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Essays in climate and energy economics

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To my grandfather, Mario.

Pour soulever un poids si lourd,
Sisyphe, il faudrait ton courage!
Bien qu'on ait du coeur à l'ouvrage,
L'Art est long et le Temps est court.

Baudelaire

Preface

First and foremost, my deepest gratitude goes to my supervisor Prof. Bruno Lanz, for providing me with the opportunity to pursue this thesis. His guidance, expertise and invaluable support were crucial in enabling me to complete this dissertation. I also want to deeply thank Milad Zarin-Nejadan for giving me the opportunity to conduct this dissertation. A special thanks goes to late Alain Schönenberger for his support and precious advices at the beginning of this journey. My sincere thanks are extended to Matthieu Stigler and Eric Strobl for their constructive and very useful feedbacks.

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Résumé

Dans ces trois chapitres, j'analyse les conséquences économiques du changement climatique en examinant les coûts d'adaptation et d'atténuation associés aux chocs climatiques et à la transition énergétique. Plus précisément, je quantifie deux dimensions de ces coûts. Premièrement, j'analyse les impacts économiques des chocs climatiques dans les pays en développement, en soulignant la vulnérabilité des ménages et leurs capacités d'adaptation. Deuxièmement, j'étudie la manière dont les émissions de carbone du secteur des transports sont liées à la structure démographique dans les économies développées, apportant de nouvelles évidences sur les interactions entre structure démographique et efforts d'atténuation du changement climatique.

Le premier chapitre étudie comment les vagues de chaleur marines (VCM) influencent le marché du travail dans les zones côtières de l'Inde. Les résultats indiquent que les VCM augmentent le chômage, réduisent l'emploi dans le secteur de la pêche et augmentent la part des emplois saisonniers.

Le deuxième chapitre étudie l'impact de l'exposition à des vagues de chaleur sur l'incidence de maladies chez les enfants en afrique sub-Saharienne. Je montre que l'exposition à des températures comprises entre 30 et 35°C augmente significativement l'incidence de la fièvre, de la diarrhée et des infections respiratoires. Ces effets sont moins prononcés dans les zones rurales et chez les enfants de mères scolarisées.

Le troisième chapitre étudie l'impact de la retraite sur la consommation d'essence des ménages en Suisse. Je montre que la retraite réduit significativement la consommation d'essence, avec des effets plus marqués pour les ménages seuls.

Ensemble, ces chapitres soulignent la nécessité de politiques climatiques qui tiennent compte des inégalités de vulnérabilité des ménages aux chocs climatiques dans les pays en développement et des tendances démographiques dans les pays développés.

Mots-clés : Impacts économiques; Changement climatique; Adaptation; Transition énergétique; Consommation d'essence; Retraite; Enquête sur les dépenses des ménages; Température; Afrique de l'Ouest; Maladies Infantiles; Vagues de chaleur marines; Inde.

Summary

In these three chapters, I provide novel insights into the economic consequences of climate change by examining both the adaptation and mitigation costs associated with weather shocks and the energy transition. Specifically, I quantify two specific aspects of these costs. First, I analyze the economic impacts of weather shocks in developing countries, shedding light on household vulnerability and adaptive responses. Second, I investigate how carbon emissions from the transport sector are linked to the demographic structure of developed economies, providing new evidence on the interplay between population aging and climate mitigation efforts.

The first chapter investigates how marine heatwaves (MHWs) influence labor market outcomes in coastal India. Results indicate that MHWs increase unemployment, reduce employment in the fisheries, and increase seasonal type of employments at the expense of all year type of employment.

The second chapter investigates the impact of heat exposure on disease incidence in children in sub-Saharan Africa. I show that exposure to temperatures of 30–35°C significantly increases the incidence of fever, diarrhea, and acute respiratory diseases. The effects are less pronounced in rural settings and among children of educated mothers.

The third chapter investigates how retirement affects households' gasoline consumption in Switzerland. I show that retirement significantly reduces gasoline consumption in Swiss households, with larger effects among single-person households.

Together, these chapters highlight the need for climate and energy policies that account for the differential burdens that climate shocks impose on households in developing countries and for demographic trends in developed countries.

Keywords: Economic impacts; Climate change; Adaptation; Energy transition; Gasoline consumption; Retirement effect; Household expenditure survey; Fuzzy regression discontinuity design; Temperature; West Africa; Child diseases; Marine heatwaves; India; Household surveys.

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Introduction

Climate change and the transition to low-carbon energy systems impose significant economic costs on societies worldwide. These costs arise both from the need to adapt to the unavoidable impacts of a changing climate and from the need to mitigate greenhouse gas emissions by transforming energy systems and consumption patterns. In the context of climate change, adaptation costs include measures which aim at supporting households and communities facing increased exposure to extreme weather events. At the same time, demographic changes such as population aging affect energy demand and emissions, with important implications for mitigation costs.

Anthropogenic climate change has a direct impact on human health and ecosystems around the world through increased temperatures (Barreca, 2012; Deschenes, 2014; Deschênes & Greenstone, 2011). Environmental shocks, such as heatwaves and marine heatwaves, increasingly disrupt livelihoods, health, and economic stability, particularly in vulnerable regions. Understanding how these shocks affect households is key as they will likely increase both in intensity and frequency in the coming decades (Sen Gupta et al., 2020). In addition, analyzing how households respond and adapt to these weather shocks is detrimental for designing effective climate adaptation policies. These patterns can inform broader research efforts as they are a key determinant in projecting climate change impacts in developing economies. Integrating this information into existing frameworks will support the development of more precise models and enhance our understanding of future trajectories.

At the same time, as societies confront the challenges of the energy transition, understanding how demographic change interacts with energy demand is increasingly critical. Population aging, in particular, can influence both the pace of this transition and the associated mitigation costs, as shifts in consumption patterns reshape energy use across sectors. Changes in demographic structure, such as population aging, have an impact on households' consumption patterns through retirement (Banks et al., 1998; Haider & Stephens Jr, 2007; Hamermesh, 1984; Schwerdt, 2005). Retirement also affects households' commuting behavior, mobility choices, and energy consumption. Previous research shows a clear consensus on the relationship between age and energy use: while getting older is generally associated with higher residential energy consumption due to more sedentary lifestyles (Yamasaki and Tominaga, 1997; Tonn and Eisenberg, 2007; Fan et al., 2021), it tends to reduce transport-related energy use (Okada, 2012). Understanding how demographic changes shape energy demand, particularly in transport, is crucial to assess whether aging trends may facilitate or hinder efforts to reduce CO_2 emissions and to evaluate the costs required to achieve a low-carbon future in developed countries.

In my doctoral dissertation, I provide novel insights into the economic consequences of climate change by quantifying specific aspects of both adaptation and mitigation costs. I bring a new perspective on how environmental and demographic dynamics shape the economic challenges of addressing climate change. Specifically, I quantify two dimensions of these costs. First, I analyze the economic impacts of weather shocks in developing countries, shedding light on household vulnerability and adaptive responses. Second, I investigate how carbon emissions from the transport sector are linked to the demographic structure of developed economies, providing new evidence on the interplay between population aging and climate mitigation efforts. The first and second chapters focus on the effects of climate shocks in developing countries: I analyze how heatwaves influence child disease incidence in sub-Saharan Africa and how marine heatwaves impact labor markets in coastal India. In the third chapter, I study how retirement affects transport-related consumption in Switzerland and discuss its implications for emissions from the transport sector.

In my first chapter, I examine how exposure to marine heatwaves (MHW) affects numerous labor market outcomes among coastal households in India. Using data from the 2015–2016 wave of the Demographic and Health Survey (DHS), I combine micro-level household data with the National Oceanic and Atmospheric Administraton (NOAA) Coral Reef Watch program, which provides high-resolution (5 km) satellite-based heat stress monitoring products. To measure exposure to MHW, I use NOAA's Degree Heating Weeks (DHW), a cumulative measure of unusually warm ocean temperatures over time. I calculate an average DHW value within a 20 km buffer around each household's GPS location in the three months preceding the survey date. I also define a binary indicator for households exposed to intense marine heat stress

(DHW ≥ 4), a threshold beyond which damage to marine ecosystems becomes more likely (Van Woesik et al., 2022). For identification, I employ a linear probability model using both spatial and temporal fixed effects to account for unobserved heterogeneity across space and time. This setup allows me to estimate how MHW influence the coastal labor market in India.

My findings show that exposure to a MHW significantly reduces employment among coastal households in India. Specifically, an additional DHW in the three months prior to the survey increases the probability of household unemployment by 1.9–2.5 percentage points. Exposure to intense marine heat stress (DHW ≥ 4) has a large impact, raising the probability of unemployment by 5.5–6.5 percentage points. Beyond unemployment, I find that one additional DHW reduces employment in the fisheries sector by 1.3–1.4 percentage points relative to other sectors, and by 5.2–6.5 percentage points relative to unemployment. For households exposed to intense marine heat stress (DHW ≥ 4), these reductions amount to around 15 percentage points relative to other sectors and 20 percentage points relative to unemployment. Furthermore, MHW exposure seems to increase female labor force participation: one additional DHW raises the probability that a household head's wife is employed by 2.0–2.4 percentage points, with this effect growing to 5.4–6.7 percentage points when exposed to an important episode of heat stress. Finally, exposure to intense MHW also indicate a reallocation from all-year to seasonal employment. These findings highlight the vulnerability of coastal labor markets to marine heat stress.

The second chapter examines how exposure to high temperatures affects the incidence of diseases in children in Sub-Saharan Africa. I use multiple waves of the Demographic and Health Survey (DHS) from three countries (Benin, Ghana, Togo), which contains micro-level household and health data. I combine it with the Global Meteorological Forcing Dataset (GMFD), which provides gridded daily temperature and precipitation data. To measure heat exposure, I construct hour-degree bins of temperatures following Schlenker and Roberts, 2009 and Blom et al., 2022. I use a sine curve to model daily temperature variations within each grid cell. This approach allows me to estimate the effect of heat exposure in the two weeks before the survey on child disease incidence such as fever, diarrhea, and acute respiratory disease (ARD). For identification, I employ a linear probability model with region-year and region-month fixed effects to account for local seasonality and temporal trends in disease incidence.

My results show that heat exposure significantly increases the incidence of fever, diarrhea, and ARD in children. Specifically, an additional 10 hours of exposure to 30–35°C in the 14 days before the interview raises the probability of fever by 1.5 3.0, and 3.5 percentage points, respectively for fever, diarrhea and ARD. Exposure to extreme temperatures (>35°C) only affects diarrhea, increasing its incidence by 1.8 percentage points, but this effect is smaller than for the 30–35°C range. This aligns with literature showing the correlation of temperatures with mosquito traits relevant to transmission that are found to peak between 23°C and 34°C (Mordecai et al., 2017; Polgreen & Polgreen, 2018). I find stronger effects of heat exposure on fever and ARD in urban settings than in rural ones (by 1.0 percentage point and 1.8 percentage points respectively). Maternal education appears protective: children of mothers with at least primary education are 1.3 percentage points less likely to contract fever and 1.5 percentage points less likely to contract diarrhea.

The third chapter explores the relationship between retirement decision and households' gasoline consumption. I employ several waves of the Swiss Household Budget Survey (SHBS), a cross-sectional household-level survey, from 2006 to 2017. This provides monthly information on households' gasoline consumption and employment status in Switzerland. My main identification strategy uses a fuzzy regression discontinuity design (RDD). Specifically, I identify a local average treatment effect (LATE) using 2SLS and exploit the Swiss statutory retirement age as an exogenous shock to measure my treatment effect.

My empirical results suggest that there is a strong negative impact of retirement on households' gasoline consumption. Quantitatively, I show that retirement decreases households' gasoline consumption on average by 32-36 percent over my main parametric specifications. I further find that the probability to use any gasoline decreases by 5-6 percent at retirement (13-16 percent for single-person households). My results can be interpreted as an illustration of the potential effects that population aging could have on both gasoline demand as well as on the CO_2 emissions associated with it. With back of the envelope calculations, given projected demographic changes from SFSO, 2020, I estimate that the increase in the share of retired people in Switzerland could save 0.36 millions of tons of CO_2 by 2050.

This thesis provides new insights on how weather shocks and demographic change shape critical aspects of society. Across chapters one and two, I underscore that effective climate policies must be tailored to the specific contexts and vulnerabilities of countries and communities. Specifically, in chapter one, I highlight how climate shocks, through their impact on ecosystems, can affect local labor markets. I underline the need for targeted adaptation policies aimed at supporting coastal households, through income diversification, early warning systems, and more resilient employment strategies. In chapter two, my results provide novel evidence on the health risks posed by heat exposure in sub-Saharan Africa, and highlight the unequal burden faced by vulnerable groups (e.g. children of low educated mothers or living in urban areas). Better understanding the heterogeneity of these effects is key to designing more effective and equitable adaptation strategies. Finally, in chapter three, I highlight how demography in a country like Switzerland is linked to its CO_2 emissions and that demographic trends represent an important driver of CO_2 emissions associated with private mobility in developed countries.

There are several implications for policymakers. First policy implications from findings in chapter one underline the need for targeted adaptation policies aimed at directly supporting coastal households. Local governments should promote livelihood diversification, early warning systems, and more resilient employment strategies. Other findings from chapter two underline the importance of incorporating health adaptation into climate policy. Specifically, awareness campaigns and early warning systems in West Africa should target the most vulnerable groups, particularly children of less-educated mothers and those living in urban areas. Moreover, improving access to basic education may also strengthen households' resilience to climate-related health risks. In urban areas, targeted investments in infrastructure, clean water and sanitation may help mitigate the additional burden of rising temperatures.

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1 Hot waters, cold realities: Assessing the labor market impacts of marine heatwaves on coastal India†

Abstract: I employ geo-coded household-level data over 2015-2016 combined with a gridded dataset to quantify the impact of marine heatwaves (MHW) on labor market outcomes in coastal India. I construct an average measure of exposure to MHW for each household by using the degree heating week (DHW), a cumulative measure of unusually warm ocean temperatures over time. I find that one additional DHW increases the probability of being unemployed by 1.9-2.5 percentage points. The effect is larger for households experiencing higher levels of marine heat stress, with an increased probability to be unemployed of 5.5-6.5 percentage points. Other findings highlight a decreased probability to work in the fisheries sector, an increased labor market participation of women as well as a lower chance of having an all year employment after a marine heatwave. These findings highlight the potential socio-economic challenges that climate change may pose to coastal households in the coming decades.

JEL classification: I15, O10, Q54

Keywords: Climate change; marine heatwaves; India; Household surveys.

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1.1 Introduction

Anthropogenic climate change has a direct impact on ecosystems around the world, deeply transforming their functioning and structure. Oceans have absorbed more than 90% of the excess heat generated by human activities, resulting in an increase of $0.11°\mathrm{C}$ of the global seas surface temperature (SST) between 1950 and 2020, with ocean heat currently at unprecedented high levels (Venegas et al., 2023). This consistent and durable warming has impacted many marine species by shifting their distributions, leading to widespread changes in ecosystems globally (Collins, 2020; Smith et al., 2021). Beyond the global warming of the oceans, both the frequency and the intensity of marine heatwaves (MHW) have increased significantly, with eight of the ten most extreme events of MHW occurring in the last 15 years (Sen Gupta et al., 2020). Moreover, the global count of MHW days per year has also increased over its historical record (Oliver et al., 2021).

Coastal ecosystems are critical to the livelihoods of millions of people, particularly through their role in supporting fisheries and related industries. MHW events are powerful drivers of ecological disruption, causing mass mortalities, coral bleaching, and profound changes to ecosystems leading to reduced fish stock availability (Capotondi et al., 2024; Frölicher & Laufkötter, 2018; Hughes et al., 2017; Smith et al., 2021).[1] MHW can also affect marine resources by shifting their geographic distribution and seasonal cycles (Mills et al., 2013). These events can lead to important socio-economic consequences, as households depending on fisheries may lose access to marine resources, causing unemployment in both fishing and related sectors (Capotondi et al., 2024).

The main objective of this paper is to provide empirical evidence on the impact of MHW on coastal households' labor market outcomes. I employ data from the Demographic and Health Survey (DHS), a cross-sectional household-level survey, from 2015 to 2016 in India. This provides micro-level data on population and labor status for this region. The Indian case is of particular interest because of its recent exposure to a mass bleaching

[1] It has been shown that MHW in the Indian Ocean have an impact on monsoon winds and rainfall, threatening both water and food security, while also affecting tropical cyclones(Capotondi et al., 2024).

event, to its large availability of micro-level data, and to its important fisheries sector.[2,3] I match the gathered household data with NOAA's coral reef watch (CRW) program, which contains various daily global 5km-resolution satellite heat stress monitoring products.

To estimate the impact of MHW on coastal communities, I construct a measure of exposure to MHW for each household.[4] Specifically, I observe NOAA's Degree Heating Week (DHW), a cumulative measure of unusually warm ocean temperatures over time, relative to seasonal norms, in a 20 km ray around the GPS location of the household over the last three months prior to the interview date. Next, I also use a binary variable equal to one for households exposed to an average DHW value above or equal to 4. Research has shown that, beyond this threshold, damages to marine ecosystems become more likely (Van Woesik et al., 2022).

My main identification strategy uses a linear probability model combined with fixed effects at the regional, rural, yearly and monthly level. I employ spatial fixed effects at the regional level to control for time-invariant differences between regions that could possibly affect household unemployment. I also employ fixed effects at the rural level to control for time-invariant characteristics of rural areas that could impact unemployment rates.[5] I also include a vector of covariates, which includes the age, gender and years of education of the household head, household size as well as the wealth index. My main outcomes of interests are whether the household head is currently unemployed and whether the household head is employed in the fisheries sector. Moreover, I also test whether the impact of MHW has an impact on the household heads' wifes employment rate and on the type of labor activity (all year or seasonal).

Overall, my empirical results suggest a strong negative impact of MHW on households' employment. Quantitatively, I show that one more degree heating week is associated with an increase in the probability of a household being unemployed on average by

[2] Considered one of the rising sector of the economy, the Indian fisheries sector has changed itself from a subsistence, supplementary activity to an important commercial activity in the economy (Rajeev & Bhandarkar, 2022). The sector contributes to the livelihood of more than 16 million fishermen at the primary level, and twice this number across the whole supply chain (Rajeev & Bhandarkar, 2022).

[3] The relative importance of the fisheries sector is also reflected in its rising contribution to both the gross domestic product and foreign exchange earnings of the country. In 2017–18, the share of the sector to GDP rose by nearly 160% in the past 65 years (Rajeev & Bhandarkar, 2022). Moreover, India ranks third in fish exporting among all countries in the world (Das et al., 2024).

[4] Households in the DHS are interviewed at different points in time throughout the whole year.

[5] Most industries in rural areas, such as agriculture or fishing, may inherently affect employment levels. For example, areas very reliant on seasonal farming could have persistently higher seasonal unemployment.

1.9-2.5 percentage points. These results are robust to several robustness checks such as weather controls, alternative buffering distances and placebo tests. Moreover, estimates using a binary variable equal to one for households that have been exposed to high levels of heat stress (DHW above 4) are in line with the results found using the continuous DHW variable. When using this threshold, I find that the magnitude of my estimates are significantly larger than with the continuous DHW variable. In this setting, the estimated effect reaches 5.5-6.5 percentage points over my different specifications.

Next, I further examine the potential impacts of marine heatwaves on labor market outcomes by distinguishing between two types of transitions out of fisheries employment: toward other sectors and into unemployment. I find that one additional DHW decreases the probability of being employed in the fisheries sector by approximately 1.3 to 1.4 percentage points when compared to other sectors, and by 5.2 to 6.5 percentage points when compared to unemployment. For households exposed to DHW ≥ 4, these reductions amounts to around 15 percentage points relative to other sectors and 20 percentage points relative to unemployment. These findings suggest that MHW are drivers of both sectoral reallocation and significant employment loss, reflecting the vulnerability of coastal employment to weather shocks. This is consistent with evidence that, beyond certain thresholds, MHW damage ecosystems (Van Woesik et al., 2022) and reduce the availability of marine resources for fishing and related activities.

I also investigate whether female labor market participation is affected by episodes of marine heat stress. Specifically, I estimate how the employment of the household head's wifes is altered after MHW. I find that episodes of marine heat stress positively affect female labor participation. Numerically, one additional DHW increases the probability that the household head's wife is employed by 2.0-2.4 percentage points. Again, and in line with my other results, women living in households exposed to values of DHW above the 4 DHW threshold display an even larger probability to work. Women exposed to this kind of MHW have a 5.4-6.7 percentage points higher chance to work relative to women exposed to no MHW or to low to moderate levels of heat stress.

Next, I test whether MHW change the type of employment that coastal Indian households have, respectively all year or seasonal employments. I find that households that faced a intense and long episode of marine heat stress are more likely to have a seasonal job and less likely to have an all year type of employment. Quantitatively, being exposed to an average DHW value above 4 in the past three months prior to the interview date decreases the probability of having a all year employment by 6.7 to 7.5 percentage points and increases the probability of having a seasonal employment by 6.1 to 6.9 percentage points. These findings highlight that marine heat stress likely cause instability in the labor market at least in the short term.

Finally, I conduct several robustness checks to test the validity of my estimates. First, I present results from the inclusion of air temperature controls in my main models. Second, I explore how sensitive my main estimates are to the choice of the buffering zone by re-estimating my main specifications using several buffering distances. Third, I conduct a placebo treatment test for all households by randomly re-assigning exposure to MHW across households interviewed in the same survey year to verify that the observed results are not driven by random spatial or temporal correlations or unobserved factors.

There is an important consensus on the large impacts that MHW have on many ecosystems (Frölicher & Laufkötter, 2018; Smale et al., 2019; Ummenhofer & Meehl, 2017), on mortality and reproductive failure of marine species (Caputi et al., 2016; Piatt et al., 2020), on disease outbreaks in commercially viable species (Oliver et al., 2017), and mass coral reef bleaching (Depczynski et al., 2013; Hughes et al., 2017). It has also been shown that MHW induce important physiological stress, leading to reduced viability or increased mortality, changes in population structure and species' distributions, and altered ecosystem structure and functioning (Collins, 2020).

While there is much evidence on the ecological impacts of MHW, less is known about the direct economic consequences that local communities can face after episodes of marine heat stress. For instance, Cheung and Frölicher, 2020 and Cheung et al., 2021 show that MHW are expected to cause losses in fisheries revenues and livelihoods in most maritime countries. A well know studied example in Chile shows that a MHW in 2016 caused the largest fish farm mortality ever recorded globally, resulting in an export loss of US $800 million. A similar case was recorded in the United States in 2015, where episodes of MHWs led to closures of shellfisheries, costing the economy in excess of US $185 million (Moore et al., 2019; Rogers-Bennett & Catton, 2019). Mills et al., 2013 also show that MHW had major economic impacts on the US lobster industry in 2015. Specifically, they show that the 2013–2015 episodes of MHW led to closing of both commercial and recreational fisheries, causing important losses among fishing industries (Cavole et al. 2016).

Other papers have investigated the labor market impacts of reduced marine resources on developing countries. For instance, Chaijaroen, 2019 uses a panel data form Indonesia and exploits exogenous variations in coral bleaching to estimate potential impacts of reduced marine resources on income. The author finds that fishery households in affected areas experience a significant decrease in income relative to other households. Chaijaroen, 2019 also investigates the aggregate and distributional labor-market impacts of a large-scale marine environmental pollution event caused by an industrial accident in Vietnam. Their results show that this event led to a significant reduction in fishery work hours and an increase in the likelihood of working secondary jobs.

While previous studies have examined both the ecological and economic impacts of MHW at global or regional scales, this paper contributes to the literature by providing the first micro-level empirical evidence on the labor market impacts of MHW in coastal India. Unlike studies focusing on income loss or aggregate fisheries production, I exploit geo-coded household data to show how MHW affect unemployment, employment in the fisheries sector, and gendered labor patterns in a coastal setting. This allows me to document both direct and indirect labor effects of MHW using a clear identification at the household level.

