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Heat and Adult Health in China

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Abstract

Given projected increases in the frequency of precipitation and temperature extremes in China, we examine the extent adults may be vulnerable to climate anomalies. We link nutrition, health, and economic data from the China Health and Nutrition Survey (1989–2011) to gridded climate data to identify which socioeconomic outcomes are particularly susceptible, including adult underweight incidence, body mass index, dietary intake, physical activity, illness, income, and food prices. We find warm temperatures augment the probability of being underweight among adults, with a particularly large impact for the elderly (ages > 60). Extremely dry and warm conditions produce a 3.3-percentage point increase in underweight status for this group. Consequences on nutrition coincide with changes in illness rather than dietary, income or purchasing power shifts. Social protection targeting areas prone to excessive heat may consider supplementing bundles of goods with a suite of health care provisions catering to the elderly.

Keywords

Climate; temperature; health; adults; China

Current research indicates considerable social costs of global climate change, with disproportionate consequences for the poor (World Bank, 2010; IPCC, 2014; Carleton and Hsiang, 2016). Greater emphasis has been placed on agricultural yields and other economic outputs (Lobell et al., 2011; Lobell et al., 2012; Burke et al., 2015), with less attention to how climate variability affects broader well-being, especially in the developing world (Burke et al., 2012; Phalkey et al., 2015). Malnutrition is one of the leading global health challenges, leading to 11 percent of losses in the annual gross domestic product of Africa and Asia (IFPRI, 2016). While climate extremes can jeopardize adult survival (Deschenes, 2009; Deschenes and Greenstone, 2011; Shi et al., 2015) and child nutrition (Hoddinott and Kinsey, 2001; Dos Santos and Henry, 2008; Maccini and Yang, 2009; Skoufias and Vinha, 2012; Kumar et al., 2016), the consequences of these events for adult nutrition continue to be poorly understood. Caloric intake is anticipated to shift in response to losses to income or purchasing power where insurance is absent (Dercon, 2004; Kazianga and Udry, 2006).

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Pervasive climate effects on physiology (Graff-Zivin and Neidell, 2014; Zhao et al., 2016) and amplified risks of water- and vector-borne diseases (Pascual et al., 2006; Zhou et al., 2008; Paaijmans et al., 2010) may reinforce nutritional deficits. A nuanced understanding of the impact of climate extremes on adult populations may help to better identify vulnerable groups and thus better target aid interventions in a world experiencing climate change.

We use the China Health and Nutrition Survey (CHNS, 1989–2011) to examine the impacts of contemporaneous temperature and precipitation anomalies on adult (over 19 years old) well-being. We focus on China because of its global significance and historical precedence of devastating droughts, floods, and crop failures (IPCC, 2012; Piao et al., 2010; Ma and Maystadt, 2017). Health indicators such as underweight, body mass index, dietary intake, physical activity, and morbidity allow for measurement of social resilience to climate variability. Household price and income information are used to determine the extent that shifts in well-being coincide with economic factors. We hypothesize that climate variability affects adult well-being through both physiological *and* economic channels. Thus, we expect climate-induced malnutrition, dietary intake, illness, and physical inactivity to comove with declines in agricultural income or increases in staple prices. We further predict the relationships will be more pronounced for vulnerable subpopulations such as the elderly.

As described below, we find only partial support for the first hypothesis but strong support for the second hypothesis. Specifically, we find that positive temperature anomalies substantially increase the probability of being underweight for older adults and that this coincides with deterioration in health outcomes but not economic outcomes. The study proceeds as follows: Section 2 describes the main channels through which weather extremes can impact adult health. Section 3 describes the data and the econometric methodology. Results are presented in section 4, while section 5 concludes.

Conceptual Framework

Climate can affect nutrition and health through multiple pathways. Variations in climate alter susceptibility to water- and vector-borne diseases (Pascual et al. 2006; Zhou et al. 2008; Paaijmans et al. 2010), with consequences that include malnutrition (McNeish, 1986; Guerrant et al., 1992). Hot temperatures can further induce physiological responses, such as overheating, on working adults (Graff-Zivin and Neidell, 2014; Zhao et al., 2016). Such poor health can also lead to physical inactivity and a reduction in nutrients and caloric intake. The literature has, thus far, focused on climate-induced adult mortality, which occurs among the elderly due to weakened cardiovascular and respiratory systems and not necessarily malnutrition (Klinenberg, 2002; Patz et al., 2005; Browning et al., 2006; McMichael et al., 2006 and Gosling et al, 2009, for reviews; Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011; Barreca et al., 2012).

Perhaps more nuanced are the climate effects on other socioeconomic metrics, which can indirectly jeopardize adult health and nutrition. Linkages between climate and income losses are relatively well-established in the agricultural sector (Jayachandran, 2006; Mueller and Osgood, 2009; Schlenker and Roberts, 2009; Seo et al., 2009; Lobel et al., 2011) as well as non-agricultural sector (Hsiang, 2010; Burke et al., 2015). Yet, how these losses translate into changes in the demand for calories, nutrient-rich food, and medication to treat illnesses is poorly understood (Phalkey et al., 2015). Losses in income might cause households to ingest fewer calories, and to replace expensive, nutrient- and protein-rich foods (e.g. vegetables and meat) with cheaper, calorie-rich foods devoid of these contents (e.g, rice) (Lehmann- Uschner, and Kraehnert, 2016). Health expenditures typically allocated for (anti-diarrheal or malarial) medications may decline. Malnutrition can, thus, arise directly from a decline in caloric consumption and nutrients, or indirectly through increased exposure to illnesses.

However, the change in agricultural yields caused by a change in climate can produce an ambiguous impact on the purchasing power of households. How the subsequent changes in prices affect household welfare will depend on a variety of individual and national factors, such as the reliance on purchased food for consumption, the share of the market that is affected, and the national context for imports (Burke and Lobell, 2010). To illustrate, in the case where losses in agricultural yields induce food shortages, farmers, who are not directly affected by the climate event, may be advantaged from the profit gains added by the price premium, leading to income benefits. Furthermore, the same farmers could benefit from lower prices for non-staple food items. This could arise if enough households vulnerable to the income shock, shift their consumption away from food items like vegetables and meat causing a decline in their demand, lowering their prices in the short term. Others, however, might face food price hikes exacerbating consequences on caloric intake or dietary diversity. Urbanites or the rural landless are most vulnerable to sudden changes in food prices, as they cannot rely on their own production for consumption. Broader impacts can ensue among inhabitants of protectionist economies, preventing entry of cheap import substitutes. Together these findings make clear that climatic effects on adult health can occur via both physiological and livelihood channels. This motivates our prediction, above, that climate-induced malnutrition, dietary intake, illness, and physical inactivity will comove with declines in agricultural income or increases in staple prices.

How the direct and indirect effects of climate culminate at the individual level is contingent on several factors, such as age, gender and the intrahousehold allocation of resources. The health literature typically focuses on children under five for a variety of reasons. First, infants and young children often rely on breast milk, where the supply and quality may be compromised under changes in climate (Dos Santos and Henry, 2008). Second, any sudden modification in their caloric intake, whether it be due to disease incidence or diet, has long lasting impacts on their development and therefore on anthropometric outcomes (Hoddinott and Kinsey, 2001; Alderman et al., 2006; Maccini and Yang, 2009; Gorgens et al., 2012, Grace et al., 2012; Skoufias and Vinha, 2012; Lohmann and Lechtenfeld, 2015; Groppo and Kraehnert, 2016; Kumar et al., 2016). Third, the intrahousehold allocation of resources typically favors more productive members of the household or those with status, particularly under periods of distress (Dercon and Krishnan, 2000; Mangyo, 2008). Thus, children may be called to sacrifice calories to support the daily food requirements of other adult members of the household.

Additional attention to the health and nutrition impacts of climate for marginalized adult groups, specifically the elderly, is warranted. In the analysis, we focus on adults and distinguish between three age groups (20–40 years old, 41–60 years old, and over 60 years old). It has been established that the latter age group is physically vulnerable to increases in temperature (Browning et al., 2006; Deschenes and Moretti, 2009; Deschenes and Greenstone, 2011). Moreover, seniors may be asked to sacrifice their consumption in order for the household to cope with an income shock. Other marginalized groups, such as women, have been found to be worse affected during periods of economic crisis; they are the first to liquidate their assets, change their consumption and dietary composition, and increase their employment and domestic tasks (Quisumbing et al., 2008, Kumar and Quisumbing, 2013). These findings motivate our second hypothesis, noted above, that climate-health relationships will be more pronounced for vulnerable subpopulations such as the elderly.

