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Working Paper

Climate shocks and noncommunicable diseases among older people in India

ADB Economics Working Paper Series, No. 834

Provided in Cooperation with:

Asian Development Bank (ADB), Manila

Suggested Citation: Khanna, Arpita; Mahmud, Minhaj Uddin; Menon, Nidhiya (2026) : Climate shocks and noncommunicable diseases among older people in India, ADB Economics Working Paper Series, No. 834, Asian Development Bank (ADB), Manila, <https://doi.org/10.22617/WPS260011-2>

This Version is available at:

<https://hdl.handle.net/10419/336546>

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CLIMATE SHOCKS AND NONCOMMUNICABLE DISEASES AMONG OLDER PEOPLE IN INDIA

Arpita Khanna, Minhaj Mahmud, and Nidhiya Menon

NO. 834

January 2026

**ADB ECONOMICS
WORKING PAPER SERIES**

ADB Economics Working Paper Series

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No. 834 | January 2026

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ISSN 2313-6537 (print), 2313-6545 (PDF)
Publication Stock No. WPS260011-2
DOI: <http://dx.doi.org/10.22617/WPS260011-2>

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ABSTRACT

This study empirically investigates the impact of climate change on the incidence of noncommunicable diseases among older population in India. Using demographic and health surveys from 2019–2021 linked with georeferenced meteorological data at local levels, and a specification that controls for long-term local climate trends as well as individual and household characteristics, we show that unanticipated heat shocks have significant impacts on the prevalence of hypertension, high blood glucose levels, and overweight or obese status. The impact of heat shock on hypertension is somewhat more evident among urban, lower caste, and lower educated men, while the impact on glucose levels is more pronounced among the higher educated in urban settings. Body mass index is particularly sensitive to heat shocks in older rural women and individuals with higher education. Engagement in occupations more exposed to outdoor work (agriculture/manual) and lifestyle factors tied to wealth status are some explanatory mechanisms.

Keywords: climate, temperature, older people, blood pressure, glucose level, BMI, India

JEL codes: Q54, I12, J14, O13

Thanks to the participants of the Asian Development Bank's Economic Research and Development Impact Department (ERDI) research seminar for helpful comments. This study is funded under the Asian Development Bank's Technical Assistance TA 10191-REG: Strengthening Policies on Climate Change in Asia and the Pacific through Economic Research, 2023–2025 (Subproject 1). Corresponding author: Minhaj Mahmud (mmahmud@adb.org).

1 INTRODUCTION

The past decade has been the warmest in the last 125,000 years. Human induced global warming of 1.1°C has spurred changes to Earth's climate that are unprecedented in recent human history. Further, every 0.5°C of global temperature rise is projected to cause clearly discernible increases in the frequency and severity of heat extremes, heavy rainfall events, and regional droughts (IPCC, 2023). More than three billion people already live in areas highly susceptible to climate shocks. Climate change impacts health in several ways, including by leading to death and illness from increasingly frequent extreme weather events such as heat waves, storms, and floods; disrupting food systems; spreading diseases; and having negative impacts on physical and mental health. Furthermore, climate change is undermining many of the social determinants of good health such as livelihoods, equality, access to health care, and social support structures (World Health Organization, 2023). We focus on the impacts of the changing climate on the health of a vulnerable group that is relatively neglected, the older people, to assess impacts of this existential threat on noncommunicable diseases (NCDs) such as hypertension, high blood glucose, and the overweight or obese status in this population. This is an important question, as there is growing evidence that NCDs impose significant costs that are likely to rise even more as longevity improves around the world.

While some literature has considered the effects of climate change on health in general, there is relatively little research on older population, especially in the developing world, beyond mortality evaluations. In general, climate shocks, particularly heat waves, have been linked to cardiovascular mortality, respiratory illness, altered transmission of infectious diseases, and malnutrition from crop failure (Patz et al., 2005). Rocque et al. (2021) provide an overview of the health impacts of climate change and conclude that most systematic reviews suggest that climate change is associated with worse human health. In addition, the study concludes that temperature and humidity reveal the most consistent associations with infectious diseases and respiratory, cardiovascular, and neurological outcomes. Temperature is also consistently associated with mortality and healthcare service use. Extreme weather events are commonly associated with mortality, mental health outcomes (for example, distress, anxiety, depression), and adverse nutritional outcomes (likely via reductions in crop production and subsequent increases in food insecurity).

These climate induced health risks are disproportionately felt by the most vulnerable and disadvantaged, including women, children, older populations, and those with underlying health conditions (World Health Organization, 2023; Sarkar et al., 2023). Hot weather is associated with higher mortality in older people, most of which is due to cardiovascular, cerebrovascular, and respiratory causes (Haines et al., 2006). Temperature extremes are also associated with transitions to retirement due to declines in health arising from cardiovascular disease and stroke

(Albanese et al., 2025). A review paper considering the impact of climate change on health outcomes in older people finds that heat, temperature variability, and air pollution increase mortality risk among them, especially from cardiovascular and respiratory diseases (Leyva et al., 2017).

In this paper, we consider the impacts of rising temperature on hypertension (blood pressure), diabetes (glucose levels), and overweight or obese weight status (body mass index) among older people in India. While the epidemiology literature has a handful of studies focusing on climate effects on hypertension and diabetes (Bunker et al., 2016), to our knowledge, we are the first to consider these health outcomes using the lens of economics for this highly susceptible age group in a resource-constrained context. As far as we are aware, we are also the first to study the effects of NCDs on older people in a large developing country while considering multiple climate/weather variables in unison. The literature on modeling climate effects is evolving rapidly and it is now understood that evaluating the effects of temperature alone or rainfall alone may lead to inaccurate and biased effects, as weather measures are correlated (Zhang et al., 2017; Hanifi et al., 2022; Guimbeau et al., 2024).

Using the most recent demographic and health survey data from India—which have the advantage of large sample sizes—and considering the impact of maximum temperature conditional on rainfall and frost days on health outcomes, we find that unanticipated deviations in excess heat in particular have a negative and significant impact on hypertension, a positive and significant impact on glucose levels and high blood glucose, and a positive impact on body mass index (BMI) and overweight or obese weight status, mostly among those aged 45 and older. That is, unexpected heat shocks significantly increase the prevalence of these NCDs in these individuals. This is in a context where the incidence of these NCDs is already relatively high at baseline. Including occupational level controls explains some of these effects but leaves the impact of heat shocks, especially on hypertension, mostly unchanged. Exogenous rain shocks also matter for some of these outcomes, but impacts are relatively more muted when we condition on temperature.

Taking into account the heterogeneity in the sample encompassing those aged 45 years and older, the impacts on hypertension are evident in all sexes, educational levels, and sectors of residence. In terms of glucose level, effects are evident across gender, but mostly in those who are less educated in rural areas. High blood glucose is mostly evident in those with higher levels of education in urban areas, whereas measures on BMI and overweight or obese status are mostly present in women, those with more education, and those in rural areas. We consider caste status as another dimension of heterogeneity and find that on average, lower caste groups (scheduled caste, scheduled tribes, other backward caste groups) experience relatively more of the effects of the changing climate.

Evaluating the mechanisms behind these findings, our results reveal that, especially for hypertension, older people in agriculture and manual labor are the most affected. Taking into account lifestyle choices conditional on wealth, effects for high blood glucose and excess weight status are most pronounced among the affluent. Estimates for hypertension are evident across wealth status.

The rest of the paper is organized as follows. Section 2 provides details on the incidence of major NCDs in India that are of interest in this study. Section 3 discusses the source of our data as well as the construction of the key health variables of interest. Descriptive statistics for our sample are presented in Section 4, while Section 5 provides details on our preferred empirical specification. Results are presented and discussed in Sections 6 and 7, and heterogeneity along various dimensions is considered in Section 8. Section 9 shows the robustness of our main results from an alternate source of climate data and Section 10 evaluates potential mechanisms that are explanatory of our findings. In Section 11, we summarize our objectives, strategies and findings. Section 12 concludes the paper with implications for policy.

2 CONTEXT

India provides an apt context for considering the effect of climate change on the health of older population. It is the largest lower middle-income country in terms of population (Sharma and Popli (2023) note that 18% of the world's population resides in India) with a significant share of older people. As of 2022, 149 million people comprising 10.5% of the total population were aged 60 and older; this is projected to double to 20.8% (347 million people) by 2050 (IIPS and UNPF, 2023). Concomitantly, India is one of the largest populations at risk of climate change. India ranks seventh out of 181 economies in terms of vulnerability to climate change impacts, and recent estimates indicate that more than 75% of its districts are likely to experience extreme events such as droughts, floods, cyclones, cold spells, and heat waves, affecting close to 640 million people (Khanna et al., 2022). Taking action to mitigate the impacts of climate change and build resilience among communities is of great importance for India to sustain its developmental trajectory while simultaneously tackling climate change.

In general, the prevalence of NCDs is relatively high in the country. Hypertension, known to be the key risk factor for cardiovascular disease, is the main cause of death in India (Prenissl et al., 2019). Estimates from an earlier round of demographic and health surveys in 2015–2016 reveal that on average, 18.1% of all people 15 years old and above were affected by this health condition (Prenissl et al., 2019). Focusing on older age groups who are especially at risk, data from the Longitudinal Ageing Study in India (LASI) show that the incidence of hypertension is significantly higher at 49.1% among those aged 45 and older (Mohanty et al., 2021). Also, rates of awareness, prevention, and treatment were found to be lower among poorer individuals, those who were less

educated, and those who were socially disadvantaged. Rates were also somewhat lower for men, those in rural areas, and those who were employed (Mohanty et al., 2021).

Considering glucose levels and diabetes, the LASI data from 2017–2019 reveal that 19.8% of individuals aged 45 and older were diabetic, translating to more than 50 million people (Sekher et al., 2025). Prevalence was similar by gender, but urban rates were twice the rural rates (30.0% versus 15.0%, respectively) (Sekher et al., 2025). Further, states that were more economically advanced (measured by state domestic product per capita) had higher prevalence rates compared to those that were less economically advanced (Sekher et al., 2025). All in all, about two in three people were aware of their condition, but only about 6% of those affected were taking medications to control this NCD (Sekher et al., 2025). Thus, the need for policies to prevent, detect, and control diabetes among older age groups in India is urgent.

Finally, we consider the main contributor to unhealthy blood glucose levels that fuel diabetes, weight status. A systematic review and meta-analysis of 33 relevant studies encompassing more than 60,000 participants aged 60 and older noted that the pooled prevalence of overweight/obesity among this older group in India was 21.5% (Daniel et al., 2024). More older women were in these excess weight categories compared to older men (21.5% versus 13.8%, respectively, based on a subset of the 33 studies that considered gender). In terms of sectoral differences, overweight/obesity among older people was more prevalent in urban areas (28.4%) than in rural areas (19.0%) (Daniel et al., 2024). All in all, recent estimates indicate that about one in five older persons in India is in these excess weight categories. While this proportion is similar to those reported among older people in other Asian countries such as Malaysia and countries in the Middle East (Daniel et al., 2024), given the size of India's population, translating this proportion to actual numbers results in a significant 280 million people falling under these unhealthy weight categories, which is a significant burden for a resource-constrained country.

