Journal of Population Economics (2024) 37:59
https://doi.org/10.1007/s00148-024-01039-2

ORIGINAL PAPER

The impact of global warming on obesity

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Received: 31 October 2023 / Accepted: 9 June 2024 / Published online: 17 June 2024

Abstract
This study identifies obesity as an important channel through which global warming affects human capital. By analyzing plausibly exogenous year-to-year temperature fluctuations in 152 countries from 1975 to 2016, we find that global warming has significantly increased obesity rates in countries located in temperate zones, while only causing a reduction in a small number of tropical countries. The estimates suggest that a 1 °C increase in the annual mean temperature would result in a worldwide increase in obese adults of 79.7 million, or 12.3%. Similar patterns emerge when examining the effects of temperature bins, seasonal mean temperature, temperature variations, and temperature shocks. Furthermore, we identify substantial heterogeneity in the impact across countries with varying income levels, age structures, and education levels. Finally, by comparing the baseline model with a long-difference model, we demonstrate that long-term adaptation may not significantly mitigate the impact of global warming on obesity in temperate zones.

Keywords Global warming · Human obesity · Adaptation

JEL Classification I10 · Q54

1 Introduction

Obesity represents one of the most significant challenges in modern society (Ng et al. 2014; Bray et al. 2016). The global obesity rate has nearly tripled since 1975, with

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over 650 million adults classified as obese in 2016 (WHO 2018).[1] Even in the poorest countries, there has been widespread documentation of rapid increases in obesity (Swinburn et al. 2019). Obesity is a major cause of disability and is correlated with various diseases and conditions (Kopelman 2000; Chooi et al. 2019). In 2017, the number of people who died prematurely as a result of obesity was 4.7 million, four times the number of deaths in road accidents (Ritchie and Roser 2017). The share of global deaths caused by obesity increased from 4.5% in 1990 to 8% in 2017 (WHO 2018). The global annual economic loss from obesity amounted to US $2.0 trillion or 2.8% of the global gross domestic product in 2016 (Tremmel et al. 2017).

Global warming is expected to have a substantial impact on human obesity. It could affect calorie intake by altering incomes (Burke et al. 2015), food prices (Wheeler and von Braun 2013), and consumption preferences (Scheelbeek et al. 2020). Additionally, it could impact calorie expenditure by altering working hours (Graff Zivin et al. 2018), physical activity levels (Obradovich and Fowler 2017), and the minimum calorie requirement (Johnson and Kark 1947). These changes in calorie intake and expenditure can have significant effects on obesity. Many studies have examined the association between ambient temperature and obesity, yielding mixed results (e.g., de Jonge et al. 2002; Sadiq et al. 2019; Betz and Enerback 2018; Chaijaroen 2019; Deschenes et al. 2020). Furthermore, numerous studies have explored the impact of global warming on relevant health indicators, such as malnutrition (van der Merwe et al. 2022), mortality (Thompson et al. 2018), mental health (Hua et al. 2023), and various other health outcomes (e.g., Mora et al. 2017; Vicedo-Cabrera et al. 2021).

However, based on existing studies, we are still unable to answer the following two critical questions regarding global warming and obesity. Firstly, what is the overall impact of global warming on obesity? Existing studies primarily rely on samples from individual countries or regions, yet the impact of global warming on obesity could vary significantly across countries and regions. Furthermore, existing studies mainly focus on the impact through specific pathways, but there are multiple pathways through which global warming can generate different, and even opposing, effects on obesity. Secondly, to what extent could adaptation help reduce the impact of global warming on obesity? While numerous studies have found that adaptation could mitigate the impact of global warming on various economic outcomes (e.g., Mendelsohn et al. 1994; Adger et al. 2009; Kahn 2016; Huang and Sim 2021), no study on the impact of global warming on obesity has examined the role of adaptation.

This study estimates the overall impact of global warming on adult obesity and investigates the potential of adaptation in offsetting this impact.[2] Using data from 1975 to 2016 for 152 countries, which collectively account for 99.1% of the world's population, we employ a panel model that relies on plausibly exogenous year-to-year temperature fluctuations to identify the causal effect of warming on obesity.

[1] People are classified as obese when their body mass index (BMI), calculated as a person's weight divided by the square of their height, exceeds 30 kg/m^2.

[2] This study does not focus on the rate of childhood obesity because the available data is only from 2000 onwards, and it is less likely to be affected by global warming compared to the rate of adult obesity (refer to Sect. 3 for further details). We also do not adopt the measure of adult overweight rate as the definition of overweight can vary across countries or regions due to factors such as ethnic differences, health outcomes, and other considerations.

The estimates suggest that global warming significantly increased obesity rates in countries within temperate zones while reducing obesity only in 21 tropical countries.[3] The marginal effect on obesity of a 1 °C increase in temperature ranged from −0.56 to 1.87% across the 152 countries, with a population-weighted average of 1.06%. Combining these estimates with global warming projections, we estimate that global warming will increase the number of obese adults worldwide by 89.9 million from 2016 to 2050. A simple back-of-the-envelope calculation suggests that global warming could lead to an economic loss of US $276.6 billion by contributing to the rise of obesity worldwide.

We employ four alternative model settings to validate the estimated effect pattern of global warming on obesity. The baseline model utilizes a third-degree temperature polynomial to account for the nonlinear impact of temperature on obesity. To relax the functional form assumption and capture the effect of within-year temperature variation, we, alternatively, measure temperature using temperature bins (Schlenker and Roberts 2009), seasonal mean temperature, temperature variation (Ray et al. 2015), and temperature shocks (Ashraf and Michalopoulos 2015). Estimates based on these alternative temperature measures confirm that the marginal effect of temperature on obesity initially increases with temperature and then declines when the temperature becomes very high.

We also demonstrate substantial heterogeneity in the estimated impact across countries in different regions and with varying incomes, age structures, and education levels. However, these moderating variables do not alter the estimated effect pattern across countries. Furthermore, we endeavor to explain the estimated impact of global warming on obesity by examining six potential channels: income, food prices, minimum calorie requirements, working hours, physical activity, and consumption preferences. Both the evidence from existing studies and the additional evidence provided in this paper suggest that the estimated nonlinear impact of warming on obesity can be attributed to these six channel variables.

To infer the effect of long-term adaptation, we also estimate a “long-difference” model that relies on long-term temperature trends to identify the impact (Moore and Lobell 2014; Liu et al. 2023). This model is better equipped to capture adaptation than the baseline model because individuals have more time to adapt to long-term temperature trends compared to year-to-year temperature fluctuations. We still find that warming initially increases and then reduces obesity, although the turning point is lower. However, the long-term model suggests a larger, rather than smaller, impact of warming on obesity in temperate zones, indicating that adaptation cannot significantly offset the impact of warming on obesity. The long-term model also suggests that warming will substantially reduce obesity in subtropical and tropical zones, most likely reflecting the accumulated long-term negative impact of warming on income in poor countries from these zones.

This study makes a significant contribution to the literature on the impact of global warming on obesity. Given the widespread prevalence and substantial economic costs

[3] Temperate zones refer to regions of the Earth that lie between the tropics and the polar circles. They range between approximately 23.5° and 66.5° latitude in both the northern and southern hemispheres. These zones experience moderate temperatures and distinct seasons.

associated with obesity (Kopelman 2000; Ng et al. 2014; Tremmel et al. 2017), it is essential for policymakers and the general public to comprehend how global warming could affect obesity. However, existing studies mainly examine the impact of global warming on obesity based on data from specific countries or regions (e.g., de Jonge et al. 2002; Sadiq et al. 2019; Betz and Enerback 2018) or infer the impact of global warming on obesity through specific channels (e.g., Burke et al. 2015; Wheeler and von Braun 2013; Obradovich and Fowler 2017). For instance, An et al. (2018) conducted a systematic review and found that before 2017, only 13 empirical studies had examined the impact of global warming on obesity. Most of these studies were based on data from specific countries and indicated that higher temperatures could contribute to an increase in obesity. Similarly, Swinburn et al. (2019) concluded that climate change and obesity are simultaneous global pandemics, but very few studies have specifically investigated the effects of global warming on obesity.

Our study is most closely related to Trentinaglia et al. (2021), which examined the effect of annual mean temperature on Body Mass Index (BMI) based on data from 134 countries over 39 years, finding a U-shaped association between temperature and BMI. However, our study differs from Trentinaglia et al. (2021) in at least four major aspects. First, we examine the effect of global warming on obesity (defined as a BMI exceeding 30 kg/m^2), while they focused on the effect of global warming on BMI; the impact on BMI can stem from underweight, normal weight, overweight, and obese individuals. Second, we are able to identify both the short-run and long-run effects of warming based on different model settings, while they only examined the short-run effects based on inter-annual temperature fluctuations. Third, our study additionally evaluates the extent to which long-run adaptation could offset the impact of global warming on obesity. Finally, our study additionally examines the potential channels through which global warming affects obesity. To the best of our knowledge, our study is the first to directly examine the overall impact of warming on obesity based on long-run global data and to evaluate the potential of long-run adaptation in offsetting this impact.[4]

Our findings suggest that obesity is an important pathway through which global warming can detrimentally affect human capital and economic outcomes. A substantial body of research indicates that obesity can have adverse effects such as diminishing physical and mental health (Willage 2018), elevating the risk of premature death (Ritchie and Roser 2017), impairing academic performance (Ding et al. 2009), impeding the development of socioemotional skills (Black and Kassenboehmer 2017), limiting labor market opportunities (Prina and Royer 2014), decreasing wages (Bhattacharya and Bundorf 2009), increasing medical costs (Cawley and Meyerhoefer 2012), and imposing other social burdens (Michaud et al. 2012). By combining these findings with our estimated impact of global warming on obesity, it becomes evident that global warming could significantly reduce human capital and economic outcomes by increasing obesity.

