity in July as the main indicators. The annual precipitation and the number of days with the average daily temperature of ≤5℃ and ≥25℃ are auxiliary indicators……When considering the building’s thermal design, the average temperature of the coldest month (that is, January) and hottest month (that is, July) is used as the main index of the zoning, and the number of days with average daily temperature ≤5℃ and ≥25℃ are auxiliary indicators.”

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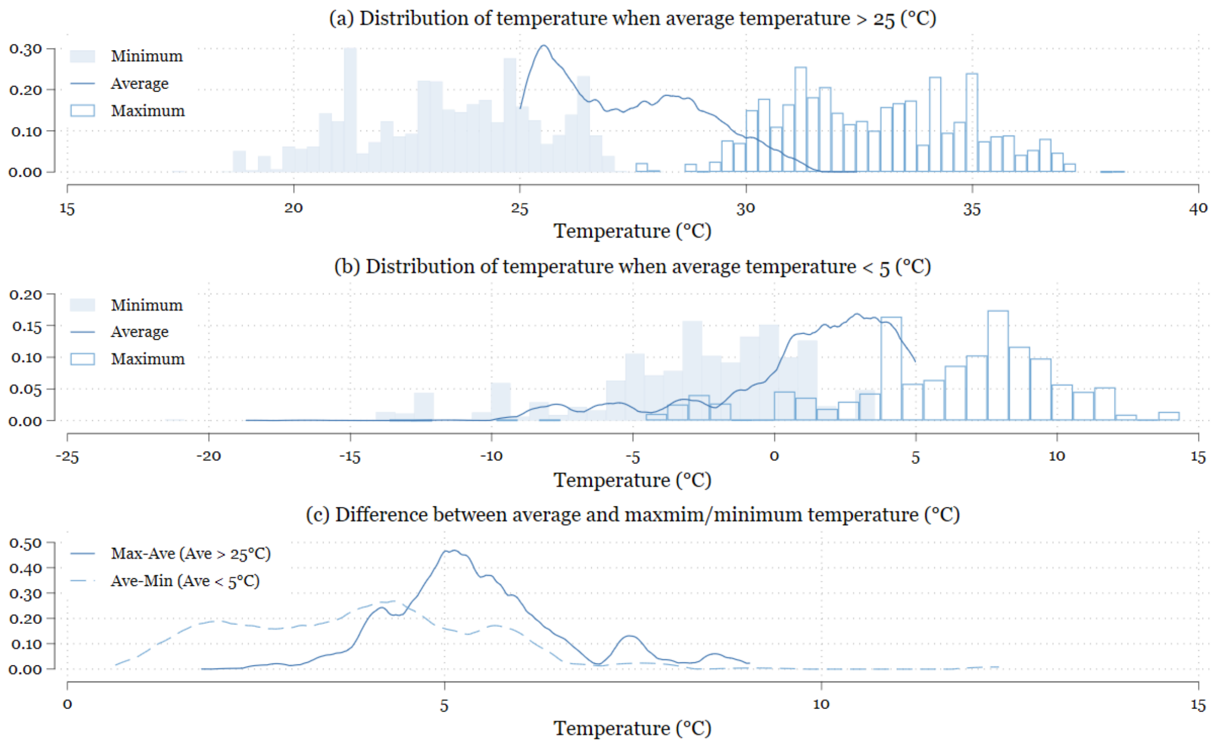

Figure A4. Summary of temperature variables in the research period.

Notes: These figures provide an additional summary of temperature variables for the research period. Figure (a) shows the distribution of temperature when the average temperature is > 25 (°C); Figure (b) shows the distribution of temperature when the average temperature is < 5 (°C); Figure (c) shows the difference between the average and maximum/minimum temperature (°C).

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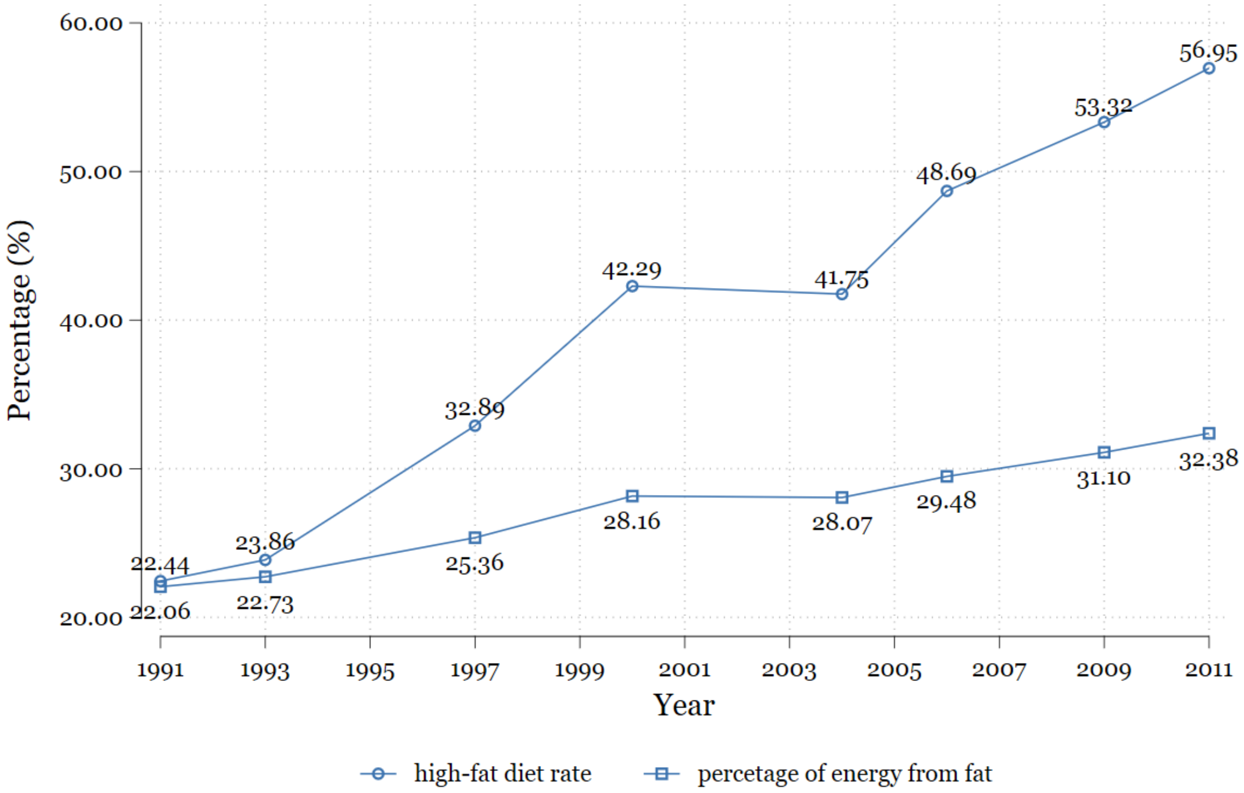

