BGPE
Bavarian Graduate Program in Economics

BGPE Discussion Paper

No. 206

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Manuela K. Fritz

April 2021

ISSN 1863-5733

Editor: Prof. Regina T. Riphahn, Ph.D.
Friedrich-Alexander-Universität Erlangen-Nürnberg

B G P E Discussion Paper Series

Temperature and non-communicable diseases: Evidence from Indonesia's primary health care system.

Manuela K. Fritz*[1,2]

[1] *University of Passau, Department of Economics*
[2] *University of Groningen, Department of Economics, Econometrics and Finance*

April 2021

Abstract

Increasing ambient temperatures will severely affect human health in the decades to come and will exacerbate a variety of chronic health conditions. In this paper, I examine the temperature-morbidity relationship in the tropical climate environment of Indonesia with a focus on chronic, non-communicable diseases, namely diabetes, cardiovascular and respiratory diseases. Drawing on detailed individual level data from the Indonesian national health insurance scheme JKN and linking it with meteorological data on daily temperature realizations on a fine spatial level, I estimate the effect of high ambient temperatures on the daily number of primary health care visits. Exploiting the panel structure of the data and using a distributed lag model, I find that all-cause, diabetes and cardiovascular disease morbidity substantially increase at days with high mean temperatures. Specifically, on a day with a mean temperature above 29.5°C, the daily visits for diabetes and cardiovascular diseases increase by 29% and 19%, respectively, and these increases are permanent and not offset by visit displacement. Contrarily, I do not find any effects on respiratory disease morbidity. Heterogeneity analyses suggest that elderly and women suffer more severely from high temperatures. Back-of-the-envelope cost calculations indicate a substantial financial burden for the Indonesian health care system due to increasing temperatures.

Keywords: Health, Non-Communicable Diseases, Temperature, Climate Change, Indonesia.
***JEL* Codes** I10, I13, I18, Q50, Q51, Q54

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* *Contact Details:* University of Passau, Chair of Development Economics, Innstraße 29, 94032 Passau, Germany. Phone: +49-851-509-5318, Email: manuela.fritz@uni-passau.de.
Acknowledgements: This paper benefited greatly from the valuable advice provided by Michael Grimm. I also thank Vitri Widyaningsih and other colleagues from the Sebelas Maret University for their support in the data access. Stephan Geschwind provided excellent research assistance.

1 Introduction

The ongoing climate change comes with a rise in average and extreme temperatures and more severe weather events such as heat waves, storms and flooding, which impair nature and humanity. There is a consensus among scientists that, without substantial efforts to constrain greenhouse gas emissions, the global average temperature will rise between 1.4° and 4.8° Celsius until 2100 (Intergovernmental Panel on Climate Change, 2015). Moreover, heat waves are predicted to occur about twice more often in the coming decades compared to the end of the 20$^{\text{th}}$ century (Lhotka et al., 2018). This will not only cause environmental degradation, but will also pose a substantial threat to human health. In fact, global warming has been identified as the major health threat in the forthcoming century, with low- and middle-income countries being the most severely affected (Costello et al., 2009).

Global warming can severely affect people's livelihoods, nutrition, physical and even mental health (Kovats et al., 2003; Ahern et al., 2005; McMichael et al., 2006; Stanke et al., 2013). Additionally, it can accelerate the spread of infectious diseases, as warmer temperatures enhance the transmission of water-, food- and vector-borne diseases (Wang et al., 2009; Bowen and Ebi, 2017; Pandey and Costello, 2019). More directly, climate change and hot temperatures can worsen all-cause and disease-specific morbidity. Extreme temperatures trigger heat stress and heat strokes. In the most severe cases, they even lead to death. Moreover, heat compromises outdoor air quality and raises ozone levels, thereby causing respiratory tract and lung irritations.

Individuals with chronic, non-communicable diseases (NCDs), namely cardiovascular diseases (CVD), chronic respiratory diseases and diabetes, are especially susceptible to suffer from extreme temperature as it exacerbates a variety of chronic health symptoms. Hence, global warming poses a disproportional health risk for people suffering or being at risk of NCDs. Whereas for a long time NCDs were uniquely a problem in rich countries, nowadays 80% of all NCD-related deaths occur in low- and middle-income countries (Islam et al., 2014; World Health Organization, 2018; Grosskurth, 2019). Unfortunately, health care systems in low- and middle-income countries are not well positioned to address NCDs and still focus to a large extent on combating infectious and transmittable diseases (Dans et al., 2011; Kostova et al., 2017).