[4] Although the main finding of this study, that global warming generally increases obesity, is consistent with the findings of existing studies (e.g., An et al. 2018; Trentinaglia et al. 2021), it is not feasible to directly compare the estimated marginal effects due to the different study areas and the different measures of overweight used. As shown in Fig. 4 the impact of warming on obesity can vary significantly across countries in different temperature zones.

The remainder of the study is organized as follows: Section 2 describes the data used, Section 3 outlines our empirical strategy, Section 4 presents the empirical findings, and Section 5 offers concluding remarks.

2 Data

Our primary analysis uses data from 1975 to 2016 for 152 countries (listed in Table A.1) with a population size larger than half a million in 2000. These countries collectively represented 99.1% of the world's population in 2000. Tables A.3 and A.4 provide the definitions, summary statistics, and data sources of key variables.

2.1 Outcome variables

The primary outcome variable in our analysis is the adult obesity rate, defined as the percentage of adults with a body mass index equal to or greater than 30. Figure 1 illustrates that the adult obesity rate has significantly increased from 1975 to 2016 across the 152 countries.[5] In our robustness checks and mechanism analysis, we will also consider various other outcome variables.

2.2 Climate variables

The climate data is obtained from the Climatic Research Unit, one of the most widely used observed climate datasets produced by the UK's National Centre for Atmospheric Science at the University of East Anglia. Monthly data for various climate measures are available from 1901 to 2018 on a $0.5° \times 0.5°$ grid covering land surfaces. We calculate country-level climate measures as the population-weighted average across all climate grids within each country. The population weightings are derived from the LandScan Program, utilizing gridded population data from the year 2000. In robustness checks, we also calculate country-level climate measures by using the population in 2016 (i.e., the last year of our sample) or in each of the sample years as the weights.

The key climate variable utilized in this study is the annual mean temperature. Figure 2 displays the distribution of the annual mean temperature across the 152 sampled countries. In robustness checks, we also employ four other temperature measures: temperature bins, seasonal mean temperature, temperature variation, and temperature shocks. The definitions and summary statistics of these variables are presented in Table A.3 and will be elaborated upon when introduced in the analysis. Additionally, we incorporate five other climate variables as control variables: annual total precipitation, wet day frequency, frost day frequency, cloud cover percentage, and vapor pressure.

[5] The most comprehensive data on country-year level obesity is provided by Our World in Data and The World Bank. The country-year data on adult obesity rates are only available until 2016 from these two data sources, even though the data for other related measures such as BMI were updated to 2022. For more details, please refer to https://ourworldindata.org/obesity (Our World in Data) and https://genderdata.worldbank.org/indicators/sh-sta-ob-18-zs/ (The World Bank).

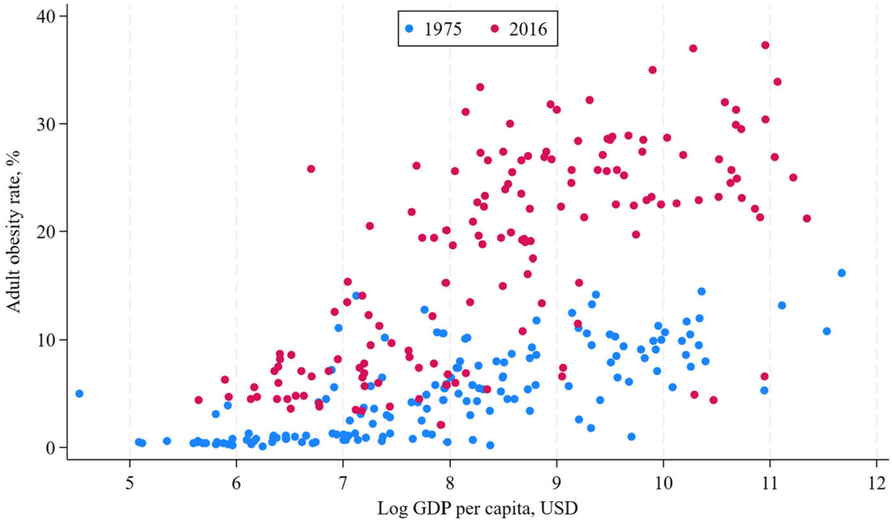

Fig. 1 The adult obesity rate in 1975 and 2016 in countries with varying income levels. Notes: Each dot in the figure represents the obesity rate in one of the 152 sampled countries in 1975 (blue) or 2016 (red). The x-axis represents the logarithm of GDP per capita in each of the two years, measured in 2011 constant USD

2.3 Climate change projections

We utilize multi-model ensemble climate projections from the Coupled Model Inter-Comparison Project Phase 6 (CMIP6) for three emissions scenarios: a low emissions scenario (SSP1-1.9), an intermediate emissions scenario (SSP2-4.5), and a high emis-

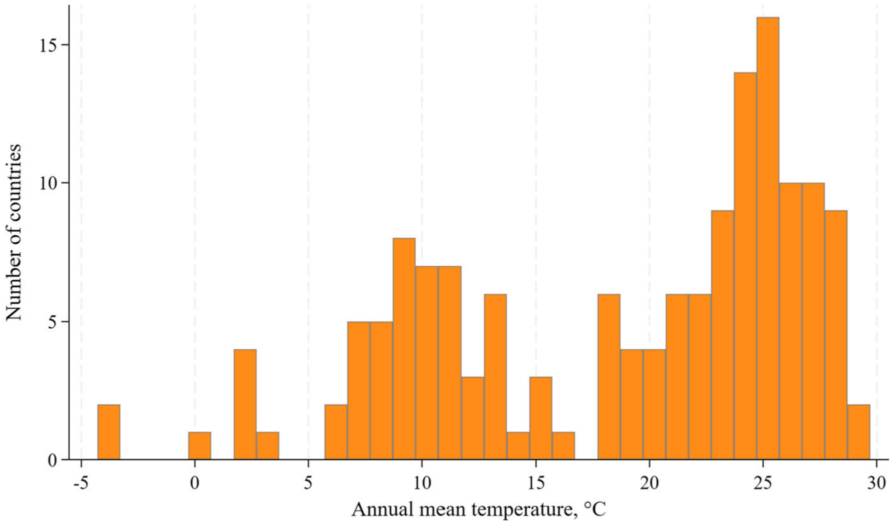

Fig. 2 Distribution of the annual mean temperature across the 152 sampled countries, averaged from 1975 to 2016

sions scenario (SSP5-8.5). Gridded monthly projection data from 2015 to 2100 can be downloaded from the Climate Change Knowledge Portal of the World Bank Group. Our analysis focuses on climate change predictions from 2016 to 2050.

2.4 Other variables

We also employ various socioeconomic variables as control variables, mediator variables, or moderator variables. These variables include GDP per capita, population size, crude death rate, average age, adult years of schooling, and total carbon emissions. All these variables are obtained from the World Bank Open Data.

3 Methods

3.1 Causal effect identification

Our goal is to estimate the causal effect of global warming on obesity. In an ideal experiment, we would compare two identical countries, warm the temperature of one, and compare its obesity rate to the other. However, in practice, we approximate this experiment by comparing a country to itself in years when it is exposed to warmer or cooler-than-average temperatures due to naturally occurring stochastic atmospheric changes. For instance, a country observed during a cool year serves as the "control" for the same country observed during a warmer "treatment" year. The identification of the causal effect is based on the fact that inter-annual temperature fluctuations are random (Paxson 1992; Miguel et al. 2004) and thus not influenced by any confounding factors. This approach has been widely adopted to identify the causal effect of climate change on various economic outcomes (see Dell et al. (2014) for a review).

3.1.1 Baseline model

Formally, we depend on the following fixed effect panel model, which compares the same country over time to estimate the causal effect of warming:

$$y_{it} = \sum_{j=1}^{J} \alpha_j tem_{it}^{j} + X_{it}\delta + \tau_i + year_{it} + year_{it}^{2} + \varepsilon_{it}, \tag{1}$$

where y_{it} represents the adult obesity rate for country i in year t; τ_i denotes the country fixed effects; $\sum_{j=1}^{J} \alpha_j tem_{it}^{j}$ represents the J-degree polynomial of annual mean temperature (to be detailed later); X_{it} is a vector of control variables; $year_{it}$ represents country-specific time trends, and $year_{it}^2$ is the square of $year_{it}$; ε_{it} is the error term; and α_j and δ are coefficients. The baseline model includes eight control variables (i.e., log GDP per capita and its square, annual total precipitation and its square, wet day frequency, frost day frequency, cloud cover percentage, and vapor pressure), and additional control variables will be introduced in robustness checks.

The country fixed effects τ_i account for cross-country, long-run temperature differences, allowing the coefficient of the temperature polynomial (α_j) to be identified through year-to-year temperature fluctuations (Deschenes and Greenstone 2007; Huang and Sim 2021). Temperature fluctuations, being random (Paxson 1992; Miguel et al. 2004) and unaffected by other determinants of obesity, allow the coefficient α_j to capture the causal effect of temperature on obesity. Year fixed effects are not included in the baseline model because they would account for the majority of inter-annual temperature fluctuations, making the estimation heavily reliant on extrapolation (Fisher et al. 2012; Huang and Sim 2021). In a robustness check, we find that the effect pattern remains the same even when year fixed effects are included in the model.

The baseline model employs a J-degree temperature polynomial to capture the well-documented nonlinear effect of temperature (e.g., Schlenker and Roberts 2009; Burke et al. 2015). In robustness checks, we will employ four other methods to capture this nonlinear effect. To visually illustrate the nonlinear effect, we will present graphs displaying the following response function of obesity to temperature:

$$Z = \sum_{j=1}^{J} \hat{\alpha_j} tem^j \quad , \tag{2}$$

where $\hat{\alpha}_j$ represents the estimated coefficient of the temperature polynomial from model (1). To calculate the marginal effect of temperature on obesity in country i, we can obtain it by taking the first-order derivative of model (1) with respect to temperature:

$$Marginal\_effect_i = \sum_{j=1}^{J} j\hat{\alpha_j} tem_i^{j-1}, \tag{3}$$

where tem_i is the average temperature of country i over the sample period.