Figure A5. Trends of energy intake from fat and high-fat diet rate (%)

Notes: This figure shows the trends of energy intake from fat and high-fat diet rate (%) in the CHNS survey sample from 1991 to 2011.

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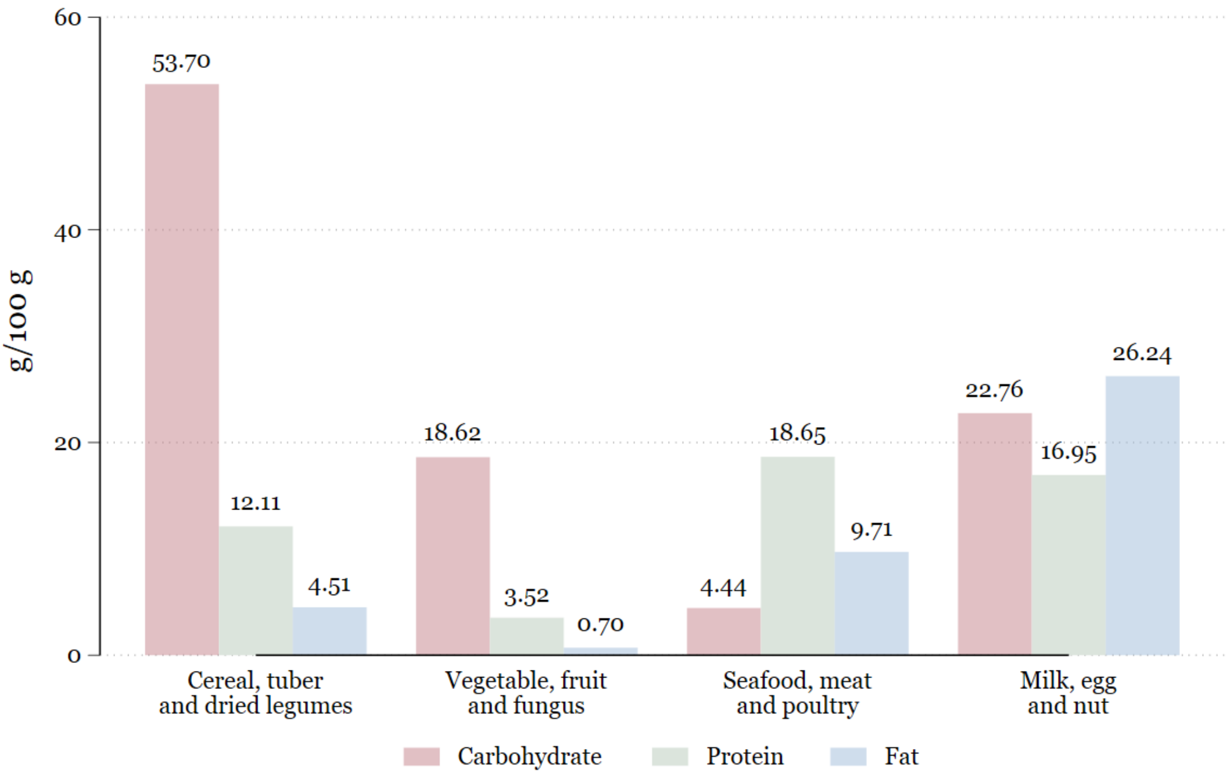

Figure A6. Contribution of the four major food groups to macronutrients

Notes: This figure shows the proportions of carbohydrates, proteins, and fats contributed by the four major food groups. The calculations rely on nutritional composition data provided by China's Nutrition of Main Foods (Chinese Center for Disease Control and Prevention, 2018). Each bar represents the average gram of carbohydrate, protein, or fat intake derived from 100g of food in the corresponding group.