3 DATA

3.1 The Demographic and Health Surveys

Our main data source is the Demographic and Health Survey (DHS) of India from 2019–2021 (the survey period was June 2019 to April 2021). The DHS, also referred to as the National Family Health Survey in India, is a nationally representative household survey with detailed information on individual and household characteristics of 636,699 households, covering 724,115 women and 101,839 men. The women's modules are answered by all women 15–49 years old, while the men's modules are answered by all men 15–54 years old (IIPS, 2021). We primarily use data from the household person's roster that includes details on every member of the household (including older people and very young children); this survey module is usually answered by the household head.

Data are collected using a stratified sample design based on separating a district into urban and rural areas. Rural areas are sampled based on village size (number of households) while urban areas are sampled based on census enumeration blocks obtained from the Office of the Registrar General and Census Commissioner of India.

The DHS data include information on several health statistics for the surveyed individuals, including their blood pressure and blood glucose levels; anthropometry, including body mass index (BMI); diabetes; hypertension; chronic respiratory disease; thyroid health; heart disease; cancer; and kidney disorders.¹

The DHS data are geocoded; we know the location of each cluster (village or locality) that is sampled.² This knowledge helps us locate climate impacts more precisely as opposed to having to rely on district level climate aggregates alone. Further, these data also have associated geospatial information at the cluster level on maximum temperature at 5-year intervals, annual rainfall, and the incidence of frost days. These are the climate variables that we use in our main empirical analysis.

The construction of our health outcome measures is outlined in detail below. Individual and household specific variables used as controls in all our specifications are constructed directly from the survey questionnaires.

On health outcomes, we begin by evaluating effects on systolic blood pressure and diastolic blood pressure that are measured directly in the DHS survey. Systolic blood pressure measures the pressure as the heart beats and pumps blood. Diastolic pressure measures the pressure when the heart is at rest between beats. Survey administrators collect blood pressure readings thrice. We consider the average of three systolic as well as the average of three diastolic blood pressure readings and evaluate them in their own right. We then classify an individual as having hypertension if the average systolic blood pressure reading is greater than 130 millimeters of mercury (*mmHg*) and/or the average diastolic blood pressure reading is greater than 80 *mmHg* (AHA, 2024; IIPS, 2021).

We next evaluate effects on glucose levels that are also measured directly in the DHS data. An individual is classified as having high blood glucose when the blood glucose level is more than 140 milligrams per deciliter (*mg/dl*) (IIPS, 2021). Further, an individual is classified as having diabetes with a blood glucose level of more than 200 *mg/dl*.³ Our analysis begins by investigating effects on glucose levels, high blood glucose, and the incidence of diabetes, but then focuses on the former two outcomes since most estimates related to diabetes are found to be statistically insignificant.

¹ Previous versions of the paper evaluated effects of temperature, rainfall, and frost on all these outcomes. This version focuses on the health outcomes for which statistically significant impacts were evident.

² To protect privacy, the DHS geocodes are randomly offset by up to 5 kilometers in location. However, the displacement procedure ensures that the clusters remain within the same administrative units so that the data can be analyzed appropriately within administrative frameworks. For more details, please see Burgert et al. (2013). Further, Michler et al. (2022) show that such locational offsets have limited to no impacts on results estimates.

³ Mayo Clinic. Diabetes. <https://www.mayoclinic.org/diseases-conditions/diabetes/diagnosis-treatment/drc-20371451> (accessed on 28 November 2024).

Weight status is determined by the BMI variable for each individual. Those whose BMI falls below 18.5 kilograms per meter squared (kg/m^2) are considered underweight, while those whose BMI is at least 23 kg/m^2 are classified as overweight or obese. In defining these categories based on BMI, we follow Dang et al. (2019). Again, we begin our analysis by evaluating effects on BMI, underweight, and overweight or obese status. We focus on a subset of these outcomes depending on which weight categories are found to be significantly impacted by changing climate.

We consider health effects separately for those aged 45 and older, and those aged 60 and older. We differentiate between these age groups for several reasons, including the fact that most surveys on older people across Asian economies gauge effects for all who are 45 years old and above (for example, LASI). Additionally, since 60 is the retirement age for most public sector jobs in India, it is harder to understand how occupational engagement matters if we do not consider effects on 45-year-olds who are likely still engaged in the labor market. Some of our outcomes of interest, such as BMI, are also not measured for those who are 60 or older. Finally, those who are 60 and above form a smaller sample than those at the younger age cutoff. Considering both groups allows us to differentiate impacts in health outcomes that may be more sensitive to sample size considerations. Going forward, the 45 and older sample will be denoted as the “45+ sample,” while the 60 and older sample will be denoted as the “60+ sample.”

Our 45+ sample includes more than 760,000 individuals, while the 60+ sample includes more than 320,000 individuals. Depending on the number of missing values for health outcomes (BMI is not collected for those 60 years old and older, as mentioned above) as well as other controls included in our specifications, our main empirical analysis is conducted on slightly lower numbers (number of observations is noted in Tables 1, 2, and 3, which present the summary statistics for our outcomes, the climate variables, and the individual and household controls).

3.2 Copernicus Climate Data

To test the robustness of our main results, we use the Copernicus climate data as an alternative source of climate data in place of the DHS geospatial data. To be more specific, we used the ERA-5 land post processed daily statistics to obtain the daily maximum 2-meter temperature⁴ for two dates each month, the 15th and the last day of the month for each month in 2020. We then averaged these data to create yearly averages in line with the DHS geospatial data. In addition, we used ERA-5 post processed daily statistics on single levels to download the daily precipitation total in millimeters (mm) for each day of the year. We then created the annual sum of precipitation in each location by adding the precipitation for every day of the year to obtain the equivalent yearly sum in line with DHS geospatial data. Using geoprocessing software, for each DHS cluster survey

⁴ This is the daily maximum temperature measured at 2-meter above the surface of the land.

location, we obtained the inverse distance average of temperature and rainfall measures from the five closest satellite locations, as is commonly done in the literature (Zhang et al., 2017).

In Figure A.1, we plot the kernel densities of the temperature data from the DHS geospatial data and the Copernicus climate data to compare them. The peak of the DHS geospatial temperature data is to the right of the Copernicus climate data, as the Copernicus temperature data are the 2-meter maximum temperature data (the near-surface air temperature measured about 2 meters above the ground, which is commonly used in climate and weather monitoring and forecasting) and this tends to be about 2°C lower than the surface temperature. In Figure A.2, we plot the kernel densities of the rainfall data from the DHS geospatial data and Copernicus data. The distributions are quite similar. The use of these alternate satellite data thus gives us comparable distributions to those from the DHS source, while being rigorously constructed (following the most up-to-date techniques) from more granular sources. Robustness checks from the use of these data are described below.

4 DESCRIPTIVE STATISTICS

Table 1 through Table 3 present the summary of the sample demarcated by the 45+ and 60+ age groups. Focusing on the outcomes in Table 1, systolic and diastolic blood pressure readings are, as expected, slightly lower in the younger age group, as is the incidence of hypertension. Similarly, the glucose level is also somewhat lower, as is the likelihood of high blood glucose, in the 45+ sample. About 7% of the 60+ sample is diabetic, while the corresponding estimate for the younger group is about 6.3%. We only have BMI measures for the younger sample and from Table 1 we note that the proportion that is underweight is vastly outweighed by the proportion that is overweight or obese. In our sample, an astonishing 54.5% of people are in the overweight or obese weight categories. That is, about one in two people in the 45+ category is highly “malnourished” by this definition.

Table 2 presents the summary statistics for the key climate variables used in our study. Since the DHS data on older people and their health outcomes are from 2019–2021, we focus on the climate indicators that were collected in 2020.⁵ The average temperature observed during the period of study was about 30.3°C (or about 86.5°F). Rainfall had a mean of 0.1 mm and on average, and there was about 0.7 frost day in 2020.

Considering individual and household characteristics in Table 3, the average age in the younger sample is about 10 years less than the average age in the older sample. The proportion of women is about 50% in both samples, and a smaller fraction of the younger sample has no

⁵ This round of the DHS was fielded in 2019 and was in the field when the coronavirus disease (COVID-19) pandemic started. These climate measures are from early 2020, while the survey was still in the field.

education. Correspondingly, a higher fraction of the younger sample has secondary or higher education (38.2% versus 30.7%).

Table 3 also presents statistics for household characteristics where we see that in the younger sample, about 33% is urban and in the older sample, about 31%. Across caste status and religion, there are few measurable differences between the 45+ and 60+ samples. This is also true when we consider sources of drinking water as well as toilet facilities. In terms of wealth status, a slightly higher fraction of the older group falls into the poorest category. Finally, in terms of occupational categories (at least one household member is engaged in a specific occupation category), a larger fraction of the 45+ sample is engaged in agriculture. There are few differences in terms of the other occupational denominations between these age groups.

Table 3 makes clear that there are a significant number of missing observations for these occupation categories. Hence, we do not control for them in our main specifications. However, results are presented separately with controls for occupational status as they are important determinants of health. We also consider them carefully in the mechanisms section of the study.

For the health outcomes of interest, we present gender disaggregated graphical depictions of the incidence of hypertension in Figure 1. It is immediately evident that in older population, the proportion of adults that fall into this category is high. For instance, in the left panel of Figure 1 that focuses on the 45+ sample, more than 70% of men and about 70% of women are in this category.

The other predominant feature in this figure is the high proportion of people with hypertension in the oldest age group. Again, more than 70% of men and about 72%–73% of women are in this unhealthy category. Compared to the 45+ sample, estimates for the 60+ group indicate that the incidence of hypertension in women rises with age, while in men, it remains about the same. All in all, Figure 1 underscores that approximately three in every four older adults in India fall into this excessively high category of blood pressure.

Figure 2 considers the incidence of high blood glucose levels in both the 45+ and 60+ age groups. In the relatively younger sample, we see that the incidence of this NCD is somewhat higher for men than for women, but still relatively high across both genders with averages that exceed 20% of this population.

Considering the 60+ sample on the right panel of Figure 2, the estimates are even more concerning as they are markedly higher than those for the 45+ group. Here, about 28% of older men and a slightly lower 26% of women fall into the range of unhealthy blood glucose levels. Hence, similar to hypertension, older people in India are significantly unhealthy when we evaluate their status against blood glucose benchmarks, with incidence increasing as people age further.

We next consider patterns in BMI as presented in Figure 3. This graph is restricted to the 45+ sample as we do not have anthropometric estimates for the oldest age group, as noted above. The figure reveals that somewhat more women than men are underweight (10% versus 8%). This is in keeping with the fact that a large proportion of less educated rural women are engaged in physically

demanding outdoor labor such as agriculture. It perhaps also reflects additional workload involved in childcare and domestic work for this group.

Focusing on those who are overweight or obese on the right side of Figure 3, the aggregate patterns in this age group reveal that more than 50% of men fall into this unhealthy weight category. The proportion is slightly higher for women at about 54%. We find below that this group is primarily urban with secondary school or higher levels of education. Figure 3 underscores that a sizable proportion of older adults in India have unhealthy weight (underweight or overweight or obese), with those who are overweight or obese vastly exceeding those who are underweight.