3.1.2 Interaction effect of income

We also investigate the extent to which the effect of warming on obesity varies across countries with different incomes. To accomplish this, we expand model (1) to incorporate the interaction between income and the temperature polynomial:

$$y_{it} = \sum_{j=1}^{J} \alpha_j tem_{it}^j + \sum_{j=1}^{J} \beta_j tem_{it}^j \times Inc_{it} + X_{it}\delta + \tau_i + year_{it} + year_{it}^2 + \varepsilon_{it} \quad , \tag{4}$$

where Inc_{it} represents log GDP per capita, and all other variables remain as defined previously. It's important to note that Inc_{it} has also been controlled for in the baseline model (1). The coefficient of the interaction term (β_j) captures variations in the marginal effect of warming among countries with different incomes. Similarly, the marginal effect of temperature on obesity for each country can be calculated as follows:

$$Marginal\_effect_i = \sum_{j=1}^{J} j\hat{\alpha}_j tem_i^{j-1} + \sum_{j=1}^{J} j\hat{\beta}_j tem_i^{j-1} \times \bar{Inc}_i \,, \tag{5}$$

where $\bar{Inc}_i$ represents the average income of country i over the same period.

3.1.3 Alternative temperature measures

The baseline model captures the nonlinear effect of temperature through the temperature polynomial. This model setting offers greater flexibility compared to models that utilize a quadratic (e.g., Deschenes and Greenstone 2007) or piecewise (e.g., Burke and Emerick 2016) temperature measure,[6] but is less flexible than models that employ temperature bins (e.g., Schlenker and Roberts 2009). Additionally, our baseline model does not account for the effect of within-year temperature variation and shocks. In robustness checks, we also measure temperature using temperature bins, within-year temperature variation, seasonal mean temperature, and positive temperature shocks. These alternative temperature measures will be explained in detail when introduced in the analysis.

3.2 Long-run impact and adaptation

The baseline model (1) primarily captures the short-run impact because it relies on year-to-year temperature fluctuations to estimate the effect. Since individuals may not have fully adapted to these fluctuations (Mendelsohn et al. 1994; Huang and Sim 2021), the baseline model may not sufficiently account for the benefits of adaptation. To address this concern, we follow the literature (e.g., Moore and Lobell 2014; Burke et al. 2015; Burke and Emerick 2016; Wing et al. 2021; Liu et al. 2023) in estimating a “long-difference” model that captures the long-run impact using long-term temperature trends.[7] As individuals have sufficient time to adapt to long-term temperature trends, the long-run model is better suited to capture the benefits of adaptation.

Specifically, we extend the baseline model (4) to the following long-difference model:[8]

$$y_{it} = \sum_{j=1}^{J} \alpha'_j \bar{tem}^j_{i(k,t)} + \sum_{j=1}^{J} \beta'_j \bar{tem}^j_{i(k,t)} \times Inc_{it} + X_{it}\delta + \tau_i + \mu_t + \varepsilon_{it} \,. \tag{6}$$

6 The piecewise model allows the linear relationship to change in slope above a threshold.

7 Another approach to capturing the long-run impact is the hedonic approach (Mendelsohn et al. 1994), which identifies the effect through long-term temperature differences across regions. However, we do not adopt this approach because cross-sectional estimates from it are likely biased due to omitted variables (Deschenes and Greenstone 2007).

8 Specifically, model (6) is a panel long-difference model, similar to the one used as a robustness check in Burke and Emerick (2016) (e.g., Table 2 of their paper). The advantages of the panel long-difference model over the cross-sectional long-difference model are that the former offers more degrees of freedom and is better at fully utilizing long-run temperature variation.

The main difference from model (4) is that here the temperature measure $t\bar{e}m_{i(k,t)}$ is the average temperature over the preceding k years (30 years in our analysis) up to year t. Specifically, to maximize the utilization of long-run temperature variation, we follow Moore and Lobell (2014) by using the long difference for each year from 1975 to 2016. These are calculated as the difference between 1945–1975 (i.e., the long difference for 1975), 1946–1976 (i.e., the long difference for 1976), 1947–1977 (i.e., the long difference for 1977), and so forth. Additionally, the model replaces the country-specific year trends with year fixed effects (μ_t) because it relies on temperature trends for identification (Moore and Lobell 2014; Huang and Sim 2021). The model still includes country fixed effects to address potential omitted variable bias. The temperature coefficient α'_j is estimated by comparing the same country over different 30-year periods, capturing the impact of warming over 30 years. Note that we estimate both the short-run model (1) and the long-run model (6) over the period from 1975 to 2016 for 152 countries, and we calculate the long difference of temperature from 1975 to 2016 based on temperature data from 1945 to 2016. The only distinction is that the short-run model relies on year-to-year temperature variations to identify the short-term effect, while the long-run model relies on 30-year temperature trends to identify the long-term effect.

We then infer the effect of adaptation by comparing estimates from the two models:

$$Diff_i = (Marginal_i^{short} - Marginal_i^{long}) * Warming_i \,, \tag{7}$$

where $Marginal_i^{short}$ is the marginal effect of temperature on obesity in country i estimated based on the baseline model (1), $Marginal_i^{long}$ is the marginal effect estimated based on the long-run model (6), and $Warming_i$ is the projected warming of country i by 2050. As detailed in Sect. 4.5.2, while $Diff_i$ can be used to infer the effect of adaptation, it is not solely driven by adaptation.

4 Results

4.1 Impact on obesity

4.1.1 Baseline estimates

As shown in Fig. 3, we estimated different versions of model (1) using first- to fifth-degree temperature polynomials as the main explanatory variables. The corresponding point estimates can be found in Appendix Table A.5. The response functions of obesity to temperature appear similar across different polynomial degrees, but the models with third to fifth degrees (panels C, D, and E) better capture the nonlinear effect compared to the linear (panel A) and quadratic (panel B) models. Since the estimates are highly similar when using a temperature polynomial higher than the third degree, we chose the third-degree polynomial as our baseline model setting. The baseline estimates indicate that warming has a significantly positive impact on the adult obesity rate

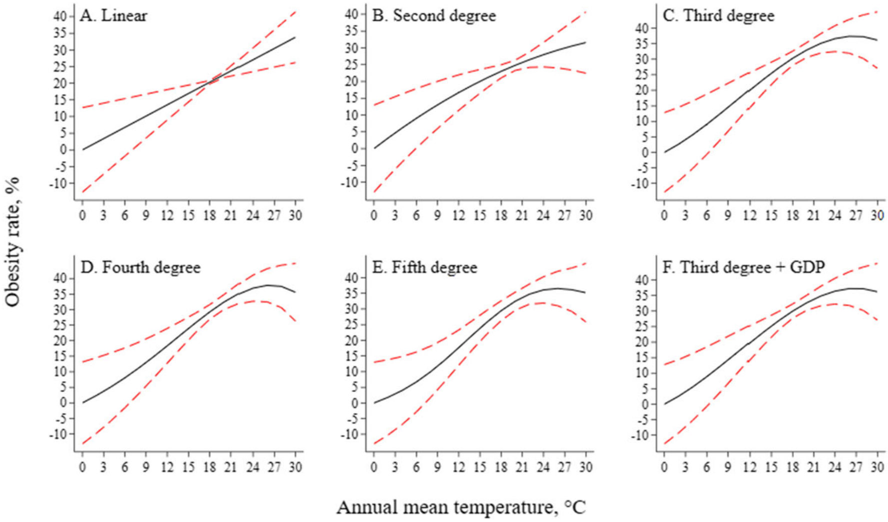

Fig. 3 Response functions of obesity to temperature. Notes: Panels A to E display response functions computed from estimates obtained using different versions of model (1), employing first- to fifth-degree temperature polynomials as the main explanatory variables, respectively. Panel F depicts the response function derived from model (4), which employs a third-degree temperature polynomial and its interaction with log GDP per capita as the primary explanatory variables. The dashed curves represent 95% confidence intervals computed based on standard errors clustered at the country level. These response functions have been normalized to start from zero. The corresponding regression estimates can be found in Appendix Table A.5

when the annual mean temperature is below 27 °C, but this effect turns negative when the temperature exceeds that threshold.[9]

Panel F in Fig. 3 displays the response function estimated using model (4), which includes an additional control for the interaction between the third-degree temperature polynomial and log GDP per capita. This model allows us to investigate the moderating effect of income. Interestingly, the resulting response function closely resembles the one without the interaction effect, as seen in panel C. This suggests a limited moderating effect of income. Moving forward, we will further explore the significance of this moderating effect at the country level in panel B of Fig. 4 and across the income distribution in panel A of Fig. 6.

Figure 4 presents the country-level marginal effects calculated based on the third-degree temperature estimates and the mean temperature of each country. Panels A and B of Fig. 4 correspond to the estimates in panels C and F of Fig. 3, respectively. In panel A, it is evident that warming has a significantly positive impact on the adult obesity rate for most countries, except for the 21 tropical countries with an annual mean temperature above 27 °C, where it has a reducing effect. The marginal effect

[9] As only two of the sample countries have an annual mean temperature below zero (see Fig. 4), there is not enough variation to accurately estimate the effect for countries with temperatures below zero. This is evidenced by the wide confidence intervals in Fig. 3 when temperatures are very low. Due to this limitation, we include all sample countries in the estimation but only present estimates for countries with mean temperatures above zero, with the exception of Fig. 4 where we calculate the marginal effect for each of the sample countries.