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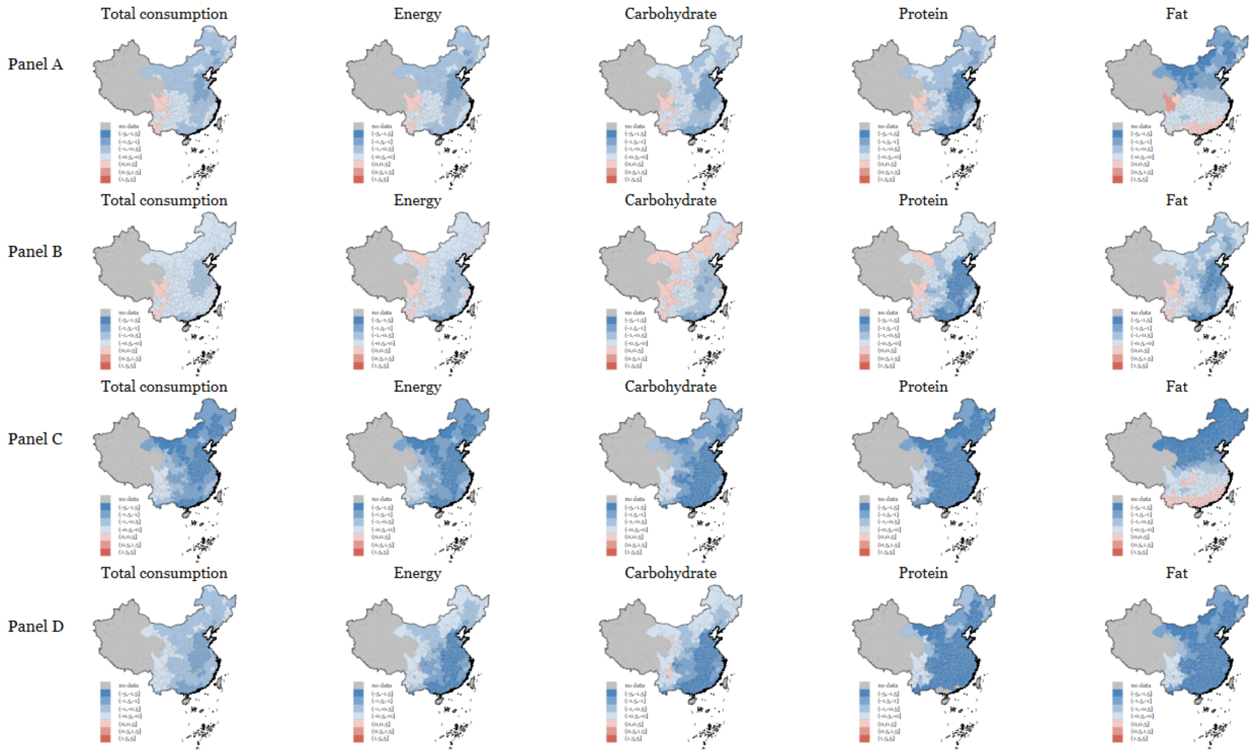

Figure A7. End-of-century projections by the city for food consumption and macronutrient intake.

Notes: This figure shows the predicted impact of off-comfort temperatures for each city in 2080-2099 relative to CHNS survey waves. Due to the limited coverage of provinces of CHNS (see Figure A1), results based on this database may not be representative of the national average, especially in the Northwest region and the Tibetan Plateau. Therefore, we remove Qinghai, Tibet, and Xinjiang provinces from the forecast. Panel A and panel C show the projection results based on equation (4) under the climate scenarios RCP4.5 and RCP8.5, respectively. Panels B and D show the projection results based on equation (5), which considers the effects of the fans, air conditioners, heating systems, and refrigerators under the climate scenarios RCP4.5 and RCP8.5. All the scales in subgraphs are uniform. Red indicates an increase in the proportion or probability, while blue shows the opposite effect.

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Appendix Tables

Table A1. Examples of the effect of temperature on agriculture in the literature

Article	Area	Time period	Results
Burke and Emerick (2016)	U.S.	1980-2000	(1) Each extra degree-day of heat above 29°C leads to a 0.44% reduction in total corn yield.
Chen et al. (2016)	China	2000-2009	(1) Crop yields have nonlinear and inverted U-shaped relationships with weather variables. (2) Over the research period, global warming has led to an economic loss of approximately $820 million for China's corn and soybean sectors.
Aragón et al. (2021)	Pure	2007-2015	(1) Extreme temperatures are associated with reductions in agricultural productivity, but an increase in area planted, which means farmers partially offset the decline in output by increasing the area planted. (2) Each additional average cumulative exposure to temperatures above 33°C during the growing season results in a 7% decrease in agricultural productivity and a 6% increase in planting area.
Chen and Gong (2021)	China	1981-2015	(1) In the short run, an additional one-day cumulative exposure to temperatures above 33°C during the whole year leads to a 2.6% decrease in agricultural TFP and a 4.4% decrease in yield. (2) The long-run impact of extreme heating on TFP and agricultural yield is about 1.6% and 2.3%, respectively.
Miller et al. (2021)	Global	1979-2016	(1) An abnormally hot day (defined as a cell-level median (mean) of 89 (86) °F) not far from being preceded by at least eight others reduces per-capita agricultural value added by approximately 1.7%.
Chen et al. (2023)	China	1995-2015	(1) An additional one-day exposure to temperatures above 35°C would lower the aggregate output of northern agriculture by about 4.95%, relative to the reference bin (10-15°C). (2) The reduction in aggregate output is mostly driven by the cropping, livestock, and fishery sectors, with output value losses of 2.58%, 2.61%, and 2.11%, respectively. (3) There's no significant impact of temperature on agricultural output in southern China.
Wang et al. (2024)	China	1981-2010	(1) During 1981-1995, an additional 100-degree-day exposure to temperatures above 28°C led to a 23% loss in corn yield, while the corresponding estimate in 1996-2010 is -11.5%. (2) During 1981-1995, an additional 100-degree-day exposure to temperatures above 26°C led to a 15.7% loss in