Materials and Methods

Data

We build a person-period dataset and a household-period dataset (which includes food prices and incomes) using information from 8 inter-survey intervals of the CHNS (1989–91, 1991–93, 1993–97, 1997–00, 2000–04, 2004–06, 2006–09, 2009–11). In this dataset, explanatory variables such as assets are measured at period baseline, climate exposure is measured during the survey interval, and outcomes are measured at period follow-up.[1] Outcomes include body mass index (kilograms over meters squared), daily caloric intake (kcal), daily fat intake (grams), daily protein intake (grams), an indicator for being underweight (body mass index less than 18.5), intensity of physical activity (indexed 1 through 5), and self-reported illness (dichotomous).[2] Dietary intake was collected via a 24-hour dietary recall (Zhai et al., 2014). Explanatory variables include age, education, household size, a consumer asset index (Kolenikov and Angeles, 2009), a business asset index, and an urbanicity index (Zhai et al., 2014). The consumer asset index is defined as the first polychoric principal component from a set of 22 binary measures for asset ownership and housing quality, with large positive weights on consumer assets. The business index is defined as the second principal component, with large positive weights on productive assets. Our dataset includes 63,597 person-periods from 20,990 individuals in 9 provinces (Table A1).[3] Because participants who leave the study communities are not tracked for re-interview, we carefully examine the robustness of our results to potential attrition bias as described below.

Temperature and precipitation were extracted from the Climate Research Unit's Time Series (CRUTS) version 3.22 at the county level as a spatial average (Harris et al., 2014). CRUTS

[1]Thus, the first year in which an outcome enters the analysis is in 1991, in order to include lagged explanatory variables in our regression model.

[2]The physical activity scale is the following: 1) very light physical activity (working in a sitting position, e.g., office worker, watch repairer, etc.); 2) light physical activity (working in a standing position, e.g., salesperson, laboratory technician, teacher, etc.); 3) moderate physical activity (e.g., student, driver, electrician, metal worker, etc.); 4) heavy physical activity (e.g., farmer, dancer, steel worker, athlete, etc.); and 5) very heavy physical activity (e.g., loader, logger, miner, stonecutter, etc.).

[3]Thirty percent of the sample of individuals appears in all 8 rounds. Thirty-seven percent of the sample has 5 to 7 repeated observations. Twenty-two percent of the individuals have 3 to 4 panel observations. Only 6 percent of the individuals each have 2 observations in the sample. We keep the 2 percent of the individuals that only have one observation in the sample when providing a general description of the adult population (e.g., in Table A1), even though they technically are dropped from the regression analysis. The majority of the people that have one observation in our sample are adult members that joined the family in the latest wave (78 percent).

uses a spatial statistical approach to combine data on climate anomalies from over 4000 weather stations, including a large number in China, with an underlying static climatology. This produces a monthly global dataset at 0.5 ° resolution from the year 1900 to present (Harris et al, 2014). To extract Climate Research Unit (CRU) values at the county level, the CRU gridcells were resampled from native 0.5° resolution to 0.1667° resolution in order to better accommodate smaller counties that would otherwise not be adequately represented. The grid resample process retained source data values unaltered and produced values for the new interpolated grid cells via bilinear interpolation from the four nearest cells. The interpolated gridded values were then extracted using time-varying county boundaries produced by the Australian Consortium for the Asian Spatial Information and Analysis Network.

Climate variability is measured as standardized anomalies or z-scores, defined as the deviation of the climate during the calendar year of interview from the mean climate from 1981–2010 divided by the standard deviation of the climate measure over the same period. Because interviews were conducted in October-December, we use the year of interview as the period of exposure in order to capture a full annual weather cycle. The 1981–2010 reference period is selected to capture the relative deviation of the local climate from the recent past and to be consistent with the recommendation of the United Nation's World Meteorological Organization for defining climate anomalies. These time-varying measures of climate variability were linked to the person-period and household-period datasets using county location at the beginning of the inter-survey interval.

Sample Description

The individuals in our sample originate from nine provinces in China: Heilongjiang, Jiangsu, Shangdong, Henan, Hubei, Hunan, Guangxi, Guizhou, and Liaoning. The average county in each province has become increasingly urban over time (Figure A1). All provinces, with the exception of Henan, had an urbanicity value of 50 points or greater by 2000 indicating an interesting point of departure from the traditional rural environment (Jones-Smith and Popkin, 2010). Located in southern China, Guangxi has the highest temperature (Figure A2) and one of the highest precipitation levels (Figure A3) of the 9 provinces. [4] Northern provinces Liaoning and Heilongjiang have much cooler climates (Figure A2); Heilongjiang is the driest of the provinces (Figure A3). Annual temperature and precipitation averaged 14.90 degrees Celsius and 83.54 millimeters per month for the person-period sample, with standard deviations of 4.6 and 30.63 units respectively (Table A1). The anomaly values indicate that inter-survey conditions were slightly warm (temperature z score=0.03) and dry (precipitation z score =-0.15) relative to the reference period.

The individuals in our sample are equally split between male and female. Forty-two and twenty-one percent of the sample are within the 41 to 60 and over 60 age groups. Only 19 percent completed upper middle school or above (Table A1). The average household earns 23,411 yuan (or 3624 USD) a year (Table A2). The average adult ingests 2,294 calories, 343 grams of carbohydrates, 70 grams of fat, and 69 grams of protein per day (Table A1).

[4]Despite the limited provincial coverage in the sample (9 provinces), the variation in our climate exposure measures come from using data over 54 counties and across 7 survey years over a 20 year-period.

His/her body mass index averages 22.77, within the normal range of 18.5 to 24.9. Only 7 percent are classified as underweight. Mean physical activity is 2.8 on a scale of 1 to 6. Twelve percent of the sample reported being sick or injured in the 4 weeks prior to the survey, with respiratory illnesses the most common (4 percent).

Statistical Approach

We estimate the following linear (probability) regression model to identify the age-differentiated impact of temperature T and P precipitation anomalies on the individual continuous (discrete) outcome Y_i:

$$Y_{it} = \gamma_0 + \gamma_i + \gamma_t + \sum_{j=1}^{3} \alpha_j Age_j T_{it} + \sum_{j=1}^{3} \beta_j Age_j P_{it} + \sum_{j=2}^{3} \rho_j Age_j + \sum_{k=1}^{K} \delta_k X_{it} + \varepsilon_{it} . \quad (1)$$

The dependent variables are indicators of nutrition (the probability of being underweight or obese, body mass index (BMI)); dietary intake (total caloric, carbohydrate, fat, and protein intake); and health (physical activity, the probability of being sick, having a fever, sore throat, or cough, having diarrhea or a stomachache, having a headache or dizziness, having joint or muscle pain, having a rash or dermatitis, and having heart disease or chest pain). We differentiate effects by age using categorical variables denoted by Age_j: Age 41–60 years old, Age > 60 years old; Age 20–40 years old omitted. Vector X_{it} includes variables that likely determine changes in nutrition and health, such as: lagged (previous round's) education categorical variables (completed primary school, completed lower middle school, completed upper middle school, completed technical school degree, completed university degree, completed graduate degree; no school completion omitted); lagged household size; lagged indicators for above median consumer assets, above median business assets, and above median urban index.[5] In all models, standard errors are corrected for clustering at the county level, accounting for the non-independence of climate exposure within counties.

The panel structure of the data is conducive for reducing concerns over omitted variable bias on the parameters of interest, α_j and β_j. We are interested in whether these parameters are consistent across nutrition, health and economic outcomes (Hypothesis 1), and whether older age groups are more vulnerable to these effects (Hypothesis 2). First, since CHNS repeatedly collected nutrition and health outcomes for each individual over time, we are able to include an individual fixed effect γ_i in (1). This allows us to control for any unobserved time invariant factors at the individual, household, and county level that typically influence nutrition and health. At the individual and household level, the individual fixed effect is inclusive of factors such as hygiene practices and access to health care facilities and services. More importantly, we are also addressing excluded variables at the county level

[5]As education, household size, and assets are potentially endogenous to a contemporaneous shock, we incorporate these variables in lagged form, using the values from the previous round.

(our unit of exposure) that may be correlated with climate, such as ecological zone. Thus, we are accounting for the non-random distribution of climate variability across space.

Second, the inclusion of a year fixed effect γ_t captures features of the national context that might vary over time. The models are thus identified by the between-interval variation in climate within counties. The underlying threat to interpreting our estimates of α_j and β_j as causal is the omission of time-varying factors that are correlated with climate and our outcomes of interest. To mitigate this issue, we include numerous time-varying variables in vector X_{it}. Given the coarse definition of climate exposure and the survey's limited provincial coverage, we are unable to control for all relevant county-specific factors that vary over time by using county by year fixed effects. Thus, our estimates can only be interpreted as causal as long as many of these relevant factors are embodied in the current demographic, wealth, and urban explanatory variables.[6]

We additionally validate that the main specifications are insensitive to individual attrition across waves. Individual attrition in the sample ranges from 15 percent to 37 percent across waves, and is mainly attributable to the migration of individuals and households not being re-interviewed (Table A3). In 1997, the year of highest attrition, Liaoning province was excluded for logistical reasons. We estimate a pooled probit regression, conditioning on province and survey year, to detect the factors that are correlated with the probability of an individual remaining in the sample. Education and wealth reduce the probability of remaining in the sample over time (Table A4). Lagged household size and marriage increase the probability of staying in the sample. Lagged age has a non-linear effect on the probability of staying in the sample. Of the climate anomalies, only temperature has a modest, negative effect on the probability of remaining in the sample. To address concerns over attrition bias, we present results from a set of regressions in which we adjust our estimates for attrition using inverse probability weights (Fitzgerald et al., 1998). The inverse probability weights are constructed using the ratio of the predicted probabilities from a restricted version (excludes the county attrition rate,[7] province, and urban variables) and unrestricted version (all variables) of the model presented in the Appendix (Table A4).