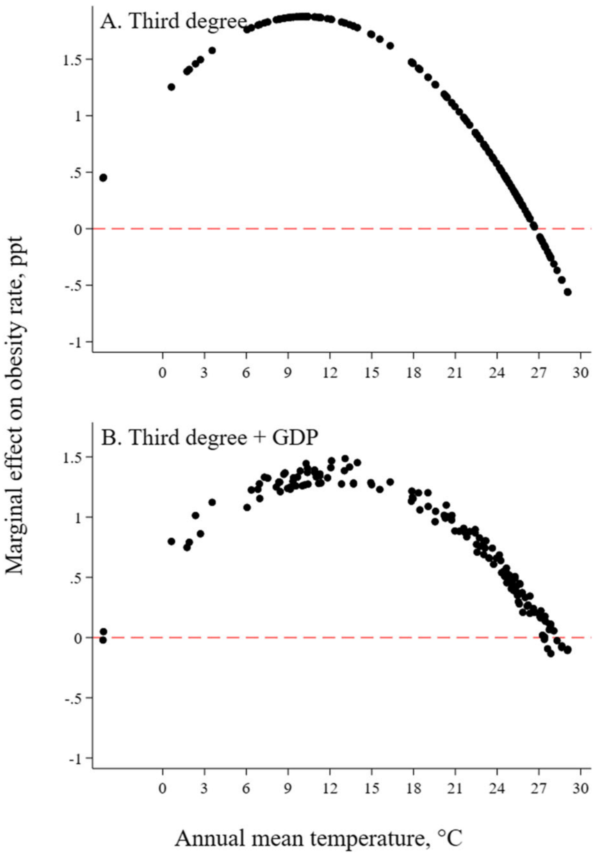

Fig. 4 Marginal effect of warming on the adult obesity rate. Notes: This figure presents the marginal effect of warming on obesity in each country, calculated based on estimates from the third-degree model and the mean temperature of each country. Panel A is calculated based on the baseline model (1), while panel B is calculated based on model (4), which takes into account the interaction effect of income. Specifically, the marginal effects are calculated based on Eqs. (3) (panel A) and (5) (panel B)

of a 1 °C increase in temperature on obesity ranged from −0.56 to 1.87 percentage points across countries, with a population-weighted country average of 1.06 percentage points. Based on an estimated global population of 7.49 billion in 2016, this suggests that a 1 °C increase in annual mean temperature results in 79.7 million more obese adults worldwide. The estimates presented in panel B, which account for the moderating effect of income, are more dispersed but comparable to those in panel A.

4.1.2 Robustness

Figure 5 examines the robustness of the baseline estimates concerning omitted variables, fixed effects, and population weights. In panel A, eight control variables are excluded, and it reveals similar estimated effects, thereby reducing concerns that the estimated impact could be primarily driven by omitted variables. In panel B, an addi-

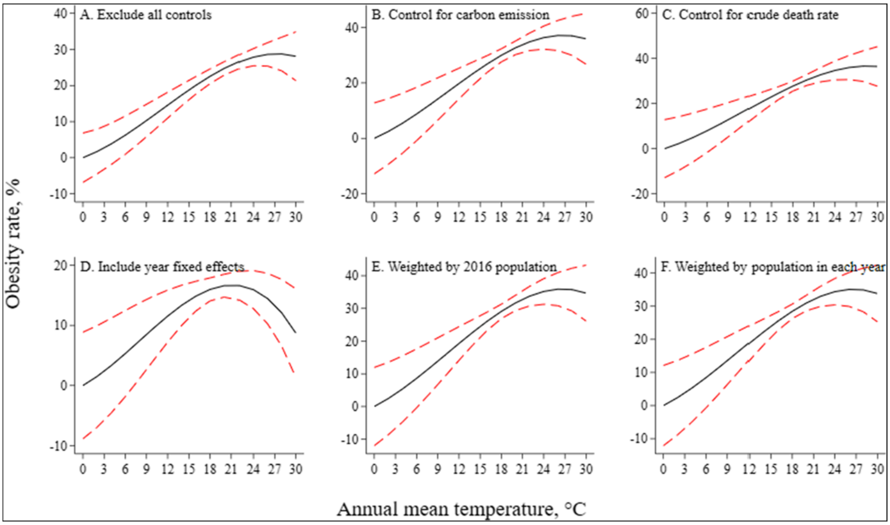

Fig. 5 Robustness checks. Notes: This figure presents robustness checks for the baseline estimates presented in panel C of Fig. 3. Panels A, B, and C, respectively, exclude the eight control variables, additionally control for carbon emissions, and also control for the crude death rate. Panel D additionally controls for the year fixed effects. Panels E and F respective utilize the country-level mean temperature calculated based on gridded population weights from 2016 and from each sample year. The dashed curves represent the 95% confidence intervals calculated based on standard errors clustered at the country level

tional control is introduced for the country's total carbon emissions to address concerns of reverse causality from carbon emissions to warming. The resulting estimates remain identical. Moving on to panel C, it controls for the country's crude death rate to address concerns that the estimated effect on obesity could be caused by other omitted determinants of health. The resulting estimates also remain very similar. In panel D, an additional control for the year fixed effects, which were excluded from the baseline model to avoid concerns of extrapolation (Fisher et al. 2012; Huang and Sim 2021), is introduced. The estimated effect pattern is comparable, but the confidence intervals are much wider. Panels E and F utilize the country-level mean temperature calculated based on gridded population weights from 2016 and from each of the sample years, respectively. The resulting estimates are nearly identical to the baseline estimates, suggesting a minor effect of within-country population migration and other sources of differential population growth on the estimated effect.[10] This finding also suggests a weak connection between within-country adaptation and changes in population weight through factors such as migration, births, and deaths (Table 1).

4.1.3 Heterogeneity

This subsection examines the heterogeneity of the impact concerning income level, age structure, education level, gender, and geographic region. To facilitate comparisons

[10] This is likely because migration and other sources of cross-sectional differences in population growth within a country are very small relative to the temperature differences across regions of the country.

Table 1 Heterogeneity of the effect

	Base line	Moderating effects	By gender		Excluding:				
			Male	Female	Africa	Americas	Eastern Mediterranean	Europe	Asia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	1.127***	1.013***	1.281***	0.806***	1.294***	1.571***	0.877***	1.152***	0.753***
	[0.117]	[0.114]	[0.118]	[0.117]	[0.132]	[0.117]	[0.123]	[0.163]	[0.121]
Temperature × Log GDP per capita		−0.202***							
		[0.010]							
Temperature × Adult age		0.026***							
		[0.001]							
Temperature × Years of schooling		0.019***							
		[0.002]							
Year trends and its square	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6258	5376	6258	6258	4494	5250	5418	4,494	5,376
R-squared	0.921	0.948	0.902	0.944	0.915	0.932	0.916	0.913	0.927

Notes: This table presents the estimates of model (8). Column 1 displays the baseline estimates, which do not include the interaction term. In column 2, the analysis includes the interaction between temperature and log GDP per capita, average adult age, and adult years of schooling in 1975. Columns 3 and 4 estimate the effects separately for males and females, respectively. Columns 5–9 each exclude one region from the estimation. Significance levels are denoted as *p< 0.1; **p< 0.05; ***p< 0.01

across models, we assess the heterogeneity effect using a linear version of model (1):[11]

$$y_{it} = \alpha tem_{it} + \beta_j \sum_j tem_{it} \times Moderator_{it}^j + X_{it}\delta + \tau_i + year_{it} + year_{it}^2 + \varepsilon_{it} \quad , \quad (8)$$

where $Moderator_{it}^j$ is the moderating variable j, τ_i denotes the country fixed effects, X_{it} is a vector of control variables; $year_{it}$ represents country-specific time trends, and $year_{it}^2$ is the square of $year_{it}$. We examine the effect of three moderating variables: Log GDP per capita, average adult age, and average adult years of schooling. As climate change can impact these three moderating variables, we chose to use their 1975 values to avoid the "bad control problem." All three moderating variables are included in a single regression to determine which one is most influential in explaining the heterogeneity. The coefficient β_j captures the moderating effect of variable j.

Column 1 presents the baseline estimates that do not include the interaction term. It reveals a marginal effect of 1.13 percentage points, which is comparable to that of the third-degree model (i.e., 1.06 percentage points). Column 2 investigates the moderating effects of log GDP per capita, adult average age, and adult average years of schooling. To visually demonstrate the significance of each moderating variable, Fig. 6 illustrates the changes in the marginal effect across the distribution of each moderating variable.

The estimates suggest that a one-unit increase in log GDP per capita would reduce the impact of warming on obesity by 0.202 percentage points. Panel A of Fig. 6 reveals that the marginal effect of warming on obesity is 1.62 percentage points higher in the poorest countries compared to the richest countries. One possible explanation for the lower impact in wealthy countries is that they are better equipped to adapt to warming (Berrang-Ford et al. 2011). For example, affluent countries are more likely to mitigate the effects of high temperatures on sports by moving them indoors with air conditioning.

The estimates also suggest that a 1-year increase in the adult average age would raise the impact of warming on obesity by 0.026 percentage points. Panel B of Fig. 6 illustrates that the marginal effect of warming on obesity is 0.85 percentage points higher for countries with the oldest population structure than for countries with the youngest population structure. This finding aligns with the observation that the elderly have lower climate change adaptation abilities (Jones et al. 2021) and are more susceptible to obesity (Tam et al. 2020) compared to young individuals.

We also find that a 1-year increase in the average schooling of adults would increase the impact of warming on obesity by 0.019 percentage points. Panel C of Fig. 6 reveals

[11] Appendix Figure A.1 presents the moderating effects estimated based on a nonlinear bins model. Specifically, we estimate a version of model (9) that additionally includes the interactions of each temperature bin with each of the moderating variables (i.e., the log GDP per capita, adult average age, and adult average years of schooling in 1975). The figure then displays the interaction effects of each temperature bin with each of the moderating variables. Consistent with the moderating effects estimated based on the linear model (column 2 of Table 1), the nonlinear model also suggests a negative moderating effect of GDP per capita and positive moderating effects of education and age. However, since the temperature bins reflect the effects of different temperatures within a year while the moderators are at the year level, interpreting the moderating effects on each specific bin can be challenging.