The remainder of this paper is organized as follows: Section 1.2 displays information on both the weather and household data as well as the empirical strategy used in my analysis. Section 1.3 reports my estimated results. Finally, Section 1.4 provides a brief conclusion.

1.2 Empirical strategy

1.2.1 Data

To analyze the impact of MHW on Indian households, I need data that includes information on households' employment status. Then the data must be gathered from a geographic region where there is sufficient exposure to a marine heatwave for there to be a plausible impact on coastal communities. Moreover, households must be geo-referenced so that I can match them to a weather dataset containing information on water temperatures.

Weather data

The main weather data source stems from NOAA's coral reef watch (CRW) program, which contains various daily global 5km-resolution satellite heat stress monitoring products. These products are based on satellite measurements of sea surface temperature

(SST), offering high spatial resolution for heat stress monitoring. I use the DHW to quantify accumulated oceanic heat waves in India. The DHW metric measures the cumulative heat stress in the ocean by tracking how long and how much sea surface temperatures exceed the normal seasonal maximum. It is expressed in °C-weeks. The DHW cumulates HotSpots greater than 1 °C than the Maximum Monthly Mean (MMM), a baseline for the hottest monthly sea surface temperature measured at each location over the three months period. It is therefore a rolling sum (84-day window), updated daily. Glynn and D'Croz (1990) showed that water temperatures $1°\mathrm{C}$ above the maximum summertime mean temperature are sufficient to cause heat stress on ecosystems and cause coral bleaching for instance. Therefore, the DHW shows how much heat stress has accumulated in a specific area over the past three months.

For the calulcation of the DHW, the NOAA accumulates HotSpot values that are equal to or greater than $1°\mathrm{C}$. Specifically, over the past three months, a HotSpot value is counted in the DHW calculation only when the sea surface temperature reaches or is above the heat stress threshold (MMM $+1°\mathrm{C}$). A HotSpot value is therefore not taken into account on days when the SST is under the heat stress threshold. Nonetheless, a location can have a non-zero DHW value on a day where the HotSpot value is less than $1°\mathrm{C}$ or even $0°\mathrm{C}$. This condition indicates that a certain degree of heat stress was present in this area within the past three months, but local actual conditions are not stressful on the ecosystems such as coral reefs for example.

The DHW value in a specific 5km area is calculated as follows:

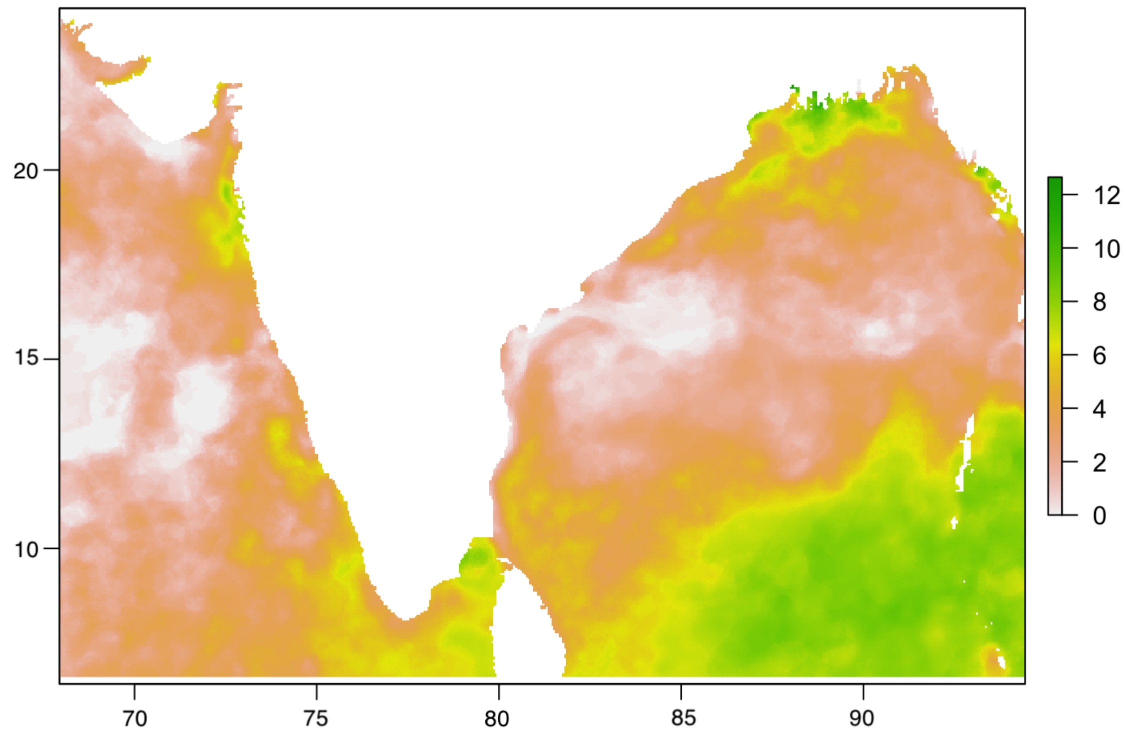
$$DHW_i = \sum_{j=i-83}^{i} \left(\frac{HS_j}{7}\right), \text{ where } HS_j \geq 1$$

Where the DHW value for a given day i (DHW_i) is calculated as the sum, over a three months (84 days) running period up to and that day included (i), of $1/7$ of each temperature HotSpot (HS_j) value of $1°\mathrm{C}$ or more. The factor of $1/7$ expresses the DHW value in terms of degree Celsius-weeks ($°\mathrm{C}$-weeks), as the stress on marine ecosystems such as coral reefs is usually occurs over weeks. The final units for the DHW are therefore in "degree Celsius-weeks" (or $°\mathrm{C}$-weeks), which combines both intensity and duration of the heat stress.[6] Figure 1.1 displays the values of the DHW for a particular day of the year around the Indian coast.

Additionally, I also used the ERA5 reanalysis data, a high-resolution global dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF),

[6]See Appendix 1.A for a detailed numerical example.

Figure 1.1 — DHW values example for a day



Note: The figure depicts an example of the different DHW values observed in a day (1st August 2015) around the Indian coast.

which is part of the Copernicus Climate Change Service (C3S). The dataset contains hourly estimates of a wide set of atmospheric, land surface, and sea state parameters. I use the 2-meter temperature variable. The dataset has a global spatial resolution of $0.25° \times 0.25°$, which translates approximately to grid squares of 28 km × 28 km. I use this information to calculate the average temperature over the 90 days preceding the interview date for each household and match this with my household data.

Household data

This paper uses data from the Demographic and Health Survey program (DHS), which contains accurate and representative data on population, health, HIV, and nutrition through more than 400 surveys in over 90 developing countries. I use the 2015-2016 geo-referenced round of survey from India. The initial dataset gathered contains 111'681 households across the whole Indian territory. As this paper focuses on households living on coastal areas, I crop the initial dataset and keep households living within a 20 km distance from the shore. Indeed, coastal communities rely on marine ecosystems for fishing activities not just as a direct form of employment but also for related activities such as fish processing, boat constructions, and net mending. After the cropping of the data, my final sample contains 6608 households around the Indian coast. Figure 1.2 shows the cluster location for all my households.

In its methodology, the DHS uses a stratified two-stage sampling approach. In the first stage of the process, enumeration areas (EAs) are randomly chosen from the census files, with a stratification based on a regional and urban/rural classification. In the second stage, surveyed households are randomly selected for interviews within the enumeration areas also referred to as clusters. In addition, the coordinates of the cluster locations are also recorded in order to facilitate the matching of the DHS household data with other geo-coded information such as weather data. One important feature of the data is the displacement of the cluster coordinates. To ensure household confidentiality, the DHS uses a random displacement of cluster coordinates, up to 5km for clusters in rural areas and up to 2km in urban areas.[7][8] The displacement of the clusters can cause some measurement errors, but given the important spatial correlation of weather data at small distances, I do not correct for this displacement as (Blom et al., 2022) has shown that it is unlikely to have a significant impact on the results. Moreover, the potential issue of inclusion and exclusion errors of the samples owing to the displacement of the clusters is verified in the alternative buffering distances section of the robustness checks section.

I used the individual recode of the DHS, which contains informations on households employment status. My main outcome of interest is whether the household head is currently unemployed or not.I construct a binary variable equal to one for all households with working-age members who reported being unemployed at the time of the interview, and zero otherwise. Table 1.1 summarizes the main variables used in the analysis for the 6608 households in my sample. 2.9 percent of the interviewed household heads in my sample declare to be unemployed at the time they were surveyed. Most of the workers are all year workers (84.5 percent) and only a fraction represent seasonal workers (14.4 percent). Also, 15.8 percent of the interviewed men's wifes are currently employed. The mean age and years of education in my sample are respectively 33 years old and 4 years. Household having a female person as head of the household represent 12.4 percent of all households. On average, the household size is of nearly 5 persons.

[7]An additional 1% of rural clusters are displaced up to 10 km.

[8]The direction of the displacement is randomly determined, ensuring that coordinates remain within the specified region.

Table 1.1 — Descriptive statistics

Continuous variables	Mean	St. Dev.	Min	Max
Age (years)	33.0	11.0	15.0	54.0
Education (years)	4.1	1.7	0.0	8.0
Household size	4.9	2.2	1.0	21.0
Wealth index	3.7	1.1	1.0	5.0
Average DHW value	1.0	1.8	0.0	9.8
Binary variables	Percentage (%)			
Unemployed	2.9			
Wife employed	15.8			
All year worker	84.5			
Seasonal worker	14.4			
Occasional worker	1.1			
Head of household is female	12.4			
High DHW zone (DHW ≥ 4)	7.4			

Notes: Data source stems from the demographic and health survey (DHS) and the National Oceanic and Atmospheric Administration.

As an indirect measure of well-being and economic status, I use the wealth index of the DHS which takes a value of 1 for the poorest households and a maximum value of 5 for the wealthiest households.[9] The average value for the wealth index in my sample is 3.7. Regarding the exposure to MHW, the average DHW value across my households is 1. 7.4 percent of the households have been exposed to a DHW value that is very high.[10] Figure 1.3 presents a histogram of the distribution of the average DHW value observed across my sample of household in a 20 km buffer zone. It can be seen that a majority of households (more than 30 percent) have not been exposed to a marine heatwave. This can either be explained by the timing of the interview or by the specific location of the household.

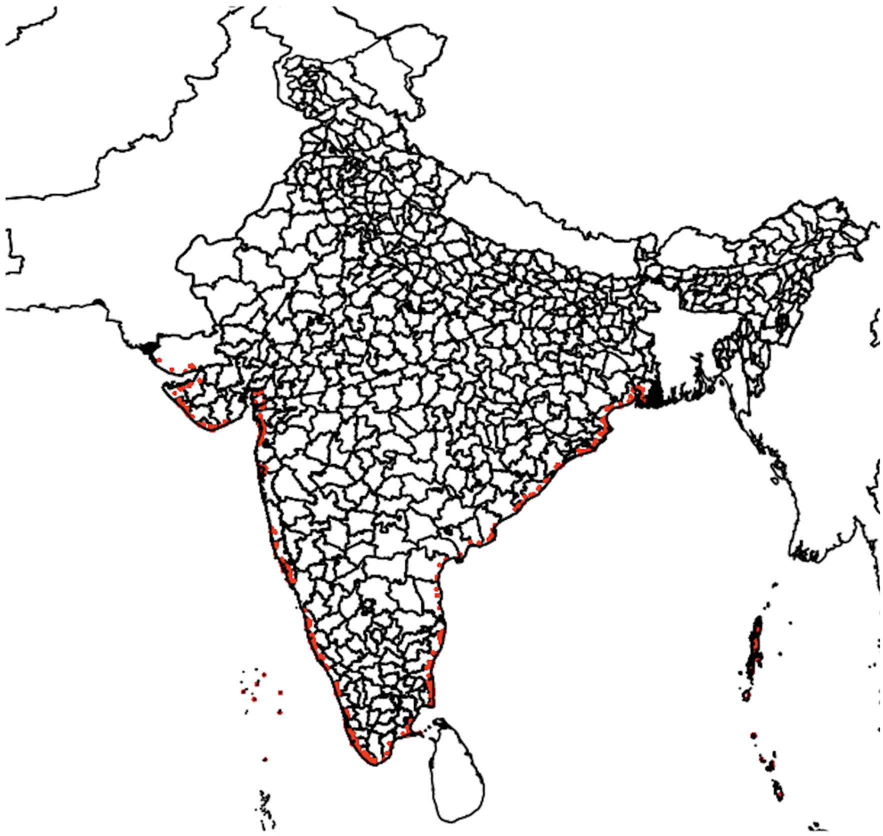
For the matching process of the household data with the weather data, I use the GPS coordinates of the DHS clusters to determine the exposure to MHW. I use DHW values up to 20 km from the cluster location.[11] I compute an average DHW value of exposure

[9] The DHS wealth index is a composite measure of the household's socio-economic status. The Index is calculated using principal component analysis by considering various housing characteristics, access to utilities like electricity or water, ownership of durable goods, and assets like land or livestock. The resulting wealth index scores categorize households into quintiles for relative comparison.

[10] Research has shown that by the time the cumulated heat stress on ecosystems (the DHW) reaches 4 °C-weeks, you can expect to observe significant impacts on marine ecosystems such as reef-wide coral bleaching.

[11] While fishing practices and distances vary based on regional differences and the type of fishing, local Indian households usually fish within a short distance from the coast, typically within 12 nautical miles (22.2 kilometers) from the coast.

Figure 1.2 — Geo-coded cluster locations from the cropped DHS data and country boundaries



Note: The red dots in the figure represent the different household clusters from the cropped DHS data in India. Each cluster is geo-referenced with a random displacement of cluster coordinates, up to 5km for clusters in rural areas and up to 2km in urban areas. The figure also shows the delimitation of the different regions in India.

for each household as the mean DHW value observed at the time of the interview in a 20 km ray around the GPS location of the household. The average DHW value of exposure can hence be defined as follows:

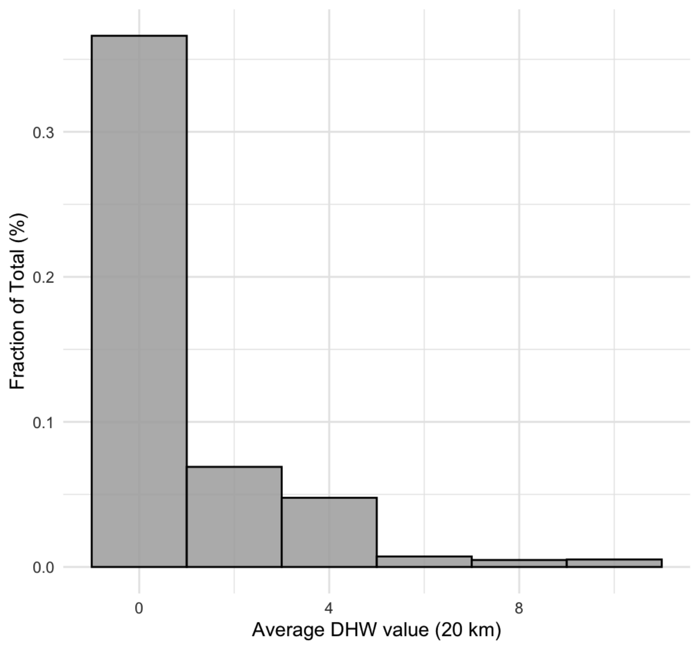
$$\overline{\text{DHW}}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} \text{DHW}_j$$

Where n_i is the number of valid raster cells within the 20 km buffer zone around household i and DHW_j corresponds to the DHW value of the j-th raster cell within the 20 km buffer zone for household i.[12]

As a secondary measure of heat stress, I use a binary variable equal to one if the average

[12] Results using different distances can be found in the alternative buffering distances section in the robustness checks section.

Figure 1.3 — Distribution of average DHW values across sample



Note: The displayed values correspond to the exposure of households to MHW measured as the average DHW value observed in a 20km buffer zone.

DHW value oberved for household i as defined above is equal or greater than 4. The High DHW value is defined as follows:

$$\text{HighDHW}_i = \begin{cases} 1 & \text{if } \overline{\text{DHW}}_i \geq 4 \\ 0 & \text{if } \overline{\text{DHW}}_i < 4 \end{cases}$$

This distinctions helps capture potential nonlinear effects of MHW on employment outcomes by distinguishing between low and high heat stress. This specific threshold is used because research has shown that, beyond this limit, damages to marine ecosystems become more likely (Van Woesik et al., 2022).

1.2.2 Identification strategy

In this section, I describe my identification strategy to test whether recent exposure to MHW has an impact on coastal communities in India. Specifically, I examine the impact on local labor markets by assessing the impact of MHW on households' unemployment, type of employment, employment in the fishery sector and on the participation of the head of the households' wife in the labor market. My main model exploits both spatial and temporal fixed effects, to control respectively for region specific characteristics and for systematic year-to-year and month-to-month variations that could bias my results.

I employ fixed effects at the regional level to control for time-invariant differences between regions that could possibly affect household unemployment such as regional economic structures, cultural and climatic factors and local governance. I complement this by adding fixed effects at the rural/urban level to control for structural differences in the labor markets between rural and urban areas that may confound my main estimates. I also include month fixed effects to account for seasonal variation that influence unemployment and household conditions such as seasonal employment patterns or temporary weather conditions. Moreover, my model also contains year fixed effects to take into account time-varying unobserved heterogeneity at the year level, that have an impact on all households.

To measure the impact of MHW on households' unemployment, I use a Linear Probability Model model that can be written as follows:

$$\mathbf{Y}_{irudmy} = \beta_0 + \beta_1 \overline{\text{DHW}}_{i,d,m,y} + \mathbf{X}_{i,r,u,d,m,y}\gamma + \alpha_r + \omega_u + \delta_m + \lambda_y + \epsilon_{i,r,u,d,m,y} \tag{1.1}$$

Where $\mathbf{Y}_{irudmy}$ is an unemployment binary variable equal to one if the person i living in region r on day d of month m in year y is currently unemployed and zero otherwise. $\overline{\text{DHW}}_{i,d,m,y}$ defined as $\frac{1}{n_i}\sum_{j=1}^{n_i} \text{DHW}_j$ represents the average DHW for household i, calculated as the mean of the DHV values (DHW_j) from the raster cells (j) within a 20 km distance, corresponding to the household's interview date. $\mathbf{X}_{i,r,d,m,y}$ is a vector of covariates for household i, which include the age and the years of education of the household head, the wealth index of the household, the size of the household as well as a dummy indicating a female household head. Finally, α_r, ω_u, δ_m and λ_y are respectively region, urban/rural, month and year fixed effects.

I also investigate potential non linear effects of heat stress on employment outcomes. I do this by re-estimating equation (1) above and by replacing my measure of heat stress exposure with a binary variable equal to one if the average DHW value observed for household i is above 4 and 0 otherwise. I use this threshold as research has shown that by the time the cumulated heat stress on ecosystems (the DHW) reaches 4 °C-weeks, there is a very high probability to observe significant impacts on marine ecosystems. The model estimated hence becomes:

$$\mathbf{Y}_{irudmy} = \beta_0 + \beta_1 \text{HighDHW}_{i,d,m,y} + \mathbf{X}_{i,r,u,d,m,y}\gamma + \alpha_r + \omega_u + \delta_m + \lambda_y + \epsilon_{i,r,u,d,m,y} \tag{1.2}$$

Next, I explore whether exposure to MHW changes the probability to be employed in the fisheries sector. MHW have been shown to induce important physiological stress as temperature thresholds are increasingly exceeded, inducing increased mortality, changes in population structures and reduced viability in marine resources (Bouwer et al., 2022; Collins, 2020). In the DHS, occupation is only defined for active workers, while unemployed individuals are recorded as a separate category. Therefore, I cannot directly estimate the impact of MHW on unemployment within the fisheries sector. Instead, I re-estimate Equations (1) and (2) using a binary outcome variable equal to one if the respondent currently works in the fisheries sector and zero otherwise.[13] I run two separate specifications. In the first, the control group includes individuals employed in other sectors, so the coefficient captures the impact of MHW on the likelihood of working in fisheries relative to other sectors. In the second, the control group consists of unemployed individuals, allowing me to measure the impact of MHW on the probability of working in fisheries relative to not working at all.

Then, I further test potential changes in the type of employment done by coastal workers by looking at changes in the probability to have an all year employment or a seasonal employment after being exposed to a marine heatwave. Finally, I investigate whether MHW encourage the household heads' wife labor marker participation by testing whether the probability for them to be employed changes after being exposed to high temperatures.

1.2.3 Robustness checks

I conduct several robustness checks. First, I add ambient temperatures to the model to test whether my results are sensitive to controlling for the mean air temperature experienced by coastal households. I use the ERA5 reanalysis data to calculate the average temperature over the 90 days preceding the interview date for each household and match this with my household data. Second, I check whether changing the buffer zone alters my main findings. I re-estimate my main specifications by changing the ray of the buffer that determines the maximum distance from the shore where households can be exposed to MHW and compute an average of the DHW values in every valid cell found in this specific area. Specifically, I compute this for a buffering distance of 5, 10, 15 and 25 km. Third, I conduct a placebo treatment test by randomly re-assigning an average DHW value from another household 100 times. In each iteration, the average DHW or HighDHW dummy is randomly drawn from another household interviewed

[13] Specifically, the occupation variable in the DHS standard classifies this group as fishermen and related workers.

in the same survey year, preserving seasonality. I then re-estimate the main specification using these placebo values.

1.3 Results

This section reports my empirical results. First, I quantify the impact of MHW on the probability of being unemployed in coastal India. Second, I specifically investigate whether MHW have an effect on the probability of being employed in the fisheries sector relatively to other sectors in the economy and to being unemployed. Finally, I also look at possible impacts of MHW on both the employment of women and also on the type of employment of households.

1.3.1 Effect of MHW on unemployment

Table 1.2 displays results from a LPM model, using coastal households from the 2015-2016 DHS standard survey in India. All model specifications include region, year and month fixed effects. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates such as age, education, household size, the level of wealth of the household and a dummy indicating a female household head. Columns (1) to (3) estimate the impact of marine heatwaves (MHW) on unemployment using the continuous DHW variable as the main regressor, while columns (4) to (6) use a binary indicator equal to one if the household was exposed to an average DHW above 4 in the past three months. Estimates in columns (1) to (3) reflect the effect of a one-unit increase in DHW on the probability of being unemployed, while columns (4) to (6) report the effect of exposure to an average DHW value exceeding 4.

Starting in columns (1) and (2), the estimated effect of the DHW on unemployment is positive and lies between 2.3 and 2.5 percentage points when including all my fixed effects and is statistically significant at the respectively five and one percent level of significance. In column (3), when adding covariates, the estimated effect is slightly reduced to 1.9 percentage points but remains statistically significant at the five percent level of significance. Therefore, MHW seem to have a strong positive impact on coastal households' unemployment.

In columns (4) and (5), the estimated impact of being exposed to a high level of DHW is positive and much larger than what was observed under columns (1) to (3). Being exposed to an average DHW value above 4 in the past three months increases the probability of being unemployed by respectively 6.3 and 6.5 percentage points and is statistically significant at the five percent level of significance. Under column (6),

Table 1.2 — Effect of MHW on unemployment

	Unemployment					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	0.023^{**}	0.025^{***}	0.019^{**}			
	(0.010)	(0.010)	(0.009)			
HighDHW				0.063^{**}	0.065^{**}	0.055^{**}
				(0.031)	(0.031)	(0.028)
Observations	6,608	6,608	6,159	6,608	6,608	6,159
Adjusted R^2	0.022	0.023	0.278	0.022	0.023	0.278
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rural FE	No	Yes	Yes	No	Yes	Yes
Covariates	No	No	Yes	No	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (1) to (3) estimate the impact of MHW on unemployment by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of MHW (DHW above 4) in the past three months as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age, education, wealth index, household size and a dummy indicating a female household head. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

adding covariates slightly reduces the estimate to 5.5 percentage points, but remains nonetheless statistically significant at the five percent level of significance. Results under columns (4) to (6) therefore show that estimates are broadly consistent and of a significantly larger magnitude than the results from columns (1) to (3).