			soybean yield, while the corresponding estimate in 1996-2010 is -8.3%. (3) The overall impacts of 100-day exposure to extreme high temperatures on corn and soybean yields from 1996 to 2010 are 40% to 50% less than those from 1981 to 1995. This results in a loss reduction by about 14.5% of the national corn production and 7% of the national soybean production.
Cui and Zhong (2024)	China	1981-2015	(1) In cold regions where the average temperature in 1980 was below 10°C, a 0.1°C increase in the 30-year average temperature leads to a 2.4% expansion in cropland. (2) In mild regions, where the initial temperature ranges between 10-20°C, a 0.1°C long-term warming decreases total cropland areas by 1.2%. (3) This negative impact in hot regions is about 1.9% per 0.1°C.
Cui and Tang (2024)	Northeast China	2004-2014	(1) An additional degree-day accumulated above 32°C in the growing season (i.e., April to October) reduces corn yields by approximately 5.4% and household total corn outputs by about 5.0%. (2) This also leads to a reduction in aggregate farm revenue and net household income for corn households by 2.9% and 2.1%, respectively.

Notes: This table shows some of the results about the effects of temperatures on agriculture in the literature.

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Table A2. Descriptive statistics

Variables	Unit	Number	Mean	SD	Min	Max
Total consumption	100g/3-day	91,570	30.58	10.67	6.750	72.73
Energy	100kcal/3-day	92,500	63.98	20.20	12.34	155.2
Carbohydrate	100g/3-day	93,899	9.705	3.764	2.151	23.78
Protein	100g/3-day	93,900	1.953	0.697	0.451	4.581
Fat	100g/3-day	93,899	1.929	1.056	0.156	6.365
Proportion of energy from fat	-	92,500	0.272	0.115	0.0181	0.780
High-fat diet	-	92,500	0.395	0.489	0	1
Cereal, tuber, and dried legumes	100g/3-day	91,570	15.54	6.580	0	60.50
Vegetable, fruit, and fungus	100g/3-day	91,570	10.85	6.076	0	55.70
Seafood, meat, and poultry	100g/3-day	91,570	3.110	3.146	0	34.03
Milk, egg, and nut	100g/3-day	91,570	1.072	1.810	0	21.90
Sugar and salt	100g/3-day	64,627	0.328	0.255	0	2.946
Oil	100g/3-day	64,924	1.137	0.774	0	6
BMI	-	68,933	22.75	3.287	14.79	39.37
Urban	-	102,089	0.292	0.455	0	1
High school	-	77,630	0.223	0.416	0	1
Age	Year	102,931	36.85	20.91	0	101
Male	-	102,942	0.497	0.500	0	1
Air conditioner	-	102,942	0.137	0.344	0	1
Fan	-	102,942	0.749	0.434	0	1
Refrigerator	-	102,942	0.403	0.490	0	1
Heating system	-	102,942	0.0799	0.271	0	1
3-day CDD	°C	102,942	0.668	2.433	0	20.42
3-day HDD	°C	102,942	0.504	2.913	0	45.79
3-day average humility	%	102,942	73.39	11.09	31.76	98.12
3-day average precipitation	mm	102,942	1.948	3.874	0	33.16
3-day average wind speed	m/s	102,942	1.838	0.843	0.140	6.630
3-day average sunshine duration	h	102,942	5.356	3.104	0	12.09

Notes: This table shows the statistics of key variables in the empirical analysis. The variables related to food and macronutrients calculate the total consumption in the past 3 days, and the units are in 100g (or 100 kcal).

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Table A3. Baseline results

Variables	(1) Total consumption	(2) Energy	(3) Carbohydrate	(4) Protein	(5) Fat	(6) Proportion of energy from fat	(7) High-fat diet
3-day CDD	-0.0027***	-0.0029***	-0.0039***	-0.0059***	0.0003	0.0009***	0.0046***
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0015)	(0.0003)	(0.0013)
3-day HDD	0.0015**	0.0015**	0.0010	0.0015**	0.0034***	0.0003	0.0018*
	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0010)	(0.0002)	(0.0010)
Observations	85,236	86,147	87,612	87,593	87,584	86,147	86,147
R-squared	0.4691	0.5077	0.5723	0.4782	0.4809	0.5361	0.4354
Dep. Var. Mean	30.58	63.98	9.705	1.953	1.929	0.272	0.395
Individual FE	YES	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES	YES
Province-month FE	YES	YES	YES	YES	YES	YES	YES

Notes: (1) We use the logarithmic form of total consumption, energy, carbohydrate, protein, and fat to explore the changes in growth rates due to heat and cold. For the proportion of energy from fat and the high-fat diet index, we use the actual value, as it already represents the proportion. (2) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (3) Standard errors shown in parentheses are clustered at the individual level. (4) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (5) The observations are smaller than those in the descriptive statistics because single observations (singleton observations) are removed during the estimation process. (6) Dep. Var. Mean shows the mean of Y in its original levels, instead of log(Y).