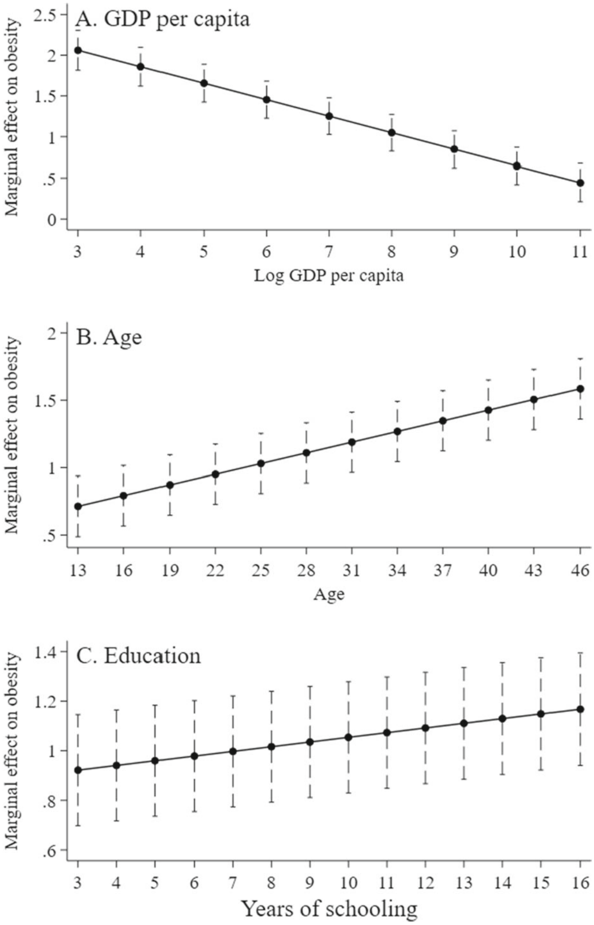

Fig. 6 Heterogeneity of the impact of warming on obesity. Notes: This figure presents the marginal effect of warming on obesity across the distribution of country-level log GDP per capita (panel A), adult average age (panel B), and adult average years of schooling (panel C). The marginal effects are calculated based on estimates from column 2 of Table 1. The capped spikes represent the 95% confidence intervals

that the marginal effect of warming on obesity is 0.25 percentage points higher for countries with the highest education levels than for countries with the lowest education levels. One possible explanation is that individuals with a higher level of education are more likely to engage in non-physical labor, with their physical exercise relying more on sports activities. However, sports activities are more susceptible to reduction under high temperatures than physical labor (Graff Zivin and Neidell 2014).

In columns 3 and 4, the analysis estimates the effects of warming on the obesity rate of adult males and females, respectively. The estimates suggest that the marginal effect of warming on male obesity is roughly one-third larger than that on female obesity. Specifically, the estimates indicate that a 1 °C increase in the annual mean temperature would increase the male obesity rate by 1.28 percentage points, while it would only increase the female obesity rate by 0.81 percentage points. This finding is consistent with the observation that males are more exposed to the impact of global warming as they typically engage in more work that exposes them to high temperatures. The differential impact of global warming on the obesity rates of males and females also has important economic and policy implications.

Columns 5–9 assess the significance of each geographic region in the estimated impact of warming on obesity. Specifically, in each column, we exclude one region from the sample. The advantage of this approach is that it can elucidate the importance of each region in the estimated impact while avoiding concerns about imprecise estimation due to small sample sizes. We observe that the impact on Africa (column 5) and the Americas (column 6) is smaller because excluding these two regions results in larger estimates. Conversely, the impact on the Eastern Mediterranean (column 7) and Asia (column 9) is larger because excluding these two regions results in smaller estimates. The impact on Europe is very similar to the global average impact because excluding it leads to a very similar estimate.

4.2 Alternative temperature measures

This subsection examines the impact of obesity using four alternative temperature measures that are better equipped to capture the nonlinear effect of warming or the impact of within-year temperature variation. These alternative temperature measures were not employed in our baseline analysis primarily because estimates based on them are less straightforward to interpret.

4.2.1 Temperature bins

We follow the literature (e.g., Schlenker and Roberts 2009; Graff Zivin et al. 2018) to construct 3 °C temperature bins. Specifically, we utilize country-level monthly minimum and maximum temperatures to create 3 °C bins ranging from 0 °C to 30°C (e.g., 0–3, 3–6,..., 27–30). Each bin's value represents the number of days when the mean temperature falls within that specific range.[12] Additionally, we include a bin for temperatures below 0 °C and another for temperatures above 30 °C, resulting in a total of 12 temperature bins. We then estimate the following modified version of the baseline model:

$$y_{it} = \sum_{j=1;j\neq 6}^{12} \gamma_j bin_{it}^{j} + X_{it}\delta + \tau_i + year_{it} + year_{it}^{2} + \varepsilon_{it} \ , \qquad (9)$$

where bin_{it}^{j} is the temperature bin j for country i in year t, τ_i denotes the country fixed effects, X_{it} is a vector of control variables; $year_{it}$ represents country-specific

[12] To approximate the daily mean temperature for each day within a month, we rely on the monthly minimum and maximum temperatures and assume a sinusoidal distribution of temperature across days within a month.

time trends, and $year_{it}^2$ is the square of $year_{it}$.[13] The sixth bin (corresponding to 12–15 °C) is omitted due to perfect collinearity, allowing us to estimate the marginal effect of each bin relative to the sixth bin.

As shown in Fig. 7, the estimate of γ_j is consistent with the baseline estimates in suggesting that higher temperature increases obesity. Specifically, the estimates suggest that more days with temperatures under 9 °C would reduce obesity (compared to the 12–15 °C bin). However, more days with temperatures above 15 °C would increase obesity. It's important to note that the specific marginal effect of each bin is not of interest on its own because it must be interpreted relative to the base bin. In addition, the coefficient of the bins model is more challenging to interpret compared to the coefficient of the baseline polynomial model. Specifically, we can directly derive the marginal effect of temperature based on estimates from the polynomial model. However, the marginal effect in the bins model must be assessed by aggregating the effects across bins and interpreted relative to the omitted base bin. Additionally, there are concerns about potential multicollinearity among temperature bins in the bins model (Carter et al. 2018).

4.2.2 Seasonal temperature

We also investigate the variation in the impact of warming across seasons. We anticipate observing a larger marginal effect of warming on obesity during seasons with higher temperatures. We employ a uniform definition of seasons based on temperature rankings across months within each country. Specifically, we rank the 12 months in each country according to their monthly mean temperatures and then evenly divide these 12 months into four groups. We sequentially define these four groups as the first, second, third, and fourth seasons.[14] Based on this definition, we estimate the following version of the baseline model:

$$y_{it} = \sum_{j=1}^{4} \eta_j season_{it}^j + X_{it}\delta + \tau_i + year_{it} + year_{it}^2 + \varepsilon_{it} \ , \tag{10}$$

where $season_{it}^j$ represents the mean temperature of season j for country i and year t, while other variables remain as previously defined.

As presented in Fig. 8, the estimates suggest that while the warming of high-temperature seasons (i.e., seasons 3 and 4) significantly increases obesity, the warming of low-temperature seasons (i.e., seasons 1 and 2) has a negligible effect on obesity.[15]

[13] Appendix Figure A.2 presents the estimates of a version of model (9) that replaces the country-specific time trends with year fixed effects. The estimated effect pattern is comparable, although the estimated marginal effects of high-temperature bins are larger.

[14] We do not adopt the normal four seasons for two reasons. First, countries near the equator may have only two main seasons (a wet season and a dry season) instead of four distinct seasons, while countries at higher latitudes may experience variations in the length of each season. Second, the timing of each season can vary across countries and regions. For example, in the Northern Hemisphere, spring typically begins around March or April, while in the Southern Hemisphere, it starts around September or October.

[15] We have also estimated the coefficients for each season in separate regressions and found comparable results: the estimated coefficients for seasons 1 to 4 are −0.19, 0.04, 0.70, and 0.82, respectively. Our

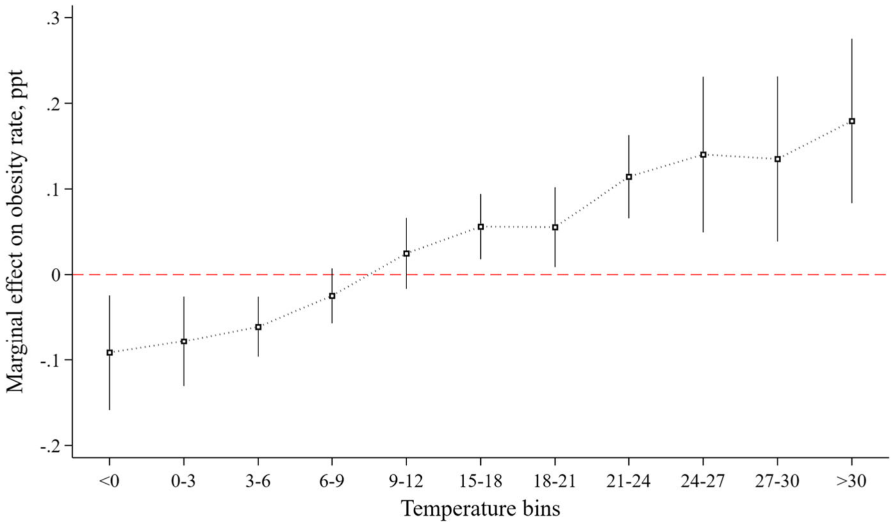

Fig. 7 Impact of temperature bins on obesity. Notes: This figure presents the estimates of model (9). The sixth bin (12–15 °C) has been excluded due to perfect collinearity. The spikes represent the 95% confidence intervals calculated based on standard errors clustered at the country level

preference is to estimate the effects of the four seasons in a single model as it could help mitigate potential biases arising from temperature correlations across seasons.