The estimates presented in Figures 1, 2, and 3 paint a graphic picture of the precarious overall health of older people in India when hypertension, high blood glucose, and excess weight are considered. For none of these NCDs evaluated are population proportions within healthy ranges. Against this backdrop, the changing climate acts to further worsen the physical health of older people.

5 EMPIRICAL METHODOLOGY

To investigate the impact of climate change on the incidence of NCDs among older people, we focus on temperature, rainfall, and frost, while conditioning on a series of fixed effects. These fixed effects absorb local conditions such that we estimate the effect of *unanticipated* changes in these weather indicators on older people's health. This is important especially in a country as vast as India where topography and geography change dramatically with distance, with concomitant effects on weather patterns. The use of fixed effects at different levels also ensures that we are measuring plausibly causal estimates that are independent of (less contaminated by) adaptive behaviors that may have already been adopted in response to changing climate patterns.

In light of the above, our primary estimation strategy is the following:

$$y_{ihcd} = \beta MaxTemp(2020)_{cd} + \gamma C_{cd} + \theta X_{ihcd} + \delta H_{hcd} + \lambda_d + \epsilon_{ihcd} \quad (1)$$

where y_{ihcd} represents the outcome of interest for individual i , in household h , in cluster c , in district d . For our main specification, y_{ihcd} is a dummy variable taking the value 1 if the person has an NCD (for example, hypertension). The variable of interest $MaxTemp(2020)$ is the average maximum temperature at the DHS cluster location in the year 2020. C_{cd} consists of other climate variables such as the average annual rainfall at the DHS cluster location in 2020, the average number of days per month in which the minimum temperatures of the DHS survey cluster location met the

criteria to be categorized as a “frosty” day in 2020, and interview month–year fixed effects, which control for seasonal and long run weather trends.⁶

Controls in X_{ihcd} consist of individual level variables (such as age, gender, and education dummies). H_{hcd} comprises household level controls such as caste and religion indicators, dummies for different types of water facilities, access to electricity, dummies for wealth quintiles, and dummies for having at least one household member employed in agriculture, manual work, services, sales and/or professional activities. Finally, λ_d represents district fixed effects. These district fixed effects capture district level time invariant unobservables such as health, culture, local seasonality, and differences in eating habits. The standard error term is ϵ_{ihcd} . In all our specifications, standard errors are clustered at the level of the DHS cluster and we weight regressions to make them nationally representative using the appropriate weights provided by DHS.

The identifying assumption is that there are no omitted variables that are correlated with both weather variables and older people’s health outcomes, so that average maximum temperature, rainfall, and frost days, conditional on the other variables in the models, are *unanticipated and as good as random*.

In Figure 4, we use scatter plots to evaluate the one-way relationship between maximum temperature and hypertension, high blood glucose levels, and the incidence of overweight/obesity. This is for the 45+ sample alone since we lack data on BMI for the oldest section of our population. These initial evaluations show that there is a negative association between maximum temperature and hypertension, and positive associations between temperature and high blood glucose levels as well as BMI status. The empirical results that follow confirm these patterns hold even after we condition on other climate controls, as well as individual and household variables and month–year fixed effects as well as district fixed effects.

6 RESULTS

6.1 Blood Pressure

Table 4 reports our results on the effect of climate shocks on the health of older people, gauged by various blood pressure measures. Each odd numbered column pertains to the 45+ sample while each even numbered column conveys estimates for the 60+ sample. All columns include individual and household controls in Table 3 as well as interview month–year and district fixed effects. Across all columns of this table, maximum temperature is negative and significant. For

⁶ We estimated models in a distributed lag framework with temperature going back every 5 years to 2000 (that is, a model that included heat shocks in 2000, 2005, 2010, 2015 and 2020). Heat shocks in prior years were measured with error and only the 2020 value had significance. Hence our main specification includes only this most recent indicator of heat shocks. Similarly for rainfall.

example, the estimate in column (5) indicates that for a 1°C decrease in maximum temperature, the likelihood of hypertension in the 45+ sample rises by 1.5 percentage points. Compared to the mean of hypertension in this sample, this is a 2.1% increase. The corresponding effect in the older age group is about the same at 1.5 percentage points. Since the mean in this age group is slightly higher than expected, this translates into a 2.0% increase. These coefficients suggest that when the temperature is colder than expected, the probability of this NCD rises by a small amount. This may reflect both the physiological effects of temperature on health (we discuss some of these explanations from the public health literature below), but also secondary factors such as restricted exercise/physical activity in cold spells which can have adverse impacts on blood pressure.⁷

Rainfall is also significantly negatively associated with blood pressure, but only in columns (3) and (4) for diastolic readings. In general, with controls for heat shocks and other variables in equation 1, unexpected rainfall deviations from trend values are mostly insignificant in this table.

6.2 Glucose Level

Table 5 considers the effects of heat and rainfall shocks on blood glucose levels. Here we see that maximum temperature raises glucose levels for the 45+ sample. More specifically, a 1°C increase in temperature raises blood glucose levels by 0.9 *mg/dl*. Compared to the average level for this outcome among this relatively younger age group, this is a 0.7% increase. Correspondingly, a rise of similar magnitude in maximum temperature raises the likelihood of high blood glucose by 0.5 percentage points for the 45+ sample. This translates into a 2.1% increase relative to the mean value of high blood glucose in column (3). There are few measurable impacts on the 60+ sample in terms of this NCD outcome. In particular, we find little evidence that heat shocks or rainfall shocks influence diabetes in either the 45+ or 60+ age groups, which is somewhat surprising given the widespread relevance of this disease in India.

6.3 Weight Status

We find that unexpected rainfall shocks reduce BMI and increase the likelihood of being underweight. For a 1 mm increase in rainfall, BMI declines by 0.2 *kg/m²*, a 0.9% decline relative to the mean value of this outcome in column (1). An increase in rainfall of similar magnitude results in 0.02 percent increase in the likelihood of being underweight in column (2). While small, this estimate is about 21.5% of the mean value of this health measure in column (2), which is notable. In rural populations in particular (about 70% of our sample), these results likely reflect changes in nutrition and food security as a consequence of reduced harvests when rainfall is suboptimal (both too much rain and too little rain are detrimental to harvests). With controls for

⁷ We do not have details on exercise/physical activity to be able to check this directly in the DHS data.

temperature shocks, impacts of rainfall shocks are less evident in column (3), which considers overweight/obesity.

6.4 Conditioning on Occupational Categories

Given that the inclusion of occupational variables reduces the sample size drastically, our preferred specification does not include these controls. Instead, in Table 7, we separately evaluate all our health outcomes conditioning on occupational categories. We find that heat shocks continue to exert effects on various categories of blood pressure, although we lose our original result for high blood glucose and for overweight or obese status. The fact that we lose significance for these two variables suggests that occupation is an important explanatory variable in terms of the results of these outcomes that we previously documented.

Rain shocks continue to maintain their significance in column (8) and remain an important predictor of underweight status. The climate variable's impact on other outcomes in this table are mostly measured imprecisely.

7 DISCUSSION OF MAIN RESULTS

We place our main empirical estimates on the effect of changing temperature and rainfall on NCDs in Tables 4, 5, and 6 among older people in the context of this section. Since there are few economic studies that we can reference in this area that focus on the impacts of climate change on NCDs among older people in a developing context as far as we are aware, we place our findings in the context of studies that are mostly in public health literature. We also focus on the impacts of unexpected temperature changes only, since that is the main weather indicator that has been consistently significant in Section 6.

On average, we find that the effect of temperature deviations on hypertension is in the range of about 2%. More specifically, higher temperatures are associated with lower blood pressure, or conversely, and in keeping with our interpretation above, lower temperatures are associated with higher blood pressure. Other studies that find an inverse relationship between temperature and blood pressure in these ranges depending on samples analyzed include Alperovitch et al. (2009), Kim et al. (2012), and Van den Hurk et al. (2015). Medical reasons provided for this inverse relationship include the subcutaneous vasoconstriction that occurs in cold temperatures, which can subsequently raise vascular resistance and thus blood pressure. Alternatively, in times of excess heat, veins in the skin expand to regulate body temperature (diffuse body heat), thus lowering blood pressure (Kim et al., 2012), (Van den Hurk et al., 2015). Importantly, this inverse relationship between temperature and blood pressure tends to be especially pronounced among older people and those who are relatively disadvantaged (Kim et al., 2012).

Our findings underline a positive relationship between temperature deviations and blood glucose levels as well as the incidence of high blood glucose. Another recent study by Miyamura et al. (2022) notes a positive relationship between heat stress and glucose levels, and finds that dehydration that results from perspiring to regulate excess heat can lead to a higher concentration of blood glucose levels, especially in older individuals. Older people are susceptible since they may have multiple risk factors such as the use of numerous medications and lower thermoregulatory response (Miyamura et al., 2022). While Miyamura et al. (2022) study the relationship between heat stress and blood glucose levels among older people in Japan, the fact that our results are similar suggests that these patterns hold in India, where the risk of dehydration during heat shocks is likely to be especially severe.

We end by considering other studies that find a positive association between temperature and BMI as well as excess weight/obesity, as documented in our main results in Table 6. These include Ampofo et al. (2025), who use the tools of economics (longitudinal data and an individual fixed effects model) to evaluate the relationship between excess temperatures and overweight or obese status in survey data from a developed country. This study finds that an additional day of exposure to temperatures higher than 30°C in Australia is associated with a 0.02% increase in BMI and a 0.2% increase in the likelihood of being obese. This is an order of magnitude lower than those we find in our study, but note that the temperature variable is measured differently in that we consider unanticipated deviations for long run trends while Ampofo et al. (2025) use a nonparametric definition. Explanations provided for this positive association are similar to ones that we propose. That is, hotter days are associated with reduced exercise/physical activity. Interestingly, they also find associations of extreme heat and low internal locus of control measures (that influence dietary intake patterns), which we cannot study with our data, unfortunately.

A second related review of the literature on this topic highlights two additional channels that underlie the positive relationship between temperature shocks and unhealthy weight levels: food supply/price shocks and “adaptive thermogenesis” (An et al., 2018). Food supply and price shocks relate to global warming reducing agricultural productivity, which makes *all* foods, including healthy options such as fresh fruits and vegetables, more expensive. This can directly translate into consumption of less nutritionally optimal foods. “Adaptive thermogenesis” relates to the body’s ability to maintain body temperature in cold seasons. When winters become less cold, the body needs to expend less energy to maintain an equilibrium body temperature; the excess energy is then converted and stored as body fat, leading to weight gain (An et al., 2018).

The studies discussed in this section provide additional context and explanations for our results and underline that heat shocks in particular have statistically significant impacts on hypertension, high blood glucose, BMI, and the overweight or obese status of older individuals in India.

8 HETEROGENEITY IN IMPACTS

This section investigates heterogeneity along gender, education, sectoral status (rural or urban), and caste dimensions, for the NCD outcomes evaluated above including hypertension, glucose level, high blood glucose, BMI, and overweight or obese status.