Results

Main Specifications

Table 1 presents the effects of climate anomalies (and their associated standard errors) on nutrition, dietary intake, physical activity, and self-reported health outcomes. The results suggest that temperature anomalies increase underweight incidence of adults that are 41 to 60 or over 60 years old. There is weaker evidence that temperature anomalies might also reduce the body mass indices for these same age groups. The coefficients on the temperature parameters in the BMI specification are negative but imprecisely estimated, however, the F statistic testing the joint significance of the temperature parameters suggests that we reject

[6]Note that the urbanicity index is constructed using several time-varying communal characteristics that one might otherwise include in this regression: population density, economic activity, traditional markets, modern markets, transportation infrastructure, sanitation, communications, housing, education, diversity, health infrastructure, and social services (Jones-Smith and Popkin, 2010).
[7]The county attrition rate is defined as the percentage of people within the county that exited the sample in that wave. For each observation, we exclude itself from the calculation to provide an exogenous measure of attrition at the county level.

that they are all equal to zero (p-value=0.07). The age-specific temperature effects are also statistically meaningful according to the F statistic which tests whether the age by temperature parameters are equal (p-value=0.05).

In contrast, adult underweight incidence changes little with an increase in precipitation. While the F statistic of joint significance indicates that the effects are statistically different from zero, the coefficients themselves are small and insignificant at the 10 percent critical level. There is also weak evidence that precipitation anomalies decrease the body mass indices of the younger adult age groups.[8] The negative coefficients on the precipitation parameters are statistically significant at the 10 percent critical level and we cannot reject that the magnitudes necessarily differ across age groups. Concerning the latter, we cannot reject the null hypothesis from an F statistic testing the equality of the precipitation coefficients across age groups (p-value=0.10).

One may be concerned that the reductions witnessed in Table 1 may be beneficial for a population suffering from obesity (IFPRI, 2016). However, we show that in spite of the temperature anomalies being associated with the underweight incidence of adults over 40 years old, they do not affect obesity (Table 1). We define a person as obese if his/her BMI is greater than or equal to 30. Although there is a slight, positive and statistically significant effect of temperature variability on the obesity of adults ages 20 through 40, both F statistics testing the joint significance of the set of variables that interact age and temperature and age and precipitation indicate we cannot reject that the parameters are equal to zero.

We observe similar null effects of temperature and precipitation anomalies on the dietary intake of adults. For all outcomes, we reject that the temperature and precipitation parameters are jointly equal to zero according to the F tests at the 10 percent critical level. We similarly cannot reject that the temperature and precipitation coefficients are equal across age groups, with one exception. According to an F test, precipitation anomalies may have varying effects on the protein intake of adults from different age groups at the 10 percent critical level. However, no single precipitation coefficient in the protein intake specification is statistically different from zero following the standard t statistics.

In line with the temperature effects on nutrition, we observe similar deleterious consequences on physiological status but only for the elderly population (Age > 60). The elderly become sicker, but there is no corresponding effect on physical activity. The magnitude of the increase in illness due to a 1-standard deviation increase in temperature (0.012) is equivalent to the magnitude of the increase in becoming underweight (0.011) from an equal change in temperature. This effect is statistically different than the effect detected for the other adult age groups (F test, p-value=0.00). The elderly become more susceptible to respiratory symptoms (fever, sore throat, cough in last 4 weeks), gastrointestinal symptoms (diarrhea or stomachaches), headaches and dizziness, joint and muscle pains, and skin conditions (rash and dermatitis) with increases in temperature anomalies (Table 2).

[8]Since z score values are negative for dry anomalies, a negative parameter on the anomaly coefficient actually implies a dry anomaly would have a positive effect on BMI.

Income and price responses appear to exclude the possibility that economic conditions underlie observed malnutrition and health consequences among the elderly (Table 3). Prices of staples decline (rather than increase) with an increase in the temperature anomaly. Moreover, there is no net effect of temperature on income.

We use the predictions from (1) to predict the probability of an adult being underweight when temperature and precipitation z scores are −2, 0, and 2. Figures 1–3 display the predicted probabilities for the various scenarios per age group. For example, a scenario which assumes normal temperature (temperature z score is equal to 0) and normal precipitation (precipitation z score is equal to zero) would lead to a 0.118 probability of the elderly being underweight. An extremely hot and dry scenario (temperature z score is equal to 2 and precipitation z score is equal to −2) would alarmingly increase the probability of the elderly being underweight by 28 percent.

In summary, we find only partial support for the first hypothesis but strong support for the second hypothesis. Temperature anomalies substantially increase the probability of being underweight for older adults and this coincides with deterioration in other health outcomes but not economic outcomes. For the youngest adults (ages 20–40), temperature anomalies have positive but non-significant effects on underweight and this does not coincide with increases in illness, suggesting that this age group is partly protected. Consistent with previous studies (Carleton and Hsiang, 2016), we find that precipitation anomalies are generally less important than temperature. Precipitation has negative effects on BMI for the two younger age groups, but this does not translate into changes in either underweight or obesity.

Robustness Checks

We evaluate whether our results using specification (1) are robust to accounting for attrition and to alternative climate definitions. When accounting for the attrition of individuals (Table A5), the temperature effects for the elderly on underweight status are similar in magnitude and statistical significance, while the impact on their propensity of being sick remain similar in magnitude but lose precision (Sick p-value=0.10) (Tables A5). All F tests continue to support the joint statistical significance of the temperature variables (Underweight p-value=0.02; Sick p-value=0.02). We can reject the equality of temperature effects across age groups at the 10 percent critical level for being Sick (p-value=0.01) but not being Underweight (p-value=0.13).

We additionally estimate underweight regressions which replace the current anomaly variables with anomaly variables for the year prior to the interview, raw temperature and precipitation levels for the survey year, and a set of indicators for temperature and precipitation values which are above and below 1 and −1 standard deviation (SD), respectively.[9] The incidence of being underweight continued to be positively associated with

[9]We create four dummy variables to reflect whether hot/cold or wet/dry shocks are driving the observed effects. The first variable, Temp. anomaly > 1 SD, is assigned a value of 1 if the temperature anomaly (or z-score) has a value greater than 1. The second variable, Temp. anomaly < −1 SD, is assigned a value of 1 if the temperature anomaly (or z-score) has a value less than −1. The variable omitted from the model is scenarios in which the temperature z score is within the range of −1 and 1. The third and fourth variables create similar indicators using precipitation instead of temperature anomaly values.

raw temperature levels for the elderly sample (Table 4). From the specification that discretizes the climate anomaly variables into hot/cold and wet/dry indicators, it seems that the temperature effects on the elderly are mainly driven by hot periods. In Table 1, the coefficient on the temperature anomaly variable is 0.011. In Table 4, the coefficient is 0.012 for the temperature anomalies above 1 SD but imprecisely estimated. The estimated coefficient for the temperature anomalies below −1 SD, in contrast, is only 0.002.

Discussion

The frequency of droughts and heat waves is expected to increase in China over the next century according to global climate models (Ma and Maystadt, 2017). The implications for the well-being of one of the largest demographic groups in China, older adults, is of growing concern. Not only may this impose strains on existing welfare programs, but it could potentially compromise overall productivity, given the reliance of prime-aged workers on this demographic for child rearing and other familial support (Pei and Pillai, 1999). When evaluating the impact of both temperature and precipitation anomalies on a suite of well-being outcomes, we show that heat waves are likely to have the most pervasive effects. In particular, the probability of being underweight increases with a positive deviation in normal temperature for all adults over 40 years of age. However, the consequences extend to other health outcomes for the elderly (greater than 60 years old) population. The elderly population is more likely to report being sick during heat events and the magnitude of the change in morbidity corresponds with the magnitude of the change in the probability of being underweight. This suggests strong temperature-related nutrition-health linkages exist for this demographic group.

Our empirical model predicts that changes in temperature will have a substantive impact on the percentage of the elderly population that will become malnourished. For example, in an extremely dry and warm scenario, i.e. temperature and precipitation reach two standard deviations above and two standard deviations below the historical mean, respectively, the elderly will experience a 3.3-percentage point increase in being underweight. Since the elderly population of China consisted of 178 million people in 2010 (United Nations Statistics Division, 2017), our empirical estimates show a lower bound estimate of an additional 5.9 million elderly people expected to become malnourished during heat and drought conditions.

Given the relative size of the elderly population and its increasing role in child care provision, the question becomes what policies might one consider in making seniors more resilient to heat. Information campaigns may be necessary to bring awareness of the health risks posed by fluctuations in temperature and the preventive measures available to seniors in China to mitigate such risks. Alternatively, existing social protection programs which target the poor and areas prone to heat waves may consider supplementing their bundles of goods and services with a suite of health care provisions catering to the elderly.