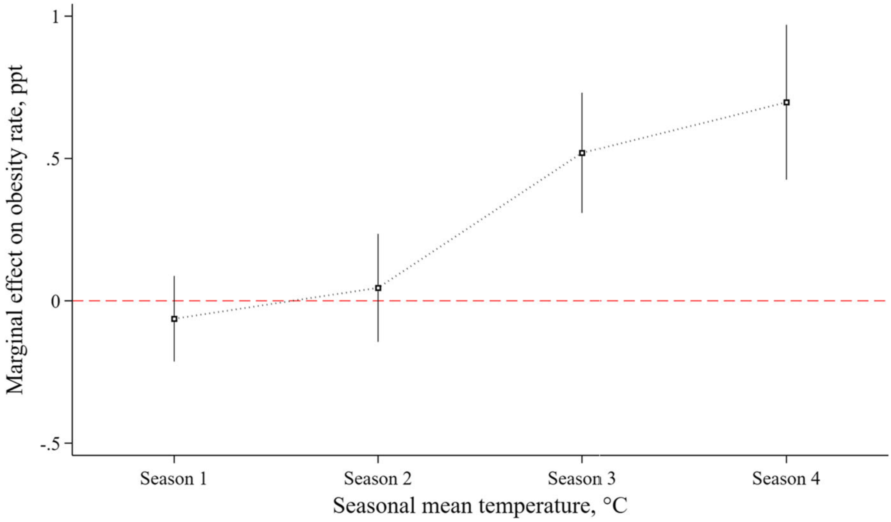

Fig. 8 Impact of seasonal temperature on obesity. Notes: This figure presents the estimates of model (10). The seasons are defined based on the ranking of monthly mean temperatures, with temperatures increasing from the first to the last seasons. The spikes represent the 95% confidence intervals calculated based on standard errors clustered at the country level

Two model settings are critical for interpreting the estimated coefficients. Firstly, the definition of the four seasons dictates that temperatures increase from season 1 to season 4. Secondly, the model includes country fixed effects to eliminate the mean temperature of the country. Therefore, the implication of the insignificant coefficients in the "low-temperature" seasons (i.e., seasons 1 and 2) is that temperature increases in seasons with low temperatures (relative to the country mean) have no significant effect on the obesity rate. Conversely, the coefficients in the "high-temperature" seasons (i.e., seasons 3 and 4) indicate that temperature increases in seasons with high temperatures significantly raise the obesity rate. The overall positive effect of warming on obesity across the four seasons confirms the baseline finding that the effect of warming generally increases with temperature. However, the seasonal model provides additional information: it suggests that only the warming of high-temperature seasons can increase obesity rates. This aspect cannot be captured in our baseline analysis because the baseline model uses an annual average temperature measure. In addition, the seasonal model is unable to capture the nonlinear effect observed when temperatures are very high, as found in the baseline polynomial model and the bins model.

4.2.3 Temperature variation

To more directly examine the effect of within-year temperature variation on obesity, we follow the literature (e.g., Ray et al. 2015) and construct the following measure of temperature variation:

$$variation_{it} = \sqrt{\frac{1}{12}\sum_{m=1}^{12}(tem_{it}^{m} - tem_{it})^2}\ , \tag{11}$$

where tem_{it}^{m} is the mean temperature of month m in year t for country i, and tem_{it} is the annual mean temperature in year t. We then estimate the following modified version of the baseline model:

$$y_{it} = \sum_{j=1}^{J}\vartheta_j variation_{it}^{j} + X_{it}\delta + \tau_i + year_{it} + year_{it}^2 + \varepsilon_{it}\ , \tag{12}$$

where $variation_{it}^{j}$ is a third-degree polynomial of temperature variation, and all other variables are defined as previously stated.

Figure 9 presents the response function of obesity to temperature variation, calculated based on the estimates of ϑ_j from model (12). We observe that the marginal effect of temperature variation on obesity first increases with temperature variation and then levels off when the variation is very high. This finding aligns with the literature that demonstrates how not only mean temperatures but also temperature variation can impact socioeconomic outcomes (e.g., Bohra-Mishra et al. 2014; Ray et al. 2015; Kotz et al. 2021).

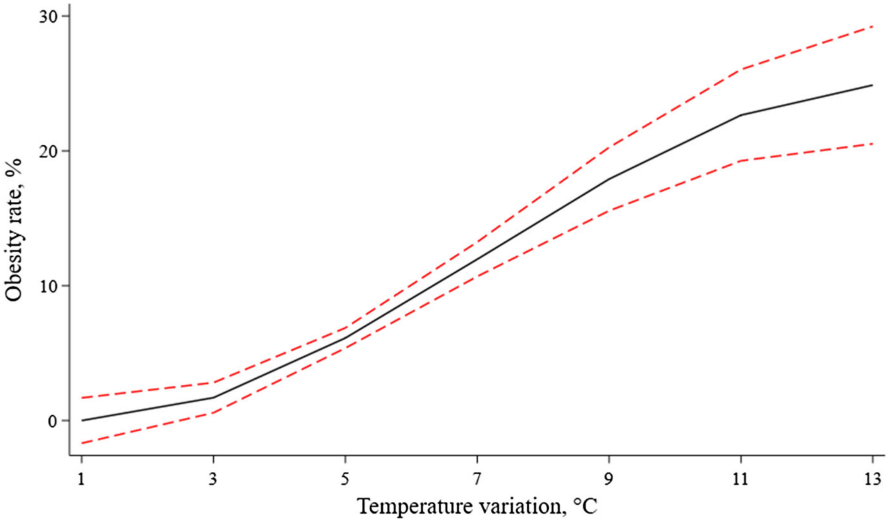

Fig. 9 Response function of obesity to temperature variation. Notes: This figure presents the response function of obesity to temperature variation, constructed based on the estimates of ϑ_j from model (12). The temperature variation is defined according to Eq. (11). The dashed lines represent the 95% confidence intervals calculated based on standard errors clustered at the country level

4.2.4 Temperature shocks

Finally, we investigate the impact of positive temperature shocks on obesity. We adopt a method from the literature (e.g., Ashraf and Michalopoulos 2015; Miller et al. 2021) to measure positive temperature shocks. This is done by considering the months in each year where the temperature exceeds one standard deviation above the long-run average temperature for the same month.[16] Therefore, the value of the shock measure can range from 0 to 12 in each year. Subsequently, we estimate the following modified version of the baseline model:

$$y_{it} = \sum_{j=1}^{J} \lambda_j shock_{it}^{j} + X_{it}\delta + \tau_i + year_{it} + year_{it}^{2} + \varepsilon_{it} \ , \tag{13}$$

where $shock_{it}^{j}$ represents the third-degree polynomial of the positive temperature shock, and all other variables are defined as previously mentioned.

Figure 10 presents the response function of obesity to positive temperature shocks, calculated based on the estimates of λ_j from model (13). We observe that positive temperature shocks initially enhance and then reduce the adult obesity rate, consistent with the effect pattern of annual mean temperature found in the baseline model. This

[16] More specifically, for a given country in a given year, if there exists a month with a temperature exceeding one standard deviation from the average temperature for that month over the past 30 years, then the shock indicator takes on a value of 1; otherwise, it remains 0. The temperature shock indicator is then calculated as the count of months in each year that meet the criteria for a positive temperature shock as defined.

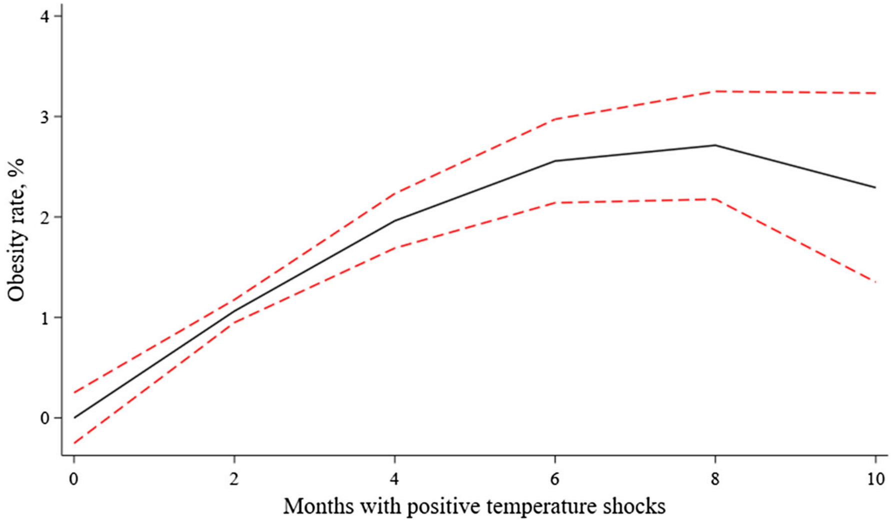

Fig. 10 Response function of obesity to positive temperature shock. Notes: This figure presents the response function of obesity to positive temperature shocks, constructed based on the estimates of λ_j from model (13). Positive temperature shocks are defined as the months in each year with temperatures at least one standard deviation above the long-run average for the same month. The dashed lines represent the 95% confidence intervals calculated based on standard errors clustered at the country level

finding is as expected because a greater number of months with positive temperature shocks corresponds to a higher mean temperature.

4.3 Mechanisms of the impact

Figure 11 summarizes potential channels through which global warming may affect obesity. Global warming can influence calorie intake by altering income (Burke et al. 2015), food prices (Wheeler and von Braun 2013), and consumption preferences (Scheelbeek et al. 2020). Global warming may also impact calorie expenditure by changing working hours (Graff Zivin and Neidell 2014), levels of physical activity (Obradovich and Fowler 2017), and minimum calorie requirements (Johnson and Kark 1947). Additionally, changes in working hours, levels of physical activity, and minimum calorie requirements may also influence calorie intake. Any alterations in calorie intake and expenditure naturally have an impact on obesity.