8.1 Hypertension

We begin by evaluating the impact of climate shocks on hypertension. Results for heat and rainfall shocks are presented in Table 8 for the 45+ age group.⁸ Interestingly, recent heat shocks are relevant for both men and women (columns 1 and 2), those with below and above secondary levels of schooling (columns 3 and 4), and in both rural and urban areas (columns 5 and 6).⁹ The estimate in column (2) indicates that for a 1°C decline in temperature, the likelihood of hypertension rises by 1.4 percentage points for women and in column (1), by 1.7 percentage points for men. Relative to the means, this is a 2.0% and 2.3% change for women and men, respectively.

The particular susceptibility of those with low education to heat shocks is evident from noting that for a similar decrease in temperature, the incidence of hypertension rises by 1.6 percentage points (2.3% increase) for those who do not have secondary schooling (the more educated are slightly more protected). While the impact of recent heat shocks is significant in column (5) for rural areas, we find that these climate shocks are especially relevant in urban settings where a 1°C decrease in temperature raises hypertension by 1.9 percentage points (2.5% rise relative to the mean in this column).

Another dimension in which we check for heterogeneity in hypertension results is caste status. Results for this are presented in the last two columns of Table 8 and show that on average, negative impacts of heat shocks are most evident in lower caste groups such as scheduled tribes, scheduled castes, and other backward castes. There are no statistically measurable effects for those who are not in these groups, that is, those who belong to the upper caste in column (8) of this table.¹⁰

In general, Table 8 shows that in the presence of temperature shocks, rainfall shocks are not measured with significance across the various categories we consider.

8.2 Glucose Level

We next consider heterogeneity in glucose levels in the 45+ sample and consider estimates presented in Table 9. Across most demarcations considered, heat shocks have a positive and significant effect. For instance, in column (2), a 1°C increase in temperature raises women's

⁸ For heterogeneity analyses, we focus on this age group given the larger sample sizes.

⁹ As noted in Table 8, these differences are not statistically distinct, however.

¹⁰The difference along the caste dimension is statistically distinct.

glucose levels by 0.89 *mg/dl*. This is a 0.7% increase relative to the mean. The effects on men of a corresponding increase are higher at 1.01 *mg/dl* (0.8% rise relative to the mean). There are few effects on those who are relatively more educated, but for those with below secondary schooling, temperature shocks increase glucose levels by about 1.2 *mg/dl* (0.9% change). Effects are evident by sector as well, although this time, effects are more pronounced in rural settings. In particular, a 1°C increase in heat shocks raises glucose levels by about 1.0 *mg/dl* in rural areas, a 0.8% change relative to the mean. The last two columns of this table underline that lower caste groups are especially susceptible.¹¹

As before, coefficients in Table 9 underline that after conditioning on temperature shocks, unexpected rainfall deviations have few significant effects.

8.3 High Blood Glucose

Table 10 analyzes heterogeneity in high blood glucose in the 45+ sample. Rain shocks continue to have few separately measurable effects in the presence of heat shocks. The latter also are only selectively significant in this table. Column (4) that considers more educated individuals in the 45+ sample indicates that for a 1°C increase in maximum temperature, the incidence of being diagnosed with high blood glucose increases by 1.0 percentage point (3.7% relative to the mean). Column (6) in this table underlines that most of these effects are in urban settings. While the coefficient in column (5) for rural areas is not significant, it has a t-statistic of over 1.0, indicating its relevance. There are no precisely measured effects by caste status in the last two columns of this table.

8.4 Body Mass Index

Our discussion of heterogeneity in impacts concludes with our discussion of estimates in Tables 11 and 12. As before, these are only for the 45+ age group. Focusing on Table 11, heat shocks raise BMI for women significantly. A 1°C increase raises BMI for this subgroup by about 0.2 *kg/m²* (0.7% increase relative to the average). The effects are similar for those who are educated and for those in rural areas. Relative to the mean value of BMI in these cases, this is a 0.9% and 0.7% increase, respectively. There is evidence that lower caste groups are especially impacted in the case of this outcome in column (7) of Table 11.¹² Rain shocks continue to be measured imprecisely when temperature is controlled.

The right extreme end of weight status is evaluated in Table 12 where we study the effect of recent heat and rain shocks on excess weight or obesity. Here we find that heat shocks continue

¹¹These differences are not statistically distinct, however.

¹²Again, these differences are not statistically distinct.

to have deleterious effects on women, those who are more educated, and those in rural areas. The coefficient in column (2) indicates that for a recent heat shock of the magnitude considered before, the likelihood of overweight or obese status rises by 1.6 percentage points (2.9% relative to the mean) for women. In terms of education, for a similar magnitude of heat shocks, the probability of being overweight or obese rises by 1.9 percentage points (2.9% relative to the average) for those with higher than secondary levels of schooling. Considering sectoral effects, the estimate in column (5) indicates that such shocks increase the likelihood of this weight status by 1.2 percentage points (2.5% relative to the mean in this column) in rural areas. Again, lower caste groups are particularly susceptible.

Alternatively, and consistent with results above, recent rain shocks are not found to have any significant systematic impacts across the columns of Table 12 when temperature is taken into account. Most coefficients for recent rain shocks are negative, again indicating the (weak) beneficial effects of such shocks on unhealthy weight status, perhaps through more healthy nutritional changes.

9 ROBUSTNESS CHECKS

Alternative Climate Data

This section presents robustness checks for our main results. We consider more refined data on our climate shocks. The main specification above uses cluster (village) level geocoded weather data that are available directly in the surveys. An advantage of using these data is consistency—we are confident that the climate indicators are correctly matched to the location of individuals surveyed. However, as these data were not constructed by us, we check the sensitivity of our estimates to an alternate source, the Copernicus satellite data, which provide more granular, detailed, and comprehensive weather information. The advantage of the Copernicus data is accuracy given both satellite and in situ monitoring sources. With the inverse distance weighting of the five closest points, these data also allow for more robust readings of the weather parameters. This is important since it is well known that effects of measurement errors may be exacerbated in a fixed effects framework such as ours.

Table A.1 presents the reestimated blood pressure results using Copernicus climate data instead of DHS geospatial data. Most of our previous results in Table 4 remain evident. Similar to the main results, these results also show that there is a decline in systolic blood pressure and diastolic blood pressure, and a decline in the likelihood of hypertension associated with higher maximum temperature (the magnitude of these estimates is lower than in Table 4). In terms of rain shocks, we now see additional results for systolic pressure. The effects of rain shocks on hypertension remain insignificant, however.

Table A.2 presents the corresponding results for blood glucose. The results for 45+ individuals are in line with the corresponding main results in Table 5. The glucose level and high blood glucose results for the 60+ group are statistically insignificant using DHS geospatial data but are larger in magnitude and statistically significant when using Copernicus climate data. There is also weak evidence that recent rain shocks increase the incidence of diabetes in the 45+ age group in this table.

Table A.3 presents the robustness results for BMI for the 45+ group. In relation to the estimates in Table 6, the few heat shock results in that table lose significance, while the rain shock results remain unaltered with the use of climate data from this alternate source.

9.1 Use of Air-conditioning

A factor that mitigates the impact of temperature on health outcomes is the presence of an air-conditioner. The DHS household level dataset provides information on assets owned by the household, including whether they have an air-conditioner. To test whether the presence of an air-conditioner influences the relationship between temperature and health, we divide the sample into households with air-conditioners and those without, and rerun the analysis for key health outcomes (hypertension, high blood glucose, and overweight or obese status) to test whether the coefficients on temperature are statistically distinct across these samples. We find that for hypertension and excess weight status, there is no evidence that owning an air-conditioner matters. However, for high blood glucose, there is weak evidence (significant at the 10% level) that access to air-conditioning alleviates the impact of heat (results available upon request).

9.2 Migration

In our analysis, we study the relationship between temperature in the “cluster” of residence and health outcomes of older people. The exposure of an individual to the climate in their cluster of residence depends on the number of years that they have been living in that specific area. Migration could thus be a confounding factor. To evaluate its importance, we divide the sample into those whose years in current residence are above or below the median years of residence in the sample. We then test whether coefficients are statistically different across these two samples for the key health outcomes of hypertension, high blood glucose, and excess weight status, and find that they are not (results available on request). We conclude that migration is not confounding in our context.

10 POTENTIAL MECHANISMS

10.1 Occupational Status

We analyze the potential mechanisms behind the impact of temperature on hypertension, diabetes, and BMI status among older people in India. We begin by focusing on occupational status and consider whether work that is more exposed to the changing climate—such as work in agriculture or manual labor, which tends to be outdoors—may be an explanatory factor. Given the relevance of work status, we focus on the 45+ age group, who are relatively more likely to be in the labor force compared to the 60+ age group (official retirement age in India is 60).

Results are presented in Table 13 where occupations are demarcated into “agriculture/manual,” the category of work that is likely to be especially exposed to heat and rain shocks, and “others” which include service work, work in professional/managerial capacities, and sales work. Estimates in Table 3 underline that about 69% of those in the 45+ sample are in households where at least one person is engaged in agriculture or manual work. This is a significant proportion of people in work categories who are likely to bear the brunt of unexpectedly changing weather patterns.

Estimates in Table 13 confirm that heat shocks are especially detrimental to those in agriculture/manual work. As evident from column (1), a 1°C decrease in temperature raises by about 2.0 percentage points the incidence of hypertension in people in the 45+ age group who are engaged in more climate exposed occupations. In addition to the medical explanations discussed above, if relative cold waves affect the security of harvests and, subsequently, agricultural income, this may affect hypertension through multiple channels, including physiologically as well as by increasing stress. We hope to investigate the latter channel further in subsequent work. Impacts of heat shocks on those in more protected work categories are mostly measured with error in this table. We find few significant effects of temperature shocks on the other NCD outcomes considered, including high blood glucose levels and overweight or obese status in this table.¹³

Table 13 also notes effects for rain shocks conditional on temperature shocks. Again, those in agriculture and manual work are relatively more affected. In particular, a 1 mm increase in rain shocks raises the likelihood of hypertension for those in exposed work categories by about 4.3 percentage points. Rain shocks are found to reduce the incidence of excess weight/obesity for those in agriculture or manual work. This likely reflects nutritional aspects where suboptimal levels of rain reduce harvests, resulting in food insecurities. Finally, the finding that rain shocks have this effect on this excess weight category is also notable given the fact that the propensity of this weight categorization for those in physically demanding work groupings such as agriculture and manual labor is likely to be relatively low compared to the population level average.

¹³Within outcomes, coefficients across occupational categories are not statistically distinct in this table.

Overall, results in Table 13 underscore that people working in agriculture and manual work, compared to other types of jobs such as sales, services, professional, technical, and managerial work, are particularly affected, especially in the case of hypertension.

10.2 Lifestyle Factors

The next mechanism we consider in this section includes lifestyle factors. The idea is that higher economic status is likely to be correlated with a more sedentary lifestyle with lower levels of physical activity, and so, the adverse health outcomes we document are driven by the overall lack of exercise and physical engagement. As a proxy for lifestyle factors, those with wealth above median levels and those with wealth below median levels are considered separately, with results presented in Table 14.