These results also represent an important contribution to the small literature on adult morbidity and climate change. We show that for older adults in a key middle-income country that the negative effects of warming on health are large at temperature levels that will increasingly be experienced this century. The narrow focus of the climate vulnerability literature to date on agriculture, mortality and migration clearly needs to be expanded to encompass a wider array of target populations and social outcomes, with the goal of giving a broad picture of the multidimensional consequences of climate change and variability.

Our study also has several methodological features that could be profitably incorporated by future studies. First, we make use a long panel dataset with a large spatial extent, ensuring exposure to a wide range of baseline and time-varying climate conditions. This permits measurement of micro-level covariates that predate the climate shock and also enables an analytical strategy that fully accounts for time-invariant factors as well as national-level time-varying factors that might confound the effects of climate. Second, we measure climate as both temperature and precipitation anomalies, advancing many previous studies which have focused on a single factor or have ignored the role of historical climate variability. Finally, rather than focusing narrowly on single social outcome, we examine a range of outcomes related to our core measure of interest, providing novel insight into the mechanisms of climate vulnerability in this context. Given the increasingly availability of rich, household panel datasets from the developing world, these features should increasingly be adopted by future studies.

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Appendix

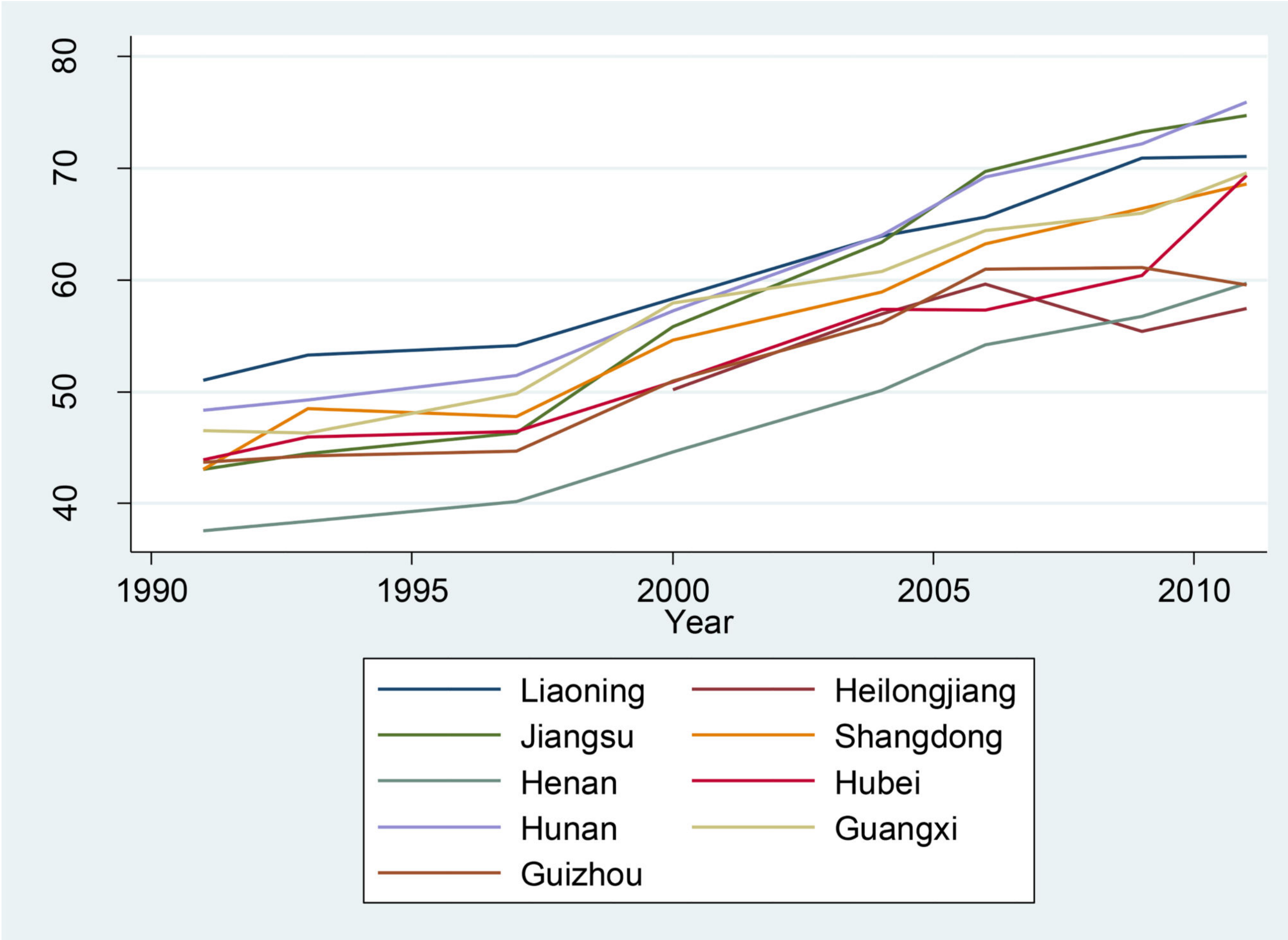

Figure A1. Province Level Urbanicity (Scale from 0 to 100)

Source: China Health and Nutrition Survey

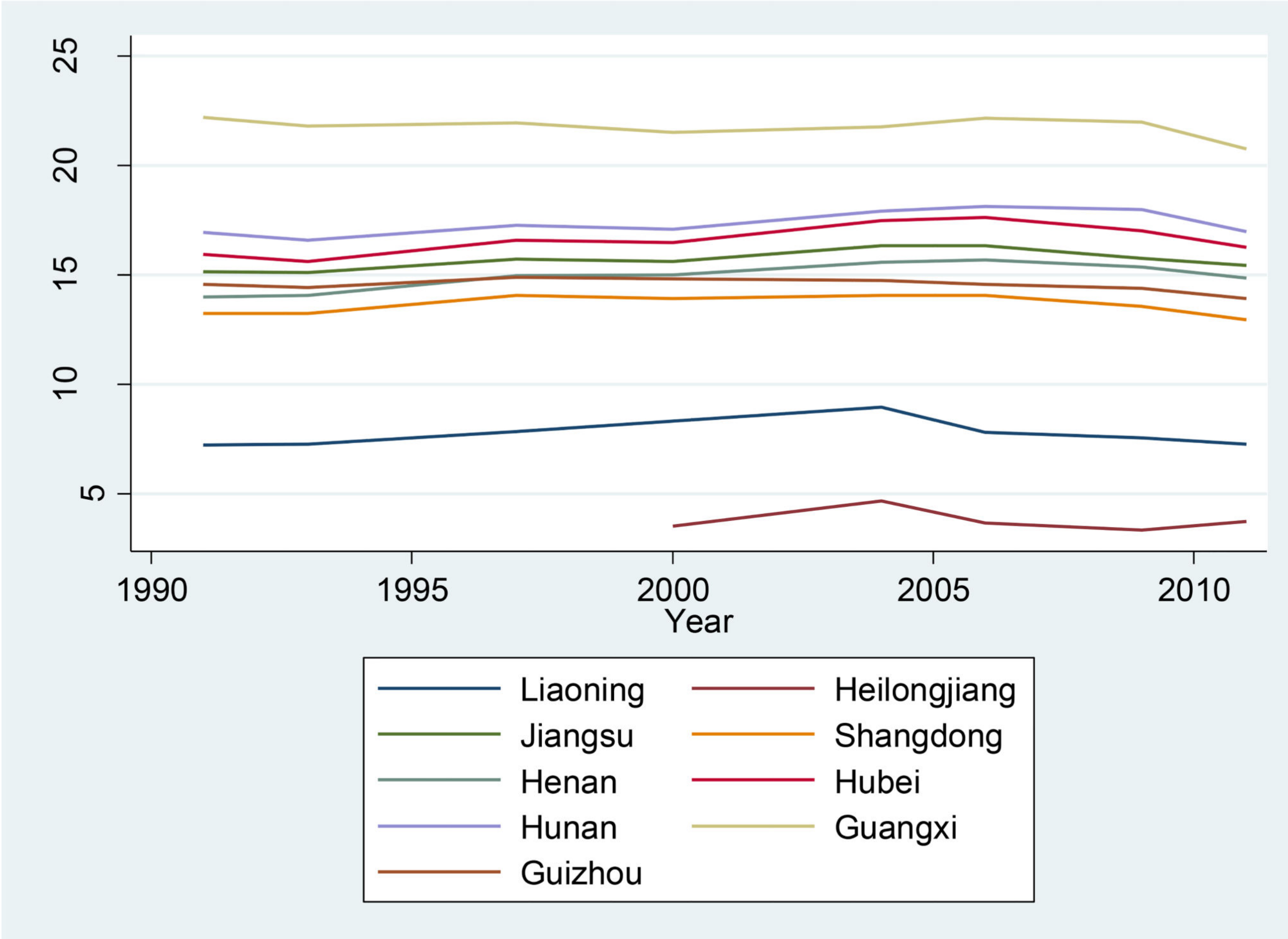

Figure A2. Province Level Temperature (C°)
Source: China Health and Nutrition Survey