In addition to these micro-level factors, global warming could also impact the macro-level population structure and scale through changes in birth rates (Thiede et al. 2022), death rates (Barreca 2012), and migration patterns (Huang et al. 2020). If the effects of global warming on birth rates, death rates, and migration vary across population groups with different obesity rates, it can influence the overall obesity rate of society. This macro-level effect may be particularly significant for Small Island Developing States, where population sizes are small and the potential for within-country adaptation is limited (Vousdoukas et al. 2023). However, examining these macro-level channels is challenging due to the requirement of data on the impact of

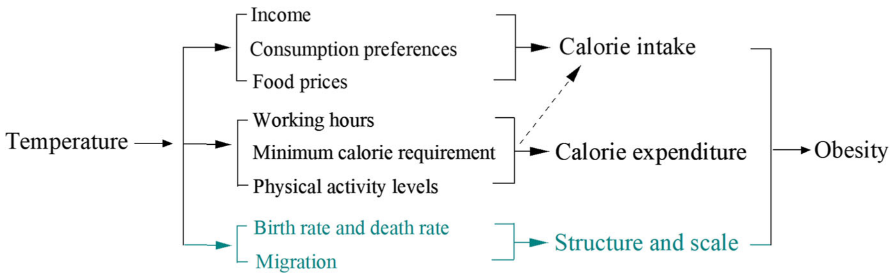

Fig. 11 Potential pathways for global warming to affect obesity

warming on birth rates, death rates, and migration among population groups with different obesity rates. Therefore, the subsequent analysis will principally focus on the micro-level channels.

Since identifying the specific channels through which warming impacts obesity is beyond the scope of this study, we rely primarily on findings from existing literature to infer these channels. Previous studies suggest that the impact of warming through the first two channels (i.e., income and food prices) likely varies across regions. Specifically, numerous studies indicate that global warming tends to reduce income and increase food prices (e.g., Schlenker and Roberts 2009; Huang and Sim 2021; Dell et al. 2012; Burke et al. 2015). These changes are likely to have distinct effects on obesity in countries situated in temperate and tropical zones. In poorer countries in tropical zones, lower real income tends to reduce obesity by limiting consumption. In contrast, in wealthier countries located in temperate zones, lower real income often leads to an increase in obesity. This occurs because individuals in these countries may shift their consumption patterns towards cheaper foods that are often higher in oils and sugar content (Zhen et al. 2011; Masood et al. 2012; Turner et al. 2016). This prediction aligns with our findings, where we observe a positive impact on obesity in temperate zones and a negative impact on obesity in tropical zones.

Existing studies suggest that global warming is likely to increase obesity through the latter four channels, namely, consumption preferences, working hours, physical activity, and minimum calorie requirements. Higher ambient temperatures require less energy to maintain body temperature (Johnson and Kark 1947; Moellering and Smith 2012), potentially reducing the minimum calorie requirement. Additionally, global warming may lead to a decrease in outdoor sports (Feinglass et al. 2011; Obradovich and Fowler 2017) and shorter working hours (Graff Zivin et al. 2018; Jessoe et al. 2018) in tropical and temperate zones, further reducing calorie expenditure. However, due to the persistence of consumption preferences (Ferson and Constantinides 1991; Kiley 2010), dietary habits may not immediately adjust to reflect the declining energy demand. Abundant energy intake and reduced energy expenditure inevitably contribute to obesity (Hubacek 2009; Sarma et al. 2015).

Figure 12 presents additional evidence supporting the positive impact through the latter four channels. We utilize a modified version of model (1) to estimate the effects of temperature on minimum calorie demand, physical exercise, calorie intake, and fat intake. Consistent with the literature, we observe that warming reduces the minimum

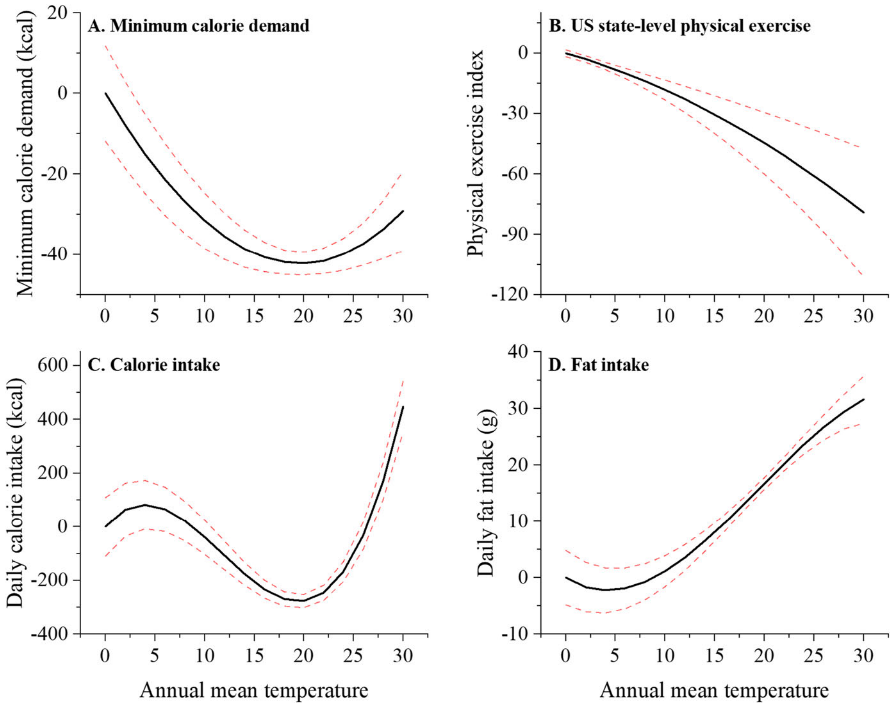

Fig. 12 Mechanisms of the impact of warming on obesity. Notes: In each panel, we estimate a modified version of model (1) with a distinct dependent variable. Panel A employs the minimum calorie demand as the dependent variable, while panel B uses the physical exercise index, panel C employs per capita calorie intake, and panel D utilizes per capita fat intake. Panels A, C, and D are based on country-level data, whereas panel B relies on US state-level data (since country-level data is not available). The dashed lines in the figures represent the 95% confidence intervals

calorie requirement in cold and temperate regions (panel A), diminishes physical exercise (panel B), and increases calorie and fat intake in tropical and temperate zones (panels C and D). Panels A, C, and D utilize country-level data, while panel B relies on US state-level data (due to the unavailability of country-level exercise data). The definitions and summary statistics of these variables are presented in Appendix Table A.3.

4.4 Long-run impact

Figure 13 presents the estimated long-run impact of warming on obesity based on model (6). To ensure comparability with the short-run model, the key explanatory variable in the long-run model remains the third-degree temperature polynomial. In panel A, we present the response function, while panel B provides the calculated marginal effect for each of the 152 sample countries. The corresponding point estimates are presented in Appendix Table A.7. The calculation of the marginal effect takes into account the interaction effect between temperature and income, making it directly

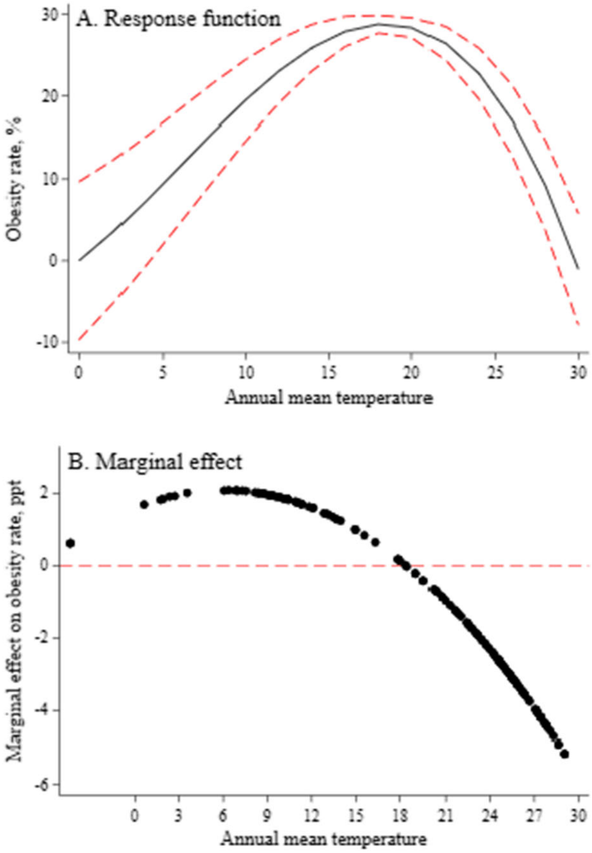

Fig. 13 Long-run impact of warming on obesity. Notes: This figure presents the response function (panel A) and marginal effects (panel B) estimated based on the long-run model (6), utilizing the third-degree temperature polynomial as the primary explanatory variable. The dashed curves in the figures represent the 95% confidence intervals, which were calculated based on standard errors clustered at the country level. It's worth noting that the response function has been normalized to start from zero

comparable to the short-run marginal effect presented in panel B of Fig. 4.[17] Given that the identification of the long-run model (6) is based on 30-year temperature trends, the estimated effect can be roughly interpreted as the impact of warming over a 30-year period.

The effect pattern of warming on obesity estimated from the long-run model (panel A of Fig. 13) is similar to that estimated from the short-run model (panel F of Fig. 3). Specifically, both models estimate that higher temperatures initially increase and then reduce obesity. However, there are significant differences in the estimated threshold temperatures. The long-run model estimates a threshold temperature of 18.5°C, while the short-run model estimates a threshold temperature of 27.3°C. Consequently, the

[17] Since the estimated coefficient of the interaction term is small and statistically insignificant in the long-run model, the variation in the marginal effect across countries in Fig. 13 is purely driven by differences in temperature.

long-run model predicts a much larger number of countries with a negative impact of warming on obesity. The next subsection provides a more in-depth comparison between estimates from these two models.