From Table 14 we find that lifestyle is explanatory across most NCDs. In particular, those who are relatively wealthier depict significant effects when it comes hypertension, high blood glucose levels, and overweight or obese categories. Considering the impact on hypertension first, for a 1°C decrease in temperature or heat shocks, the relatively wealthy in the 45+ age group experience a 1.4 percentage point increase in the likelihood of hypertension. The magnitude of this effect is about the same for older people of lower wealth status as well (these coefficients are statistically equivalent). This suggests that at least for this health outcome, the effect of heat shocks is unlikely to be tempered by affluence, affecting individuals in this age group without discrimination.

When we consider the impact on high blood glucose and BMI status, the lifestyle explanation shows a positive association, that is, those who are relatively wealthier are especially impacted. For instance, the estimate in column (3) indicates that a 1°C increase in temperature raises the incidence of high blood glucose among the wealthy by 0.7 percentage point. There are no significant impacts of heat shocks for the less wealthy.¹⁴ Similarly, a 1°C increase in temperature is found to increase the likelihood of being overweight or obese by 3.2 percentage points. Again, there are few measurable effects of heat shocks on the relatively less wealthy.¹⁵

Overall, in addition to occupational categories, lifestyle factors associated with higher economic status are also likely explanatory mechanisms that underlie associations between temperature and rainfall shocks and older people NCD health outcomes such as high blood glucose and obesity in India.

¹⁴This difference is statistically equivalent, however.

¹⁵In this instance, the coefficients across wealth categories are statistically distinct.

10.3 Nutritional Changes

We also test how climate shocks relate to food consumption patterns. Given the information available in our data, we create an indicator variable for if an individual consumes green leafy vegetables or fruits at least weekly. This is a (crude) measure of consumption of nutritious foods, and we regress it on climate variables and the same controls as in our baseline specification. The results show a negative (and insignificant) relationship between temperature and the consumption of nutritious foods. The noise in this measure likely contributes to the larger standard errors. Focusing on the sign of the coefficient, however, results indicate that with heat shocks (conditional on rain and frost days), relatively frequent consumption of healthy foods becomes less likely. This could thus be a reason for why heat shocks are associated with increased prevalence of glucose, high blood glucose, and excess weight, as our main results depict.

11 SUMMARY

We document the impact of climate change on the incidence of noncommunicable diseases among older people in a developing country context. The main contributions of our study are threefold. First, the NCDs that we study have not been analyzed before in the health economics literature on climate change. Second, the focus on the health consequences of the changing climate has been on other vulnerable groups such as children, not the older people. Third, we consider climate variables in unison, as opposed to either temperature or rainfall alone.

In a framework that models climate variables as deviations from long run weather trends in a specification that is saturated with individual and household level controls, as well as controls for local seasonality, district level unobservables, and time trends, we find that while historical temperature deviations from trend are not explanatory, unanticipated contemporaneous heat and rain shocks have significant detrimental consequences on the health of older populations. Estimates from the DHS from 2019–2021 linked with georeferenced meteorological data at the cluster level (annual temperature, annual rainfall, annual incidence of frost) reveal that unexpected heat shocks in particular significantly increase the prevalence of hypertension, glucose levels, the incidence of high blood glucose, body mass index, and overweight or obese status in individuals aged 45 years and above. This is for a population where the incidence of these NCDs is already relatively high at baseline. Exogenous rain shocks also matter for some of these outcomes, but impacts are relatively more muted when we condition on temperature and other climate controls. This is likely as weather measures in general tend to be correlated (thus necessitating their joint estimation).

We consider heterogeneity by gender, educational level, sector of residence, and caste status to find that as a consequence of the changing climate, hypertension affects men, those with relatively low levels of schooling, and urban residents. Alternatively, weight is particularly responsive to climate change for older women, those with more schooling, and those in rural areas. There is some evidence that heat and rain shocks have disproportionately large impacts on disadvantaged caste groups including scheduled castes, scheduled tribes, and other backward caste groups, compared to other (general) categories.

Analyzing potential mechanisms, we find that engagement in occupations more exposed to outdoor, physically demanding work—such as agriculture or manual labor—is explanatory for hypertension. Lifestyle factors tied to wealth status are explanatory mechanisms for blood glucose levels and classification in the excess weight categories of overweight and obese. We find weak evidence that relatively frequent consumption of nutritious foods such as fruits and vegetables declines with heat shocks.

12 CONCLUSION AND IMPLICATIONS FOR POLICY

Our results underscore the importance of policy in mitigating the harmful consequences of climate change on older populations in developing countries. These populations are already vulnerable in terms of poor health when the incidence of hypertension, diabetes, and unhealthy weight levels are considered. Our research reveals that against this backdrop, there are clear measurable effects of varying climate which will impose a significant additional health burden. The inverse relationship between temperature deviations and blood pressure that we document is especially concerning when we place it in the context of the medical literature that documents well established links in colder temperatures (winter) between blood pressure and mortality, the incidence of cardiovascular diseases, stroke, and cerebral hemorrhage (Alperovitch et al., 2009). Alternatively, unexpectedly warm temperatures, which lower blood pressure, have been found to have significant effects on morbidity and mortality, especially among older people (Alperovitch et al., 2009).

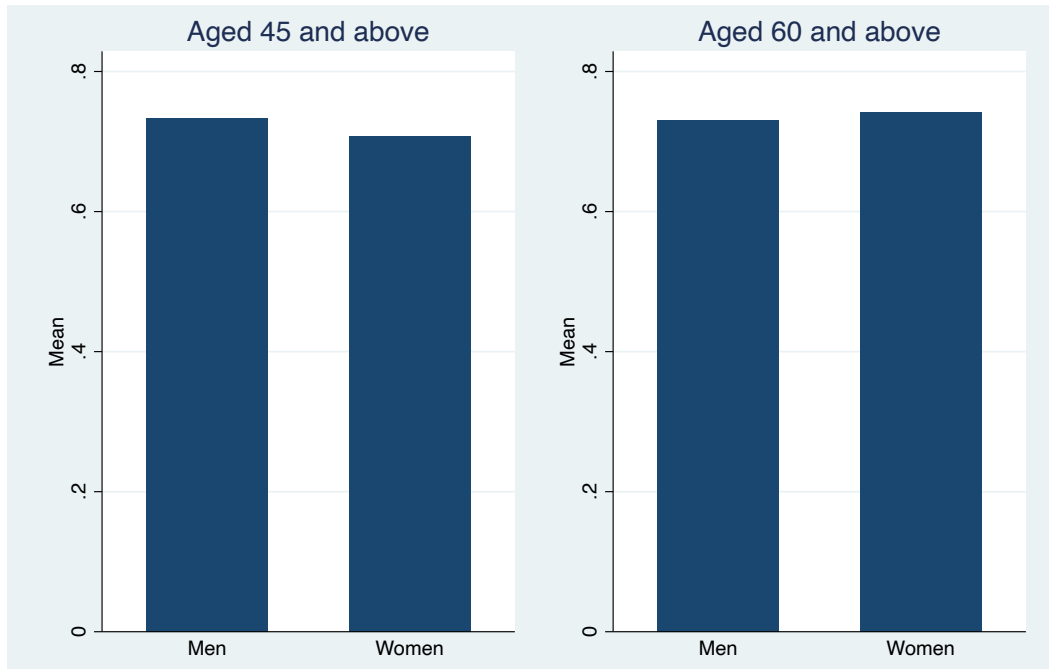
Along these lines, medical literature has also found dangerous impacts of heat on blood glucose levels among older people resulting from dehydration and reduced thermoregulatory ability. In resource-rich economies, this manifests in the form of higher levels of hospitalizations (Miyamura et al., 2022). In developing contexts, the likely outcome is increased mortality. Similarly, the pathological consequences of heat shocks on BMI and overweight or obese status are likely to be dire (An et al., 2018). In light of this, it is essential that older persons, particularly those who are socially isolated, are monitored closely when climate shocks such as heat waves occur. Early warning systems for heat waves may reduce some of the associated negative impacts (Haines and Patz, 2004), while subsidizing air-conditioners for older people may be a policy outcome worth investing in given our results that this technology helps to mitigate effects

when it comes to the incidence of high blood glucose. Specific to India, existing programs like the National Program for Health Care of the Elderly as well as the National Action Plan for Climate Change and Human Health could be prioritized to better prevent, detect, and support those of advanced age who are most susceptible to climate shocks.

Further, many in the developing world are now living longer, indicating that unlike in the past, relatively very large groups of older people will need to be supported in the future. The results of our study call for raised awareness of the impacts of climate change on older people in less developed contexts, and underline the need for government resources and interventions to enable mitigation of some of the negative health consequences of changing climate on these at-risk age groups. Given the scale of the investments needed, private groups are unlikely to be able to fully meet needs even with coordinated actions. Thus, government support is critical.