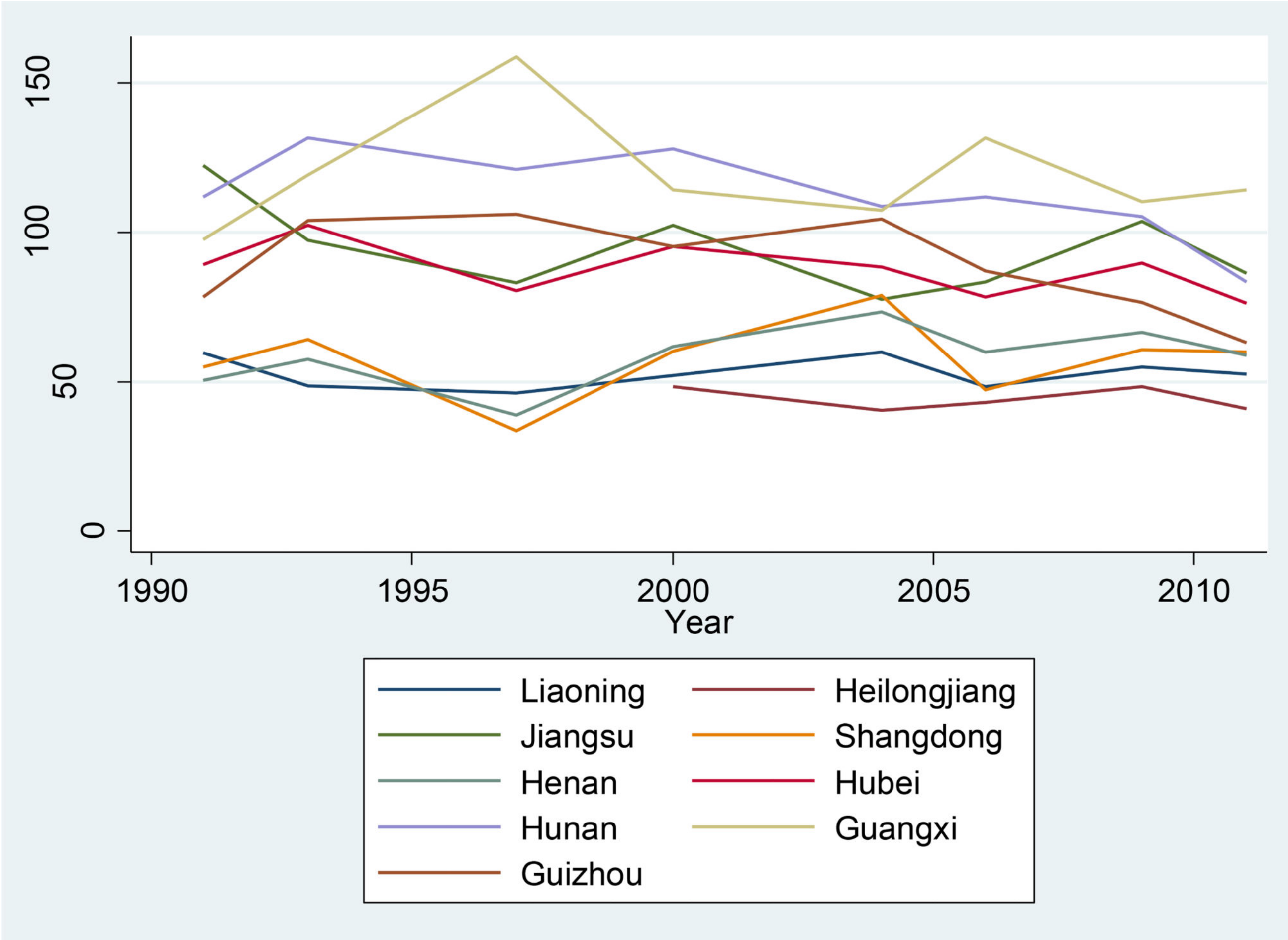

Figure A3. Province Level Precipitation (mm)
Source: China Health and Nutrition Survey

Table A1

Descriptive Statistics of Individual Variables and Outcomes

	Mean	Std.	N
Female	0.512	0.500	63,597
Age 41–60 years old	0.424	0.494	63,597
Age >60 years old	0.213	0.409	63,597
Completed primary school	0.219	0.414	62,936
Completed lower middle school	0.293	0.455	62,936
Completed upper middle school	0.118	0.322	62,936
Completed technical school degree	0.044	0.205	62,936
Completed university degree	0.027	0.164	62,936
Completed graduate degree	0.000	0.019	62,936
Married	0.815	0.388	63,597
Household size	3.677	1.541	63,597

	Mean	Std.	N
Consumer asset index	5.323	1.913	61,357
Business asset index	2.950	1.263	61,357
Urbanization index	0.480	0.500	63,597
Northern China indicator	0.504	0.500	63,597
Heilongjiang province	0.066	0.248	63,597
Jiangsu province	0.118	0.322	63,597
Shangdong province	0.115	0.319	63,597
Henan province	0.124	0.330	63,597
Hubei province	0.119	0.324	63,597
Hunan province	0.116	0.321	63,597
Guangxi province	0.137	0.344	63,597
Guizhou province	0.123	0.328	63,597
1993	0.136	0.343	63,597
1997	0.110	0.313	63,597
2000	0.129	0.335	63,597
2004	0.123	0.329	63,597
2006	0.120	0.325	63,597
2009	0.115	0.319	63,597
2011	0.124	0.329	63,597
Mean annual temperature	14.896	4.610	63,597
Mean annual monthly precipitation	83.543	30.629	63,597
Temperature anomaly, annual, year of survey	0.032	0.990	63,597
Precipitation anomaly, annual, year of survey	−0.153	0.954	63,597
Temperature anomaly, annual, year before survey	−0.053	0.854	63,597
Precipitation anomaly, annual, year before survey	0.153	0.868	63,597
Temperature anomaly is less than −1, year of survey	0.160	0.366	63,597
Temperature anomaly is greater than 1, year of survey	0.195	0.396	63,597
Precipitation anomaly is less than −1, year of survey	0.186	0.389	63,597
Precipitation anomaly is greater than 1, year of survey	0.103	0.304	63,597
Body mass index	22.765	3.293	56,567
Underweight	0.071	0.256	56,567
Obese	0.028	0.164	56,567
3-day Average: Energy intake, kcal (ages > 19)	2,294.375	822.747	60,739
3-day average carbohydrate intake, g (ages > 19)	342.615	133.710	60,739
3-day average fat intake, g (ages > 19)	69.615	58.189	60,739
3-day average protein intake, g (ages > 19)	68.846	24.430	60,739
Physical Activity Score, 1–6 (ages > 19)	2.819	1.220	59,273
Was sick or injured in the last month (ages > 19)	0.121	0.326	63,117
Had fever, sore throat, or cough in the last month	0.041	0.199	62,924
Had diarrhea or stomachache in the last month	0.014	0.118	62,893
Had headache or dizziness in the last month	0.031	0.173	62,927
Had joint or muscle pain in the last month	0.024	0.153	62,908

	Mean	Std.	N
Had rash or dermatitis in the last month	0.002	0.049	62,877
Had heart disease or chest pain in the last month	0.010	0.097	62,890

Notes: The omitted education, province, and time binary variables are: no schooling, Liaoning, and 1991.

Table A2

Descriptive Statistics of Household Variables and Outcomes

	Mean	Std.	N
Household size	3.314	1.453	26,394
Consumer asset index	5.307	1.878	25,467
Business asset index	2.873	1.281	25,467
Urbanization index	0.475	0.499	26,394
Northern China indicator	0.504	0.500	26,394
Heilongjiang province	0.074	0.262	26,394
Jiangsu province	0.117	0.321	26,394
Shangdong province	0.109	0.311	26,394
Henan province	0.119	0.324	26,394
Hubei province	0.125	0.330	26,394
Hunan province	0.122	0.327	26,394
Guangxi province	0.124	0.330	26,394
Guizhou province	0.126	0.332	26,394
1993	0.121	0.326	26,394
1997	0.097	0.295	26,394
2000	0.123	0.328	26,394
2004	0.134	0.340	26,394
2006	0.137	0.344	26,394
2009	0.134	0.341	26,394
2011	0.127	0.333	26,394
Mean annual temperature	14.736	4.691	26,394
Mean annual monthly precipitation	82.881	30.100	26,394
Temperature anomaly, annual, year of survey	0.075	1.006	26,394
Precipitation anomaly, annual, year of survey	−0.175	0.943	26,394
Temperature anomaly, annual, year before survey	−0.044	0.867	26,394
Precipitation anomaly, annual, year before survey	0.163	0.874	26,394
Temperature anomaly is less than −1, year of survey	0.152	0.359	26,394
Temperature anomaly is greater than 1, year of survey	0.217	0.412	26,394
Precipitation anomaly is less than −1, year of survey	0.187	0.390	26,394
Precipitation anomaly is greater than 1, year of survey	0.097	0.296	26,394
Business income	3,200.198	17,398.286	26,394
Farm income	2,537.677	7,428.237	26,394
Fishing income	71.088	1,473.964	26,394
Garden income	2,459.521	6,113.776	26,394
Livestock income	442.323	3,702.456	26,394

	Mean	Std.	N
Other income	2,430.274	7,456.877	26,394
Subsidy income	580.033	2,951.534	26,394
Retirement income	2,734.079	9,099.741	26,394
Wage income	8,955.961	20,845.247	26,394
Total income	23,411.155	32,071.248	26,394
Good rice price	4.361	1.654	26,394
Common rice price	3.431	1.005	26,394
Bleached flour price	3.973	1.275	26,394
Unbleached flour price	3.385	1.034	26,394
Bleached noodles price	4.655	1.599	26,394
Unbleached noodles price	3.890	1.243	26,394
Corn flour price	3.517	1.580	26,394
Millet price	5.428	2.246	26,394
Sorghum price	4.410	2.285	26,394

Notes: Income and prices are presented in 2011 real terms. The omitted province and time binary variables are Liaoning and 1991. Temperature and precipitation levels are expressed in degrees Celsius and millimeters per month.