1.3.2 Effect of MHW on employment in fisheries

In this section, I investigate whether the probability for coastal households of being employed in the fishery sector is reduced after an exposure to a marine heatwave. Specifically, I measure the effect of MHW on the probability of being employed in the fisheries sector relatively to being employed in another sector.

1.3.3 Transition from fisheries into another sector

Table 1.3 displays results from a LPM model, using coastal households from the 2015-2016 DHS standard survey in India. Columns (1) to (3) estimate the impact of MHW on the probability of being employed in the fisheries sector by using the DHW as main regressor. Columns (4) to (6) examine the impact of the exposure to high levels of MHW on employment in the fishery sector by using a binary variable equal to one if the household was exposed to an average DHW value higher than 4. Estimates in

Table 1.3 — Effect of MHW on Employment in the Fisheries Sector — Transition from Fisheries into Another Sector

	Employment in the Fisheries Sector					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	-0.014***	-0.013***	-0.014***			
	(0.004)	(0.004)	(0.004)			
HighDHW				-0.158***	-0.147***	-0.149***
				(0.036)	(0.036)	(0.035)
Observations	5,402	5,402	4,988	5,402	5,402	4,988
Adjusted R^2	0.151	0.153	0.155	0.152	0.154	0.158
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rural FE	No	Yes	Yes	No	Yes	Yes
Covariates	No	No	Yes	No	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently employed in the fisheries sector and zero if employed in an other sector. In columns (1) to (3) estimate the impact of MHW on the probability to be employed in the fisheries sector by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of MHW in the past three months as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age, education, wealth index, household size and a dummy indicating a female household head. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

columns (1) to (3) show the impact of an increase of the DHW of 1 on the probability for an Indian household living on the coast of being employed in the fisheries sector relatively to other sectors. Columns (4) to (6) show the effect of being exposed to an average DHW value above 4 on the probability of being employed in the fisheries sector relatively to being employed in another sector.

Starting in columns (1) to (2), the estimated effect of the DHW on the probability of being employed in the fisheries sector is negative and lies between 1.3 and 1.4 percentage points when including all my fixed effects and is statistically significant at the one percent level of significance. In column (3), adding the set of covariates does not seem to have an impact on the results as it is of the same magnitude and still statistically signifcant. Results suggest that episodes of marine heatwave reduce the probability of employment in the fisheries sector relative to other sectors, among employed individuals.

In columns (4) and (5), the estimated impact of being exposed to a high level of DHW on the probability of being employed in the fishery sector is negative and of a significantly larger magnitude than what was observed under columns (1) to (3). Being being exposed to an average DHW value above 4 in the past three months decreases the probability of being employed in the fishery sector relative to other sectors by respectively 15.8 and 14.7 percentage points and is statistically significant at the one percent level of significance. Under column (6), the preferred specification, I add a set of covariates, which does not alter the results. Estimates remain statistically significant at the one percent level of significance and indicate a decrease in the probability of being employed in the fishery sector relative to other sectors by 14.9 percentage points.

1.3.4 Transition from fisheries into unemployment

Next, I repeat the above analysis but change the baseline category to unemployed workers. Meaning that I measures the effect of MHW on the probability of being employed in the fisheries sector relatively to being unemployed. Results are displayed in Table 1.4. Starting in columns (1) to (3), the estimated effect of the DHW on the probability of being employed in the fisheries sector is negative and lies between 6.5 and 5.2 percentage points when including all my fixed effects and is statistically significant at the one percent level of significance.

In columns (4) to (6), the estimated impact of being exposed to a high level of DHW on the probability of being employed in the fishery sector is of a larger magnitude than what was observed under columns (1) to (3). Being exposed to an average DHW value above 4 in the past three months decreases the probability of being employed in the fishery sector relative to being unemployed by 25.1 to 19.7 percentage points. Results suggest that episodes of marine heatwave, especially important ones (DHW above 4) reduce significantly the probability of employment in the fisheries sector relatively to being unemployed, indicating therefore an important net loss of employment after an exposure to MHW.

1.3.5 Effect of MHW on wifes' emplyoment

In this section, I further investigate the impact of MHW on the labor market in coastal India by looking at the possible impacts on the household heads' wifes employment. Table 1.5 above shows results from a LPM model, the configuration of all columns is similar to Tables 1.2. Columns (1) to (3) estimate the impact of MHW on the employment of household head's wife by using the DHW as main regressor. Columns (4) to (6) examine the impact of the exposure to high levels of MHW on the employment of wifes. Estimates in columns (1) to (3) show the impact of an increase of the DHW of 1 on the probability of the household head's wife to be employed. Columns (4) to (6) show the effect of being exposed to an average DHW value above 4 on the probability of employment of the household head's wife.

Table 1.4 — Effect of MHW on Employment in the Fisheries Sector — Transition from Fisheries into Unemployment

	Employment in the Fisheries Sector					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	-0.065***	-0.062***	-0.052***			
	(0.014)	(0.014)	(0.013)			
HighDHW				-0.251***	-0.232**	-0.197**
				(0.093)	(0.094)	(0.081)
Observations	1,353	1,353	1,300	1,353	1,353	1,300
Adjusted R^2	0.233	0.235	0.388	0.226	0.228	0.383
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rural FE	No	Yes	Yes	No	Yes	Yes
Covariates	No	No	Yes	No	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently employed in the fisheries sector and zero if unemployed. In columns (1) to (3) estimate the impact of MHW on the probability to be employed in the fisheries sector by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of MHW in the past three months as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age, education, wealth index, household size and a dummy indicating a female household head. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Starting in columns (1) and (2), which include region, year, month and rural fixed effects, the estimated effect of the DHW on the probability that the household head's wife is employed is positive and lies between 2.0 and 2.1 percentage points and is statistically significant at the ten percent level of significance. In column (3), which further controls for age of the household head, age of the wife, education and the level of wealth of the household, the estimated effect is similar than in previous columns at 2.4 percentage points and is statistically significant at the five percent level of significance. Therefore, it seems that there is a positive impact of MHW on the employment of women among coastal households.

In columns (4) and (5), the estimated impact of being exposed to a high level of DHW on the probability of women being employed is larger than what previously observed under columns (1) to (3). Estimates suggest an effect more than twice larger for households exposed to levels of DHW above 4 on average. Exposure to a high average value of the DHW in the past three months increases the probability of labor market participation by women by around 5.4 to 5.5 percentage points and is statistically significant at the ten percent level of significance. The estimate is of 6.7 percentage points and is statistically significant at the five percent level of significance. Results under the last three columns

Table 1.5 — Effect of MHW on Wife's Employment

	Employment of Household Head's Wife					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	0.020*	0.021*	0.024**			
	(0.011)	(0.011)	(0.011)			
HighDHW				0.054*	0.055*	0.067**
				(0.030)	(0.030)	(0.031)
Observations	4,031	4,031	3,661	4,031	4,031	3,661
Adjusted R^2	0.029	0.028	0.032	0.028	0.028	0.032
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rural FE	No	Yes	Yes	No	Yes	Yes
Covariates	No	No	Yes	No	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household's wife is currently employed and zero otherwise. Smaller sample sizes with respect to Table 1.2 is due to many missing values for this variable. In columns (1) to (3) estimate the impact of MHW on the probability household head's wife to be employed by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of bleaching in the past three months as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age, education, wealth index and household size. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

therefore suggest that episodes of MHW tend to increase female employment, especially when the exposure to marine heat stress is prolonged and intense.

1.3.6 Effect of MHW on type of employment

In Table 1.6 below, I explore another possible impact of MHW on the labor market in coastal India by looking whether these events affect the probability to have an all year employment versus a seasonal one. Columns (1) to (4) estimate the impact of MHW on the probability of having an all year employment while columns (5) to (8) on the probability of having a seasonal employment. Columns (2), (4), (6) and (8) contain a set of controls such as age, education, household size, the level of wealth of the household and a dummy indicating a female household head. Columns (1), (2), (5) and (6) estimate the impact of MHW on the probability of having an all year or seasonal type of employment by using the DHW as main regressor. Columns (3), (4), (7) and (8) examine the impact of the exposure to high levels of MHW on the type of employment by using a binary variable equal to one if the household was exposed to an average DHW value higher than 4.

Table 1.6 — Effect of MHW on Type of Employment

	All-Year Employment				Seasonal Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DHW	-0.006	-0.004			0.005	0.003		
	(0.009)	(0.009)			(0.008)	(0.008)		
HighDHW			-0.067**	-0.075***			0.061**	0.069**
			(0.027)	(0.028)			(0.027)	(0.027)
Observations	5,402	4,988	5,402	4,988	5,402	4,988	5,402	4,988
Adjusted R^2	0.132	0.150	0.133	0.151	0.129	0.145	0.130	0.146
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	No	Yes	No	Yes

Notes: In columns (1) to (4), the dependent variable is a binary variable equal to one if the head of the household currently has an all year employment and zero if he has a seasonal or occasional employment. In columns (5) to (8), the dependent variable is a binary variable equal to one if the head of the household currently has a seasonal employment and zero if he has an all year or occasional employment. Smaller sample sizes with respect to Table 1.2 is due to many missing values for these variables. In columns (1) to (4) estimate the impact of MHW on the probability of the housheold head to have an all year employment by using the DHW as main regressor. Columns (5) to (8) use a binary variable equal to one if the household was exposed to high levels of bleaching in the past three months as main regressor. All columns contain month, year, region and rural fixed effects. Columns (2) and (4), (6) and (8) contain a set of covariates as controls such as age, education, wealth index, household size and a dummy indicating a female household head. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Starting in columns (1) and (2), the estimated effect of the DHW on the probability of having an all year type of employment is small and negative and not statistically significant over all my specifications. However, In columns (3) and (4), estimates show different results for households with an exposure to high levels of DHW. Indeed, estimates indicate that, on average, households that experienced a strong and long MHW have a 6.7 to 7.5 lower probability of having an all year employment. The estimates are statistically significant at the respectively five and one percent level of significance. Therefore, results suggest that all year employments on coastal India are only affected by MHW after passing a certain threshold of intensity and duration.

Next, in columns (5) and (6), and similarly than for all year employment, there does not seem to be a statistically significant impact of low to moderate heat stress on the probability of having a seasonal job. Nonetheless, columns (7) and (8) tell a different story again for high levels of marine heat stress. Estimates indicate that households that experienced high levels of marine heat stress in the past three months have a 6.1 to 6.9 higher probability of having a seasonal job. These results are in line with the findings for all year employments. MHW therefore seem to create instability on the labor market at least in the short run.

1.3.7 Robustness checks

In the next sections, I display results from several robustness checks. First, I present results from the inclusion of air temperature controls. Second, I show how sensitive my main estimates are to alternative buffering distances. Third, I run a placebo treatment test by re-runing my main specifications, using randomly reassigned marine heatwave exposure for each household in the sample.

Air temperature control

In this section, I control whether my results are sensitive to the inclusion of the mean air temperature over the last three months preceding the interview date of each household.[14] As air temperature could be a possible confounder, I re-run my main specifications from above and add the mean temperature over the past 3 motnh preceding the interview date as weather control. Therefore, in columns (1) and (2), the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (3) and (4), a binary variable equal to one if the head of the household is currently employed in the fisheries sector and zero if employed in an other sector or unemployed. In columns (5) and (6), a binary variable equal to one if the head of the household's wife is currently employed and zero otherwise.

In columns (1), (3) and (5), I estimate the impact of MHW on unemployment by using the DHW as main regressor. In columns (2), (4) and (6), I use a binary variable equal to one if the household was exposed to high levels of MHW (DHW above 4) in the past three months as main regressor. All columns contain rural fixed effects, a set of covariates as controls as well as region, year and month fixed effects. Results are displayed in Table 1.7. As can be seen over all columns, results are robust and mostly unchanged. In columns (1) and (2), the impact of MHW on the probability of being unemployed is still large and statistically significant but is slightly reduced after the inclusion of the weather control. The same is also observed under columns (5) and (6) for the impact on the probability of the head of the household's wife to be employed.

Alternative buffering distances

Next, I explore how sensitive my main estimates are to the choice of the buffering zone. I re-estimate columns (3) and (6) from Table 1.2, which are my preferred specifications, by changing the ray of the buffer that determines the maximum distance from the shore where households can be exposed to MHW. In other words, a circle of x-km is drawn

[14] Details on the temperature data used are described in section 1.2.1.

Table 1.7 — Effect of MHW on Unemployment, Employment in Fisheries, and Wife's Employment — Adding Air Temperature Controls

	Unemployment		Employment in Fisheries		Wife's Employment	
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	0.016*		-0.014***		0.021*	
	(0.009)		(0.003)		(0.012)	
HighDHW		0.049*		-0.104***		0.061**
		(0.028)		(0.027)		(0.031)
Observations	6,159	6,159	6,159	6,159	3,661	3,661
Adjusted R^2	0.280	0.280	0.123	0.124	0.037	0.037
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rural FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Weather Control	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In columns (1) and (2), the dependent variable is a binary indicator equal to one if the head of the household is currently unemployed and zero otherwise. In columns (3) and (4), it is equal to one if the head is employed in the fisheries sector and zero if employed in another sector. In columns (5) and (6), it is equal to one if the household head's wife is currently employed and zero otherwise. Columns (1), (3), and (5) estimate the effect of MHW using the Degree Heating Week (DHW) as main regressor. Columns (2), (4), and (6) use a binary indicator equal to one if the household was exposed to high levels of MHW (DHW > 4) in the past three months. All regressions include rural, region, year, and month fixed effects, covariates (age, education, wealth index, household size, female head), and average air temperature over the past 90 days as weather control. Heteroskedasticity-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

around each household and I subsequently compute an average of the DHW values in every valid cell found in this specific area. Specifically, I compute an average for a buffering distance of 5, 10, 15 and 25 km.

Results can be found in Table 1.8. Estimates across all columns seem to indicate that the impact of MHW on the probability of being unemployed is stable and consistent with my main estimates in Table 1.2 regardless of the choice of the buffer size. Estimates in columns (1) and (2) using a 5km buffering distance, which only considers households living very close to the shore, display the strongest effect of MHW on unemployment. Overall, these results indicate that the observed impact is unsensitive to the choice of the buffering size.

Placebo tests

In this section, I further assess the robustness of my estimates and conduct a placebo treatment test by randomly re-assigning an average DHW value from another household 100 times. In each iteration, the average DHW or HighDHW dummy is randomly drawn from another household interviewed in the same survey year, preserving seasonality. I then re-estimate the main specification using these placebo values.

Table 1.8 — Effect of MHW on Unemployment — Alternative Buffering Distances

	5km		10km		15km		25km	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DHW	0.029**		0.016*		0.016*		0.015*	
	(0.015)		(0.010)		(0.009)		(0.009)	
HighDHW		0.070*		0.045*		0.049*		0.051*
		(0.038)		(0.024)		(0.029)		(0.029)
Observations	2,194	2,194	4,133	4,133	5,348	5,348	6,701	6,701
Adjusted R^2	0.304	0.304	0.296	0.296	0.289	0.289	0.275	0.275
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rural FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

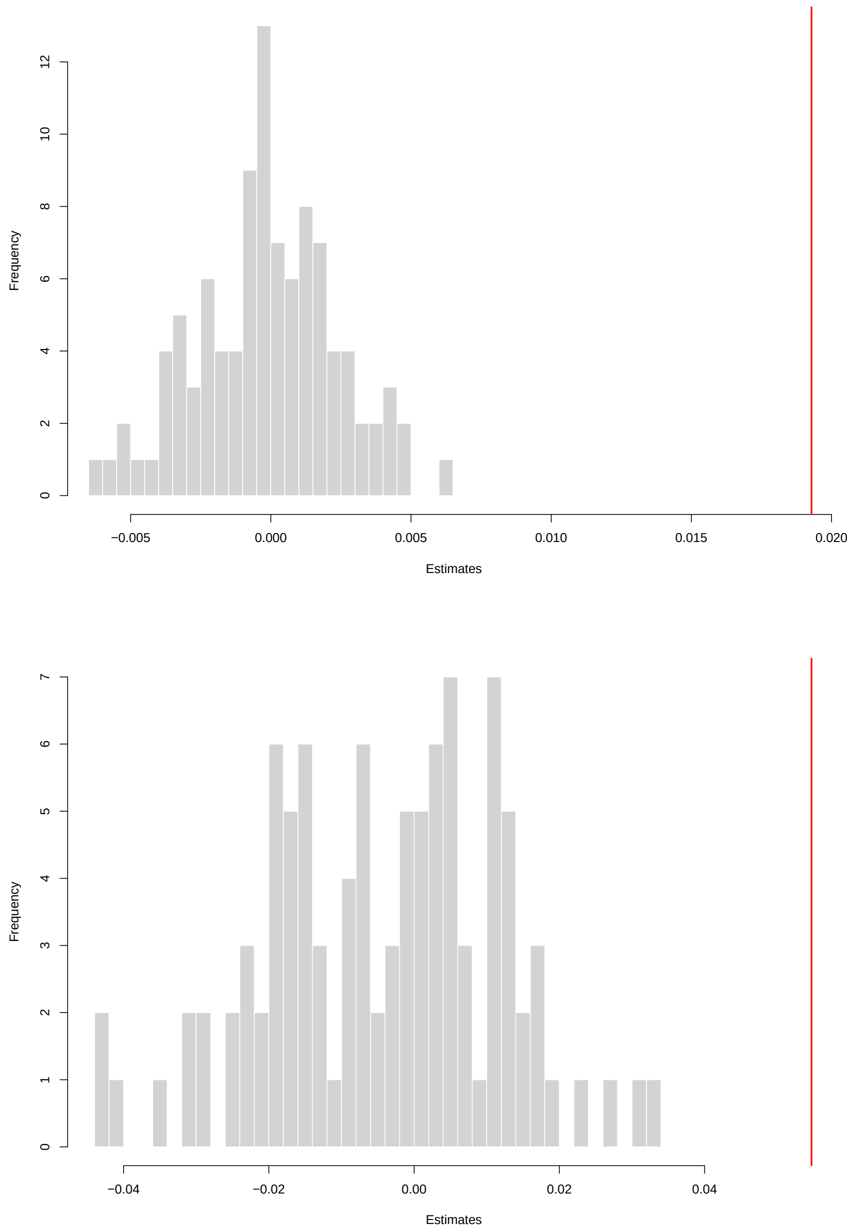
Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (1), (3),(5) and (7), I estimate the impact of MHW on unemployment by using the DHW as main regressor. Columns (2), (4), (6) and (8) use a binary variable equal to one if the household was exposed to high levels of MHW (DHW above 4) in the past three months as main regressor. Columns (1) and (2) use a 5km buffering zone around each household to estimate the average exposure to MHW, columns (3) and (4) a 10km buffering zone, columns (5) and (6) a 15km zone and columns (7) and (8) a 25km zone. All columns contain rural fixed effects, a set of covariates as controls such as age, education, wealth index, household size and a dummy indicating a female household head as well as region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Figure 1.4 displays the distribution of placebo estimates for the DHW variable (top panel) and the HighDHW dummy (bottom panel). In both cases, the true estimate obtained from the actual data (red vertical line) lies well outside the range of placebo estimates, indicating that the observed effects are highly unlikely to be driven by random spatial or temporal correlations. This reinforces the causal interpretation of the results.

1.4 Conclusion

In this paper, I use household-level microdata from the Demographic and Health Survey in coastal India, matched with gridded weather data from NOAA, to study the effects of MHW on labor market outcomes. Exposure to MHW is measured by constructing an average DHW value for each household over the three months prior to the survey, using a 20 km buffer around the GPS location. My results show that MHW have a strong negative impact on employment among coastal households. One more DHW is associated with an increase in the probability of being unemployed by 1.9 to 2.5 percentage points. This effect is larger among households exposed to high marine heat stress (DHW ≥ 4), as the probability of unemployment increases by 5.5 to 6.5 percentage points.

Figure 1.4 — Distribution of Placebo Estimates for the Effect of Marine Heatwaves on Unemployment — (Top: DHW, Bottom: HighDHW)



Note: The top panel shows the distribution of 100 placebo estimates obtained by randomly reassigning the average DHW values across households interviewed in the same survey year. The bottom panel displays the corresponding distribution using the High DHW dummy variable. This placebo procedure preserves the temporal structure of the data while breaking any systematic relationship between MHW exposure and labor outcomes. The red vertical line in each panel indicates the true estimate from the actual data.

When focusing on households employed in the fisheries sector, the negative effects are even more pronounced. One more DHW is associated with a reduction in the probability of being employed in fisheries by 1.4 percentage points relative to other sectors, and by 5.2 percentage points relative to being unemployed. For households exposed to high DHW levels, the probability of being employed in fisheries decreases by around 15 percentage points compared to other sectors, and by 20 percentage points relative to unemployment. These results suggest that MHW not only push workers out of fisheries, but also lead to net employment losses. A likely mechanism is the degradation of marine ecosystems, such as coral reefs and nearshore fisheries, upon which many of these households rely directly or indirectly. This is consistent with evidence showing that MHW have large impacts on ecosystems (Frölicher & Laufkötter, 2018), mortality of marine species (Caputi et al., 2016), and declines in fish stocks (Cheung & Frölicher, 2020), all of which can impact fisheries-based employment (Capotondi et al., 2024; Mills et al., 2013).

I also find that MHW are associated with a rise in female labor force participation. Household heads exposed to high levels of marine heat stress are 5.4 to 6.7 percentage points more likely to have their wifes working. This may reflect intra-household labor substitution in response to lost male income. In addition, exposure to MHW increases the probability of having a seasonal job and decreases the probability of being employed year-round, pointing to a shift toward more precarious and informal forms of work following weather shocks. This finding is in line with Hoang et al., 2020, which finds that fishery households exposed to a decrease in marine resources tend to have a higher probability to have secondary jobs.

Taken together, these results highlight how climate shocks, through their impact on ecosystems, can affect local labor markets and reinforce economic vulnerability. They underline the need for targeted adaptation policies aimed at supporting coastal households, through livelihood diversification, early warning systems, and more resilient employment strategies.

While this study provides new empirical evidence on the socioeconomic effects of MHW, some limitations remain. First, the use of cross-sectional data does not allow me to track longer-term household responses or migration decisions. Second, although I control for fixed effects and multiple covariates, potential measurement error from unobserved local shocks may still bias the estimates. Given the lack of studies on the economic impacts of marine heat stress, future research should aim to study longer-term household responses using panel data and investigate migration outcomes that follow these shocks.

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Appendix 1.A Numerical example for DHW calculation

Degree Heating Weeks (DHW) are a cumulative measure of marine heat stress calculated over a rolling 12-week (84-day) period. They quantify both the intensity and duration of heat exposure by summing all daily *HotSpot* values (i.e., the number of degrees Celsius that sea surface temperature exceeds the Maximum Monthly Mean, or MMM), but only when the HotSpot is at least 1°C.