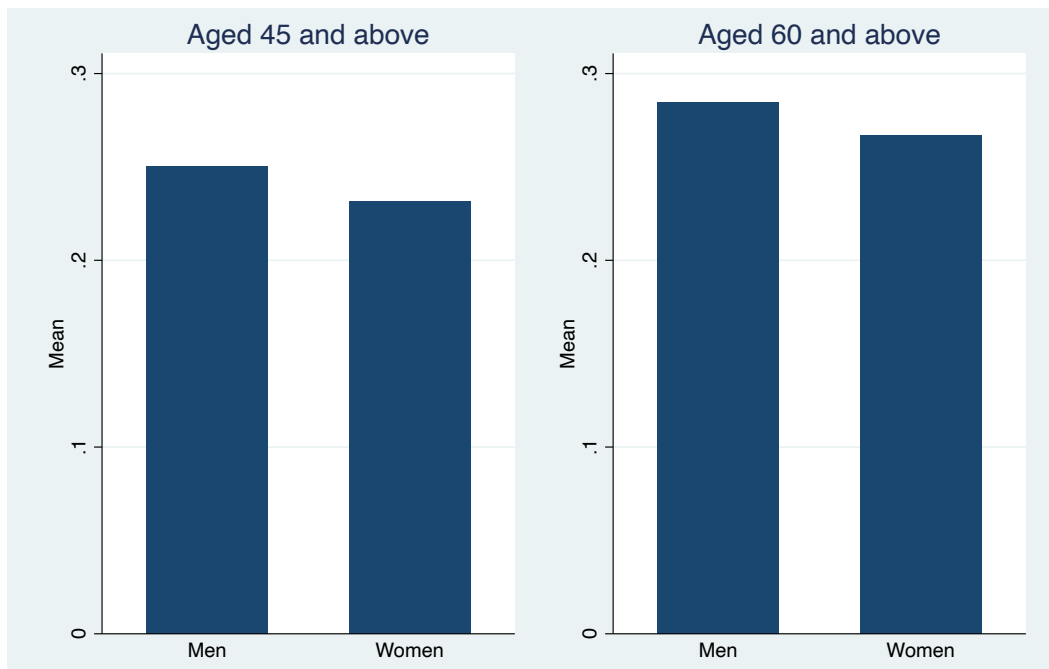
FIGURES AND TABLES

Figure 1: Hypertension



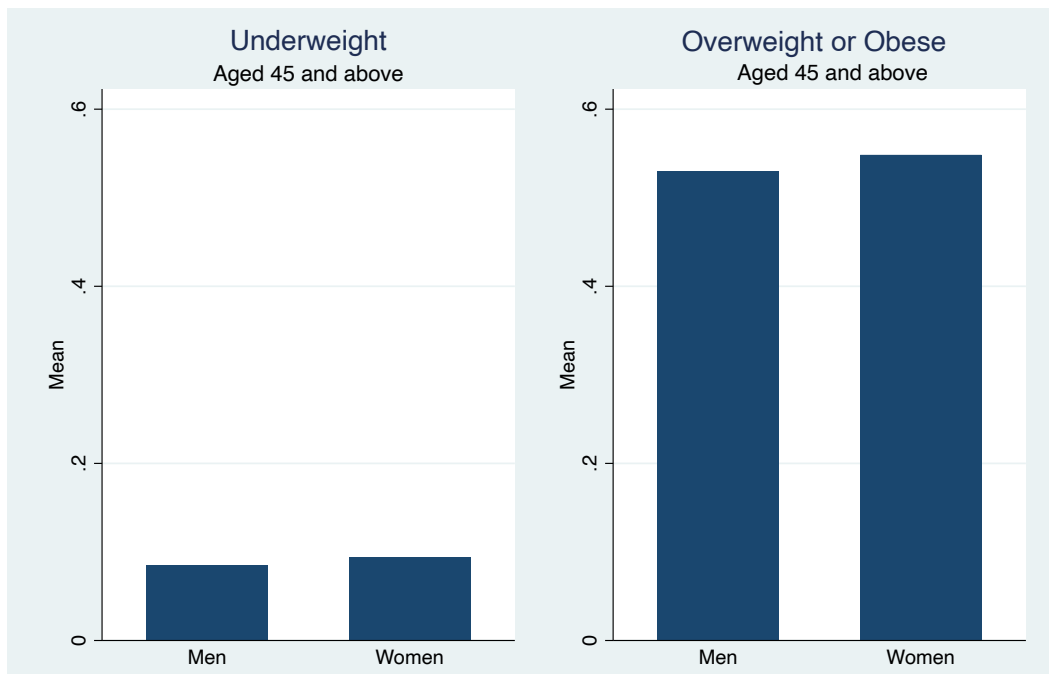
Source: Demographic and Health Survey of India, 2019–2021

Figure 2: High Blood Glucose



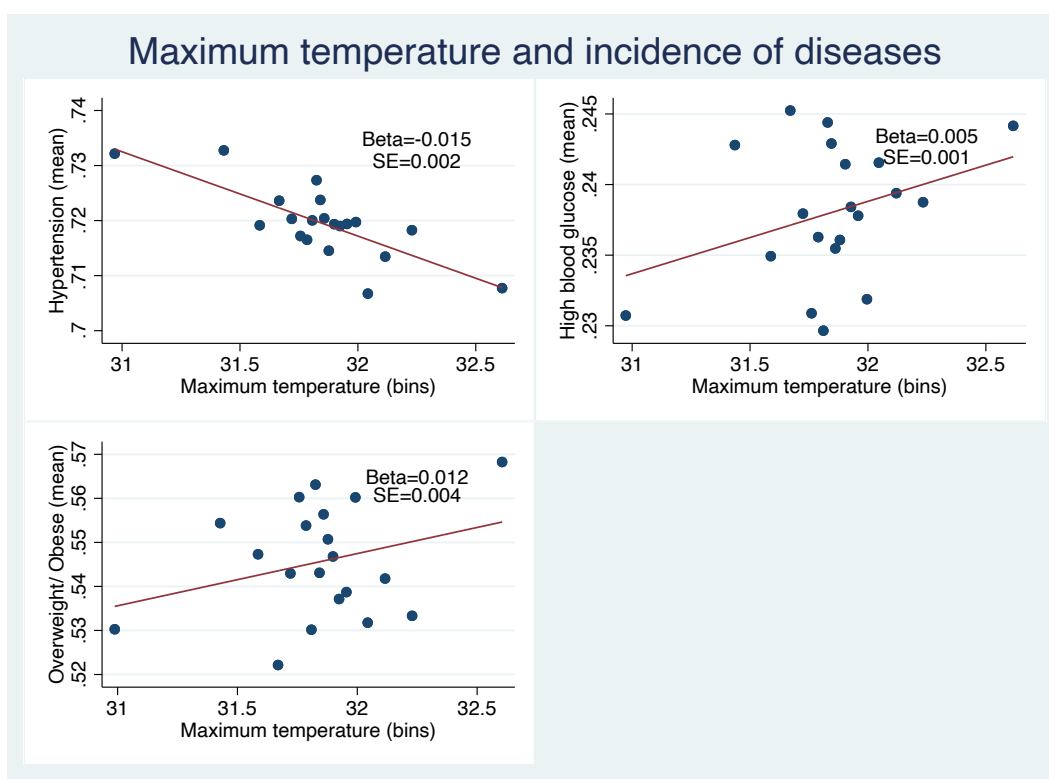
Source: Demographic and Health Survey of India, 2019–2021 .

Figure 3: Body Mass Index



Source: Demographic and Health Survey of India, 2019–2021 .

Figure 4: Binscatter Plots



Source: Demographic and Health Survey of India, 2019–2021.

Table 1: Summary Statistics: Outcome Variables

	Aged 45 and Above		Aged 60 and Above	
	Mean	SD	Mean	SD
Systolic blood pressure in millimeters of mercury (mmHg)	132.545	19.513	136.461	20.993
Diastolic blood pressure in millimeters of mercury (mmHg)	84.029	10.758	83.725	11.226
Hypertension	0.720	0.449	0.736	0.441
Glucose level in milligrams per deciliter (<i>mg/dl</i>)	131.775	50.009	134.592	51.100
High blood glucose	0.241	0.427	0.276	0.447
Diabetes	0.063	0.243	0.070	0.256
Body mass index in kilograms per meter squared (<i>kg/m²</i>)	23.992	4.596		
Underweight	0.092	0.289		
Overweight or Obese	0.545	0.498		

Note: Systolic and diastolic blood pressure is the average of three readings. Hypertension is an indicator variable that takes value 1 if mean systolic blood pressure is greater than 130 mmHg and/or mean diastolic blood pressure is greater than 80 mmHg. Glucose level readings are reported for each respondent. High blood glucose is an indicator variable that takes value 1 if an individual has a blood glucose level of more than 140 *mg/dl*. Diabetes is an indicator variable that takes value 1 if an individual has a blood glucose level of more than 200 *mg/dl*. Body mass index is reported for each individual aged 45 years and above. Underweight is an indicator variable that takes value 1 if an individual's BMI is less than 18.5 *kg/m²*. Overweight/obese is an indicator variable that takes value 1 if a respondent's BMI is at least 23 *kg/m²*. "SD" denotes standard deviations and "N" denotes number of observations.

Source: Authors' calculations from Demographic and Health Survey data.

Table 2: Summary Statistics: Climate Variables

	Mean	SD	N
Maximum temperature in 2020 (°C)	30.342	4.505	926765
Total annual rainfall in 2020 (mm)	0.149	0.075	928416
Number of frost days in 2020	0.637	2.378	926765

Note: "SD" denotes standard deviations and "N" denotes number of observations.
Source: Authors' calculations from DHS data.

Table 3: Summary Statistics: Individual and Household Controls

	Aged 45 and Above			Aged 60 and Above		
	Mean	SD	N	Mean	SD	N
<i>Individual Controls:</i>						
Age	58.434	10.114	763963	67.936	7.396	323212
Female	0.508	0.500	763918	0.494	0.500	323185
No education	0.439	0.496	763263	0.511	0.500	322815
Primary education	0.179	0.384	763263	0.182	0.386	322815
Secondary or higher	0.382	0.486	763263	0.307	0.461	322815
<i>Household Controls:</i>						
Urban	0.331	0.471	763963	0.313	0.464	323212
Scheduled caste	0.209	0.407	732798	0.200	0.400	311107
Scheduled tribe	0.089	0.285	732798	0.083	0.277	311107
Other backward class	0.442	0.497	732798	0.445	0.497	311107
Hindu	0.831	0.375	763963	0.837	0.369	323212
Muslim	0.108	0.311	763963	0.100	0.300	323212
Christian	0.029	0.167	763963	0.029	0.167	323212
Sikh	0.018	0.133	763963	0.020	0.139	323212
Buddhist	0.007	0.085	763963	0.008	0.087	323212
Piped water	0.359	0.480	763963	0.358	0.479	323212
Public tap water	0.128	0.334	763963	0.127	0.333	323212
Tubewell water	0.351	0.477	763963	0.356	0.479	323212
Well water	0.067	0.250	763963	0.070	0.255	323212
Spring water	0.007	0.081	763963	0.006	0.078	323212
River water	0.007	0.082	763963	0.007	0.082	323212
Flush toilet	0.714	0.452	763963	0.712	0.453	323212
Pit latrine	0.069	0.253	763963	0.067	0.250	323212
No facility	0.167	0.373	763963	0.173	0.378	323212
Access to electricity	0.972	0.166	763963	0.968	0.175	323212
Poorest	0.179	0.383	763963	0.192	0.394	323212
Poorer	0.186	0.389	763963	0.189	0.392	323212
Middle	0.196	0.397	763963	0.192	0.394	323212
Richer	0.204	0.403	763963	0.197	0.398	323212
Richest	0.234	0.423	763963	0.229	0.420	323212
Agriculture	0.385	0.486	85213	0.364	0.481	32131
Manual	0.308	0.462	85213	0.304	0.460	32131
Service	0.126	0.332	85213	0.124	0.329	32131
Professional/managerial	0.133	0.340	85213	0.140	0.347	32131
Sales	0.125	0.330	85213	0.124	0.329	32131

Note: "SD" denotes standard deviations and "N" denotes number of observations.
Source: Authors' calculations from DHS data.