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Table A4. Correlation between BMI and nutrient intake

Variables	(1) BMI	(2) BMI	(3) BMI
Fat	0.0306***		
	(0.0104)		
Proportion of energy from fat		0.1373*	
		(0.0798)	
High-fat diet			0.0525***
			(0.0167)
Energy	0.0012**	0.0022***	0.0022***
	(0.0006)	(0.0005)	(0.0005)
Observations	59,931	59,931	59,931
R-squared	0.8360	0.8360	0.8360
Dep. Var. Mean	22.75	22.75	22.75
Individual FE	YES	YES	YES
Year-month FE	YES	YES	YES
Province-month FE	YES	YES	YES

Notes: (1) We use the BMI of adults (age $\geq$ 18) as the outcome variable. (2) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (3) Standard errors shown in parentheses are clustered at the individual level. (4) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (5) The observations are smaller than those in the descriptive statistics because single observations (singleton observations) are removed during the estimation process. (6) Dep. Var. Mean shows the mean of BMI in adults.

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Table A5. Robustness tests

Variables	(1) Total consumption	(2) Energy	(3) Carbohydrate	(4) Protein	(5) Fat	(6) Proportion of energy from fat	(7) High-fat diet
Panel A							
3-day CDD	-0.0027**	-0.0029***	-0.0039***	-0.0059***	0.0003	0.0009**	0.0046***
	(0.0013)	(0.0010)	(0.0012)	(0.0012)	(0.0021)	(0.0004)	(0.0018)
3-day HDD	0.0015	0.0015*	0.0010	0.0015*	0.0034**	0.0003	0.0018
	(0.0010)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0003)	(0.0013)
Panel B							
3-day CDD	-0.0025***	-0.0028***	-0.0038***	-0.0056***	0.0004	0.0009***	0.0048***
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0015)	(0.0003)	(0.0013)
3-day HDD	0.0021***	0.0024***	0.0018**	0.0026***	0.0041***	0.0003	0.0019*
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0011)	(0.0002)	(0.0010)
Panel C							
3-day CDD	-0.0014	-0.0027***	-0.0030***	-0.0051***	-0.0010	0.0005	0.0037**
	(0.0010)	(0.0008)	(0.0010)	(0.0010)	(0.0016)	(0.0003)	(0.0015)
3-day HDD	0.0051***	0.0015*	0.0005	0.0022**	0.0052***	0.0006**	0.0017
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0003)	(0.0013)
Panel D							
3-day CDD	-0.0672**	-0.1699***	-0.0317***	-0.0109***	-0.0006		
	(0.0270)	(0.0459)	(0.0074)	(0.0016)	(0.0027)		
3-day HDD	0.0452**	0.1036***	0.0135**	0.0025*	0.0046**		
	(0.0214)	(0.0388)	(0.0064)	(0.0013)	(0.0020)		

Notes: (1) We use the logarithmic form of total consumption, energy, carbohydrate, protein, and fat to explore changes in growth rates due to heat and cold, except panel D. As for the proportion of energy from fat and high-fat diet index, we use the original levels because they already represent the proportion. (2) In panel A, the standard errors are clustered within individuals and household-year; in panel B, we add provincial-year linear trends; in panel C, we drop observations that do not have an exact date of each day in the 3-day dietary intake survey; in panel D, we change the explained variables to their original levels. (3) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (4) Standard errors shown in parentheses except in panel A are clustered at the individual level. (5) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Table A6. Robustness tests – different temperature definition

Variables	(1) Total consumption	(2) Energy	(3) Carbohydrate	(4) Protein	(5) Fat	(6) Proportion of energy from fat	(7) High-fat diet
Cutoff: Ave-temp 4-26°C							
3-day CDD	-0.0020*	-0.0027***	-0.0049***	-0.0058***	0.0032*	0.0016***	0.0074***
	(0.0012)	(0.0010)	(0.0011)	(0.0011)	(0.0019)	(0.0003)	(0.0017)
3-day HDD	0.0015*	0.0011	0.0005	0.0012	0.0035***	0.0004*	0.0023**
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0012)	(0.0002)	(0.0011)
Cutoff: Ave-temp 6-24°C							
3-day CDD	-0.0032***	-0.0032***	-0.0036***	-0.0059***	-0.0017	0.0005**	0.0031***
	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0012)	(0.0002)	(0.0010)
3-day HDD	0.0013**	0.0017***	0.0014**	0.0017***	0.0030***	0.0002	0.0012
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0009)	(0.0002)	(0.0009)
Cutoff: Ave-temp 10-20°C							
3-day CDD	-0.0014***	-0.0015***	-0.0017***	-0.0026***	-0.0005	0.0002**	0.0020***
	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.0001)	(0.0005)
3-day HDD	0.0010***	0.0018***	0.0018***	0.0019***	0.0022***	-0.0000	-0.0003
	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.0001)	(0.0005)
Cutoff: Max-temp 30°C, min-temp 5°C							
3-day CDD	-0.0037***	-0.0032***	-0.0040***	-0.0056***	0.0000	0.0008***	0.0033***
	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0011)	(0.0002)	(0.0010)
3-day HDD	0.0018***	0.0012***	0.0012***	0.0018***	0.0022***	0.0000	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0001)	(0.0006)