Example:

Assume the Maximum Monthly Mean (MMM) for a coastal region is 29°C. Over a 12-week period (84 days), suppose the daily sea surface temperatures (SST) were as follows:

- Weeks 1–4: SST = 30°C $\rightarrow$ HotSpot = 1°C
- Weeks 5–6: SST = 31°C $\rightarrow$ HotSpot = 2°C
- Weeks 7–12: SST = 29°C or lower $\rightarrow$ HotSpot = 0°C

DHW is computed by summing the HotSpots >= 1°C, dividing each by 7 to convert daily values to degree-weeks, and summing them over the last 12 weeks:

$$\text{DHW} = \sum_{\text{days with HotSpot}\geq 1^\circ C} \frac{\text{HotSpot}_d}{7}$$

Step-by-step:

- Weeks 1–4: 4 weeks × 7 days × 1°C = 28°C-days
- Weeks 5–6: 2 weeks × 7 days × 2°C = 28°C-days
- Weeks 7–12: SST below threshold $\Rightarrow$ ignored in DHW

Total heat stress = $28 + 28 = 56$°C-days

Convert to DHW:

$$\text{DHW} = \frac{56}{7} = 8\,^\circ\text{C-weeks}$$

2 Heat exposure and the incidence of diseases in children: Evidence from sub-Saharan countries[†]

Abstract: I combine multiple rounds of geo-coded household survey data with a globally gridded climate dataset to quantify the impact of heat exposure on child disease incidence in sub-Saharan Africa. I construct hour-degree bins of temperature exposure and find that 10 additional hours of exposure to temperatures between 30–35°C in the 14 days preceding the interview increase the probability of fever, diarrhea, and acute respiratory infection by 1.5, 3.0, and 3.5 percentage points, respectively. The effects are more pronounced in urban areas as exposure in the 30–35°C range raises the incidence of fever and acute respiratory infection by an additional 1.0 and 1.8 percentage points, respectively, compared to rural settings. Finally, I also find that the effects are smaller among children of educated mothers. These findings show the health related risks posed by heat exposure in sub-Saharan Africa, and highlight the unequal burden faced by vulnerable households.

JEL classification: I15, O10, Q54

Keywords: Climate change; Temperature; West Africa; Child diseases.

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2.1 Introduction

Climate change may have severe consequences on human health through increased temperatures (Barreca, 2012; Deschenes, 2014; Deschênes & Greenstone, 2011). Extreme heat may cause a raise in the incidence of child diseases through a higher probability in contracting infectious diseases or through direct, physiological effects on child health (Zivin & Shrader, 2016). Infants and young children may be more vulnerable to heat exposure as they cannot control or react to the stress induced by the prolonged exposure to elevated temperatures (Zivin & Shrader, 2016).

This issue is widespread in sub-Saharan countries, where temperatures frequently reach levels posing high risks to human health.[1] Moreover, this region of the world is also highly susceptible to encountering frequent deadly heat waves in the coming decades (Mora et al., 2017). Its rapid urbanization is likely going to facilitate the spread of infectious diseases due to higher population densities, poor sanitation and increased breeding sites (Bickler et al., 2018).[2] Evidence on the health effects of temperature variability is a topic of great interest for understanding and projecting health impacts under climate change scenarios and urbanization dynamics (Amegah et al., 2016).

The main objective of this paper is to provide empirical evidence on the impact of exposure to high temperatures on the incidence of diseases in children. I employ several waves of the Demographic and Health Survey (DHS), a cross-sectional household-level survey, from Benin, Ghana and Togo. This provides micro-level data on population and health for this region. I match the gathered household data with the Global Meteorological Forcing Dataset (GMFD), a globally gridded dataset offering daily near-surface temperature and precipitation data.

I build a measure of exposure to temperatures by constructing hour-degree bins of temperatures. Following Schlenker and Roberts, 2009, I employ a sine curve to model the daily minimum and maximum temperatures for every grid square, aiming to estimate the temperature variations throughout the day. I use this measure of temperatures to estimate the impact of heat exposure in the two weeks prior to the survey date on the incidence of fever, diarrhea and acute respiratory disease (ARD) in children. These three symptoms are a good indicator to assess the incidence of malaria, pneumonia and gastrointestinal infections. Globally, these diseases are a leading cause of mortality

[1] There is a general consensus in the literature on the temperature threshold of 32°C where effect on mortality have been found (Banerjee & Maharaj, 2020; Deschênes & Greenstone, 2011).

[2] Approximately 94% of the world's malaria cases and deaths occured in sub-Saharan Africa in 2019.

among children under the age of five (UNICEF, 2024), with a significant proportion occurring in sub-Saharan Africa.[3]

My main identification strategy uses a linear probability model combined with region-year and region-month fixed effects separately to control for local seasonality and year-to-year trends in disease incidence. I follow the standard strategy in the weather-health economics literature that uses both spatial and temporal fixed effects to control for differences in disease incidence due to variations in temperatures. My main outcome of interest is whether the child has contracted a disease in the preceding 14 days prior to the interview date. Specifically, I estimate my model separately for fever, diarrhea and ARD as heat exposure can have an heterogeneous impact on the probability of contracting one of these diseases.

I also test whether the impact of exposure to high temperatures has a stronger effect on the incidence of diseases in children in a rural or urban setting. Even though the exact mechanisms are not yet known, urbanization has been related to decreased transmission of diseases in developing countries (Neiderud, 2015). Indeed, urban households are less exposed both to the transmission of diseases and severe diseases than households living in rural areas (Hay et al., 2005). I test whether location acts as a modulator of the extent by which heat exposure affects disease incidence in children by using an interaction term between a rural dummy variable and my different temperature exposure bins.

Moreover, I also investigate whether the impact of exposure to high temperatures differs depending on maternal education. Maternal education has been shown to influence child health through multiple channels, including better general health knowledge, awareness of hygiene, and improved caregiving practices (Glewwe, 1999). These factors may play an important role in protecting children from the negative effects of heat. I test whether maternal education moderates the relationship between heat exposure and disease incidence in children by interacting each temperature bin with a dummy variable equal to one if the child's mother has completed at least primary education. This allows me to assess whether children of more educated mothers are less affected by heat exposure in terms of disease incidence.

I use children in the 1-59 month preschool age group in my analysis. First, because most of the studies in the weather-health literature tend to focus on the impact of climate shocks in utero (Banerjee & Maharaj, 2020; Deschênes et al., 2009; Geruso &

[3]For example, In 2019, diarrhea was responsible for approximately 480,000 deaths of young children across the globe, accounting for 9 per cent of all deaths among children under age 5.

Spears, 2018). Second, the preschool age group is the most vulnerable to both prolonged heat exposure (Zivin & Shrader, 2016) and to the contraction of infectious diseases like malaria, diarrhea and other respiratory diseases like pneumonia (UNICEF, 2016; WHO, 2021). Lastly, infectious diseases are one of the major cause of mortality in young children under the age of 5, representing approximately 30 percent of global deaths among children in this age category (UNICEF, 2024)

My empirical results suggest that heat exposure has a significant impact on the incidence of fever, diarrhea and ARD in children in West Africa. Quantitatively, the probability that a child contracts a fever, diarrhea and ARD increases by respectively 1.5, 3.0 and 3.5 percentage points for 10 more hours of exposure to 30-35°C in the 14 days prior to the interview date over my main specifications. These results are robust to the inclusion of weather, socio-demographic and economic controls as well as region-year and region-month fixed effects. Next, I find that exposure to extreme temperatures (>35°C) only has an impact on the incidence of contracting a diarrhea, although, this impact is smaller than that observed for an additional 10h of exposure to the 30-35°C temperature range. Specifically, a child's probability of contracting diarrhea increases by 1.8 percentage points. This finding can potentially be explained by the correlation of temperatures with mosquito traits relevant to transmission that are found to peak between 23°C and 34°C in the literature (Mordecai et al., 2017; Polgreen & Polgreen, 2018).

Results on whether the impact of exposure to high temperatures have a stronger effect on the incidence of diseases in children in a rural or urban setting are puzzling. My findings contrast with results from the literature as urbanization has been associated with lower levels of disease transmission and severe illness compared to rural populations (Eder et al., 2018; Hay et al., 2005). I find that an additional 10 hours of exposure to temperatures between 30-35°C increases the incidence of a fever and ARD more in an urban setting compared to a rural one by respectively 1.0 and 1.8 percentage points. This finding may partly be explained by higher rates of interpersonal contact, heterogeneity in health of urban dwellers, and increased human mobility, which can contribute to elevated risks of disease transmission in urban areas (Alirol et al., 2011).

Results on the impact of heat exposure by maternal education show that children of more educated mothers are less exposed. In the case of fever, the probability of contracting the disease is 1.3 percentage points lower for children with a mother that completed at least primary education. A similar difference of 1.5 percentage points is observed for diarrhea. These findings suggest that maternal education plays a protective role in reducing the health risks associated with heat exposure, possibly through improved health knowledge, hygiene practices, or access to healthcare. No significant difference is found for ARD, indicating that the protective effect of maternal education may be specific to certain types of illnesses. These results support findings in the literature showing that maternal education can act as a protective factor in child health by improving knowledge, health-seeking behavior, and responsiveness to environmental risks (Desai & Alva, 1998; Glewwe, 1999; Grace et al., 2012).

My results are robust to the inclusion of covariates such as socio-demographic controls, characteristics of the mother and access to electricity that could confound my estimates. I also control for the water source used by the household as it could be a strong predictor of the incidence of diarrhea. While the controls capture part of the identifying variation, my main results still hold. I also conduct a placebo treatment test by randomly re-assigning heat exposure. Each child drawn from a given country has its count of hours of exposure for each respective bin randomly assigned from another child from the same country but from a different round of survey. Results from these specifications are all near-zero and not statistically significant, reinforcing the validity of my identification strategy. However, my approach does not fully account for household-level adaptive behaviors, e.g. temporary migration during extreme temperatures, which may limit the external validity of my findings to the examined sample (Spencer & Strobl, 2025).

Finally, my results are also robust to the inclusion of fixed effects at the cell level. Controlling for geographical fixed effects at the spatial unit of interest is optimal (Headey & Venkat, 2024) as areas that are likely to face heat waves may also exhibit other characteristics, such as remoteness or bad infrastructures, which are factors that could impact a child's health regardless of weather conditions. As all cells are not repeatedly observed over time, I am only able to include cell fixed effects for a fraction of households. I re run my main specifications by using a 5km tolerance threshold to further include cells that were close to the ones observed in the previous period.

The core of the weather-health literature focuses on the impact of rising temperatures on mortality (Banerjee & Maharaj, 2020; Barreca, 2012; Deschenes, 2014; Deschênes & Greenstone, 2011; Gasparrini et al., 2015), birthweight (Deschênes et al., 2009; Grace et al., 2015) and nutrition (Baker & Anttila-Hughes, 2020; Blom et al., 2022). Apart from vector-borne diseases like malaria, there's scarce research on the impacts of climate change on human health in sub-Saharan countries, despite increasing awareness of the region's susceptibility to climate-related challenges (Amegah et al., 2016).[4]

The negative effects of increased temperatures on the incidence of diarrheal diseases in developing countries has been explored in a number of previous studies. Increased hospital admissions for diarrhea due to elevated temperatures were observed in Peru (Checkley et al., 2000), Bangladesh (Hashizume et al., 2007) and in the Pacific Islands (Singh et al., 2001). In Africa, the findings on the impact of elevated temperatures on the incidence of Diarrhea are contrasted. For instance, Bandyopadhyay et al., 2012 study how climate variations impact the regional incidence of diarrhea in children under the age of three in sub-Saharan Africa. They find that an increase in monthly average maximum temperature raises the incidence of diarrhea. In their study, Alexander et al., 2013 examine the impact of climate change on children's health in South Africa and find that elevated maximum temperature was not associated with increased diarrheal incidence.

As pointed out in their systematic review of the literature, Amegah et al., 2016 suggest that the exposure to higher ambient temperatures might add to the disease and mortality burden in sub-Saharan Africa. However, the overall evidence is somewhat weakened by the scarcity, methodological constraints, and notable inconsistencies in the findings of those studies. To the best of my knowledge, this is the first empirical analysis studying the relation between heat exposure and disease incidence in children using a precise measure of temperature exposure and a clear identification strategy.

Finally, attention has been given to how vulnerability to heat-related illness may differ across households. In particular, maternal education has been shown to influence child health outcomes through improved hygiene practices, better health knowledge, and increased use of healthcare services (Desai & Alva, 1998; Glewwe, 1999). A few recent papers also suggest that maternal education can help buffer the effects of environmental shocks on child nutrition and health (Grace et al., 2012). By testing whether the effect of heat exposure on disease incidence varies by maternal education, this paper also contributes to the limited literature on the heterogeneous impacts of climate on health in developing countries.

The remainder of this paper is organized as follows: Section 2.2 displays information on the data and the empirical strategy used in my analysis. Section 2.3 reports my

[4] Although sub-Saharan countries have a minor contribution to climate change (Kula et al., 2013), they are expected to experience the largest health-related impacts with 34% of global Disability-Adjusted Life Years (DALYs) attributed to climate change effects (Costello et al., 2009).

estimated results followed by sensitivity checks. Finally, Section 2.4 provides a brief conclusion.

2.2 Empirical strategy

In this section, I first give a summary of my household and weather data, and then present my identification strategy to estimate the impact of heat exposure on the incidence of child diseases in West Africa.

2.2.1 Data

To analyze the impact of high temperatures on children's health, I need data with several features. First, I need several surveys with geographical and temporal spread. Second, the data must include information on children's diseases that appeared in a short time span prior to the survey. Third, the data must be gathered from a geographic region where there is sufficient exposure to high temperatures for there to be a biologically plausible impact on children's health. Fourth, households must be geo-referenced so that I can match them to a weather dataset containing information on temperatures and precipitations.

Household data

This paper uses data from the Demographic and Health Survey program (DHS), which contains data on population, health, Human Immunodeficiency Virus, and nutrition through more than 400 surveys in over 90 developing countries. I use 6 geo-referenced rounds of survey from three West African countries where maximum temperatures often exceed 32 °C, a threshold known to have a significant impact on health and mortality (Deschênes & Greenstone, 2011). Specifically, I gather data from Benin (2001, 2012), Ghana (2008,2014) and Togo (1998, 2013).

In its methodology, the DHS employs a stratified two-stage sampling approach. In the first stage, enumeration areas (EAs) are randomly chosen from the census files, with a stratification based on a regional and urban/rural classification. In a second stage, surveyed households are selected randomly for interviews within the EAs also referred to as clusters.[5] In addition, the coordinates of the cluster locations are also recorded in order to facilitate the matching of the DHS household data with other geo-coded information such as weather data.

One important feature of the data is the displacement of the cluster coordinates. To

[5]The DHS specifically interviews all women within the reproductive age range of 15 to 49 years.

Table 2.1 — Descriptive statistics

Continuous variables				
Variable	Mean	St. Dev.	Min	Max
Age of mother (years)	29.6	6.6	15.0	49.0
Education of mother (years)	1.8	3.2	0.0	21.0
Age of child (months)	26.6	16.7	0.0	59.0
Household members	7.5	4.0	1.0	46.0
Number of children	2.2	1.3	0.0	12.0
Hours exposed to <20°C	3.4	5.5	0.0	26.0
Hours exposed to 20–25°C	59.1	22.6	5.0	121.0
Hours exposed to 25–30°C	145.1	43.4	68.0	238.0
Hours exposed to 30–35°C	99.3	15.7	72.0	143.0
Hours exposed to >35°C	31.5	30.1	0.0	123.0
Binary variables				
Variable	Percentage (%)			
Living in urban area	29.3			
Living in rural area	70.7			
Had diarrhea in last two weeks	13.3			
Had fever in last two weeks	17.4			
Had ARD in last two weeks	15.8			

Notes: Data source is the Demographic and Health Survey (DHS) and the Global Meteorological Forcing Dataset (GMFD) from the Terrestrial Hydrology Research Group at Princeton University.

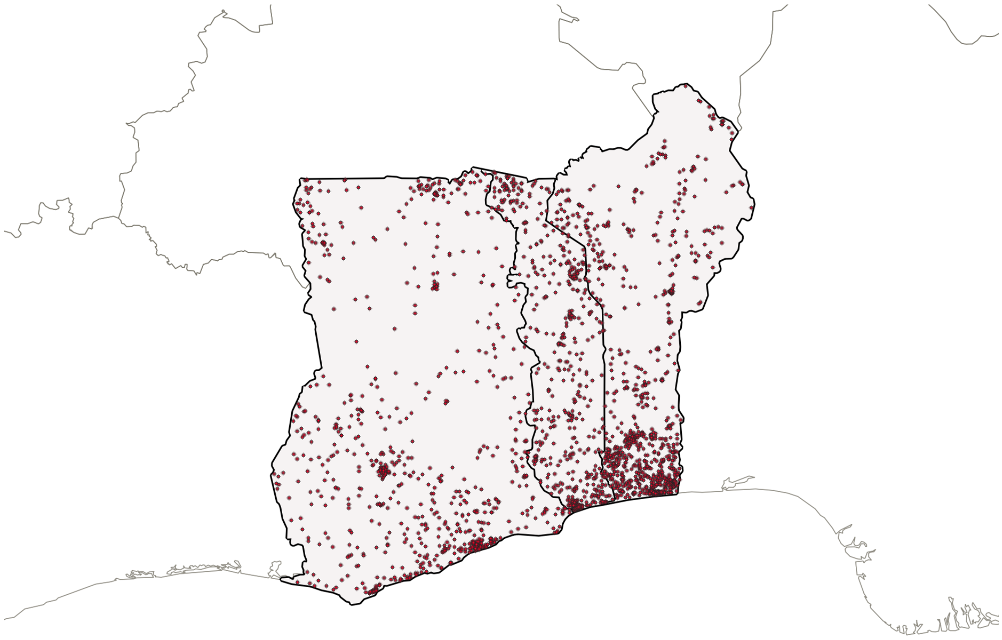
ensure household confidentiality, the DHS uses a random displacement of cluster coordinates, up to 5km for clusters in rural areas and up to 2km in urban areas.[6][7] The displacement of the clusters can cause some measurement errors, but given the important spatial correlation of weather data at small distances, I do not attempt to correct for this displacement as it is unlikely to have a significant impact on the results (Blom et al., 2022). Figure 2.1 depicts the cluster location from the 6 different geo-coded rounds of survey. To link DHS data with weather data, I utilize GPS coordinates of DHS clusters and grid squares. The weather data corresponding to a particular grid square is matched to a cluster if the cluster falls within that grid square.

From the many variables available in the survey, many focus on child health. My main outcomes of interest use information on whether children have had fever, diarrhea and acute respiratory diseases (ARD) in the 2 weeks prior to the survey date or not. Table 2.1 summarizes key characteristics of the sample. Mothers are, on average, 29.6 years

[6]An additional 1% of rural clusters are displaced up to 10 km.

[7]The direction of the displacement is randomly determined, ensuring that coordinates remain within the specified region.

Figure 2.1 — Geo-coded cluster locations from the DHS and country boundaries



Note: The red dots in the figure above represent the different household clusters from the DHS data in Ghana, Benin and Togo. Each cluster is geo-referenced with a random displacement of cluster coordinates, up to 5km for clusters in rural areas and up to 2km in urban areas.

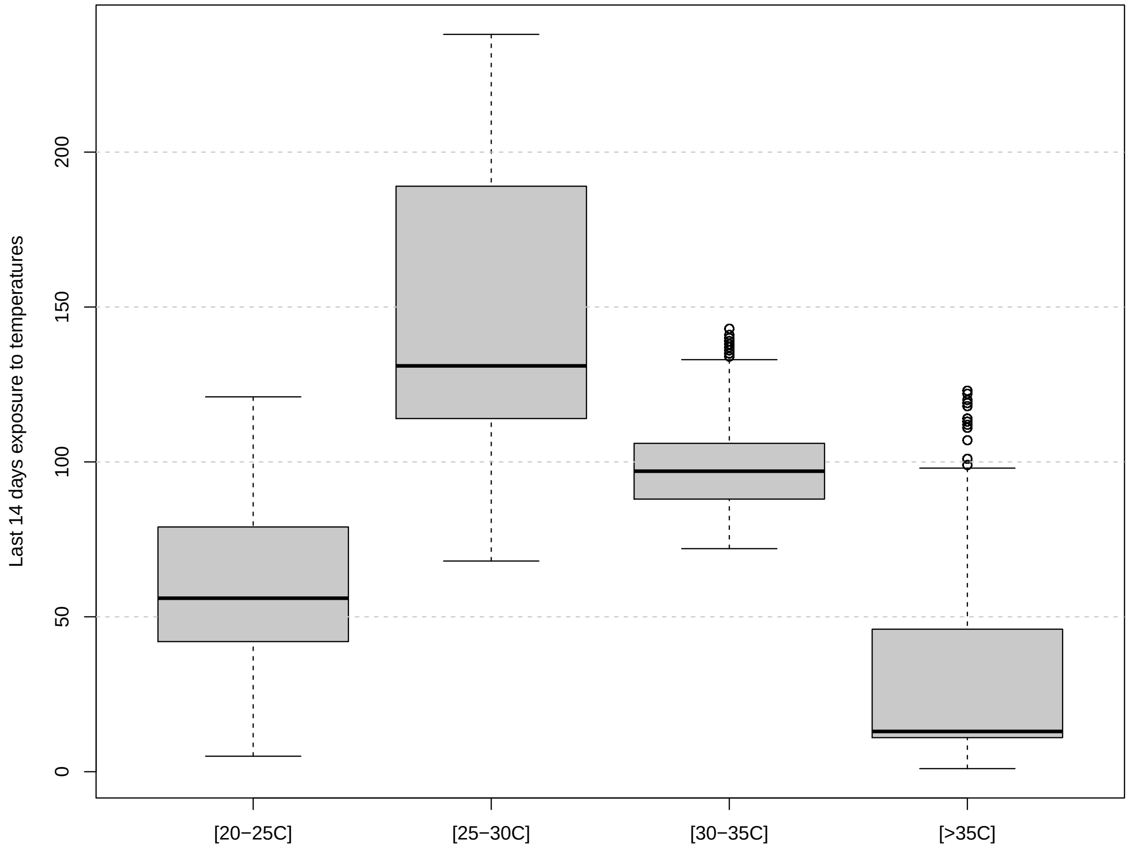
old with 1.8 years of education. Children have a mean age of 26.6 months. Households are relatively large, with an average of 7.5 members and 2.2 children. Most households in the sample (70.7%) are located in rural areas, while 29.3% in urban areas. In terms of child health outcomes, 13.3% of children experienced diarrhea, 17.4% had a fever, and 15.8% suffered from an acute respiratory disease (ARD) in the two weeks prior to the survey.

Weather data

The Global Meteorological Forcing Dataset (GMFD), provided by the Terrestrial Hydrology Research Group at Princeton University, is a globally gridded dataset that contains daily maximum and minimum near-surface temperature and precipitation data spanning from 1948 to 2016. The dataset is presented at a spatial resolution of 0.25° × 0.25°, which translates approximately to grid squares of 28 km × 28 km. [8] This dataset stands out as one of the few publicly accessible datasets that meets the necessary

[8] The GMFD dataset was compiled from multiple observational meteorological datasets and reanalysis data from the National Centers for Environment Prediction/National Center for Atmosphere Research (NCEP/NCAR) (Sheffield et al., 2006).

Figure 2.2 — Distribution of temperatures in the sample



Note: The above figure displays the distribution hours of exposure for each respective temperature bin in the 14 days prior to the interview date for each child in my sample.

temporal and spatial criteria for my analysis.

Following Schlenker and Roberts, 2009, I employ a sine curve to model the daily minimum and maximum temperatures for every grid square, aiming to estimate the temperature variations throughout the day. I assume a symmetric daily temperature curve, where temperatures ascend from the minimum to the maximum and then descend back to the same minimum.[9] Sine curves are estimated for the past 14 days prior to the specific interview date of each household. I employ the standard binning approach to determine how different levels of heat exposure affect the probability that a

[9]See section 2.A in the appendix for a detailed decomposition of the parameters in the sine curve.

child contracts a disease. My bins count the number of hours that each household was exposed to a specific temperature bin in the past 14 days prior the interview date. The bins are categorized in the following manner: $\leq 25°\mathrm{C}, (25-30]°\mathrm{C}, (30-35]°\mathrm{C},$ and $> 35°\mathrm{C}$.