Table 4: Climate Change and Blood Pressure

	Systolic Pressure (mmHg)		Diastolic Pressure (mmHg)		Hypertension	
	45 plus (1)	60 plus (2)	45 plus (3)	60 plus (4)	45 plus (5)	60 plus (6)
Max temp (2020)	-0.818*** (0.120)	-1.143*** (0.186)	-0.612*** (0.070)	-0.650*** (0.100)	-0.015*** (0.003)	-0.015*** (0.004)
Rainfall (2020)	-0.417 (0.305)	-0.290 (0.438)	-0.412** (0.200)	-0.574** (0.290)	-0.000 (0.007)	-0.004 (0.009)
Observations	659,144	281,102	659,144	281,102	659,144	281,102
Mean of dep var	132.559	136.482	84.038	83.723	0.720	0.735
R-Squared	0.068	0.041	0.033	0.039	0.028	0.028

Note: The outcome variable in columns (1) and (2) is the mean systolic blood pressure and in columns (3) and (4), it is the mean diastolic blood pressure. In columns (5) and (6), the outcome variable is a dummy variable for hypertension which takes value 1 if mean systolic blood pressure is greater than 130 mmHg and/or mean diastolic blood pressure is greater than 80 mmHg. All columns include individual and household controls, interview month–year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the DHS cluster. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table 5: Climate Change and Blood Glucose

	Glucose Level (<i>mg/dl</i>)		High Blood Glucose		Diabetes	
	45 plus (1)	60 plus (2)	45 plus (3)	60 plus (4)	45 plus (5)	60 plus (6)
Max temp (2020)	0.941*** (0.296)	0.226 (0.400)	0.005* (0.003)	0.003 (0.004)	0.001 (0.001)	-0.001 (0.002)
Rainfall (2020)	0.291 (0.665)	-0.100 (1.011)	0.006 (0.006)	0.008 (0.009)	0.004 (0.003)	-0.002 (0.006)
Observations	631,953	265,870	631,953	265,870	631,953	265,870
Mean of dep var	131.508	134.331	0.238	0.273	0.063	0.070
R-Squared	0.041	0.044	0.039	0.040	0.027	0.032

Note: The outcome variable in columns (1) and (2) is the glucose level reading for a respondent. In columns (3) and (4), the outcome variable is a dummy variable taking the value 1 if an individual has a blood glucose level of more than 140 *mg/dl*. In columns (5) and (6), the outcome variable is a dummy variable taking the value 1 if an individual has a blood glucose level of more than 200 *mg/dl*. All columns include individual and household controls, interview month–year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the DHS cluster. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table 6: Climate Change and Body Mass Index: Aged 45 and Above

	Body Mass Index (1)	Underweight (2)	Overweight or Obese (3)
Max temp (2020)	0.134** (0.058)	-0.003 (0.004)	0.012* (0.006)
Rainfall (2020)	-0.227* (0.129)	0.020** (0.008)	-0.011 (0.014)
Observations	95,129	95,129	95,129
Mean of dep var	24.004	0.093	0.546
R-Squared	0.176	0.066	0.134

Note: The outcome variable in column (1) is body mass index, as provided in the demographic and health survey. In column (2), the outcome variable is a dummy variable taking the value 1 if an individual's body mass index (BMI) is less than 18.5 kg/m^2 . In column (3), the outcome variable is a dummy variable taking the value 1 if a respondent's BMI is at least 23 kg/m^2 and thus, is in the overweight or obese categories. All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the DHS cluster. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table 7: Climate Change and Health: Including Occupation Controls for Those Aged 45 and Above

	Systolic Pressure (1)	Diastolic Pressure (2)	Hypertension (3)	Glucose Level (4)	High Blood Glucose (5)	Diabetes (6)	BMI (7)	Underweight (8)	Overweight /Obese (9)
Max temp (2020)	-1.089*** (0.294)	-0.592*** (0.177)	-0.019*** (0.007)	0.436 (0.760)	-0.002 (0.007)	0.001 (0.004)	-0.015 (0.106)	0.004 (0.007)	0.004 (0.013)
Rainfall (2020)	0.893 (0.678)	0.284 (0.429)	0.007 (0.015)	2.621 (1.997)	0.012 (0.014)	0.018 (0.011)	-0.259 (0.230)	0.046*** (0.014)	-0.039 (0.028)
Observations	73,823	73,823	73,823	70,958	70,958	70,958	28,261	28,261	28,261
Mean of dep var	131.757	84.049	0.718	131.063	0.230	0.063	23.774	0.089	0.538
R-Squared	0.092	0.056	0.048	0.051	0.049	0.037	0.193	0.086	0.152

BMI = body mass index.

Note: The outcome variable in column (1) is the mean systolic blood pressure and in columns (2), it is the mean diastolic blood pressure. In columns (3), the outcome variable is a dummy variable for hypertension which takes value 1 if mean systolic blood pressure is greater than 130 mmHg and/or mean diastolic blood pressure is greater than 80 mmHg. Glucose level readings are reported for each respondent. High blood glucose is an indicator variable that takes value 1 if an individual has a blood glucose level of more than 140 mg/dl. Diabetes is an indicator variable that takes value 1 if an individual has a blood glucose level of more than 200 mg/dl. Body mass index is reported for each individual aged 45 years and above. Underweight is an indicator variable that takes value 1 if an individual's BMI is less than 18.5 kg/m². Overweight/obese is an indicator variable that takes value 1 if a respondent's BMI is at least 23 kg/m². All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of demographic and health survey cluster. In addition, all columns include controls for at least one member of the household being involved in agriculture, manual labor, services, professional, or sales occupations. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table 8: Heterogeneity in Hypertension (Aged 45 and Above)

Heterogeneity by:	Gender		Education			Sector			Caste	
	Men (1)	Women (2)	Below secondary (3)	Secondary or higher (4)	Rural (5)	Urban (6)	Lower caste (7)	Upper caste (8)		
Dep var: Hypertension										
Max temp (2020)	-0.017*** (0.004)	-0.014*** (0.003)	-0.016*** (0.003)	-0.014*** (0.004)	-0.010*** (0.003)	-0.019** (0.008)	-0.018*** (0.003)	-0.006 (0.005)		
Rainfall (2020)	0.004 (0.009)	-0.003 (0.008)	-0.006 (0.007)	0.014 (0.010)	0.001 (0.007)	0.024 (0.016)	-0.006 (0.007)	0.019 (0.013)		
Observations	317,539	341,605	431,868	227,276	503,685	155,459	506,174	149,379		
Mean of dep var	0.733	0.707	0.710	0.736	0.706	0.750	0.715	0.734		
R-squared	0.032	0.030	0.029	0.031	0.028	0.031	0.028	0.031		

All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the demographic and health survey cluster. The results are statistically not different from each other for gender, education, and sector categories. For caste, the results are significantly different between lower caste and upper caste. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.
Source: Authors' calculations.

Table 9: Heterogeneity in Glucose Level (Aged 45 and Above)

Heterogeneity by:	Gender		Education				Sector			Caste	
	Men (1)	Women (2)	Below secondary (3)	Secondary or higher (4)	Rural (5)	Urban (6)	Lower caste (7)	Upper caste (8)			
Dep var: Glucose level											
Max temp (2020)	1.010*** (0.375)	0.885** (0.381)	1.184*** (0.314)	0.452 (0.507)	0.978*** (0.301)	0.320 (0.856)	1.013*** (0.338)	0.733 (0.555)			
Rainfall (2020)	0.955 (0.908)	-0.295 (0.818)	0.025 (0.761)	1.014 (1.104)	-0.057 (0.697)	1.517 (1.796)	0.040 (0.732)	0.997 (1.395)			
Observations	305,320	326,633	412,906	219,047	483,183	148,770	485,197	143,364			
Mean of dep var	131.795	131.244	129.148	135.554	128.779	137.601	130.599	134.231			
R-Squared	0.044	0.043	0.039	0.043	0.037	0.041	0.043	0.040			

All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the demographic and health survey cluster. The results are not statistically different across the categories of gender, education, sector and caste. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table 10: Heterogeneity in High Blood Glucose (Aged 45 and Above)

Heterogeneity by:	Gender		Education		Sector			Caste	
	Men (1)	Women (2)	Below secondary (3)	Secondary or higher (4)	Rural (5)	Urban (6)	Lower caste (7)	Upper caste (8)	
Dep var: High blood glucose									
Max temp (2020)	0.006 (0.004)	0.005 (0.003)	0.003 (0.003)	0.010** (0.005)	0.004 (0.003)	0.013* (0.007)	0.005 (0.003)	0.005 (0.005)	
Rainfall (2020)	0.012 (0.008)	0.001 (0.007)	0.002 (0.006)	0.014 (0.009)	0.003 (0.006)	0.022 (0.016)	0.001 (0.006)	0.020 (0.013)	
Observations	305,320	326,633	412,906	219,047	483,183	148,770	485,197	143,364	
Mean of dep var	0.247	0.229	0.220	0.268	0.217	0.285	0.229	0.263	
R-Squared	0.041	0.040	0.036	0.044	0.034	0.045	0.039	0.044	

All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the demographic and health survey cluster. The results are not statistically different across the categories of gender, education, sector and caste. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. Source: Authors' calculations.

Table 11: Heterogeneity in Body Mass Index (Aged 45 and Above)

Heterogeneity by:	Gender		Education			Sector			Caste	
	Men (1)	Women (2)	Below secondary (3)	Secondary or higher (4)	Rural (5)	Urban (6)	Lower caste (7)	Upper caste (8)		
Dep var: BMI										
Max temp (2020)	-0.009 (0.116)	0.172*** (0.067)	0.100 (0.069)	0.217** (0.103)	0.156*** (0.061)	0.037 (0.174)	0.114* (0.065)	0.161 (0.124)		
Rainfall (2020)	-0.326 (0.273)	-0.220 (0.146)	-0.186 (0.159)	-0.272 (0.206)	-0.205 (0.134)	-0.504 (0.340)	-0.146 (0.135)	-0.443 (0.329)		
Observations	17,876	77,253	58,274	36,855	71,492	23,637	74,720	19,934		
Mean of dep var	23.525	24.112	23.261	25.129	23.288	25.523	23.726	24.934		
R-Squared	0.196	0.183	0.154	0.155	0.151	0.136	0.180	0.160		

BMI = body mass index.

All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of demographic and health survey cluster. The results are not statistically different across the categories of gender, education, sector and caste. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table 12: Heterogeneity in Overweight or Obese (Aged 45 and Above)

Heterogeneity by:	Gender		Education			Sector		Caste	
	Men (1)	Women (2)	Below secondary (3)	Secondary or higher (4)	Rural (5)	Urban (6)	Lower caste (7)	Upper caste (8)	
Dep var: Overweight/obese									
Max temp (2020)	-0.002 (0.016)	0.016** (0.007)	0.010 (0.008)	0.019* (0.010)	0.012* (0.007)	0.009 (0.017)	0.013* (0.007)	0.008 (0.013)	
Rainfall (2020)	-0.040 (0.036)	-0.009 (0.015)	0.001 (0.018)	-0.028 (0.022)	-0.011 (0.015)	-0.039 (0.032)	-0.000 (0.015)	-0.041 (0.034)	
Observations	17,876	77,253	58,274	36,855	71,492	23,637	74,720	19,934	
Mean of dep var	0.531	0.549	0.473	0.656	0.481	0.683	0.519	0.636	
R-Squared	0.164	0.140	0.116	0.114	0.115	0.109	0.135	0.129	

All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the demographic and health survey cluster. The results are not statistically different across the categories of gender, education, sector, and caste. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table 13: Employment in Occupations Exposed to Climate

Occupation:	Hypertension		High Blood Glucose		Overweight or Obese	
	Agri/ manual	Others	Agri/ manual	Others	Agri/ manual	Others
	(1)	(2)	(3)	(4)	(5)	(6)
Max temp (2020)	-0.020** (0.008)	-0.011 (0.011)	0.000 (0.008)	-0.000 (0.012)	0.001 (0.015)	0.004 (0.023)
Rainfall (2020)	0.043** (0.018)	-0.043 (0.026)	0.026 (0.018)	-0.028 (0.026)	-0.049* (0.030)	-0.003 (0.059)
Observations	48,833	24,990	46,948	24,010	20,832	7,429
Mean of dep var	0.708	0.735	0.210	0.267	0.499	0.641
R-Squared	0.050	0.075	0.051	0.071	0.152	0.200

Note: In columns (1), (3) and (5), we focus on households in which the female respondent is involved in agricultural or manual work. In columns (2), (4) and (6), the occupations we consider are all besides agriculture and manual work. All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the demographic and health survey cluster. The results are not statistically different across the occupational categories of agriculture/manual work and other occupational groups. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. Source: Authors' calculations.