Notes: (1) We use the logarithmic form of total consumption, energy, carbohydrate, protein, and fat to explore the changes in growth rates due to heat and cold. As for the proportion of energy from fat and the high-fat diet index, we use the original levels because they already represent the proportion. (2) In this table, we change the cutoff standard used in baseline regression. Ave-temp, max-temp, and min-temp mean daily average temperature, daily maximum temperature, and daily minimum temperature, respectively. (3) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (4) Standard errors shown in parentheses are clustered at the individual level. (5) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Table A7. Robustness tests – temperature bins

Variables	(1) Total consumption	(2) Energy	(3) Carbohydrate	(4) Protein	(5) Fat	(6) Proportion of energy from fat	(7) High-fat diet
≤1°C	0.0107*	0.0216***	0.0132**	0.0192***	0.0475***	0.0053***	0.0167**
	(0.0060)	(0.0050)	(0.0054)	(0.0054)	(0.0085)	(0.0016)	(0.0073)
(1°C, 3°C]	0.0105	0.0165**	0.0288***	0.0008	-0.0064	-0.0065***	-0.0231**
	(0.0078)	(0.0072)	(0.0081)	(0.0076)	(0.0122)	(0.0023)	(0.0108)
(3°C, 5°C]	0.0006	0.0108***	0.0149***	0.0167***	-0.0094	-0.0035***	-0.0107
	(0.0047)	(0.0040)	(0.0046)	(0.0045)	(0.0068)	(0.0013)	(0.0069)
(25°C, 27°C]	-0.0126***	-0.0115***	-0.0071**	-0.0155***	-0.0209***	-0.0027***	0.0020
	(0.0031)	(0.0029)	(0.0033)	(0.0033)	(0.0052)	(0.0009)	(0.0044)
(27°C, 39°C]	-0.0108***	-0.0085***	-0.0052	-0.0251***	-0.0100*	0.0000	-0.0022
	(0.0039)	(0.0033)	(0.0038)	(0.0037)	(0.0061)	(0.0011)	(0.0053)
>29°C	-0.0118**	-0.0175***	-0.0299***	-0.0240***	0.0092	0.0075***	0.0381***
	(0.0051)	(0.0044)	(0.0050)	(0.0050)	(0.0081)	(0.0015)	(0.0074)
Observations	85,236	86,147	87,612	87,593	87,584	86,147	86,147
R-squared	0.4693	0.5080	0.5726	0.4785	0.4813	0.5365	0.4357
Dep. Var. Mean	30.58	63.98	9.705	1.953	1.929	0.272	0.395
Individual FE	YES	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES	YES
Province-month FE	YES	YES	YES	YES	YES	YES	YES

Notes: (1) We use the logarithmic form of total consumption, energy, carbohydrate, protein, and fat to explore the changes in growth rates due to heat and cold. As for the proportion of energy from fat and the high-fat diet index, we use the original levels because they already represent the proportion. (2) Temperature bins are defined as the number of days in the past three days for which the average temperature falls into a specific bin. (3) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (4) Standard errors shown in parentheses are clustered at the individual level. (5) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (6) The observations are smaller than those in the descriptive statistics because single observations (singleton observations) are removed during the estimation process. (7) Dep. Var. Mean shows the mean of Y in its original levels, instead of log(Y).

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Table A8. Different foods

Variables	(1) Cereal, tuber, and dried legumes	(2) Vegetable, fruit, and fungus	(3) Seafood, meat, and poultry
3-day CDD	-0.0244*	-0.0114	-0.0367***
	(0.0132)	(0.0175)	(0.0072)
3-day HDD	-0.0074	0.0327***	0.0045
	(0.0132)	(0.0123)	(0.0047)
Observations	85,236	85,236	85,236
R-squared	0.5327	0.3895	0.5732
Dep. Var. Mean	15.54	10.85	3.110
Individual FE	YES	YES	YES
Year-month FE	YES	YES	YES
Province-month FE	YES	YES	YES
	(4) Milk, egg, and nut	(5) Sugar and salt	(6) Oil
3-day CDD	0.0053	0.0003	-0.0002
	(0.0038)	(0.0007)	(0.0022)
3-day HDD	0.0153***	-0.0014**	0.0041**
	(0.0050)	(0.0006)	(0.0021)
Observations	85,236	58,133	58,441
R-squared	0.5276	0.4302	0.3965
Dep. Var. Mean	15.54	10.85	3.110
Individual FE	YES	YES	YES
Year-month FE	YES	YES	YES
Province-month FE	YES	YES	YES

Notes: (1) We use the original levels as dependent variables in the regression because there are zeros in each of the outcome variables. (2) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (3) Standard errors shown in parentheses are clustered at the individual level. (4) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (5) The observations are smaller than those in the descriptive statistics because single observations (singleton observations) are removed during the estimation process. (6) Dep. Var. Mean shows the mean of Y, which is the original levels of each type of food in total food consumption, measured in 100g/3-day.