By counting the number of hours within each temperature bin, I follow the approach proposed by Blom et al., 2022 that allows to more precisely capture the intensity of temperature exposure.[10] By estimating the number of hours within each temperature bin, I am able to capture more precisely the intensity of temperature exposure. This is particularly meaningful in this case as there is a general consensus that young children suffer more from diseases such as diarrhea due to underdeveloped immune system. For example, 72 percent of diarrhea related mortality occurs in the 0-2 year old range (Walker et al., 2013).

Figure 2.2 displays the distribution hours of exposure for each respective temperature bin in the 14 days prior to the interview date. The 25–30°C bin is the most densely represented, with a median of 131h of exposure, reflecting the concentration of mean temperatures within the 25–30°C range. Exposure to temperatures between 30-35°C is less pronounced with a median of 100h of exposure in the preceding 14 days. The extreme temperature bin (above 35°C) is by far the smallest bin with only a median of 13h of exposure in the past 14 days.

2.2.2 Linear Probability Model

In this section, I describe my empirical strategy to test whether recent exposure to high temperatures increases the risk to contract a disease for a young child. My main model follows the conventional empirical approach in the weather-health literature that exploits both spatial and temporal fixed effects. I use region-level fixed effects and interact them with both month and year fixed effects. Following Blom et al., 2022, I separately interact the region fixed effects with controls for month and year of interview to control for local seasonality and year-to-year trends in disease incidence.

It is important to emphasize that controlling for geographical fixed effects at the spatial unit of the weather variables of interest (grid) is optimal (Headey & Venkat, 2024). This ensures that any variation in weather is solely attributed to temporal changes. If sufficient granular fixed effects are not included, then variation in weather will partially come from spatial variation, which can lead to a bias in my estimate of interest (Headey

[10] As emphasized by Deschenes, 2014, the counting of days within specific temperature intervals, has become standard in the weather–health literature.

& Venkat, 2024). Areas that are likely to face extreme temperature shocks may also exhibit other characteristics, such as remoteness or bad infrastructures, which are factors that could impact a child's health regardless of weather conditions.

Ideally, I would like to use fixed effects at the cell-level, which is the smallest possible unit in the dataset. Unfortunately, as cells are not observed over time in this setup, it is not possible to utilize this type of fixed effects for the whole dataset.[11] In consequence, some temporal variation (comparing children in the same region interviewed in the same month but different years) and spatial variation (comparing children in the same month and year but residing in different climatic areas within the same region) cannot be fully eliminated. Nonetheless, I am able to exploit these cell fixed effects for a fraction of clusters that are repeatedly observed over time, which will serve as a robustness check for the main results using region fixed effects. I am able to use these cell fixed effects for a sub-sample of 3779 households in the robustness checks section. My main model also include a set of covariates at the individual or household level such as child's age and sex, maternal education, household size, access to electricity, and living in a rural area. My empirical strategy cannot fully account for household-level adaptive behaviors, such as water use or migration during episodes of extreme temperatures. Therefore the external validity of my results will likely be limited to my examined sample (Spencer & Strobl, 2025). The main Linear Probability Model model can be written as follows:

$$\mathrm{D}_{icrdmy} = \sum_l \beta_1^l T^l_{cdmy} + \beta_2 P_{cdmy} + \gamma_{rm} + \delta_{ry} + \epsilon_{icrdmy}$$

D_{icrdmy} is a disease binary variable equal to one if the child i in cell c of region r on day d of month m in year y has had the disease in the 14 days prior to the survey date and equal to zero if not. I estimate the model separately for fever, diarrhea and ARD. I measure exposure in the 14 days prior to the day-of-interview, d : $T^l_{cdmy} = \sum_{n=d-14}^{d} l_{cn}$ is the number of hours per month in each temperature bin l in cell c in the 14 days prior to the date of interview. I re-scale T^l_{cdmy} to be in tens of hours to ease both interpretation and readability. My main coefficient, β_1^l, can be interpreted as the effect on the probability that child i contracts a disease of an increase of exposure of $10\ \mathrm{h}$ in temperature bin, l, relative to the omitted bin, $\leq 25°\mathrm{C}$. P_{cdmy} controls for precipitations in cell c on the 14 days prior to the survey date. X_{icrdmy} : is a vector of covariates at the individual or household level such as child's age and sex, maternal education, household size, access to electricity, and living in a rural area. γ_{rm} and δ_{ry} are respectively region-month and

[11] Not all cells are observed in the different waves of the survey as it is not a panel data. Therefore only a fraction of the cells are observed over time and allow for the inclusion of fixed effects at the cell level.

region-year fixed effects respectively.

I also investigate whether the impact varies depending on whether the household resides in a rural or urban setting. Urbanization is often associated with decreased transmission even though the exact mechanisms are not yet known (Neiderud, 2015). Urban population are on average subject to decreased levels of disease transmission and severe disease than their rural counterparts (Hay et al., 2005). I test whether heat exposure has a stronger effect on the incidence of diseases among children living in a rural setup by using an interaction term between a rural dummy variable and my different temperature exposure bins.

Moreover, I also examine whether the effect of heat exposure differs by maternal education. To do this, I interact each temperature exposure bin with a binary indicator equal to one if the child's mother has completed at least primary education and zero otherwise. This interaction allows me to test whether children of more educated mothers are less likely to contract a disease following exposure to high temperatures, compared to those whose mothers have not completed primary schooling. This is motivated by a large literature documenting the role of maternal education in improving child health outcomes through mechanisms such as health knowledge and hygiene practices (Desai & Alva, 1998; Glewwe, 1999; Grace et al., 2012).

Finally, I conduct robustness checks of the main estimates. First, I control for the water source used by the household as this can be a possible confounder for gastro-intestinal diseases such as diarrhea. Moreover, I run a placebo treatment test by re-runing my main specifications, using randomly reassigned heat exposure for each child in the sample. Finally, I run my main specifications for a fraction of households using cell fixed effects as this ensures that any variation in weather is solely attributed to temporal changes.

2.3 Results

This section reports my empirical results. First, I quantify the impact of heat exposure on the incidence of diseases in children. Second, I estimate whether this effect is stronger in rural areas. Third, I test whether there is an heterogeneous effect by maternal education. Finally, I test the robustness of my results by providing various sensitivity checks.

2.3.1 Effect of heat exposure on disease incidence

Table 2.2 displays results from a LPM model, using several waves of the DHS surveys in Benin, Ghana and Togo. All model specifications include precipitations as weather control and both region-year and region-month fixed effects. Columns (2), (4) and (6) contain additional control variables such as age, household size, characteristics of the mother (age and education), access to electricity, and a dummy indicating a household living in a rural area. In columns (1) and (2), I report LPM regression estimates without and with covariates for the incidence of fever in the 14 days preceding the interview date. Columns (3) and (4) are identical to (1) and (2) but test the effect of heat exposure on the incidence of diarrhea, while columns (5) and (6) test it on the incidence of ARD. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C).

Starting in columns (1) and (2), the estimated effect of an increased exposure to high temperatures on the incidence of fever is positive and statistically significant for the 25-30°C and 30-35°C bin. The estimated effect lies between 1.0 and 1.5 percentage points of increased probability of having a fever in the past 14 days. The strongest effect is observed for the 30-35°C bin with an increase of 1.5 percentage points in the probability to contract a fever for 10 more hours of exposure to these temperatures. Estimates in columns (3) and (4), that test the impact of heat exposure on the incidence of diarrhea, also indicate a positive and statistically significant effect of heat exposure of 3.0 (for column 4) percentage points for the 30-35°C bin.

In columns (5) and (6), the estimated effect of exposure to high temperatures on the incidence of an ARD is different than what is observed in the previous columns. As can be seen under column (6), the estimated effect of heat exposure on the incidence of an ARD seems to peak sooner than for the other diseases. It can be seen that the impact of an exposure to an additional 10h to 25-30°C is slightly stronger than an additional 10h of exposure to 30-35°C , respectively 3.7 and 3.5 percentage points. As for fever, the effect is no longer significant above 35°C .

Interestingly, the effect of temperature on the incidence of both fever and diarrhea in children increases up to the 30–35°C range but declines at extreme heat levels (>35°C). Indeed, an additional 10 hours of exposure to the 30–35°C range has a consistently stronger impact on the probability of fever and diarrhea in children compared to the same increase in exposure above 35°C. This result reflects prior literature on the

Table 2.2 — Effects of Heat Exposure on the Incidence of Diseases

	Fever		Diarrhea		ARD	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours 25–30°C	0.010**	0.010**	0.026***	0.025***	0.038***	0.037***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)
Hours 30–35°C	0.014***	0.015***	0.029***	0.030***	0.033***	0.035***
	(0.005)	(0.005)	(0.009)	(0.009)	(0.010)	(0.010)
Hours >35°C	-0.005	-0.004	0.018***	0.019***	0.002	0.004
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	21,957	21,943	21,957	21,943	21,955	21,941
Adjusted R^2	0.112	0.113	0.082	0.082	0.106	0.106
Reg × Y, Reg × M FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the child has contracted the disease in the past 2 weeks preceding the interview date and zero otherwise. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C). Columns (2), (4), and (6) include additional covariates at the individual or household level such as child's age and sex, maternal education, household size, access to electricity, and living in a rural area. All specifications include precipitation as weather control and both region-year and region-month fixed effects. Heteroskedasticity robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

impact of temperatures on the spread of diseases from mosquitos.[12] All mosquito traits relevant to transmission (biting rate, egg-to-adult survival and development rate, adult lifespan, and fecundity) respond strongly to temperature and peak between 23°C and 34°C (Mordecai et al., 2017; Polgreen & Polgreen, 2018). This could potentially explain why the extreme temperature bin presents a smaller effect for fever as I only capture the incidence of the disease in children, which is directly correlated with mosquito traits relevant to transmission. Another possible mechanism for the decreasing effect at extreme temperatures (>35°C) might be explained by behavioral adaptation. Households may reduce outdoor activities or increase protective behaviors (e.g., staying indoors, improving ventilation), therefore limiting children's exposure to diseases.

2.3.2 Heterogeneity of impact in urban/rural setting

In this section, I test whether the impact of exposure to high temperatures on the incidence of diseases in children has a stronger effect in a rural/urban setting. I interact the different temperature bins with an indicator variable equal to one if the household lives in a rural setting and equal to zero otherwise. The estimated coefficient on the interaction term therefore gives me the difference in the effect of heat exposure for each bin for a household living in a rural setting with respect to a household living in an urban setting. Results are displayed in Table 2.3.

[12] Diseases transmitted by mosquitoes (MBD), including malaria, dengue, chikungunya, and Zika, pose the greatest risk of vectorborne illness contraction, especially in Africa (Giesen et al., 2020). To illustrate, Africa alone accounts for 93 percent of all malaria cases globally (Franklinos et al., 2019).

Table 2.3 — Effects of Heat Exposure on the Incidence of Diseases — Heterogeneity of Impact in Urban/Rural Setting

	Fever		Diarrhea		ARD	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours 25–30°C	0.011***	0.010**	0.027***	0.026***	0.039***	0.038***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)
Hours 30–35°C	0.022***	0.023***	0.040***	0.041***	0.048***	0.049***
	(0.006)	(0.006)	(0.012)	(0.012)	(0.013)	(0.013)
Hours >35°C	-0.004	-0.004	0.026***	0.026***	0.008	0.009
	(0.004)	(0.004)	(0.008)	(0.008)	(0.009)	(0.009)
Hours 25–30°C × Rural	-0.001	-0.001	0.00004	0.0003	-0.0003	-0.0001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Hours 30–35°C × Rural	-0.011**	-0.010**	-0.014	-0.014	-0.020**	-0.018*
	(0.005)	(0.005)	(0.009)	(0.009)	(0.010)	(0.010)
Hours >35°C × Rural	-0.001	0.0003	-0.009	-0.008	-0.006	-0.006
	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	21,957	21,943	21,957	21,943	21,955	21,941
Adjusted R^2	0.112	0.113	0.082	0.082	0.106	0.107
Reg × Y, Reg × M FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the child has contracted the disease in the past 2 weeks preceding the interview date and zero otherwise. The different temperature bins are interacted with an indicator variable equal to one if the household lives in a rural area and equal to zero otherwise. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C). Columns (2), (4), and (6) include additional covariates at the individual or household level such as child's age and sex, maternal education, household size, and access to electricity. All specifications include precipitation as weather control and both region-year and region-month fixed effects. Heteroskedasticity robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Starting with column (1), the estimated interaction term for the 30–35°C bin is negative and statistically significant at the five percent level of significance, indicating that the impact of 10 additional hours of exposure to this temperature range is stronger in urban settings compared to rural ones. Specifically, the effect is approximately 1.0 to 1.1 percentage points higher in urban areas. This result is robust to the inclusion of covariates, as shown in column (2), where the coefficient remains significant and of a similar magnitude. In other words, children living in urban areas are more likely to contract a fever when exposed to higher temperatures in the 30–35°C range. Interestingly, this result contrasts with previous literature on disease transmission dynamics, which generally associates rural areas with higher vulnerability to vector-borne illnesses. For instance, Eder et al. (2018) document that urban populations, on average, experience lower levels of malaria transmission and severe illness than rural populations.

The same conclusion does not hold for diarrhea. The interaction terms for the 30–35°C bin in columns (3) and (4) are not statistically significant, suggesting no differential

Table 2.4 — Effects of Heat Exposure on the Incidence of Diseases — Heterogeneous Effects by Maternal Education

	Fever		Diarrhea		ARD	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours 25–30°C	0.011***	0.011***	0.027***	0.026***	0.039***	0.038***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.008)
Hours 30–35°C	0.018***	0.019***	0.033***	0.035***	0.037***	0.038***
	(0.005)	(0.005)	(0.010)	(0.010)	(0.011)	(0.013)
Hours >35°C	-0.003	-0.002	0.018***	0.019***	0.005	0.005
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.009)
Hours 25–30°C × Education	-0.003	-0.003	-0.004	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Hours 30–35°C × Education	-0.013***	-0.013***	-0.015**	-0.015**	-0.006	-0.005
	(0.004)	(0.004)	(0.007)	(0.007)	(0.009)	(0.010)
Hours >35°C × Education	-0.004	-0.001	0.007	0.007	-0.001	-0.001
	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)	(0.006)
Observations	21,957	21,943	21,957	21,943	21,957	21,941
Adjusted R^2	0.112	0.113	0.077	0.082	0.106	0.107
Reg × Y, Reg × M FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the child has contracted the disease in the past 2 weeks preceding the interview date and zero otherwise. The different temperature bins are interacted with an indicator variable equal to one if the mother of the child has received primary education or more and equal to zero otherwise. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C). All columns include region-year and region-month fixed effects and precipitations as weather control. Columns (2), (4), and (6) include additional covariates at the individual or household level such as child's age and sex, maternal education, household size, access to electricity, and living in a rural area. Heteroskedasticity robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

effect of heat exposure between rural and urban settings in this case. In contrast, results in columns (5) and (6) for acute respiratory diseases (ARD) are similar to those found for fever. The interaction terms for the 30–35°C bin are again negative and statistically significant, indicating a stronger effect in urban areas. The difference is more pronounced than for fever: children living in urban households experience an increase in the probability of ARD that is approximately 1.8 to 2.0 percentage points higher than that of rural children when exposed to 10 additional hours in the 30–35°C range. These findings may partly be explained by higher rates of interpersonal contact, heterogeneity in health of urban dwellers, and increased human mobility, all of which can contribute to elevated risks of disease transmission in urban areas (Alirol et al., 2011).

2.3.3 Heterogeneous effects by maternal education

This section investigates whether the impact of heat exposure on the incidence of child diseases differs by maternal education. I interact the different temperature bins with an indicator variable equal to one if the child's mother has completed at least primary education and zero otherwise. The estimated coefficients on the interaction terms therefore capture the difference in effect between children of educated and uneducated mothers. Results are shown in Table 2.4.

Starting in column (1), the interaction term for the 30–35°C bin is negative and statistically significant, indicating that the effect of 10 additional hours of exposure to this temperature range is smaller for children whose mothers have received at least a primary education. The estimate suggests a difference of 1.3 percentage points. This finding is robust to the inclusion of covariates in column (2), where the coefficients remain nearly unchanged. Therefore, results indicate that children of more educated mothers are less likely to contract a fever under heat exposure in the 30–35°C range. This may reflect differences in protective behaviors, healthcare access, or household environments associated with maternal education.

A similar pattern is observed for diarrhea. The interaction term for the 30–35°C bin in columns (3) and (4) is also negative and statistically significant, with an estimated difference of approximately 1.5 percentage points. This suggests that maternal education attenuates the effect of heat exposure on the incidence of diarrhea in children. In contrast, no statistically significant interaction is found in the case of acute respiratory diseases (ARD), as shown in columns (5) and (6). The coefficients on the interaction terms for all temperature bins are not statistically significant. This suggests that the protective effect of maternal education observed for fever and diarrhea does not extend to ARD.

Overall, these results suggest that maternal education plays a role in mitigating the health effects of heat exposure for fever and diarrhea. This highlights the importance of educational attainment as a factor that can reduce vulnerability to climate-related health risks in children.

2.3.4 Robustness checks

In this section, In run several robustness checks. First, I control for the water source used by the household. Second, I run a placebo treatment test by re-runing my main specifications, using randomly reassigned heat exposure for each child in the sample. Third, I run my main specifications for a fraction of households using fixed effects at the cell level.

Results controlling for water source used by the household

Next, in Table 2.5, I further control whether my results are sensitive to the inclusion of the water source the household has access to. Water is known to be a large transmission channel of gastro-intestinal diseases like diarrhea and could be a possible confounder.

Table 2.5 — Effects of Heat Exposure on the Incidence of Diseases — Controlling for Water Source of the Household

	Fever		Diarrhea		ARD	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours 25–30°C	0.010***	0.010***	0.026***	0.025***	0.037***	0.038***
	(0.003)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)
Hours 30–35°C	0.013***	0.014***	0.029***	0.030***	0.035***	0.033***
	(0.004)	(0.005)	(0.009)	(0.009)	(0.010)	(0.010)
Hours >35°C	0.005**	-0.004	0.019***	0.019***	-0.004	0.003
	(0.003)	(0.004)	(0.007)	(0.007)	(0.005)	(0.007)
Piped into household	-0.024	-0.028*	-0.046	-0.052*	0.004	-0.011
	(0.016)	(0.016)	(0.028)	(0.028)	(0.031)	(0.031)
Piped outside household	-0.003	-0.007	0.002	0.001	0.009	-0.002
	(0.012)	(0.012)	(0.021)	(0.021)	(0.023)	(0.023)
Public tap water	-0.004	-0.008	-0.037***	-0.041***	-0.012	-0.018
	(0.008)	(0.008)	(0.014)	(0.014)	(0.015)	(0.015)
Unprotected well	-0.0003	-0.001	-0.010	-0.013	0.014	0.010
	(0.008)	(0.008)	(0.014)	(0.015)	(0.016)	(0.016)
Protected well	-0.006	-0.010	0.011	0.010	0.012	0.001
	(0.010)	(0.010)	(0.018)	(0.019)	(0.020)	(0.020)
Observations	21,939	21,935	21,939	21,935	21,937	21,933
Adjusted R^2	0.103	0.112	0.077	0.082	0.098	0.106
Reg × Y, Reg × M FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the child has contracted the disease in the past 2 weeks preceding the interview date and zero otherwise. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C). All columns include dummy variables for the household's primary water source: piped into household, piped outside household, public tap water, unprotected well, and protected well. These dummies are included to control for differences in disease exposure through water quality, with "other source" serving as the omitted category. Columns (2), (4), and (6) include additional covariates at the individual or household level such as child's age and sex, maternal education, household size, access to electricity, and living in a rural area. All specifications include precipitation as weather control and both region-year and region-month fixed effects. Heteroskedasticity robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Results show that all estimates remain mostly unchanged after including the water source controls. Estimates in column (2) seem to indicate that households that have their water piped into their dwelling have a statistically significantly lower probability to report a fever by 2.8 percentage points with respect to the baseline group. This result is even stronger for diarrhea under column (4) as the probability to have contracted a diarrhea for households piping their water into the dwelling is 5.2 percentage points lower than the reference category. Moreover, households using public tap water as main water source seem to be less prone to contract diarrhea. In column (4), estimates indicate a statistically significant negative impact of public tap water of 4.1 percentage points with respect to the baseline.

Placebo tests using randomly reassigned heat exposure

In this section, I conduct a placebo treatment test for all households by randomly re-assigning heat exposure. Each child drawn from a given country has its count of

Table 2.6 — Effects of Heat Exposure on the Incidence of Diseases — Placebo Tests Using Randomly Reassigned Weather Variables

	Fever		Diarrhea		ARD	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours 25–30°C	-0.0004	-0.0003	-0.002	-0.001	0.0001	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hours 30–35°C	-0.005	-0.002	-0.004	0.001	-0.004	0.005
	(0.005)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)
Hours >35°C	0.0003	-0.00003	-0.003	-0.003	0.001	0.0004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	21,957	21,957	21,957	21,957	21,955	21,955
Adjusted R^2	0.103	0.111	0.077	0.081	0.097	0.104
Reg × Y, Reg × M FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	Yes	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the child has contracted the disease in the past 2 weeks preceding the interview date and zero otherwise. Heat exposure is randomly drawn with replacement from the other survey year available within the same country. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C). Columns (2), (4), and (6) include additional covariates at the individual or household level such as child's age and sex, maternal education, household size, access to electricity, and living in a rural area. All specifications include precipitation as weather control and both region-year and region-month fixed effects. Heteroskedasticity robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

hours of exposure for each respective bin randomly assigned from another child from the same country but from a different round of survey. I then re-estimate all my main specifications for the three different diseases. Results from the placebo tests are shown in Table 2.6. Estimates of all temperature bins under all columns fail to display any statistically significant impact of heat exposure on the incidence of any disease. This further confirms the negative impact of heat exposure in my main specifications on the incidence of child diseases.

Controlling for cell fixed effects

Finally, I re-estimate my main specifications including fixed effects at the cell level, which corresponds to the spatial resolution of the weather data. Since not all cells are observed repeatedly over time, I restrict the analysis to a subsample of 3,779 households located in Togo. A 5km tolerance threshold was used to include cells that are geographically close to those observed in other periods. This subsample is not fully representative of the original sample, but allows to control for unobserved time-invariant geographic characteristics at a highly granular level, which is optimal (Headey & Venkat, 2024). In Table 2.7, columns (2), (4), and (6) show estimates from specifications including fixed effects at the cell, year, month and region levels.