Table A3

Individual Attrition Rates by Wave

	1991	1993	1997	2000	2004	2006	2009	2011
Not interviewed in wave	0.151	0.152	0.365	0.185	0.299	0.227	0.281	0.225
Reason for attrition: Unknown	0.003	0.006	0.014	0.005	0.007	0.010	0.011	0.010
Reason for attrition: No health measures	0.003	0.006	0.000	0.000	0.003	0.000	0.000	0.000
Reason for attrition: Temporary absence	0.000	0.000	0.012	0.007	0.066	0.059	0.052	0.062
Reason for attrition: Left household	0.074	0.053	0.080	0.051	0.055	0.035	0.033	0.031
Reason for attrition: Died	0.013	0.015	0.021	0.017	0.020	0.011	0.017	0.013
Reason for attrition: Household not interviewed	0.058	0.066	0.061	0.091	0.132	0.107	0.156	0.095
Reason for attrition: Community not interviewed	0.000	0.005	0.049	0.014	0.016	0.005	0.013	0.015
Reason for attrition: Province not interviewed	0.000	0.000	0.128	0.000	0.000	0.000	0.000	0.000
N	10,721	10,204	11,004	10,050	11,175	9,897	10,164	10,168

Table A4

Pooled Probit Regression Specifying the Probability an Individual Remains in the Sample in Each Wave

Female	−0.006
	(0.004)
Age	0.028
	(0.001)***

Age-squared	−0.000
	(0.000)***
Completed primary school	−0.018
	(0.007)**
Completed lower middle school	−0.036
	(0.008)***
Completed upper middle school	−0.040
	(0.009)***
Completed technical school degree	−0.022
	(0.013)*
Completed university degree	−0.080
	(0.015)***
Completed graduate degree	−0.256
	(0.062)***
Married	0.073
	(0.008)***
Household size excluding migrants at baseline	0.078
	(0.004)***
Consumer asset score, 0–10	−0.007
	(0.002)***
Business asset score, 0–10	−0.017
	(0.002)***
County attrition rate, excluding self	−0.604
	(0.033)***
Above median urbanization index	−0.004
	(0.007)
Temp anomaly, annual, year of survey	−0.006
	(0.003)**
Precip anomaly, annual, year of survey	0.002
	(0.002)
N	77,847

Notes: Marginal effects reported. County-clustered standard errors in parentheses. Province and survey year fixed effects included.

* $p<0.1$

** $p<0.05$;

*** $p<0.01$.

Table A5

Table 1, Regression Using Inverse Probability Weights

	Under.	Obese	BMI	Cal.	Carb.	Fat	Prot.	Activity	Sick
Temp anomaly × Age 20–40	0.002	0.003	0.049	−50.787	−12.123	0.113	−1.606	0.024	−0.011
	(0.004)	(0.002)*	(0.042)	(33.168)	(5.897)**	(1.476)	(1.047)	(0.022)	(0.006)

	Under.	Obese	BMI	Cal.	Carb.	Fat	Prot.	Activity	Sick
Temp anomaly × Age 41–60	0.006	0.002	−0.030	−38.437	−9.629	0.078	−1.086	−0.004	0.002
	(0.003) **	(0.002)	(0.035)	(32.283)	(5.191) *	(1.837)	(1.006)	(0.026)	(0.006)
Temp anomaly × Age > 60	0.011	0.002	−0.056	−36.855	−8.452	−0.337	−0.769	−0.045	0.012
	(0.004) ***	(0.002)	(0.043)	(29.906)	(4.984) *	(1.635)	(0.988)	(0.032)	(0.008)
Precip anomaly × Age 20–40	0.004	0.001	−0.045	−3.536	1.574	−0.387	−0.878	−0.005	−0.001
	(0.003)	(0.002)	(0.029)	(23.049)	(4.300)	(0.969)	(0.809)	(0.012)	(0.004)
Precip anomaly × Age 41–60	0.002	0.001	−0.034	2.389	0.928	0.531	−0.778	0.021	0.004
	(0.002)	(0.001)	(0.023)	(21.791)	(3.879)	(1.000)	(0.759)	(0.018)	(0.006)
Precip anomaly × Age > 60	−0.004	−0.000	0.029	31.115	4.608	1.004	0.524	0.045	0.000
	(0.003)	(0.002)	(0.039)	(23.484)	(4.135)	(1.177)	(0.774)	(0.026) *	(0.009)
R^2	0.65	0.67	0.86	0.53	0.64	0.49	0.47	0.73	0.38
N	54,062	54,062	54,062	58,021	58,021	58,021	58,021	56,663	60,319
Hypothesis Testing									
Joint significance of Temp parameters	0.020	0.323	0.213	0.499	0.249	0.984	0.326	0.123	0.017
Joint significance of Precip parameters	0.119	0.820	0.105	0.337	0.526	0.552	0.223	0.188	0.727
Equality of AgexTemp parameters	0.126	0.577	0.113	0.720	0.494	0.925	0.304	0.064	0.006
Equality of AgexPrecip parameters	0.069	0.850	0.161	0.216	0.394	0.357	0.118	0.095	0.523

Notes: We include the same explanatory variables as in Table 1. County-clustered standard errors in parentheses.

* p<0.1

** p<0.05;

*** p<0.01.

BMI=body mass index, Under.=underweight, Cal.=calories, Carb.=carbohydrates, Prot.=protein.

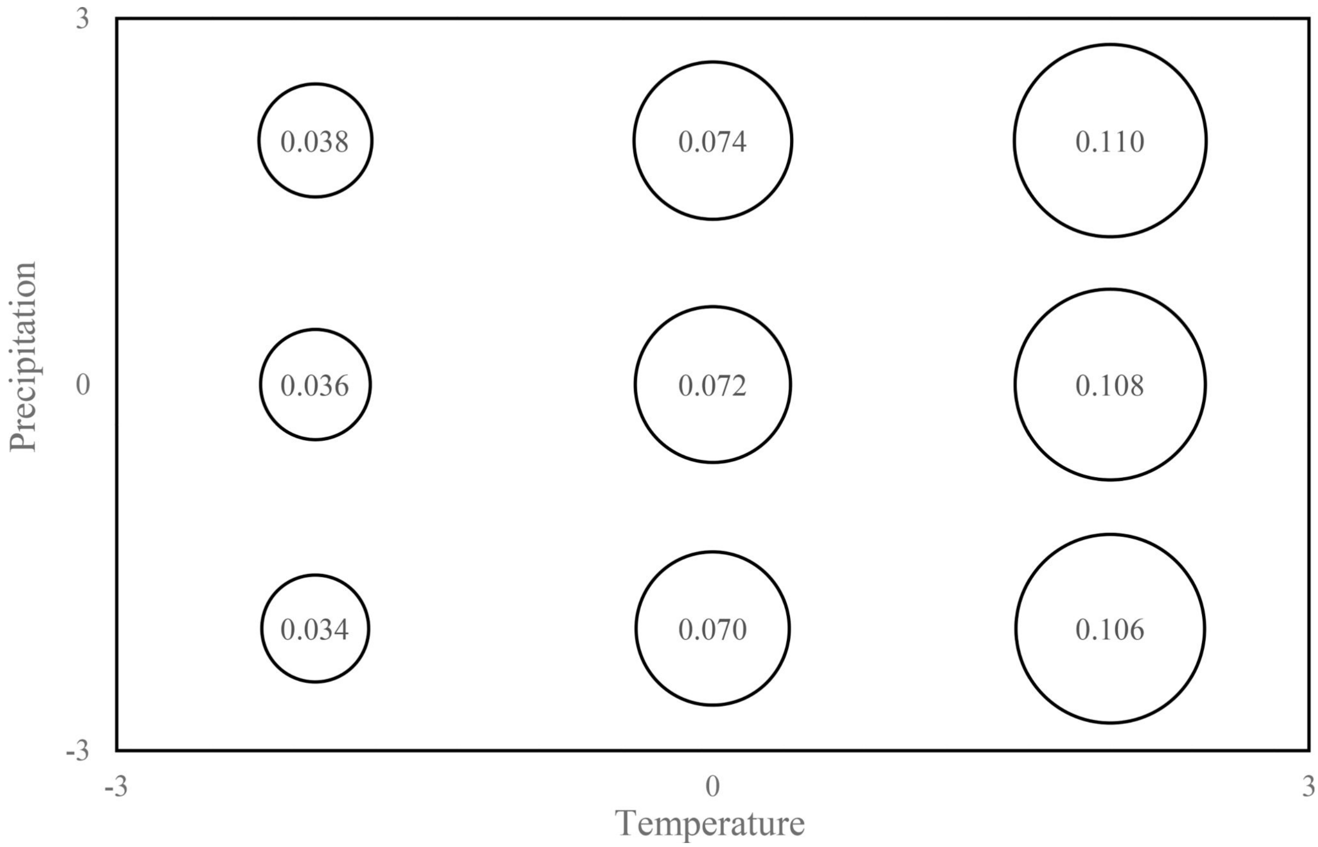

Figure 1. Probability of Being Underweight (Age 20–40)