4.5 Impact prediction and adaptation possibility

4.5.1 Predicted impact by 2050

Figure 14 presents the predicted country-level impact of global warming on obesity by the year 2050. These predictions are generated by combining the estimated country-level marginal effects with the projected temperature changes for each country from 2016 to 2050. Specifically, the predictions are made through three steps. Firstly, we estimate the nonlinear marginal effects of temperature on obesity using a third-degree version of model (1). These estimates are presented in panel F of Fig. 3. Secondly, we combine the estimated nonlinear marginal effects from the first step with the mean temperature of each country to calculate the country-level marginal effect. These estimates are presented in panel B of Fig. 4. Lastly, we multiply the country-level marginal effects with the predicted warming in each country to determine the projected effect of global warming on obesity in each respective country. We utilize the global warming prediction based on the intermediate emissions scenario SSP2-4.5 from CMIP6. The country-level projected warming used in these calculations is presented in Appendix Figure A.3. For a comprehensive view, Appendix Figures A.4 and A.5 depict the predicted impacts under the low emissions scenario SSP1-1.9 and the high emissions scenario SSP5-8.5, respectively.

Panel A presents the predicted impact based on the short-run model. It indicates that global warming is likely to increase obesity in the majority of countries, with reductions observed in only a few tropical countries. Among countries with a positive impact, 77 of them are expected to experience an impact greater than 1 percentage point, 41 with an impact exceeding 2 percentage points, and 7 with an impact surpassing 3 percentage points. We calculate that the population-weighted average impact of warming on obesity across the 152 sample countries is 1.2 percentage points, which is statistically significant compared to the global obesity rate of 17.8% in 2016. Based on an estimated global population of 7.49 billion in 2016, this estimate suggests that global warming will increase the number of obese individuals worldwide by 89.9 million from 2016 to 2050. A simple back-of-the-envelope calculation suggests that global warming could result in an economic loss of approximately $276.6 billion by increasing obesity worldwide.[18]

Panel B presents the predicted impact based on the long-run model. It indicates that global warming is likely to increase obesity in most countries from temperate zones while reducing obesity in most countries from subtropical and tropical zones. The impact varies significantly across countries. The average impact across countries from

[18] It has been estimated that there were 650 million adults classified as obese in 2016 (WHO 2018), and the global annual economic loss from obesity amounted to US $2.0 trillion in 2016 (Tremmel et al. 2017). Therefore, the economic costs of 89.9 million individuals classified as obese would be expected to reach US $276.6 billion.

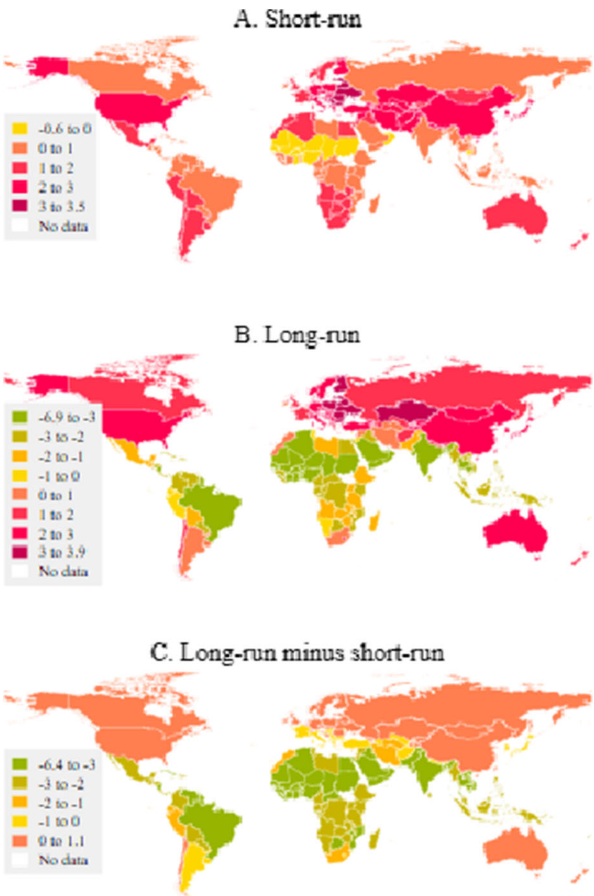

Fig. 14 Predicted impact of warming on obesity by 2050 (percentage points). Notes: We combine the estimated marginal effects with the projected warming from 2016 to 2050, using the intermediate emissions scenario SSP2-4.5, to predict the impact of global warming on obesity. Panel A is based on the short-run marginal effect estimates presented in panel B of Fig. 4, whereas panel B relies on the long-run marginal effect estimates presented in panel B of Fig. 13. Panel C presents the difference between the impacts in panels A and B

temperate zones is 2.1 percentage points, whereas the average impact across countries from subtropical and tropical zones is −2.8 percentage points. Based on an estimated global population of 7.49 billion in 2016, these estimates suggest that global warming from 2016 to 2050 would result in 76.8 million more obese individuals in temperate zones and 106.9 million fewer obese individuals in subtropical and tropical zones.

4.5.2 Adaptation possibility

We attempt to infer the effect of adaptation by comparing the predicted impacts from the short-run and long-run models. As previously explained, the long-run model relies on long-term temperature trends for identification, while the short-run model relies on year-to-year temperature fluctuations for identification. Given that individuals are more likely to adapt to long-term trends than to short-term fluctuations, the difference between these two models reflects the effect of adaptation. Specifically, by combining the estimated country-specific marginal effects of warming based on the short-run model with the country-level predicted warming, panel A of Fig. 14 presents the estimated short-run impact of global warming. Likewise, by combining the estimated country-specific marginal effects of warming based on the long-run model with the country-level predicted warming, panel B of Fig. 14 presents the estimated long-run impact of global warming. Finally, the difference between the estimated long-run and short-run impacts, as reported in panel C of Fig. 14, captures the potential for adaptation.

However, besides adaptation, there are two other important determinants of the difference between the short-run and long-run models. The first factor is the variation in the impact due to income. Global warming tends to reduce income in countries from the tropical and temperate zones (Dell et al. 2012; Burke et al. 2015). Lower income may have a limited impact on obesity in the short run if individuals can smooth consumption by using savings and borrowing. However, lower income is likely to reduce obesity in poor countries in the long run when consumption smoothing is infeasible. The second factor is the cumulative effect over time. If the impact of warming on obesity accumulates over time, the long-run impact could be larger than the short-run impact.

Now we are prepared to interpret the difference in the predicted impacts between the short-run and long-run models. Panel C of Fig. 14 presents the contrast between the estimates in panels A and B. It reveals that the long-run model predicts a more positive impact in temperate zones but a more negative impact in subtropical and tropical zones. This finding suggests that long-term adaptation does not significantly reduce the impact of warming on obesity. If adaptation had a substantial effect in reducing obesity, we would expect to observe a smaller positive impact in temperate zones, not a larger one. The greater positive impact in temperate zones suggests that the cumulative effect over time outweighs the effect of adaptation. Conversely, the more negative impact in subtropical and tropical zones likely reflects that warming reduces income and, consequently, long-term consumption in these economically disadvantaged areas. The finding that long-term adaptation may not significantly mitigate the impact of global warming on obesity calls for a more active role of the public sector in addressing the effect of global warming on obesity through the channels highlighted in Fig. 11.

5 Concluding remarks

While obesity represents one of the most significant challenges in modern society, and global warming is expected to have a substantial impact on human obesity, existing studies have not thoroughly examined this impact. Specifically, based on existing studies, we do not know the overall impact of global warming on obesity or how adaptation could help offset its effects. Answers to these questions are essential for policymakers and the general public to understand how global warming could affect obesity, subsequently impacting human capital and economic performance. Our study aims to address this gap in the literature.

We estimate the causal effect of global warming on obesity using plausibly exogenous year-to-year temperature fluctuations. The estimates suggest that global warming significantly increased obesity in most countries, with the exception of a small number of tropical countries. We estimate that a 1°C rise in annual mean temperature would increase the number of obese adults worldwide by 12.3%. Similar patterns are observed when examining the effects of temperature bins, seasonal temperature, temperature variation, and temperature shocks. Moreover, we identify substantial heterogeneity in the impact across countries in various regions and with differing income levels, age structures, and education levels. Finally, we infer the effect of long-term adaptation by comparing the baseline model with a long-difference model. Our findings indicate that long-term adaptation may not significantly mitigate the impact of global warming on obesity in temperate zones.

We conclude by highlighting two limitations of this study. First, due to the lack of long-term sub-country data on obesity for most countries, we are unable to provide a within-country analysis with a reasonably large sample size. Considering that many countries encompass vast territories, relying solely on country-average temperature might overlook substantial variations across regions. For instance, countries like the United States, China, and Canada may experience a significant number of both hot and cold days, but the average temperature alone might suggest a mild climate trend. Therefore, this study only captures the country-average effects of warming on obesity, and the effects on different regions of a large country could be very different. Second, due to the lack of annual data on the share of the population with different BMI scales, this study focuses explicitly on the effect of global warming on obesity. However, it is possible that, in addition to the effect on obesity, global warming could also affect underweight, normal weight, and overweight individuals.[19] Future studies examining how global warming will reshape the population structure regarding the BMI scale would be an important contribution to the literature.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00148-024-01039-2.

Acknowledgements We are grateful to the editor, Xi Chen, and three anonymous referees for the insightful comments and suggestions. The work was funded by National Natural Science Foundation of China NSFC (72348003).

Data Availability The data that support the findings of this study are available from the corresponding author, Kaixing Huang, upon reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

[19] While country-year BMI data are available, they only reflect the average BMI of all groups of people with underweight, normal weight, overweight, and obesity. Therefore, it is impossible to examine the effect of global warming on underweight and overweight individuals based on the country-year BMI data.

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