Table 2.7 — Effects of Heat Exposure on the Incidence of Diseases — Including Cell Fixed Effects on a Subsample of Households

	Fever		Diarrhea		ARD	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours 25–30°C	0.009	0.005	0.020*	0.018	-0.029**	-0.032
	(0.006)	(0.010)	(0.011)	(0.019)	(0.011)	(0.020)
Hours 30–35°C	0.041***	0.026	0.080***	0.054*	0.094***	0.071**
	(0.010)	(0.016)	(0.018)	(0.030)	(0.019)	(0.032)
Hours >35°C	0.035***	0.024***	0.027***	0.004	0.036***	0.013
	(0.004)	(0.008)	(0.007)	(0.015)	(0.007)	(0.015)
Observations	3,779	3,779	3,779	3,779	3,779	3,779
Adjusted R^2	0.067	0.070	0.036	0.039	0.060	0.063
Cell FE	No	Yes	No	Yes	No	Yes
Year, Month, Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the child has contracted the disease in the past 2 weeks preceding the interview date and zero otherwise. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C). A 5km tolerance threshold to further include cells that were close to the ones observed in the previous period. Columns (2), (4), and (6) include cell fixed effects. Only households that live within a cell that is observed over two different rounds of survey are included. All specifications include precipitation as weather control as well as Year, Month, and Region fixed effects. Heteroskedasticity robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Compared to the main results, coefficients for the 25–30°C bin are no longer statistically significant across all disease outcomes once cell fixed effects are included. This suggests that the previously observed effects for moderate heat exposure may have been partly driven by geographic differences across cells. However, the 30–35°C bin remains positively associated with both diarrhea and ARD. Specifically, 10 additional hours of exposure to 30–35°C in the 14 days prior to the interview increase the probability of reporting diarrhea or ARD by 5.4 and 7.1 percentage points, respectively. No significant association is found for fever in this temperature range. Interestingly, the highest temperature bin (>35°C) now shows a significant effect on fever: the estimate in column (2) suggests that 10 more hours of exposure increases the probability of fever by 2.4 percentage points. No significant effect is detected for diarrhea or ARD in this temperature range. These results provide further support for my main findings, as the inclusion of cell fixed effects does not substantially alter the observed pattern of effects, especially in the 30–35°C bin.

2.4 Conclusion

This paper studies how exposure to high temperatures affects the incidence of child diseases in sub-Saharan Africa, using geo-coded household survey data matched with high-frequency weather observations. I construct hour-degree bins of exposure to temperatures following Schlenker and Roberts, 2009 by using a sine curve to model the daily minimum and maximum temperatures for every grid square. I find that heat exposure in the 30–35°C range significantly increases the probability that a child develops a fever, diarrhea, or an ARD. The effects are largest for diarrhea, where an additional 10 hours of exposure increases the probability of illness by 3 percentage points. These estimates are robust to a set of controls, including precipitation and fixed effects at the region-year and region-month level.

Importantly, the impact of heat exposure is not evenly distributed. I find that children living in urban settings are more affected by rising temperatures than those in rural areas, especially for fever and ARD. An additional 10 hours of exposure to 30–35°C increases the incidence of fever and ARD by 1.0 and 1.8 percentage points more in urban than in rural areas, respectively. This likely reflect the combined effects of higher interpersonal contact and greater human mobility can amplify the risk of disease transmission in urban settings (Alirol et al., 2011). I also show that maternal education plays an important protective role. The probability that a child contracts fever or diarrhea is 1.3 and 1.5 percentage points lower, respectively, for children whose mother has completed at least primary education. These results are consistent with existing literature highlighting the role of maternal education in improving child health, and may reflect better health knowledge, hygiene practices, or access to care (Glewwe, 1999).

Taken together, these findings underline the importance of incorporating health adaptation into climate policy and raise potential health hazards in areas among the swift urbanization occurring in West Africa. Awareness campaigns and early warning systems should target the most vulnerable groups, particularly children of less-educated mothers and those living in urban areas. Improving access to basic education may also strengthen households' ability to respond to climate-related health risks. In urban areas, targeted investments in infrastructure, clean water and sanitation may help mitigate the additional burden of rising temperatures.

Several limitations remain in my study. The health outcomes are self-reported and based on a 14 days recall period, which may introduce measurement error. The analysis cannot fully account for household-level adaptive behaviors, such as water use or migration during episodes of high temperatures, which therefore limits the external validity of the estimated results to the sample studied (Spencer & Strobl, 2025). Finally, random displacement of household coordinates might introduce some measurement error in the assignment of weather exposure, particularly near cluster boundaries.

My results provide novel evidence on the health risks posed by rising temperatures in sub-Saharan Africa, and underscore the unequal burden faced by vulnerable groups. Better understanding the heterogeneity of these effects is key to designing more effective and equitable adaptation strategies.

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Appendix 2.A Sinusoidal curve setting

The following expression represents the sinusoidal curve used to approximate the number of hours of exposure of each household to the different temperature bins.

$$A \cdot \sin(\omega \cdot \mathrm{T} + \phi) + C$$

Where A is the amplitude of the sinusoidal wave and is expressed by the following mathematical expression:

$$A = \frac{t_{\max} - t_{\min}}{2}$$

Where $t_{\max}$ and $t_{\min}$ represent respectively the maximum and minmum temperature observed during the day. ω represents the angular frequency of the sinusoidal wave and is expressed as follows:

$$\omega = \frac{2\pi}{24}$$

T represents the hours of the day. ϕ represents the phase shift of the curve and can allow to align the sinusoidal curve with the data. I used a value of 10 to align the curve with the data. Finally, C is the vertical shift of the curve and represents the baseline temperature. It is expressed as follows:

$$C = t_{\min} + A$$

Appendix 2.B Results controlling for socio-demographic characteristics

In this section, I consider whether my results are sensitive to the inclusion of different controls such as socio-demographic controls, characteristics of the mother and access to electricity. I check for the potential endogeneity of household characteristics like access to cooling devices within my main model. I show that, after controlling for child's age, my estimates remain unchanged regardless of the inclusion of additional controls at the child, mother, or household levels. Another relevant concern may stem from bias

Table 2.B.1 — Effects of Heat Exposure on the Incidence of Diseases — With Further Controls

	Fever		**Diarrhea**		**ARD**	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours 25–30°C	0.010***	0.010**	0.015***	0.025***	0.013**	0.037***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.006)	(0.008)
Hours 30–35°C	0.014***	0.015***	0.007	0.030***	0.024***	0.035***
	(0.004)	(0.005)	(0.007)	(0.009)	(0.008)	(0.010)
Hours >35°C	0.007**	-0.004	0.002	0.019***	-0.009*	0.004
	(0.003)	(0.004)	(0.005)	(0.007)	(0.005)	(0.007)
Age	0.0001	0.0001	-0.002***	-0.002***	-0.001*	-0.001
	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)
Electricity	-0.005	-0.005	0.002	0.001	0.006	0.004
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Education of mother (degree)	0.016	0.012	0.031	0.029	-0.001	-0.007
	(0.012)	(0.012)	(0.021)	(0.021)	(0.023)	(0.023)
Education of mother (years)	-0.004*	-0.003	-0.009*	-0.008*	0.003	0.004
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Number of children	-0.012***	-0.013***	-0.016***	-0.016***	-0.016***	-0.015***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Number of household members	0.002***	0.002**	0.002	0.002	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	21,943	21,943	21,943	21,943	21,941	21,941
Adjusted R^2	0.104	0.113	0.078	0.082	0.099	0.106
Region-Year, Region-Month FE	No	Yes	No	Yes	No	Yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the child has contracted the disease in the past 2 weeks preceding the interview date and zero otherwise. Estimates in all columns show the impact of an increase of 10h of exposure to the respective temperature bin with respect to the reference bin (<25°C). Columns (2), (4), and (6) include region-year and region-month fixed effects. All specifications include precipitation as weather control. Heteroskedasticity robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

resulting from other covariates. For instance, if larger families tend to live in warmer regions, excluding family size could reflect the association between family size and disease transmission rather than temperature and disease transmission. My analysis indicates that controlling for household size (number of household members) and the number of children does not affect the magnitude and significance of my findings.

3 Retirement decision and household's gasoline consumption: Evidence from a Regression Discontinuity Design†

Abstract: I employ household-level data over 2006-2017 to quantify the impact of retirement on gasoline consumption. Based on a fuzzy regression discontinuity design, I show that gasoline consumption declines by 32-36 percent on average over my different specifications. The reduction reaches 59-66 percent when I restrict the sample to single-person households. I further find that the probability to use any gasoline decreases by 5-6 percent at retirement (13-16 percent for single-person households). These findings suggest that demographic trends represent an important driver of CO_2 emissions associated with private mobility in developed countries.

JEL classification: C21, C23, D12, Q4

Keywords: gasoline consumption; retirement effect; Household expenditure survey; fuzzy regression discontinuity design.

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3.1 Introduction

The fast and unprecedented demographic aging of developed economies is going to have numerous impacts through labor market such as reduced labor-force participation (Börsch-Supan & Schnabel, 1998). Studies have shown that households' consumption declines sharply at retirement in many countries (Banks et al., 1998; Haider & Stephens Jr, 2007; Hamermesh, 1984; Schwerdt, 2005) and is often coupled to a decline in work-related expenditures (Battistin et al., 2009; Li et al., 2016).[1] Moreover, households' commuting behavior, mobility choices and energy consumption are also impacted by retirement. Analysing variations in consumer behavior at retirement is therefore a topic of great interest in the economic policy debate.

The main objective of this paper is to provide empirical evidence on the impact of retirement on households' gasoline consumption. I employ several waves of the Swiss Household Budget Survey (SHBS), a cross-sectional household-level survey, from 2006 to 2017. This provides monthly information on households' gasoline consumption and employment status in Switzerland. The Swiss case is of particular interest because of its rapidly aging population and its very carbon-intensive transport sector.[2] Following Battistin et al., 2009 and Li et al., 2016, my main identification strategy uses a fuzzy regression discontinuity design (RDD). Specifically, I identify a local average treatment effect (LATE) using 2SLS and exploit the Swiss statutory retirement age as an exogenous shock to measure my treatment effect. I fit both parametric and non-parametric fuzzy RDD and instrument retirement with an indicator variable equal to one for households located above the legal retirement age and zero otherwise.

Household composition can pose an important threat to the estimation of the retirement effect. In particular, the treatment effect can be understated by the consumption of other household members that are not retired yet. I also estimate a fuzzy RDD separately for single-person households only, using the same identification strategy as before. In addition, I also document whether retirement causes a change in households' probability to use any gasoline as I disentangle changes in the decision to participate or not in the

[1] This observed decline in consumption after retirement is referred to as the retirement-consumption puzzle and contrasts with the consumption-smoothing hypothesis proposed by Modigliani and Brumberg, 1954 and Friedman, 1957.

[2] In Switzerland, the share of the population aged 65 or more is expected to increase significantly and linearly in the next decades to reach 25.6 percent of the population in 2050 (SFSO, 2020b). In 2019, the transport sector was the largest source of greenhouse gas emissions in Switzerland. Transport represented over 32 percent of total greenhouse gas emissions as it emitted more than 15 million tons of C02-eq (SFOEN, 2022).

market after retirement from changes in the consumption-level decision.

My empirical results suggest that there is a strong negative impact of retirement on households' gasoline consumption.[3] Quantitatively, I show that retirement decreases households' gasoline consumption on average by 32-36 percent over my main parametric specifications. Moreover, estimates of the local average treatment effect using a non-parametric fuzzy RDD are consistent with the results found. When I consider single-person households only, I find that the magnitude and the significance of my estimates are higher than when using the whole sample. In this setting, the estimated retirement effect reaches 59-66 percent over my different specifications. Next, I find different results for the extensive and intensive margin of gasoline consumption. First, I show that retirement decreases the probability that households consume any gasoline on average by 5-6 percent (13-16 percent for single-person households). Second, the estimated retirement effect using only households with a positive amount of gasoline consumed is 12-14 percent (respectively 23-27 percent for single-person households). Last, I find no significant impact of retirement on other energy purchases such as electricity, natural gas and heating oil.

I also test for different threats to internal validity and rule out two possible confounders. First, I find that my retirement effect is not likely to be confounded with an income effect. I show evidence of an absence of statistically significant discontinuity of income at the retirement cutoff both graphically and statistically. Second, I exploit data on public transport usage to document that the observed decline in private transport usage by households after retirement is not accompanied by changes in public transport usage. My results indicate that households' public transport usage remains fairly stable after retirement, excluding thus a substitution from private to public transport at retirement.

While no study establishes a clear causal effect of retirement on transport fuel consumption, there is a rather clear consensus in the literature on the relationship between age and energy consumption. On one hand, ageing is usually linked to increased residential energy demand (electricity, heating fuel, natural gas) as older people tend to have a more sedentary lifestyle than younger households (Yamasaki and Tominaga, 1997; Tonn and Eisenberg, 2007; Fan et al., 2021). Indeed, several studies highlight that age-related factors are determinant drivers of energy consumption and greenhouse gas emissions in the residential sector (Bardazzi & Pazienza, 2020; Chancel,

[3] Results from the first stage are all statistically significant and display a partial F-statistic larger than what is recommended by Lee et al., 2022.

2014; Zagheni, 2011).

On the other hand, there seems to be a negative relationship between age and transport energy use. Okada, 2012 for instance finds a clear link between CO2 emissions from the road sector and the age structure of the population of developed countries. The author shows that CO2 emissions from the road sector of a country tend to decrease once they reach a share of elderly people of more than 16 percent, confirming thus the positive contribution of aging to curb CO2 emissions in the transport sector. These results are also confirmed by Liddle, 2014 who finds that population aging among OECD countries should have a lowering effect on carbon emissions from transport.

The literature in environmental and energy economics on the effect of retirement on energy consumption is rather scarce. Indeed, the bulk of the literature studying the energy consumption patterns of the elderly generally undervalues the effect of retirement on energy consumption and only considers the impact of the elderly population as a whole. I make use of my detailed expenditure and consumption data to provide novel evidence on the impact that retirement has on both gasoline consumption and market participation of elderly households as well. While most household expenditure surveys usually do not provide detailed information on households' consumption, the SHBS used in this paper offers rich information on households' gasoline consumption. Furthermore, the SHBS, through his employment status variable, allows me to identify retired from non-retired units.

To my knowledge, this is the first empirical analysis studying the relation between gasoline consumption and retirement using actual consumption data and a clear identification strategy. Recently, Zhu and Lin, 2022 investigated the impact of retirement on residential electricity consumption in urban China using a regression discontinuity design. The authors' findings suggest that retirement increases electricity consumption by 20-32 percent through augmented home time after retirement. Relative to this study, my results show that retirement also impacts elderly households' gasoline consumption.

My study is also closely related to the retirement-consumption puzzle literature, which studies the impact of retirement on consumer behavior. Various studies (Hamermesh, 1984; Banks et al., 1998; Bernheim et al., 2001; Schwerdt, 2005; Haider and Stephens, 2007) found an important decrease in households' consumption in the first post-retirement years. Hamermesh (1984) for instance discusses consumption patterns in the US after retirement and states that the elderly's consumption decreases significantly after retirement. Moreover, many studies show that the drop in post-retirement consumption is primarily related to a decline in work-related expenditures (Battistin et al., 2009; Li et al., 2016). For instance, Battistin et al. (2009) use Italian microdata to evaluate the causal effect of retirement on consumption. Using a regression discontinuity design, the authors find that nondurable consumption drops by 9.8 percent after retirement and is mainly due to a drop in work-related expenses. Similar findings are shown by Li et al. (2016) for China. Their results suggest a significant decrease in work-related expenditures after retirement.

While my work is directly related to the retirement-consumption literature, it contributes to a new literature linking retirement and households' energy consumption as no study explicitly identifies the retirement effect on gasoline consumption. Indeed, the major contribution of this paper is to investigate the effect that retirement has on private households' gasoline consumption, complementing thus the existing work on the effects of retirement on general consumption.

The remainder of this paper is organized as follows: Section 3.2 displays information on the data and the empirical strategy used in my analysis. Section 3.3 reports my estimated results followed by sensitivity checks. Finally, Section 3.4 provides a brief conclusion.

3.2 Empirical strategy

In this section, I first give a summary of my data, and then present my identification strategy to estimate the impact of retirement on households' gasoline consumption.

3.2.1 Data overview

This paper uses the Swiss Household Budget Survey (SHBS), a monthly cross-sectional survey conducted by the Swiss Federal Statistical Office as main data source (SFSO, 2020a). The SHBS covers the whole Swiss territory and randomly surveys around 250-300 households each month. All participants provide detailed information on their expenditures and consumption of goods for a whole month. The SHBS also contains a large variety of socioeconomic and demographic variables of the household. Combining 12 yearly waves of the SHBS from 2006 through 2017 led to a repeated cross-sectional dataset with 38,975 households.[4]

The main dependent variable used for the analysis is the natural logarithm of the

[4]The SHBS can be obtained via the Swiss federal statistical office.

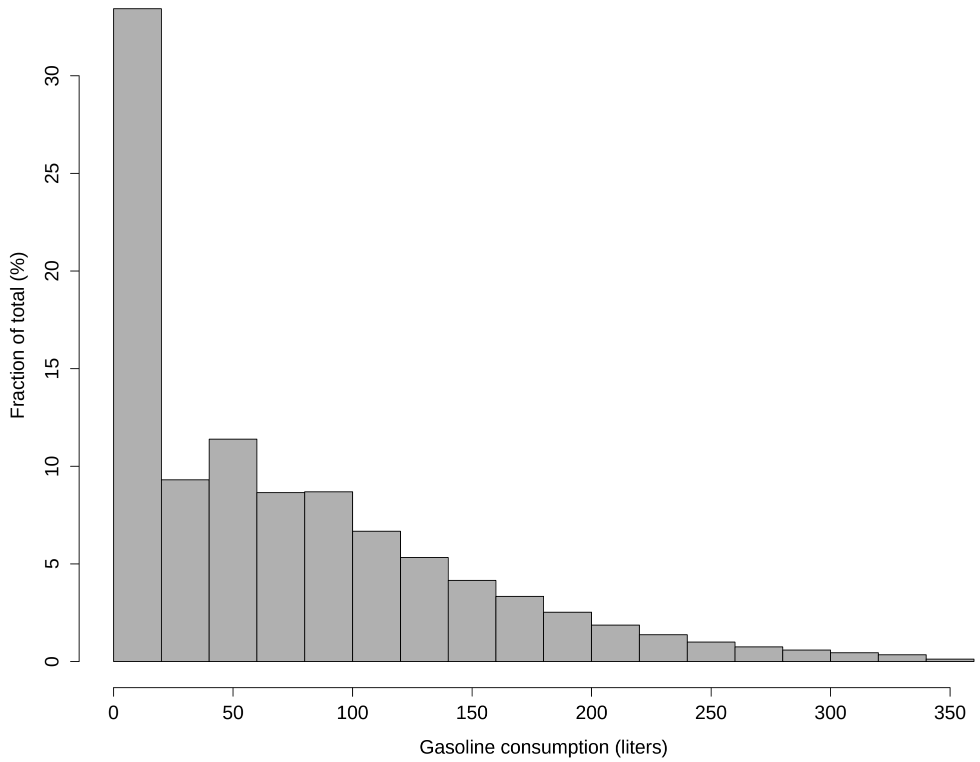
households' gasoline consumption (in liters).[5] Figure 3.1 below presents a histogram of monthly household gasoline consumption across households in the SHBS. It can be seen that a majority of households (more than 30 percent) reported zero consumption of gasoline when surveyed. Several reasons can explain this skewness. First, zero expenditures may arise from individual preferences (households refusing to consume gasoline independently of the price or income level). Second, zero expenditure may also appear in the survey due to the short period of observation. Finally, zero expenditures might also be explained by economic decisions related to price and income. In our sample, an important fraction of zeros correspond to households owning a vehicle (9105 out of 11872 zero observations over the observed period). Therefore, a lot of zeros in our sample are probably related to infrequency of purchase or abstention and less to economic factors.[6]

Table 3.1 below summarizes the variables used in the analysis. The first part of the table summarizes information on the whole sample, the second part focuses on households with a gasoline consumption of zero, and the final part relates information on households with a positive amount of gasoline consumed. The average amount of gasoline consumed by a household is 73.91 liters. In my sample, around 24 percent of households are retired and the mean age in my sample of households is 52. My sample of households is therefore significantly older than the average Swiss resident who is 42 years old. More than 4 out of 5 households possess at least one car with the proportion of used and new cars being approximately equal. Moreover, the mean disposable income earned is 6981 CHF for my sample of households.[7]

The second and third parts of the table reveal some differences between households with a zero consumption of gasoline and with households that have a positive consumption of gasoline during the surveyed month. First, households with a zero consumption of gasoline have a lower average disposable income (6165 CHF) than households with a positive consumption of gasoline (7345 CHF). Second, households are usually smaller in households with a zero consumption of gasoline. Finally, the share of retired is slightly higher for households with a zero consumption (29 percent) than for households with a positive gasoline consumption (0.22).

[5]I added 1 to the consumption of households reporting zero liters of gasoline consumed before applying the logarithmic transformation to keep these observations in my analysis.
[6]Approximately 25 percent of vehicle owners in our sample did not purchase any gasoline in the surveyed month. This can partially be explained by the short period of observation as households reported their expenditures and consumption during one month only.
[7]On July 28, 2022, 1 CHF was equal to 1.04 USD.

Figure 3.1 — Distribution of monthly household gasoline consumption (liters), 2006-2017.



3.2.2 Fuzzy Regression Discontinuity Design

I identify the effect of retirement on gasoline consumption by using a Fuzzy Regression Discontinuity Design (RDD). I use a fuzzy RDD design because unlike in a sharp RDD design, the probability of treatment in a Fuzzy RDD is not deterministic. In Switzerland, the statutory retirement age is respectively 65 for men and 64 for women. Nonetheless, many persons decide to retire prematurely either through personal choice or because their professional activity allows them to retire earlier.[8] Some persons also decide to retire after the legal statutory retirement age of 65. Therefore, since the probability of treatment does not jump by one but by less than one at the cutoff, the jump in the relationship between my outcome and my running variable can no longer be interpreted as an average treatment effect (Lee & Lemieux, 2010).[9]

[8]For example, since June 5, 2003, workers from the construction sector are allowed to retire at the age of 60 instead of 65 (Unia, 2022)

[9]Fuzzy RDD exploits discontinuities in the probability of treatment (here being retired) conditional on another variable (Angrist & Pischke, 2009).

Table 3.1 — Descriptive statistics

Whole sample	Mean	St. Dev.	Min	Max
Gasoline consumption	73.91	81.42	0	927.21
Gasoline expenditures	120.44	135.08	0	1,581.12
Age	52.63	15.52	18	100
Retired	0.24	0.42	0	1
Disposable income	6,981.64	4,510.90	0.50	163,982.60
Household size	2.32	1.22	1	14
Has at least one car	0.82	0.38	0	1
Number of New cars	0.54	0.64	0	6
Number of used cars	0.56	0.70	0	10
Zeros only	Mean	St. Dev.	Min	Max
Age	53.83	17.09	18	100
Retired	0.29	0.45	0	1
Disposable income	6,165.17	4,403.23	1	102,371.40
Household size	2.04	1.22	1	8
Has at least one car	0.50	0.50	0	1
Number of New cars	0.31	0.53	0	4
Number of used cars	0.28	0.51	0	4
Positive consumption only	Mean	St. Dev.	Min	Max
Age	52.11	14.75	18	99
Retired	0.22	0.41	0	1
Disposable income	7,343.59	4,556.56	0.50	163,982.60
Household size	2.44	1.20	1	14
Has at least one car	0.96	0.18	0	1
Number of New cars	0.64	0.66	0	6
Number of used cars	0.68	0.73	0	10

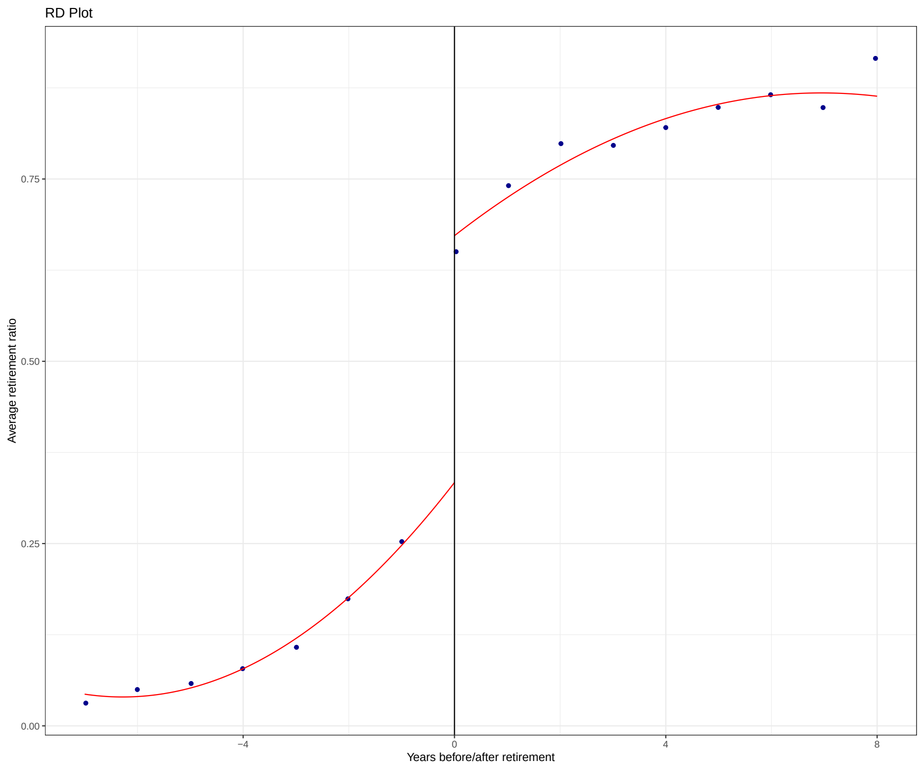
Notes: Data source is the Swiss Household Budget Survey from the Federal Statistical Office (2006-2017). Gasoline consumption is in liters and expenditures are in Swiss CHF.