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Table A9. Mechanism effects – work type and sports

Variables	(1) Total consumption	(2) Energy	(3) Carbohydrate	(4) Protein	(5) Fat	(6) Proportion of energy from fat	(7) High-fat diet
Panel A							
3-day CDD	-0.0023**	-0.0020**	-0.0037***	-0.0050***	0.0013	0.0010***	0.0045**
	(0.0012)	(0.0010)	(0.0011)	(0.0011)	(0.0021)	(0.0004)	(0.0019)
3-day HDD	0.0023**	0.0022***	0.0017*	0.0016*	0.0047***	0.0004	0.0028**
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0003)	(0.0014)
Panel B							
3-day CDD	-0.0023**	-0.0020**	-0.0037***	-0.0050***	0.0013	0.0010***	0.0045**
	(0.0012)	(0.0010)	(0.0011)	(0.0011)	(0.0021)	(0.0004)	(0.0019)
3-day HDD	0.0023**	0.0022***	0.0017*	0.0016*	0.0047***	0.0004	0.0028**
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0003)	(0.0014)
Panel C							
3-day CDD	-0.0023**	-0.0020**	-0.0037***	-0.0050***	0.0014	0.0011***	0.0045**
	(0.0012)	(0.0010)	(0.0011)	(0.0011)	(0.0021)	(0.0004)	(0.0019)
3-day HDD	0.0024***	0.0023***	0.0017*	0.0017*	0.0047***	0.0004	0.0027**
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0003)	(0.0014)

Notes: (1) This table shows the mechanism effects of work type and sports. (2) In panel A, we add the work type fixed effects; in panel B, we add work type-year linear trends; in panel C, we add work type-year linear trends, their preference for walking, exercise, bodybuilding (prefer = 1, do not prefer = 0), and the amount of time to exercise. (3) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (4) Standard errors shown in parentheses are clustered at the individual level. (5) * p < 0.1, ** p < 0.05, *** p < 0.01.

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Table A10. Mechanism effects – work hours

Variables	(1) Last week's work hours	(2) Last week's work hours
Last week's average temperature	0.0045	
	(0.0081)	
Last week CDD		-0.0095
		(0.0384)
Last week HDD		-0.0475
		(0.0324)
Observations	27,295	27,295
R-squared	0.5171	0.5172
Dep. Var. Mean	42.06	42.06
Individual FE	YES	YES
Year-month FE	YES	YES
Province-month FE	YES	YES

Notes: (1) This table shows the mechanism effects of work time. (2) Since the outcome variable considers the work hours in the last week, we calculate the last week's average temperature, CDD, and HDD for each individual. In column (1), the key independent variable is the last week's average temperature; in column (2), the key independent variables are last week's CDD and HDD. (3) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (4) Standard errors shown in parentheses are clustered at the individual level. (5) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Table A11. Adaptation effects – fans, air conditioners, heating systems, and refrigerators

Variables	(1) Total consumptio n	(2) Energy	(3) Carbohydrate	(4) Protein	(5) Fat	(6) Proportion of energy from fat	(7) High-fat diet
3-day CDD	-0.0092***	-0.0077***	-0.0113***	-0.0118***	0.0057	0.0029***	0.0096***
	(0.0025)	(0.0020)	(0.0023)	(0.0022)	(0.0036)	(0.0006)	(0.0028)
3-day HDD	0.0097***	0.0104***	0.0101***	0.0069***	0.0149***	0.0008*	0.0030
	(0.0016)	(0.0014)	(0.0015)	(0.0016)	(0.0024)	(0.0004)	(0.0021)
3-day CDD * fan	0.0064***	0.0053***	0.0079***	0.0081***	-0.0040	-0.0020***	-0.0044
	(0.0024)	(0.0020)	(0.0023)	(0.0022)	(0.0035)	(0.0006)	(0.0028)
3-day CDD * ac	-0.0019	-0.0022	-0.0026	-0.0022	-0.0052**	-0.0001	-0.0002
	(0.0015)	(0.0014)	(0.0017)	(0.0015)	(0.0022)	(0.0005)	(0.0023)
3-day HDD * heat	-0.0118***	-0.0121***	-0.0131***	-0.0076***	-0.0147***	-0.0004	-0.0009
	(0.0018)	(0.0016)	(0.0018)	(0.0018)	(0.0027)	(0.0005)	(0.0024)
3-day CDD * ref	0.0030**	0.0013	0.0023*	-0.0018	-0.0016	-0.0004	-0.0019
	(0.0012)	(0.0011)	(0.0014)	(0.0012)	(0.0019)	(0.0004)	(0.0019)
3-day HDD * ref	0.0023**	0.0017*	0.0027***	0.0011	0.0007	-0.0004	-0.0009
	(0.0011)	(0.0009)	(0.0010)	(0.0011)	(0.0016)	(0.0003)	(0.0014)
Observations	84,750	85,644	87,103	87,084	87,075	85,644	85,644
R-squared	0.4711	0.5102	0.5743	0.4808	0.4857	0.5395	0.4372
Dep. Var. Mean	30.58	63.98	9.705	1.953	1.929	0.272	0.395
Individual FE	YES	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES	YES
Province-month FE	YES	YES	YES	YES	YES	YES	YES

Notes: (1) This table shows the mechanism effects of home appliances. Fan, ac, heat, and ref refer to whether there are fans, air conditioners, heating systems, and refrigerators in the households in each wave. (2) We use the logarithmic form of total consumption, energy, carbohydrate, protein, and fat to explore the changes in growth rates due to heat and cold. As for the proportion of energy from fat and the high-fat diet index, we use the original levels because they already represent the proportion. (3) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (4) Standard errors shown in parentheses are clustered at the individual level. (5) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (6) The observations are smaller than those in the descriptive statistics because single observations (singleton observations) are removed during the estimation process. (7) Dep. Var. Mean shows the mean of Y in its original levels, instead of log(Y).