Notes: Predicted probabilities derived from coefficients presented in Table 1. Predicted probabilities are calculated assuming z-score values of −2, 0, and 2.

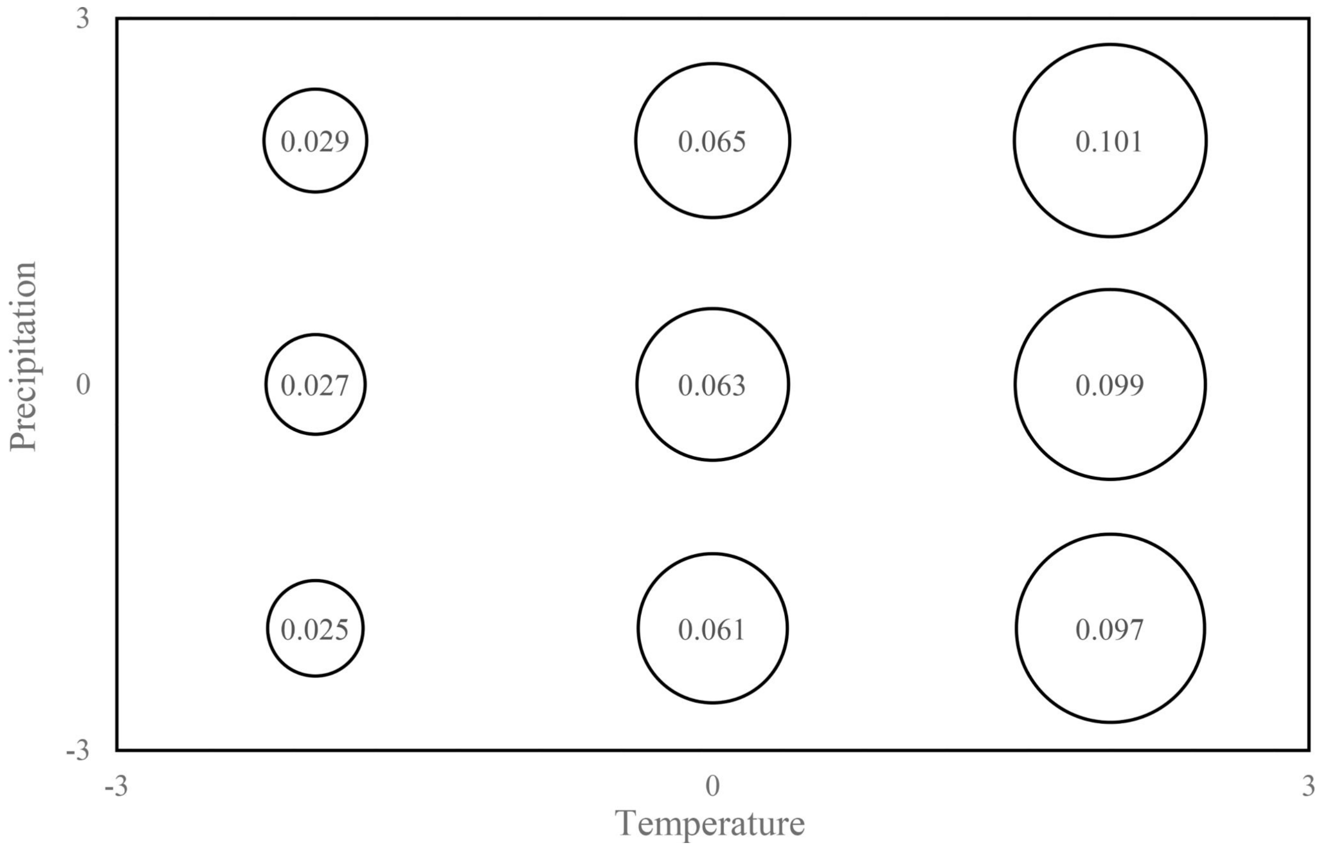

Figure 2.
Probability of Being Underweight (Age 41–60)

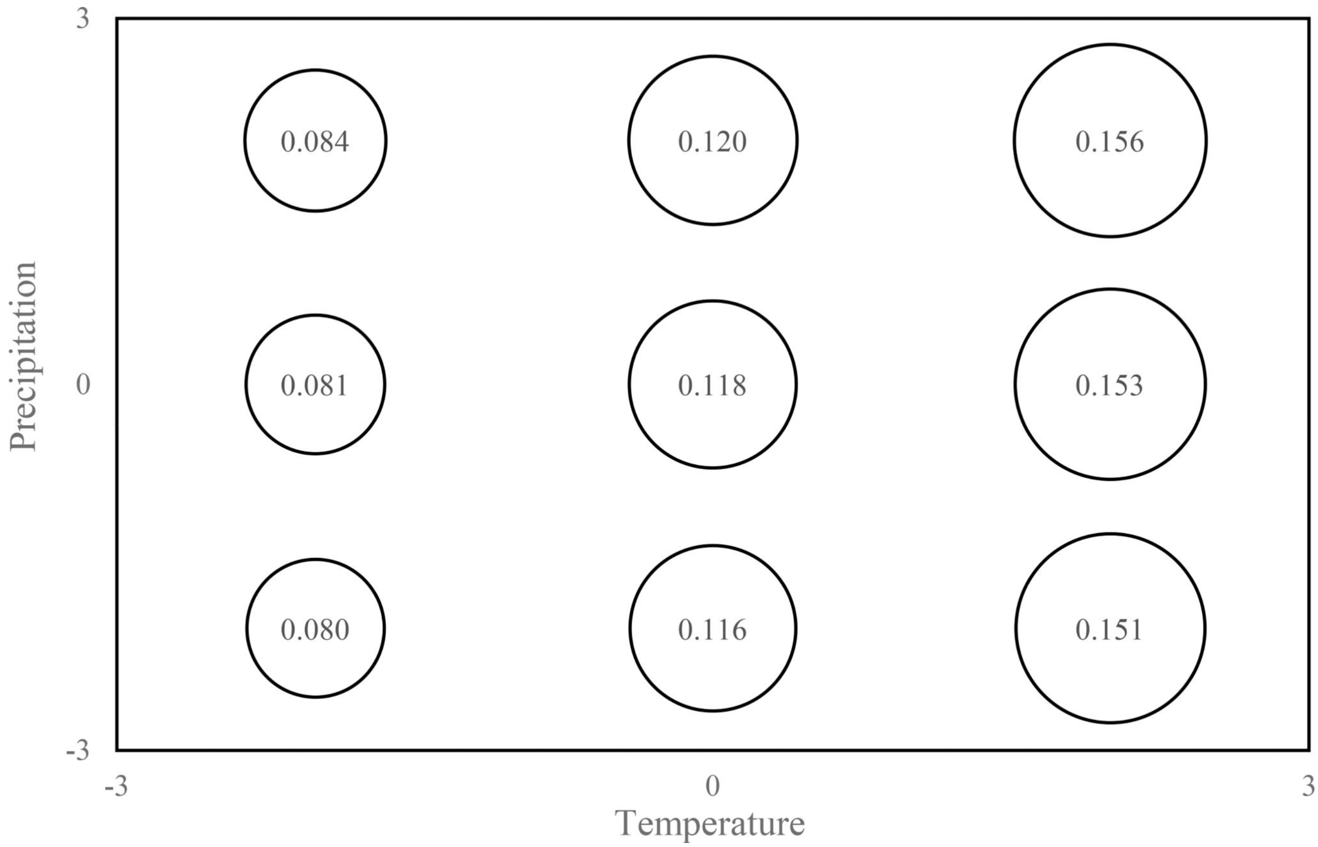

Figure 3.
Probability of Being Underweight (Age >60)