I use the employment status variable of the SHBS to define my treatment variable.[10] Figure 3.2 displays the average retirement rate (here defined as the ratio of retired households in a particular age group to the total number of households) near the threshold (retirement age).[11] As can be seen in Figure 3.2, the average retirement rate increases with age with a sharp increase in the retirement rate around the threshold. It can also clearly be seen that the probability of treatment (being retired) does not switch from zero to one at the threshold like in a sharp RDD setup, meaning that not all individuals retire once they reach legal retirement age and that some households are already retired when they reach the threshold.

[10]Households' employment status in the SHBS is either employed from an independent working activity, employed from a dependent activity, retired, training, kid younger than 15 years of age, or other status (incl. unemployed).

[11]Switzerlands' legal statutory retirement age is respectively 65 for men and 64 for women.

Figure 3.2 — Average retirement ratio near the threshold



My main strategy focuses on a parametric estimation of the retirement effect by using a quadratic polynomial function on both sides of the threshold. This model exploits data within a selected range (bandwidth) above or below retirement age to show the local average treatment effect (LATE) of retirement on gasoline consumption. I use a different set of bandwidths to show the robustness of the estimated retirement effect.[12] Moreover, I also control for Swiss canton and year of survey fixed effects as well as for several socioeconomic and demographic characteristics of the household.[13]

To estimate the effect of retirement on gasoline consumption, I use a 2SLS model following Battistin et al. (2009) and Li et al. (2016) by instrumenting retirement with a retirement indicator variable equal to one for households located above the threshold (older than the legal statutory retirement age) and 0 otherwise. The first stage of the

[12]More details on the choice of the selected bandwidths are given in section 3.2.2.

[13]Cantons are administrative subdivisions of Switzerland. There are 26 distinct cantons in the country, 17 are German-speaking, four French-speaking, one Italian-speaking, three bilingual, and one trilingual. Besides the many languages, cultural differences are also very prevalent in the country and can have important effects on revealed environmental preferences for example (Filippini & Wekhof, 2021).

2SLS applied to my fuzzy RDD can be written as follows:

$$R_i = \beta_0 + \beta_1 Z_i + f(age_i) + \gamma X_i + \alpha C + \alpha_t + \mu_{it} \tag{3.1}$$

While the second stage-equation reads:

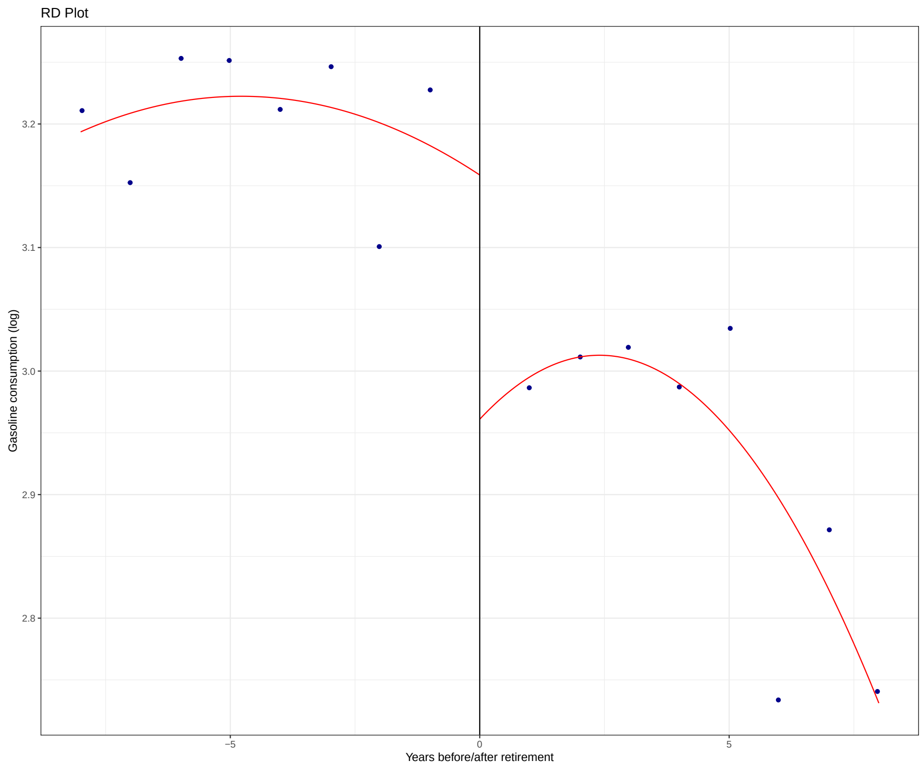
$$\ln Y_i = \beta_0 + \beta_1 \hat{R}_i + f(age_i) + \gamma X_i + \alpha C + \alpha_t + \epsilon_{it} \tag{3.2}$$

Where lnY_i is the natural logarithm of the households' gasoline consumption. Z_i is the assignment variable equal to one for households located above the statutory retirement age and 0 otherwise. R_i is the treatment variable that takes a value of 1 if individual i is retired and a value 0 if the household is not retired. $\hat{R}_i$ is the predicted value of the retirement probability from the first stage. $f(age_i)$ are the interacted multi-order terms of $f(age_i)$ to allow for different polynomial functions for treated and non treated units. I use a quadratic polynomial of the running variable and do not control for higher order polynomials of the forcing variable as it leads to noisy estimates, sensitivity to the degree of the polynomial, and poor coverage of confidence interval (Gelman & Imbens, 2019). X_i is a set of control variables that include the natural logarithm of disposable income, the number of persons living in the household and whether the household head has a public transport subscription (GA). Finally, αC and α_t represent fixed effects for canton and year of survey respectively that control for unobserved heterogeneity across Swiss cantons and years of survey.

As explained above, my setup implies that age functions as the probability of a household to be retired. To estimate the above 2SLS model, there must be a non-zero correlation between my instrument and the treatment status. Evidence of the absence of a weak instrument bias is discussed in section 3.A in the appendix. Another crucial condition that must hold to have a valid IV strategy is the exclusion restriction (see Lee and Lemieux, 2010), meaning that my instrument (being older than 65) only affects my outcome (gasoline consumption) through the treatment status (being retired). Since age is determined by year of birth, I believe that the exclusion restriction holds as households cannot precisely control it (Lee and Lemieux, 2010).

Next, to deal with the large number of households reporting a null consumption of gasoline, I use a two-step procedure to disentangle changes in the decision of households to participate or not in the market from changes in the consumption-level decision after

Figure 3.3 — Treatment effect near the cutoff



retirement.[14] In a first step, I estimate how retirement affects households' probability to consume any gasoline. I apply a fuzzy RDD by re-estimating equation (2) using a binary outcome variable equal to one for households with a positive amount of gasoline consumed in the surveyed month and zero otherwise as dependent variable. In a second step, to estimate how retirement affects the consumption-level decision of households, I apply a fuzzy RDD as done in my main identification strategy, but restrict the sample to households having a positive amount of gasoline consumed in the surveyed month.

As a complementary identification strategy, I also estimate the local average treatment effect by applying a non-parametric fuzzy RDD, using a uniform Kernel density estimation with a first-order polynomial local linear regression. This estimation method is primarily used as a robustness test. Furthermore, I also estimate the fuzzy RDD separately using single-person households only to mitigate the influence of other

[14]This procedure is similar to the double-hurdle model developed by Cragg, 1971, where null values of consumption can arise at both stages of the consumers' decision process. The major differences with regard to Cragg, 1971 are that I apply a fuzzy RDD at both stages of the decision process and I do not allow for null values in the consumption-level decision as I restrict my sample to households having a positive amount of gasoline consumed.

non-retired household members that could understate my treatment effect.

There is a well-known precision-bias trade-off in the literature regarding the choice of the bandwidth. While selecting a larger bandwidth includes more observations and therefore increased precision, choosing a smaller bandwidth will minimize bias by comparing units close to the threshold. I estimate the optimal bandwidth following the method proposed by Calonico et al., 2014 which relies on a non-parametric estimation of a fuzzy RDD. I use a first-order local polynomial as well as a coverage error probability with a uniform kernel and estimate an optimal bandwidth of 7 years. Both larger and narrower bandwidths are also used in the analysis to test the sensitivity of my estimates. Figure 3.3 above graphically displays the level of discontinuity of the outcome variable (gasoline consumption) at the threshold. As we approach retirement age, gasoline consumption seems to decrease continuously with age, but a clear discontinuity can be observed once retirement age is reached.

I conduct an extensive robustness analysis of the 2SLS estimates that I obtain. First, I present results using both smaller and larger bandwidths (respectively 5 and 10 years) than the ones used in the baseline results. Second, I also investigate both graphically and statistically possible discontinuities in my covariates to make sure that my treatment effect is not confounded with a drop in another variable used in the model. Specifically, I test for a possible discontinuity in households' disposable income at retirement, which could be confounded with the measured retirement effect. Third, I also conduct a placebo-treatment test, where I move the threshold point for the fuzzy RDD by 3 years on both sides of the cutoff. I do so by moving the point with distance zero to either direction of the cutoff by 3 years. This allows me to assign a new placebo retirement treatment and conduct a placebo-fuzzy RDD.

3.3 Empirical results

This section reports my empirical results. First, I quantify the impact of retirement on households' gasoline consumption. Second, I estimate the implied change in the probability that a household consumes any gasoline after retirement. Third, I estimate the impact of retirement on households' consumption-level decision. All the previous steps are estimated both using a sample containing all the households and separately for single-person households to avoid the influence of other household members' consumption. Fourth, I also test whether there is a change in other energy expenditures such as electricity, gas and heating oil after retirement. Finally, I test the robustness of my results by providing various sensitivity checks.

3.3.1 Main results

Table 3.2 displays results from a fuzzy RDD, using several waves of the SHBS from 2006 to 2017. All model specifications include both canton and year Fixed effects to control for unobserved heterogeneity across different Swiss cantons available and year of survey. In columns (1) and (2), I report 2SLS regression estimates without and with control variables, respectively. I use a quadratic polynomial of the running variable and the optimal bandwidth that I obtained following the method proposed by Calonico et al. (2014).[15] Columns (3) and (4) are estimated with a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression. Columns (5) to (8) are similar to columns (1) to (4) but with a sample restricted to single-person households only. Only the results of the second stage are presented, but results from the first stage can be found in the appendix.

Starting in columns (1) and (2), the estimated retirement effect on gasoline consumption is negative and lies between 32 and 36 percent under the optimal bandwidth of 7 years and is statistically significant at the one percent level of significance. Non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression results in columns (3) and (4) confirm my previous results. Estimates under these specifications also indicate a negative and statistically significant effect of retirement of -30 to -32 percent on households' gasoline consumption. Therefore, retirement seems to have a strong negative impact on households' gasoline consumption.

Next, I provide further evidence of the retirement effect by restricting the analysis to single-person households only. This allows me to avoid the mixture of the household heads' gasoline consumption with the consumption of other household members that are not retired. Similarly than in columns (1) to (4), columns (5) and (6) are estimated using a 2SLS with a quadratic polynomial of the running variable under the optimal bandwidth, without and with control variables, respectively. In columns (7) and (8) the retirement effect is estimated with a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression. Again, all columns include

[15] 2SLS regression estimates using larger and smaller bandwidths respectively 10 and 5 years to test the robustness of my estimates can be found in section 3.3.3. Larger bandwidths contain more observations and are thus more precise, but they also potentially understate the treatment effect as many confounding variables are present (Filippini and Wekhof, 2021).

Table 3.2 — Fuzzy RDD - Second stage results on gasoline consumption (log)

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.360^{***}	-0.320^{***}	-0.301^{*}	-0.321^{*}	-0.623^{***}	-0.587^{***}	-0.639^{**}	-0.659^{**}
	(0.120)	(0.119)	(0.176)	(0.174)	(0.213)	(0.210)	(0.312)	(0.311)
Observations	10,028	10,028	10,028	10,028	3,302	3,302	3,302	3,302
Adjusted R^2	0.020	0.042	–	–	0.027	0.050	–	–
Polynomial	Quadratic	Quadratic	–	–	Quadratic	Quadratic	–	–
Kernel	–	–	Uniform	Uniform	–	–	Uniform	Uniform
Bandwidth	7 years	7 years	7 years	7 years	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is the log of gasoline consumption. In columns (1) and (2), the retirement effect is estimated parametrically (2SLS) using a quadratic polynomial on both sides of the cutoff. Columns (3), (4), (7), and (8) show non-parametric fuzzy RDD estimates using a uniform kernel and a local linear regression. Columns (5) to (8) use only single-person households. All specifications use the optimal 7-year bandwidth and include canton and year fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

both canton and year Fixed effects.

Starting in columns (5) and (6), the estimated retirement effect on gasoline consumption is both larger and more precisely estimated than the effect measured previously using all households. The estimated retirement effect under these specifications lies between -58.7 and -62.3 percent and is statistically significant at the one percent level of significance. By contrast, this effect was only of -36 and -32 percent, respectively, in columns (1) and (2). In columns (7) and (8), results from the non-parametric fuzzy RDD using a local linear regression also confirm a significantly larger retirement effect for single-person households, as it is more than twice larger than under columns (3) and (4). Results under columns (5) to (8) therefore show that estimates are broadly consistent and of a significantly larger magnitude than the results from columns (1) to (4). Overall, the estimated retirement effects are also more precisely estimated even though the number of observations is much lower when considering exclusively single-person households.

3.3.2 Extensive and intensive margin of gasoline consumption

In this section, I disentangle the decision of households to participate or not in the market after retirement from their consumption-level decision.

Extensive margin

Table 3.3 displays results from a fuzzy RDD. In all columns, I use a binary variable equal to one for households with a positive amount of gasoline consumed in the surveyed month and zero otherwise as dependent variable. Again, all model specifications include both canton and year fixed effects and use the optimal bandwidth of 7 years. Similarly to Table 3.2, columns (1), (2), (5) and (6) are estimated using a 2SLS with a quadratic polynomial of the running variable. Only the results of the second stage are presented. Columns (3), (4), (7) and (8) are estimated with a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression. Columns (1) to (4) use all households available while columns (5) to (8) restrict the analysis to single-person households.

Starting in columns (1) and (2), estimates under the optimal bandwidth are respectively -0.062 and -0.054 and are both statistically significant at the 5 percent level of significance. These estimates suggest a decrease in the probability of households to consume any gasoline at retirement by 5.4 to 6.2 percent. Non-parametric fuzzy RDD results in columns (3) and (4) are of a similar magnitude than the parametric estimates but are not statistically significant.

In columns (5) and (6), results suggest a strong negative impact of retirement on households' probability to consume any gasoline. Specifically, estimates are statistically significant at the one percent level of significance and indicate a decrease in the probability to consume any gasoline by 13.4 to 14.8 percent at retirement. Results from the non-parametric fuzzy RDD under columns (7) and (8) also suggest a statistically significant decrease in market participation after retirement of 16.1 to 16.5 percent. The suggested decrease in market participation using solely single-person households is therefore much larger than what I observed in columns (1) to (4) using all types of households.

Intensive margin

In Table 3.4, I estimate the intensive margin of gasoline consumption. To estimate how retirement affects households' consumption-level decision, I restrict the sample to households having a positive amount of gasoline consumed in the surveyed month and apply a fuzzy RDD as done in my main identification strategy. Similarly to before, columns (1), (2), (5) and (6) are estimated applying a 2SLS with a quadratic polynomial of the running variable while columns (3), (4), (7) and (8) show the results of a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order

Table 3.3 — Fuzzy RDD - Second stage results on gasoline consumption (log) — Extensive margin

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.062^{**}	-0.054^{**}	-0.061	-0.060	-0.148^{***}	-0.134^{***}	-0.161^{**}	-0.165^{**}
	(0.026)	(0.026)	(0.041)	(0.041)	(0.048)	(0.048)	(0.069)	(0.069)
Observations	10,028	10,028	10,028	10,028	3,302	3,302	3,302	3,302
Adjusted R^2	0.015	0.033	–	–	0.021	0.041	–	–
Polynomial	Quadratic	Quadratic	–	–	Quadratic	Quadratic	–	–
Kernel	–	–	Uniform	Uniform	–	–	Uniform	Uniform
Bandwidth	7 years	7 years	7 years	7 years	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is a dummy equal to 1 if the household reported positive gasoline consumption. Columns (1) and (2) show 2SLS estimates using quadratic polynomials on both sides of the cutoff. Columns (3), (4), (7) and (8) present fuzzy RDD estimates using a uniform kernel and local linear regression. Columns (5) to (8) use only single-person households. All specifications use the optimal 7-year bandwidth. Robust standard errors in parentheses. All models include canton and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

polynomial local linear regression. Again, columns (1) to (4) use all households available while columns (5) to (8) restrict the analysis to single-person households.

Overall, estimates are broadly consistent across columns (1) to (4), and confirm a significant effect of retirement on households' gasoline consumption-level decision. Both parametric and non-parametric results suggest a statistically significant decrease between -12.2 and -13.9 percent. The fact that the treatment effect is larger and more precisely estimated for single-person households is also confirmed in the subsequent columns. In columns (5) and (6), estimates are statistically significant at the one percent level of significance and indicate a decrease in gasoline consumption by 23.1 to 24.9 percent after retirement. Finally, non-parametric estimates under columns (7) and (8) further confirm my previous findings. Estimates show there is also a significant negative impact of retirement on single-person households' gasoline consumption of -27.5 percent.

In sum, retirement seems to have a significant negative impact on households' gasoline consumption. Results suggest that both their consumption-level decision as well as their market participation decision are affected by retirement. Moreover, including other household members seems to have a significant impact on the measured treatment

Table 3.4 — Fuzzy RDD - Second stage results on gasoline consumption (log) — Intensive margin

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.128^{**}	-0.122^{**}	-0.124^{*}	-0.139^{*}	-0.249^{***}	-0.231^{***}	-0.274^{**}	-0.275^{**}
	(0.050)	(0.050)	(0.071)	(0.070)	(0.087)	(0.087)	(0.124)	(0.124)
Observations	7,187	7,187	7,187	7,187	1,872	1,872	1,872	1,872
Adjusted R^2	0.011	0.020	–	–	0.006	0.015	–	–
Polynomial	Quadratic	Quadratic	–	–	Quadratic	Quadratic	–	–
Kernel	–	–	Uniform	Uniform	–	–	Uniform	Uniform
Bandwidth	7 years	7 years	7 years	7 years	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the log of gasoline consumption, restricted to households with positive gasoline purchases. Columns (1) and (2) present 2SLS estimates using quadratic polynomials on both sides of the cutoff. Columns (3), (4), (7), and (8) present non-parametric fuzzy RDD estimates using a uniform kernel and local linear regression. Columns (5) to (8) focus on single-person households. All specifications use the optimal 7-year bandwidth and include canton and year fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

effect as estimates using single-person households are systematically larger and more precisely estimated in magnitude than estimates that use all types of households.

The impact of retirement on other energy purchases

This section explores potential changes in other energy consumption patterns at retirement. Specifically, I investigate whether the decline in gasoline consumption is accompanied by an increase in electricity, heating oil and natural gas expenditures due to more time spent at home after retirement. In the SHBS, the amount consumed of each of these energy sources is not available. Therefore, I used the natural logarithm of total expenditures of the household in each of these energy sources instead.

Table 3.5 displays results from a fuzzy RDD, All model specifications include a set of covariates and both canton and year Fixed effects to control for unobserved heterogeneity across different Swiss cantons available and year of survey. In all columns, I report results from a 2SLS regression. I use a quadratic polynomial of the running variable and the optimal bandwidth that I obtained following the method proposed by Calonico et al. (2014). Columns (1), (3) and (5) use all households available in the sample while columns (2), (4) and (6) only use single-person households. Columns (1) and (2), columns (3) and (4), columns (5) and (6) respectively estimate the impact of

Table 3.5 — Fuzzy RDD - Second stage results on electricity (log), natural gas (log) and heating oil (log) expenditures

	Electricity		Natural Gas		Heating Oil	
	(1)	(2)	(3)	(4)	(5)	(6)
Retirement	-0.017	-0.034	0.081	-0.003	0.076	0.135
	(0.052)	(0.089)	(0.115)	(0.154)	(0.121)	(0.190)
Observations	10,113	3,310	10,113	3,310	10,113	3,310
Adjusted R^2	0.049	0.037	0.008	0.007	0.012	0.025
Single-person household	no	yes	no	yes	no	yes
Polynomial	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Bandwidth	7 years	7 years	7 years	7 years	7 years	7 years
Covariates	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes

Notes: In columns (1) and (2), the dependent variable is the natural logarithm of electricity expenditures. In columns (3) and (4), it is the log of natural gas expenditures. In columns (5) and (6), it is the log of heating oil expenditures. All estimates are based on a fuzzy RDD (2SLS) with a quadratic polynomial on both sides of the cutoff. Columns (1), (3), and (5) use all households, while (2), (4), and (6) use only single-person households. All models use a 7-year optimal bandwidth and include canton and year fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

retirement on electricity, natural gas and heating oil expenditures.

Starting in columns (1) and (2), the estimated retirement effect on electricity expenditures is small and negative under the optimal bandwidth of 7 years but is not statistically significant when using both the whole sample and single-person households only. Next, columns (3) and (4) indicate no statistically significant impact of retirement on natural gas consumption. Lastly, columns (5) and (6) show that the estimated retirement effect on heating oil expenditures is positive but again not statistically significant when using both the whole sample and single-person households only. Therefore retirement does not seem to have a significant impact on other energy purchases among Swiss households.

3.3.3 Sensitivity checks

In this section, I present different robustness checks that were conducted. First, I present results using both smaller and larger bandwidths than the ones used in my baseline results. Second, I pursue with a placebo test for non-discontinuities points. Third, I test for discontinuities in my covariates both graphically and statistically. Fourth, I investigate changes in car ownership at retirement to further support the results from the extensive margin part. Finally, I conduct OLS regressions as complementary results to the Fuzzy RDD estimations.

Larger and smaller bandwidths

In Table 3.6, I re-estimate my fuzzy RDD applying the same 2SLS model as before but use both larger and smaller bandwidths with respect to my baseline results to test the sensitivity of my estimates. Columns (1) to (4) use all households available while columns (5) to (8) only include single-person households. Starting in columns (1) and (2), results under a 10-year bandwidth suggest a retirement effect of -20.7 to -24.8 percent, which is similar to the estimated treatment effect from my baseline results. The same conclusion can be drawn from columns (3) and (4) as it can be seen that the retirement effect under the 5-year bandwidth is still negative and statistically significant. As expected, further decreasing the bandwidth increases the standard error and thus decreases statistical significance since the number of observations is substantially smaller.