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Table A12. Heterogeneous effects

Variables	(1) Proportion of energy from fat	(2) High-fat diet
Panel A – Age		
3-day CDD * children	0.0008	0.0032
	(0.0005)	(0.0022)
3-day CDD * adult	0.0012***	0.0057***
	(0.0003)	(0.0015)
3-day CDD * elder	0.0002	0.0026
	(0.0004)	(0.0021)
3-day HDD * children	0.0011***	0.0062***
	(0.0004)	(0.0020)
3-day HDD * adult	0.0003	0.0018*
	(0.0002)	(0.0011)
3-day HDD * elder	-0.0002	-0.0016
	(0.0004)	(0.0019)
Panel B – Gender		
3-day CDD * female	0.0009***	0.0051***
	(0.0003)	(0.0015)
3-day CDD * male	0.0009***	0.0042***
	(0.0003)	(0.0015)
3-day HDD * female	0.0004*	0.0016
	(0.0003)	(0.0012)
3-day HDD * male	0.0002	0.0020*
	(0.0002)	(0.0012)
Panel C – Rural and urban		
3-day CDD * rural	0.0010***	0.0051***
	(0.0003)	(0.0014)
3-day CDD * urban	-0.0002	0.0013
	(0.0004)	(0.0021)
3-day HDD * rural	0.0009***	0.0042***
	(0.0003)	(0.0012)
3-day HDD * urban	-0.0004	-0.0014
	(0.0003)	(0.0013)
Panel D – Wealth		
3-day CDD * poor	0.0012***	0.0058***
	(0.0003)	(0.0014)
3-day CDD * rich	0.0000	0.0014
	(0.0004)	(0.0018)
3-day HDD * poor	0.0005**	0.0024**
	(0.0002)	(0.0012)
3-day HDD * rich	0.0001	0.0014
	(0.0003)	(0.0013)

Notes: (1) Each panel shows the regression results of different heterogeneity analyses. (2) We use the original levels of the proportion of energy from fat and the high-fat diet index, because they already represent the meaning of proportion. (3) Individual fixed effects, year-month fixed effects, and province-month fixed effects are involved in all regressions. (4) Standard errors shown in parentheses are clustered at the individual level. (5) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Table A13. Descriptive statistics in rural, urban, and different wealth groups

Variables	Unit	Rural	Urban	diff	t-value
Total consumption	100g/3-day	30.82	30.09	0.729	9.425***
Energy	100kcal/3-day	64.80	62.16	2.643	18.179***
Carbohydrate	100g/3-day	10.16	8.681	1.475	55.594***
Protein	100g/3-day	1.937	1.994	-0.0580	-11.574***
Fat	100g/3-day	1.828	2.163	-0.336	-44.825***
Proportion of energy from fat	-	0.255	0.311	-0.0560	-68.852***
High-fat diet	-	0.334	0.532	-0.198	-57.249***
Cereal, tuber and dried legumes	100g/3-day	16.18	14.09	2.095	44.327***
Vegetable, fruit and fungus	100g/3-day	11.09	10.34	0.757	17.185***
Seafood, meat and poultry	100g/3-day	2.702	4.067	-1.366	-61.047***
Milk, egg and nut	100g/3-day	0.845	1.602	-0.757	-58.694***
Sugar and salt	100g/3-day	0.327	0.331	-0.00300	-1.499
Oil	100g/3-day	1.118	1.179	-0.0610	-9.109***
Air conditioner	-	0.0950	0.240	-0.146	-62.672***
Fan	-	0.710	0.843	-0.134	-45.155***
Refrigerator	-	0.300	0.653	-0.353	-110.679***
Heating system	-	0.0770	0.0850	-0.00700	-3.829***
		Poor	Rich	diff	t-value
Total consumption	100g/3-day	30.06	31.45	-1.388	-19.076***
Energy	100kcal/3-day	63.66	64.51	-0.845	-6.159***
Carbohydrate	100g/3-day	10.01	9.193	0.818	32.392***
Protein	100g/3-day	1.892	2.055	-0.164	-34.993***
Fat	100g/3-day	1.779	2.181	-0.401	-57.284***
Proportion of energy from fat	-	0.254	0.302	-0.0490	-63.476***
High-fat diet	-	0.328	0.506	-0.178	-54.341***
Cereal, tuber and dried legumes	100g/3-day	16.02	14.75	1.267	28.282***
Vegetable, fruit and fungus	100g/3-day	10.71	11.09	-0.385	-9.264***
Seafood, meat and poultry	100g/3-day	2.533	4.081	-1.547	-74.064***
Milk, egg and nut	100g/3-day	0.803	1.525	-0.723	-59.549***
Sugar and salt	100g/3-day	0.316	0.350	-0.0340	-16.083***
Oil	100g/3-day	1.089	1.222	-0.133	-21.123***
Air conditioner	-	0.0940	0.210	-0.116	-53.138***
Fan	-	0.715	0.806	-0.0910	-32.644***
Refrigerator	-	0.305	0.569	-0.264	-86.572***
Heating system	-	0.0700	0.0960	-0.0260	-14.652***

Notes: (1) This table shows the mean value of outcome variables and four appliances between four subgroups. (2) The unit of food and macronutrients are shown in the table. (3) The mean value of appliances could be seen as the owning rate in each subgroup.

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