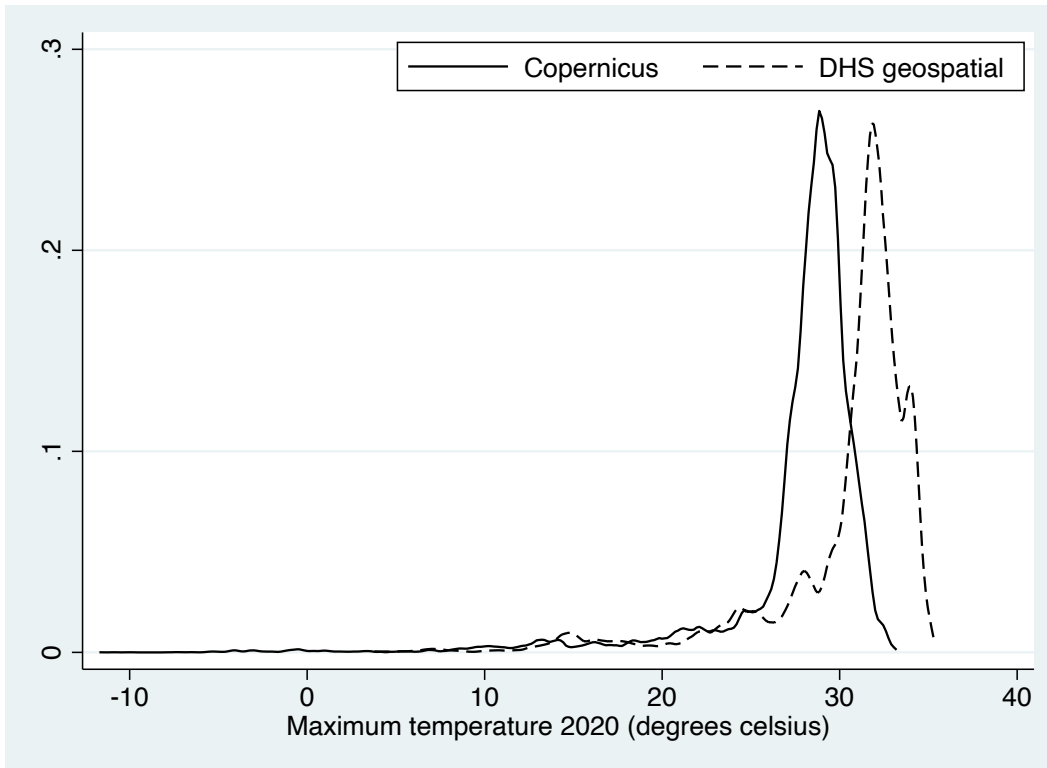
Table 14: Lifestyle Factors Based on Wealth

Wealth:	Hypertension		High Blood Glucose		Overweight or Obese	
	Above median	Below median	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
Max temp (2020)	-0.014*** (0.004)	-0.016*** (0.004)	0.007* (0.004)	0.001 (0.003)	0.032*** (0.009)	-0.006 (0.010)
Rainfall (2020)	0.006 (0.008)	0.001 (0.009)	0.014* (0.008)	-0.002 (0.007)	-0.024 (0.019)	-0.007 (0.021)
Observations	322,426	336,718	309,264	322,689	47,570	47,559
Mean of dep var	0.744	0.691	0.271	0.199	0.665	0.400
R-Squared	0.025	0.029	0.039	0.029	0.081	0.080

Note: All columns include individual and household controls, interview month-year and district fixed effects, and number of frost days in 2020. Standard errors in all columns are clustered at the level of the demographic and health survey cluster. The results are not statistically different across wealth categories for hypertension and high blood glucose. The overweight or obese results however, are statistically distinct across the wealth groupings. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. Source: Authors' calculations.

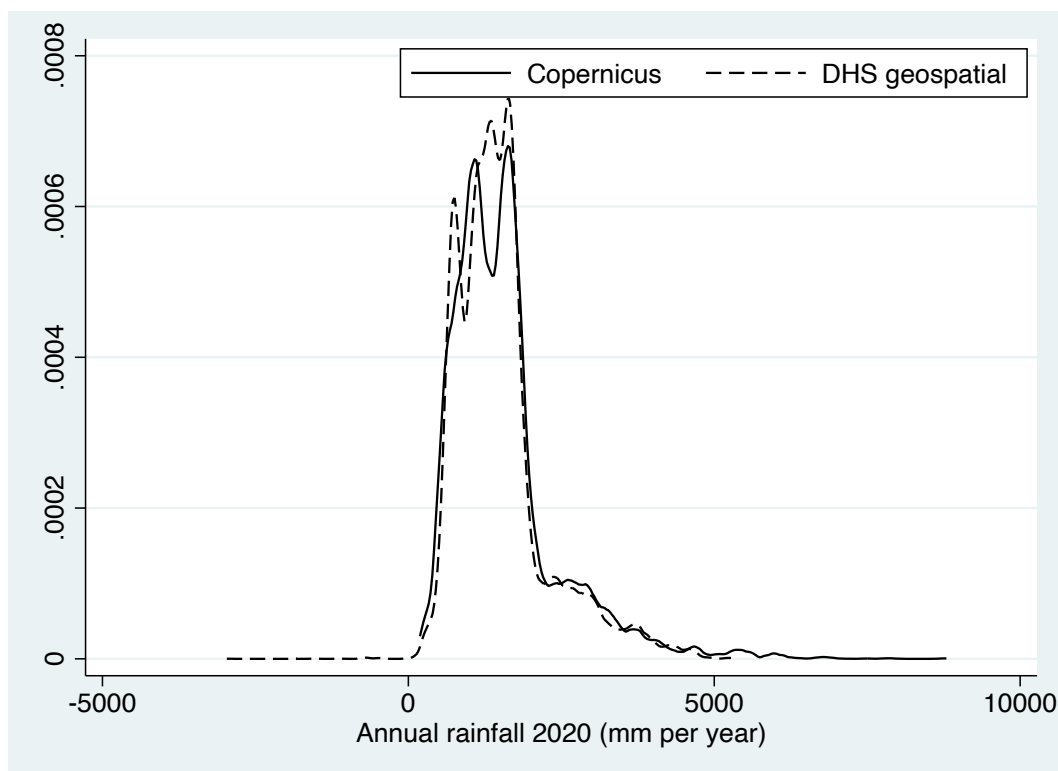
APPENDIX

Figure A.1: Comparison of DHS and Copernicus Temperature Data



Source: Authors' calculations.

Figure A.2: Comparison of DHS and Copernicus Rainfall Data



Source: Authors' calculations.

Table A.1: Robustness Checks with Copernicus Climate Data: Blood Pressure

	Systolic Pressure (mmHg)		Diastolic Pressure (mmHg)		Hypertension	
	45 plus (1)	60 plus (2)	45 plus (3)	60 plus (4)	45 plus (5)	60 plus (6)
Max temp (2020)	-0.265*** (0.068)	-0.392*** (0.104)	-0.188*** (0.041)	-0.228*** (0.058)	-0.006*** (0.001)	-0.006*** (0.002)
Rainfall (2020)	1.154*** (0.376)	1.348** (0.557)	0.533** (0.226)	0.431 (0.306)	0.006 (0.009)	0.007 (0.010)
Observations	664,337	283,276	664,337	283,276	664,337	283,276
Mean of dep var	132.555	136.476	84.038	83.723	0.720	0.735
R-squared	0.068	0.041	0.033	0.039	0.027	0.028

Note: The outcome variable in columns (1) and (2) is the mean systolic blood pressure and in columns (3) and (4), it is the mean diastolic blood pressure. In columns (5) and (6), the outcome variable is a dummy variable for hypertension which takes value 1 if mean systolic blood pressure is greater than 130 mmHg and/or mean diastolic blood pressure is greater than 80 mmHg. All columns include individual and household controls and interview month-year and district fixed effects. Standard errors in all columns are clustered at the level of the demographic and health survey cluster. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table A.2: Robustness Checks Using Copernicus Climate Data: Blood Glucose Levels

	Glucose Level (<i>mg/dl</i>)		High Blood Glucose		Diabetes	
	45 plus (1)	60 plus (2)	45 plus (3)	60 plus (4)	45 plus (5)	60 plus (6)
Max temp (2020)	0.782*** (0.152)	0.568*** (0.214)	0.006*** (0.001)	0.007*** (0.002)	0.001 (0.001)	−0.000 (0.001)
Rainfall (2020)	0.674 (0.884)	−0.231 (1.241)	0.009 (0.009)	0.006 (0.012)	0.007* (0.004)	0.005 (0.006)
Observations	636,939	267,924	636,939	267,924	636,939	267,924
Mean of dep var	131.546	134.375	0.238	0.273	0.063	0.070
R-Squared	0.041	0.044	0.039	0.040	0.027	0.032

Note: The outcome variable in columns (1) and (2) is the glucose level reading for a respondent. In columns (3) and (4), the outcome variable is a dummy variable taking the value 1 if an individual has a blood glucose level of more than 140 *mg/dl*. In columns (5) and (6), the outcome variable is a dummy variable taking the value 1 if an individual has a blood glucose level of more than 200 *mg/dl*. All columns include individual and household controls and interview month–year and district fixed effects. Standard errors in all columns are clustered at the level of the DHS cluster. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

Table A.3: Robustness Checks Using Copernicus Climate Data: Body Mass Index for Those Aged 45 and Above

	Body Mass Index (1)	Underweight (2)	Overweight or Obese (3)
Max temp (2020)	−0.002 (0.031)	0.002 (0.002)	−0.000 (0.003)
Rainfall (2020)	−0.381** (0.169)	0.026** (0.012)	−0.019 (0.018)
Observations	95,812	95,812	95,812
Mean of dep var	24.007	0.093	0.546
R-Squared	0.176	0.066	0.134

Note: The outcome variable in column (1) is body mass index (BMI), as provided in the demographic and health survey. In column (2), the outcome variable is a dummy variable taking the value 1 in an individual's BMI is less than 18.5 *kg/m²*. In column (3), the outcome variable is a dummy variable taking the value 1 if a respondent's BMI is at least 23 *kg/m²* and thus, is in the overweight or obese categories. All columns include individual and household controls, interview month–year and district fixed effects. Standard errors in all columns are clustered at the level of the DHS cluster. Statistical significance at 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Source: Authors' calculations.

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Climate Shocks and Noncommunicable Diseases Among Older People in India

This paper shares findings from a study of the impact of temperature and rainfall on the incidence of noncommunicable diseases among older people in India. The study uses estimates from the Indian Demographic and Health Surveys from 2019 to 2021 linked with georeferenced recent meteorological data at the cluster level. It finds that unexpected excess heat has significant impacts on the prevalence of hypertension, high blood glucose levels, and overweight or obese status. The findings underscore the importance of policies promoting climate resilience for older people in developing economies.

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