Table 1

Nutrition, Dietary Intake and General Health Outcomes

	Underweight	Obesity	BMI	Cal.	Carb.	Fat	Prot.	Activity	Sick
Temp anomaly × Age 20–40	0.001	0.004	0.055	−50.286	−11.942	0.102	−1.577	0.025	−0.011
	(0.003)	(0.002) **	(0.035)	(28.168) *	(5.015) **	(1.253)	(0.895) *	(0.019)	(0.006) **
Temp anomaly × Age 41–60	0.006	0.002	−0.028	−38.290	−9.456	0.020	−1.048	−0.004	0.002
	(0.002) ***	(0.001)	(0.029)	(27.078)	(4.391) **	(1.534)	(0.851)	(0.022)	(0.005)
Temp anomaly × Age > 60	0.011	0.002	−0.058	−38.051	−8.395	−0.483	−0.771	−0.044	0.012
	(0.003) ***	(0.002)	(0.036)	(25.075)	(4.206) *	(1.391)	(0.833)	(0.026)	(0.007) *
Precip anomaly × Age 20–40	0.003	0.001	−0.042	−4.190	1.243	−0.301	−0.920	−0.005	−0.001
	(0.002)	(0.001)	(0.024) *	(19.868)	(3.681)	(0.823)	(0.697)	(0.010)	(0.004)
Precip anomaly × Age 41–60	0.002	0.001	−0.032	1.416	0.697	0.536	−0.788	0.021	0.004
	(0.002)	(0.001)	(0.019) *	(18.534)	(3.278)	(0.850)	(0.647)	(0.015)	(0.005)
Precip anomaly × Age > 60	−0.004	−0.000	0.026	29.180	4.420	0.876	0.521	0.044	−0.000
	(0.003)	(0.002)	(0.032)	(19.979)	(3.488)	(1.024)	(0.645)	(0.022) **	(0.008)
R^2	0.00	0.01	0.14	0.09	0.25	0.01	0.06	0.12	0.03
N	54,062	54,062	54,062	58,021	58,021	58,021	58,021	56,663	60,319
Hypothesis Testing (p-values)									
Joint significance of Temp parameters	0.003	0.162	0.065	0.357	0.142	0.951	0.225	0.046	0.003
Joint significance of Precip parameters	0.055	0.716	0.051	0.231	0.377	0.524	0.097	0.090	0.567
Equality of Age × Temp parameters	0.051	0.433	0.029	0.679	0.397	0.845	0.220	0.022	0.001
Equality of Age × Precip parameters	0.031	0.735	0.104	0.139	0.263	0.336	0.045	0.041	0.371

Notes: All models include current age categorical variables, lagged education categorical variables, household size, indicators for above median consumer assets, above median business assets, and above median urban index, individual and time fixed effects included. County-clustered standard errors in parentheses.

* $p<0.1$

** $p<0.05$;

*** $p<0.01$.

BMI=body mass index, Cal.=calories, Carb.=carbohydrates, Prot.=protein.

Table 2

Individual Symptoms

	Respiratory	Stomach	Headache	Joint	Skin	Chest
Temp anomaly × Age 20–40	−0.001	−0.002	−0.001	−0.002	0.000	−0.002
	(0.002)	(0.001) *	(0.002)	(0.002)	(0.000)	(0.001) *
Temp anomaly × Age 41–60	0.004	0.001	0.004	0.002	−0.000	0.001
	(0.003)	(0.001)	(0.002) *	(0.002)	(0.000)	(0.001)
Temp anomaly × Age > 60	0.009	0.004	0.010	0.007	0.001	0.004
	(0.004) **	(0.002) **	(0.002) ***	(0.003) **	(0.001) *	(0.002)
Precip anomaly × Age 20–40	0.000	0.000	0.001	0.001	−0.000	−0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Precip anomaly × Age 41–60	0.003	0.001	0.002	0.002	−0.000	0.001
	(0.003)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Precip anomaly × Age > 60	−0.002	0.002	−0.002	−0.003	0.001	−0.002
	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.002)
R^2	0.01	0.00	0.00	0.01	0.00	0.01
N	60,141	60,113	60,144	60,127	60,098	60,110
Hypothesis Testing (p-values)						
Joint significance of temp parameters	0.022	0.013	0.000	0.054	0.077	0.041
Joint significance of precip parameters	0.365	0.582	0.510	0.297	0.471	0.119
Equality of Age × Temp parameters	0.012	0.005	0.000	0.035	0.090	0.047
Equality of Age × Precip parameters	0.213	0.516	0.479	0.273	0.289	0.129

Notes: The same explanatory variables are included as the models specified in Table 1. County-clustered standard errors in parentheses.

* $p<0.1$

** $p<0.05$;

*** $p<0.01$.

Respiratory=Fever, sore throat, cough in last 4 weeks, Stomach=diarrhea or stomachache in last 4 weeks, Headache=Headache or dizziness in last 4 weeks, Joint=Joint or muscle pain in the last 4 weeks, Skin=rash or dermatitis in the last 4 weeks, Chest=Heart disease or chest pain in the last 4 weeks.

Table 3

Household Prices and Income (2011 Real terms)

Panel A: Prices	**Good rice**	**Common rice**	**Bleached flour**	**Unbleached flour**	**Bleached noodles**	**Unbleached noodles**	**Corn flour**	**Millet**	**Sorghum**
Temp anomaly	−0.081	−0.036	−0.097	−0.108	−0.158	−0.170	−0.078	−0.093	−0.039
	(0.074)	(0.037)	(0.068)	(0.052) **	(0.079) *	(0.071) **	(0.064)	(0.112)	(0.067)
Precip anomaly	−0.037	0.001	−0.033	−0.029	−0.107	−0.077	−0.018	−0.027	−0.065
	(0.055)	(0.031)	(0.053)	(0.038)	(0.058) *	(0.043) *	(0.043)	(0.064)	(0.068)
F test (p-value): Anomaly variables=0	0.484	0.620	0.362	0.080	0.047	0.021	0.429	0.708	0.503
R^2	0.58	0.55	0.20	0.29	0.22	0.27	0.30	0.41	0.22
Panel B: Income	Business	Farm	Fishing	Garden	Livestock	Wage	Total		
Temp anomaly	185.803	310.219	3.534	−309.565	−30.476	215.091	462.587		
	(267.565)	(153.758) **	(9.393)	(149.359) **	(42.041)	(256.352)	(461.109)		
Precip anomaly	−86.279	83.446	−1.988	−269.609	80.622	254.340	−174.845		
	(129.816)	(90.926)	(5.835)	(117.036) **	(28.083) ***	(217.149)	(359.942)		
F test (p-value): Anomaly variables=0	0.589	0.140	0.883	0.019	0.009	0.364	0.404		
R^2	0.01	0.01	0.00	0.10	0.00	0.05	0.12		

Notes: Household-years=25, 448. All models include lagged household size, indicators for above median consumer assets, above median business assets, and above median urban index, as well as household and time fixed effects included. County-clustered standard errors in parentheses.

* $p<0.1$

** $p<0.05$;

*** $p<0.01$.

Table 4

Climate Effects on the Probability of Being Underweight, Robustness

Climate Definition	Raw, current year	Anomaly, lagged year	1/−1 SD indicators, current year
Temp × Age 20–40	0.009	0.004	
	(0.004) **	(0.004)	
Temp × Age 41–60	0.007	−0.004	
	(0.004) *	(0.002)	
Temp × Age > 60	0.011	0.001	
	(0.004) **	(0.003)	
Precip × Age 20–40	0.000	−0.000	
	(0.000)	(0.003)	
Precip × Age 41–60	−0.000	−0.000	
	(0.000)	(0.002)	
Precip × Age > 60	−0.000	0.000	
	(0.000)	(0.003)	
Temp < −1 SD × Age 20–40			0.005
			(0.006)
Temp > 1 SD × Age 20–40			0.001
			(0.009)
Temp < −1 SD × Age 41–60			−0.003
			(0.005)
Temp > 1 SD × Age 41–60			0.004
			(0.004)
Temp < −1 SD × Age > 60			0.002
			(0.007)
Temp > 1 SD × Age > 60			0.012
			(0.008)
Precip < −1 SD × Age 20–40			−0.008
			(0.007)
Precip > 1 SD × Age 20–40			0.003
			(0.006)
Precip < −1 SD × Age 41–60			−0.005
			(0.004)
Precip > 1 SD × Age 41–60			0.003
			(0.004)
Precip < −1 SD × Age > 60			−0.005
			(0.006)
Precip > 1 SD × Age > 60			−0.002
			(0.007)
R^2	0.00	0.00	0.00

Climate Definition	Raw, current year	Anomaly, lagged year	1/−1 SD indicators, current year
N	54,062	54,062	54,062
Hypothesis Testing			
Joint significance of Temp parameters	0.048	0.070	0.470
Joint significance of Precip parameters	0.036	0.997	0.762
Equality of Age × Temp parameters	0.046	0.056	0.387
Equality of Age × Precip parameters	0.016	0.982	0.934

Notes: The same explanatory variables are included as the models specified in Table 1. County-clustered standard errors in parentheses.

* $p<0.1$

** $p<0.05$;

*** $p<0.01$.