In columns (5) to (8), estimates for single-person households under a 10-year and 5-year bandwidth draw identical results than in the previous columns. Estimates under all four columns are statistically significant and of a similar magnitude to my baseline results. Overall, results derived using both larger and smaller bandwidths also imply retirement effect estimates that are very similar to my baseline results. Moreover, all estimates are still statistically significant although as expected standard errors are larger for the specifications using a smaller bandwidth of 5 years due to a loss of observations.[16]

Testing for discontinuities in covariates

One important condition for the validity of my results is the absence of discontinuity in my covariates. Indeed, they should display no discontinuous change at the threshold to exclude any correlation of my covariates with the treatment effect. Figure 3.4 graphically shows that there is no apparent discontinuity in the main socioeconomic and demographic covariates that I used in my models. Specifically, the upper-left panel of Figure 3.4 below shows that there does not seem to be an apparent change in public transport usage at retirement. Indeed, no discontinuity is observed near the cutoff for household having or not a GA travelcard.[17]

Moreover, I also apply a fuzzy RDD and use a 2SLS by replacing gasoline consumption with the log of disposable income as dependent variable to test if disposable income

[16] Similar results are found for the extensive and intensive margin. Results are available on demand.

[17] I use the detention of a GA travelcard as a proxy for public transport usage. The GA travelcard warrants full access to public transports in Switzerland and is possessed by approximately 5 percent of Swiss residents (SBB, 2024a). Moreover, men aged 65 or more (respectively 64 for women) have a 24 percent discount on the GA travelcard (SBB, 2024b).

Table 3.6 — Fuzzy RDD - Second stage results on gasoline consumption (log) — Different bandwidth sizes

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.248^{***}	-0.207^{**}	-0.281^{*}	-0.246^{*}	-0.614^{***}	-0.556^{***}	-0.615^{**}	-0.576^{**}
	(0.095)	(0.095)	(0.147)	(0.146)	(0.216)	(0.214)	(0.264)	(0.261)
Observations	13,703	13,703	7,477	7,477	4,839	4,839	2,475	2,475
Adjusted R^2	0.025	0.047	0.020	0.042	0.019	0.046	0.030	0.059
Bandwidth	10 years	10 years	5 years	5 years	10 years	10 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the log of gasoline consumption. All columns report estimates from a fuzzy regression discontinuity design using 2SLS with quadratic polynomials. Columns (1), (2), (5), and (6) use a bandwidth of 10 years; columns (3), (4), (7), and (8) use a bandwidth of 5 years. Columns (1) to (4) use all households, while columns (5) to (8) focus on single-person households. All models include canton and year fixed effects. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

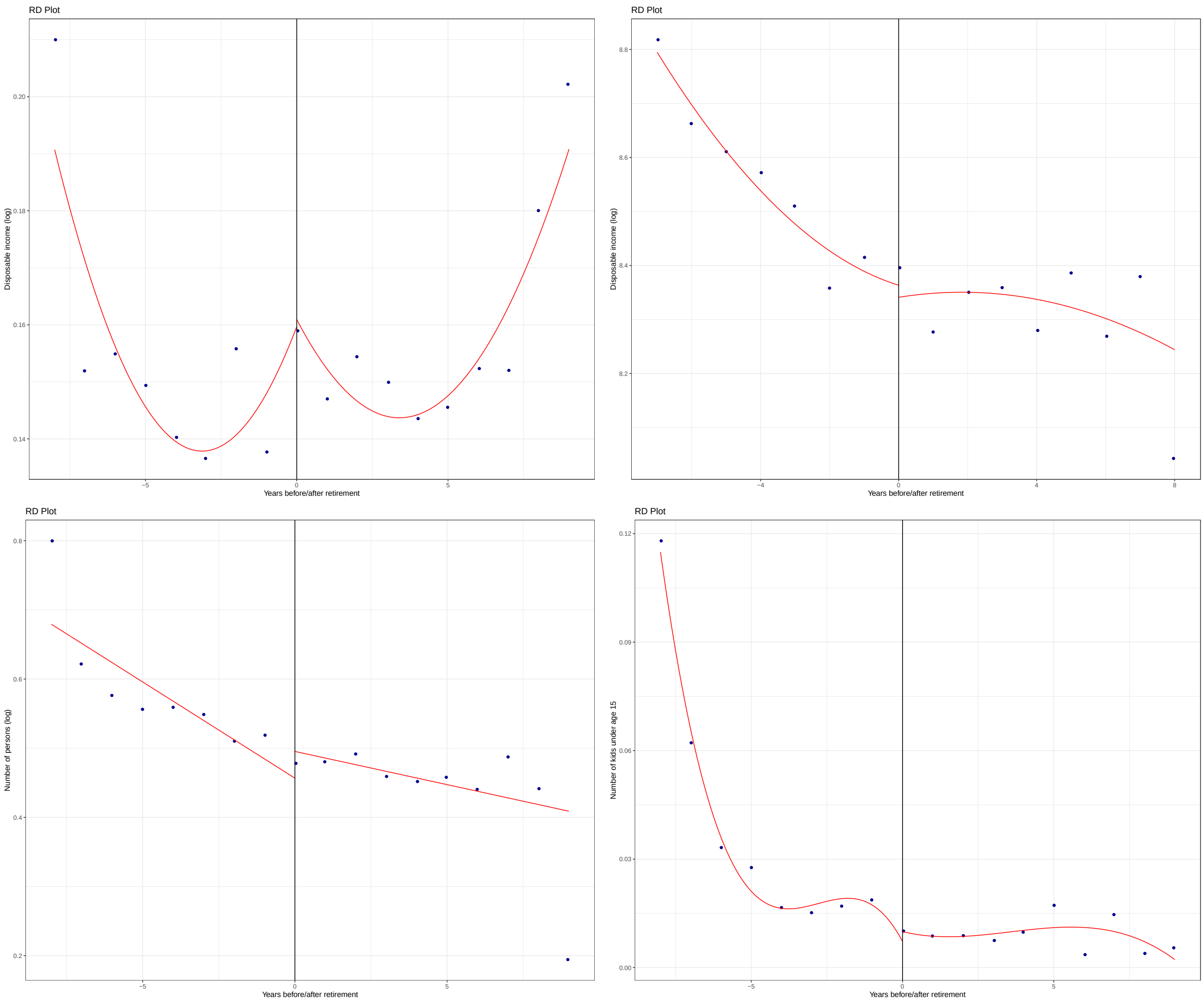
shows a jump at the threshold as my retirement effect could be confounded with an income effect. Table 3.7 shows the second stage results from the 2SLS model that I estimate using both a 7 and a 5-year bandwidth. I also estimate the model separately for single-person households only in columns (3) and (4). Results shown in all specifications of Table 3.7 confirm my previous conclusion. Indeed, elderly households' disposable income does not seem to display a significant discontinuity at the threshold as the estimated retirement effect is not statistically significant in all columns. These findings are thus in line with the intuition given in Figure 3.4 and further support my baseline results.

Placebo test for non-discontinuities points

In Table 3.8, I conduct a placebo-treatment test, where I move the threshold point for the fuzzy RDD by 3 years on both sides of the cutoff. I do so by moving the point with distance zero to either direction of the cutoff by 3 years. This allows me to assign a new placebo retirement treatment and conduct a placebo-fuzzy RDD. I conduct the placebo treatment using a 2SLS with a quadratic polynomial of the running variable. I use both the optimal bandwidth of 7 years as well as a 5-year bandwidth.

As can be seen in columns (1), (2), (5), and (6), moving the threshold 3 years prior does not produce any statistically significant effect of retirement on gasoline consumption and does not display any consistency in terms of sign or magnitude. The same conclusions

Figure 3.4 — Treatment effect near the cutoff in GA travelcard (upper left), disposable income (upper right), number of persons in the HH (lower left) and number of kids under 15 in HH (lower right)



are drawn from columns (3), (4), (7), and (8), which show that moving the cutoff 3 years later to the real threshold does not produce any statistically significant treatment effect as well.

Testing for discontinuity in car ownership

In this section, I further investigate the robustness of the results from the extensive margin section above. As discussed above, an important feature of the data is the important part of households having a null consumption of gasoline during the surveyed month. The potential issue with this is that the presence of zeros in the data might not necessarily indicate a permanent shift away from gasoline consumption. Indeed, a zero consumption for a given household may also appear in the survey

Table 3.7 — Fuzzy RDD - Second stage results on disposable income (log)

	All households		Single-person households	
	(1)	(2)	(3)	(4)
Retirement	-0.070	-0.090	-0.011	-0.053
	(0.061)	(0.080)	(0.112)	(0.140)
Observations	10,028	7,477	3,302	2,475
Adjusted R^2	0.097	0.024	0.014	0.009
Bandwidth	7 years	5 years	7 years	5 years
Covariates	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes

Notes: The dependent variable is the log of disposable income. A quadratic polynomial is used on both sides of the cutoff. Columns (1) and (3) use a 7-year bandwidth, while columns (2) and (4) use a 5-year bandwidth. Columns (1) and (2) include all household types; columns (3) and (4) are restricted to single-person households. All specifications include canton and year fixed effects, along with a set of covariates. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3.8 — Fuzzy RDD - Second stage results on gasoline consumption (log) — Placebo cutoff

	–3 years placebo				+3 years placebo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Placebo treatment	-0.049	0.128	-0.257	-0.054	-0.078	-0.115	0.252	0.274
	(0.349)	(0.351)	(0.583)	(0.587)	(0.347)	(0.343)	(0.672)	(0.670)
Observations	10,496	10,496	7,735	7,735	9,322	9,322	7,047	7,047
Adjusted R^2	0.019	0.037	0.019	0.037	0.023	0.051	0.013	0.043
Bandwidth	7 years	7 years	5 years	5 years	7 years	7 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the log of gasoline consumption. All columns estimate the retirement effect using 2SLS with quadratic polynomials. Columns (1)–(4) and (5)–(8) shift the RDD cutoff 3 years earlier and later, respectively. Columns (1), (2), (5), and (6) use a 7-year bandwidth; columns (3), (4), (7), and (8) use a 5-year bandwidth. All models include canton and year fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

simply due to the short period of observation. To control for this, I re-run my main specifications of the extensive margin section by replacing the binary variable equal to one if the household had a positive amount of gasoline consumed in the surveyed month by another binary variable equal to one if the household owns a car and zero if not. This variable might capture more precisely changes in market participation after retirement than the previous one.

Table 3.9 displays results from the test of discontinuity in car ownership after retirement. Again, all model specifications include both canton and year fixed effects and use

Table 3.9 — Fuzzy RDD - Second stage results on car ownership

	All households		Single-person households	
	(1)	(2)	(3)	(4)
Retirement	-0.036^{*}	-0.036^{*}	-0.082^{*}	-0.082^{*}
	(0.021)	(0.021)	(0.046)	(0.046)
Observations	10,028	10,028	3,302	3,302
Adjusted R^2	0.097	0.024	0.014	0.009
Bandwidth	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes
Fixed effects	yes	yes	yes	yes

Notes: The dependent variable is a binary variable equal to one if the household owns a car, and zero otherwise. A quadratic polynomial is used on both sides of the cutoff. All regressions use a 7-year bandwidth. Columns (2) and (4) include covariates. Columns (1) and (2) include all households; columns (3) and (4) are restricted to single-person households. All regressions include canton and year fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the optimal bandwidth of 7 years. Columns (1) and (2) use all households available while columns (3) and (4) restrict the analysis to single-person households. Starting in columns (1) and (2), results seem to be in line with the ones from Table 3.3 in the extensive margin section. Estimates under the optimal bandwidth are of -0.036 and are statistically significant at the ten percent level of significance. These estimates suggest a decrease in the probability of households to consume any gasoline at retirement by 3.6 percent, which is significantly lower than what was estimated in Table 3.3. In columns (3) and (4), using only single-person households, estimates are again larger than for the whole sample but smaller than the respective estimates in Table 3.3. The suggested decrease in market participation using solely single-person households is of 8.2 percent and is statistically significant at the 10 percent level of significance. Using this alternative measure of market participation confirms my first results from the extensive margin but indicate that the effect might have been slightly overestimated.

OLS estimates

In this final robustness check section, I further explore the relationship between retirement and gasoline consumption in Swiss households by using OLS regressions. The primary goal of this section is to see how OLS estimations compare to the 2SLS estimations, and therefore grasp potential endogeneity issues that can arise in OLS estimations. I estimate this by regressing the log of gasoline consumption of the household on a binary variable equal to one of the household is retired and zero

Table 3.10 — OLS - Gasoline consumption (log)

	All households		Single-person households	
	(1)	(2)	(3)	(4)
Retirement	-0.388^{***}	-0.319^{***}	-0.553^{***}	-0.498^{***}
	(0.041)	(0.041)	(0.073)	(0.072)
Observations	10,071	10,071	3,323	3,323
Adjusted R^2	0.022	0.046	0.026	0.050
Bandwidth	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes
Fixed effects	yes	yes	yes	yes

Notes: The dependent variable is the natural logarithm of household gasoline consumption. The sample includes individuals aged within 7 years above or below the legal retirement age (65 for men, 64 for women). Columns (2) and (4) include additional covariates. Columns (1) and (2) include all household types; columns (3) and (4) include only single-person households. All regressions include canton and year fixed effects. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

otherwise.

Table 3.10 displays results from an OLS estimation, All model specifications include both canton and year Fixed effects to control for unobserved heterogeneity across different Swiss cantons available and year of survey. In all columns, the sample is restricted to persons being aged up until 7 years before and after the legal retirement age of 65 (respectively 64 for women). Columns (2) and (4) include a set of controls. Columns (1) and (2) include all types of households in their sample while columns (3) and (4) only include single person households.

Starting in columns (1) and (2), the estimated retirement effect on gasoline consumption is very similar to the one estimated in Table 3.2 and is statistically significant at the one percent level of significance. For single-person households in columns (3) and (4), the effect is also similar, although a bit smaller, than the one measured with the 2SLS in Table 3.2. In conclusion, although this method was, a priori not used because of potential endogeneity issues, they seem to confirm a strong negative impact of retirement on household gasoline consumption. Furthermore, they also confirm that retirement is exogenous to gasoline consumption and that OLS is also a good way to measure the impact of retirement on gasoline consumption.

3.4 Conclusion

In this paper, I use Swiss household-level microdata to provide novel evidence on the impact of retirement on households' gasoline consumption. My data includes information on households' monthly gasoline consumption as well as a rich amount of socio-economic and demographic characteristics of the households. I exploit the Swiss statutory retirement age as an exogenous shock and apply a fuzzy regression discontinuity design as identification strategy to estimate how retirement affects gasoline consumption.

My results show that retirement decreases households' gasoline consumption significantly by 32-36 percent on average. Both the magnitude and the precision of my results are larger when considering only single-person households as the consumption of other household members is not mixed up with the household heads' gasoline consumption. The reduction reaches 59-66 percent when I restrict the sample to single-person households. In addition, I also find that retirement not only affects the consumption-level decision but also impacts households' decision to participate or not in the market. Specifically, retirement causes an average decrease in the probability of consuming any gasoline by 5-6 percent (13-16 percent for single-person households). Last, I find no significant impact of retirement on other energy expenditures such as electricity, natural gas and heating oil.

I also discuss two possible threats to internal validity and show that they are unlikely to affect my results. First, I show that my retirement effect is unlikely to be confounded with an income effect as I find no discontinuity of income at the retirement cutoff both graphically and statistically. I also did not consider the income level as a modulator of the extent by which retirement affects gasoline consumption because Baranzini and Weber, 2013 showed that income elasticity is insignificant in the short run in Switzerland. Second, I use data on households' public transport usage to document that the observed decline in private transport usage by households after retirement is not accompanied by changes in public transport usage, excluding thus a substitution from private to public transport at retirement.

My results can be interpreted as an illustration of the potential effects that population aging could have on both gasoline demand as well as on the CO_2emissions associated with it. With back of the envelope calculations, given projected demographic changes from SFSO, 2020b, I estimate that the increase in the share of retired people in

Switzerland could save 0.36 millions of tons of CO_2 by 2050.[18]

I close by emphasizing that the estimated retirement effect is by definition a local treatment effect, applying to compliers in the selected bandwidth. Given the lack of studies linking the effects of retirement on households' energy consumption, further work on this matter seems indicated. Investigating other changes in households' energy consumption patterns after retirement, such as heating fuel demand, represent important future research areas. In the present context, future studies should also consider potential welfare losses of the elderly caused by soaring energy prices.

[18] Details of the calculations can be found in section 3.B in the appendix.

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Appendix 3.A First stage results

My last sensitivity check derives results for the first stage of my 2SLS estimation for a set of different bandwidths to test for a possible weak instrument bias that would be a threat to the validity of my results. As can be seen in Table 3.A.1 and Table 3.A.2 below, all specifications display a highly statistically significant estimate as well as a very large partial F-statistic. Therefore, the presence of a weak instrument bias seems very unlikely and confirm the validity of my instrument.

Table 3.A.1 — First stage results – All households

	Retirement					
	(1)	(2)	(3)	(4)	(5)	(6)
Above age 65	0.758***	0.756***	0.695***	0.693***	0.653***	0.651***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.014)	(0.014)
Observations	13,703	13,703	10,028	10,028	7,477	7,477
Adjusted R^2	0.702	0.704	0.680	0.682	0.662	0.665
Partial F-stat	5745.6	5715.3	3354.3	3335.1	2175.5	2162.2
Polynomial	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Bandwidth	10 years	10 years	7 years	7 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is a dummy equal to one if the household head is retired. All columns use a fuzzy RDD with a quadratic polynomial on both sides of the cutoff. Columns (1)–(2) use a 10-year bandwidth; (3)–(4) use the optimal 7-year bandwidth; and (5)–(6) use a 5-year bandwidth. All models include canton and year fixed effects. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3.A.2 — First stage results – Single-person households

	Retirement					
	(1)	(2)	(3)	(4)	(5)	(6)
Above age 65	0.801***	0.801***	0.742***	0.741***	0.707***	0.704***
	(0.023)	(0.023)	(0.026)	(0.026)	(0.031)	(0.031)
Observations	2,475	2,475	1,872	1,872	1,438	1,438
Adjusted R^2	0.705	0.706	0.693	0.693	0.682	0.683
Partial F-stat	1212.8	1212.8	814.4	812.3	520.1	515.7
Polynomial	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Bandwidth	10 years	10 years	7 years	7 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is a dummy equal to one if the household head is retired. All columns estimate a fuzzy RDD using quadratic polynomials on both sides of the cutoff. Columns (1)–(2) use a 10-year bandwidth; columns (3)–(4) use 7 years; columns (5)–(6) use 5 years. All regressions include canton and year fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix 3.B Impact of Population Aging on Fuel Consumption and CO_2 Emissions in Switzerland

This section provides more detail on the back of the envelope calculations provided in the conclusion section. As households retire, I found that their gasoline consumption decreases on average by 32%. Given projected demographic changes from SFSO, 2020b, I quantify the potential reductions in fuel use and associated CO_2 emissions.

3.B.1 Calculations

The projected number of retired and non-retired persons is calculated as follows:

$$\begin{aligned}
\text{Persons retired in 2021} &= 8,737,800 \times 0.19 = 1,660,372 \\
\text{Persons retired in 2050} &= 10,440,600 \times 0.256 = 2,672,793 \\
\text{Persons retired in 2050 (No Aging Scenario)} &= 10,440,600 \times 0.19 = 1,983,714
\end{aligned}$$

Total gasoline consumption in Switzerland in 2021 was 6.16 billion liters for a total population of 8,737,800 persons. Gasoline consumption per person in 2021 was:

$$\frac{6.16}{8,737,800} = 0.000705 \text{ billion liters} = 705 \text{ liters per person}$$

Assuming constant consumption rates and applying these rates, the estimated total gasoline consumption in 2050 with aging is:

$$\begin{aligned}
(2672793 \times (1 - 0.32) + 7767807) \times 0.000705 \\
(2672793 \times 0.68 + 7767807) \times 0.000705 \\
(1817500 + 7767807) \times 0.000705 \\
9585307 \times 0,000705 = 6,76 \text{ billion liters}
\end{aligned}$$

Without aging:

$$
\begin{aligned}
(1,983,714 \times (1 - 0.32) + 8,456,886) \times 0.000705 \\
(1,983,714 \times 0.68 + 8,456,886) \times 0.000705 \\
(1,348,925 + 8,456,886) \times 0.000705 \\
9,805,811 \times 0,000705 = 6,92 \text{ billion liters}
\end{aligned}
$$

The reduction in fuel consumption due to aging is:

$$6.92 - 6.76 = 0.155 \text{ billion liters}$$

The associated reduction in CO_2 emissions is:

$$0.155 \times 10^9 \times 2.3/1000 = 357,540 \text{ tonnes of } CO_2$$

The projected demographic aging of the population under the reference scenario used by the Swiss statistical office is expected to result in a reduction of approximately 155 million liters of gasoline consumption by 2050, leading to a decrease of approximately 358,000 tonnes of CO_2 emissions.

Conclusion

This thesis explores the economic consequences of climate change by examining the adaptation and mitigation costs associated with weather shocks and the energy transition. First, it provides new evidence of the consequences that weather shocks, such as extreme temperatures or marine heatwaves, have on households in developing countries. Second, it investigates how carbon emissions from the transport sector are linked to demographic structure in a developed economy such as Switzerland.

The first chapter examines the impact of marine heatwaves (MHW) on coastal households' labor market outcomes in India. I match micro-level data from the Demographic and Health Survey (2015–2016) with NOAA's Degree Heating Week (DHW) measures. Using a linear probability model with spatial and temporal fixed effects, I show that exposure to MHW significantly increases unemployment and reduces employment in the fisheries sector. I also find that MHW increases female labor participation and shifts employment from all-year to seasonal jobs, suggesting labor market instability. Overall, the results highlight how climate-induced ocean warming affects coastal livelihoods.

In the second chapter, I study the impact of heat exposure on child disease incidence in sub-Saharan Africa. Using geo-coded DHS household surveys matched with high-frequency temperature data, I quantify the effect of heat exposure on the likelihood of fever, diarrhea, and respiratory diseases in children under five. Results show that 10 additional hours of exposure to 30–35°C increase disease incidence significantly, with stronger effects in urban areas and among children of less-educated mothers These findings highlight the need for targeted adaptation policies to mitigate climate-related health risks.

In the third chapter, I investigate how retirement affects household gasoline consumption in Switzerland by employing several waves of the Swiss Household

Budget Survey (SHBS) from 2006-2017. I use a fuzzy regression discontinuity design by exploiting the legal statutory retirement age. I show that retirement reduces gasoline consumption by 32–36%. No significant effects are found on other energy expenditures like electricity or heating. The findings suggest population aging may lower CO_2 emissions from private mobility in developed countries.

While this dissertation uses high-resolution environmental and household data to quantify certain dimensions of adaptation and mitigation costs, important questions remain about how these dynamics evolve over time and across contexts. Specifically, future research could explore the long-term consequences of repeated exposure to climate extremes by using longitudinal data. This would allow to analyze the longer-term household responses to climate shocks, such as migration decisions, income diversification, and the persistence of labor market disruptions observed in coastal India. Moreover, exploring household-level adaptation behaviors—such as changes in water use, health care seeking, or preventive measures during heat episodes could provide deeper insights into coping mechanisms that mitigate health impacts. Another avenue of refinement is the use of improved spatial data and alterative exposure metrics to enhance the precision of estimates, supporting more precise quantification of adaptation and mitigation costs under future climate scenarios. Finally, assessing the effectiveness of targeted interventions, such as early warning systems, livelihood diversification programs, and infrastructure investments, would help translate these findings into actionable policy recommendations that enhance resilience to climate and demographic transitions.