Whereas the link between temperature and mortality has already been extensively explored in the literature,[1] the effects on morbidity have less frequently been studied by the epidemiological literature and even less so by the economic literature (Campbell et al., 2018). Yet, especially with respect to chronic, non-communicable diseases, which themselves often come with high long-term treatment cost, increased morbidity due to

[1] See Basu (2009) and Benmarhnia et al. (2015) for reviews of the heat-mortality literature.

increased temperatures might drive related cost to unprecedented levels.

In this paper, I assess the effects of temperature on health with a focus on NCD-related morbidity in the context of Indonesia. Specifically, I study how the daily ambient mean temperature affects the number of daily all-cause and NCD-specific health visits, focusing on diabetes, cardiovascular diseases and chronic respiratory diseases, in the whole country over the years 2015 and 2016. The data I use consist of a nationally representative sample of 1.7 million individuals covered by the Indonesian national health insurance JKN and contain information on all their primary health care visits during the two-year observation window. I relate the daily number of visits within a district to the local daily temperature. Temperature data are extracted from a 0.25° × 0.25° gridded daily time series data set spanning total Southeast Asia. I include district, month, and year fixed effects to identify causal effects of local short-term variation in temperature on health outcomes. Finally, I derive simple cost estimates to predict the direct health care costs that the Indonesian national health insurance will incur under alternative scenarios regarding future temperature trends.

This study makes three contributions. First, I add to the epidemiological and small but growing economic literature that assesses the effect of ambient temperature and heat waves on morbidity (Kovats et al., 2004; Johnson et al., 2005; Larrieu et al., 2008; Lin et al., 2019; Bassil and Cole, 2010; Nitschke et al., 2011; Wichmann et al., 2011; Schaffer et al., 2012; Williams et al., 2012; Ye et al., 2012; Bobb et al., 2014; Dell et al., 2014; White, 2017; Song et al., 2018; Karlsson and Ziebarth, 2018; Lin et al., 2019; Mullins and White, 2019). Most of these studies investigate how temperature relates to emergency department visits and hospitalization rates. The main argument is that emergency visits are not scheduled (as opposed to, for example, surgeries) and are consequently representative for acute health issues resulting from excessive temperatures (White, 2017; Mullins and White, 2019). Yet, most likely this approach captures only visits due to very severe health problems and misses less acute cases, with the latter forming a much higher proportion of all visits. Hence, to address this gap I use an alternative approach by focusing on health visits below the hospital level. More specifically, I use data of health visits in the Indonesian primary health care facilities, where visits are also mostly unscheduled. Typically, patients appear unannounced, draw a number and wait to be examined. This feature allows for a plausible link between daily temperatures and visits occurring on the same day. Focusing on primary health care visits instead of hospitalization rates and emergency visits can provide broader information about how global warming will affect the primary health care sector, which is pivotal in many low- and middle-income countries.

Second, I use health visits data that are representative for one of the largest countries worldwide and therewith go beyond the common approach of assessing heat-related morbidity in single cities or (US) counties. Exceptions are Johnson et al. (2005), who assess the effect of the 2003 heatwave on hospital admissions for the UK, and Karlsson and Ziebarth (2018), who assess the impact of extreme temperatures on health for the entire German population from 1999 to 2008. Additionally, only few studies have been conducted in non-western and low- and middle-income countries (Campbell et al., 2018; Green et al., 2019). Hence, the relationship between temperature and health consequences in countries of the Global South, which tend to have comparably more tropical and humid climate zones, has not yet been investigated in detail. I provide evidence about the structural form of the relation in a context of tropical climate and thereby evaluate whether the temperature-morbidity nexus is equally present in a country where cold temperatures are scarce.

Lastly, I explore the direct cost of temperature increases for the newly established Indonesian national health insurance and therewith contribute to the literature on the financial burden of climate change (e.g. Diaz and Moore, 2017; Auffhammer, 2018; Carleton et al., 2020). By addressing not only the epidemiological aspect of climate change but also considering resulting economic aspects, I provide information that should be relevant to policy makers that are concerned with the financial sustainability of this immense insurance program, which ever since its implementation has suffered from annual deficits in a range between IDR 4.7 trillion (US$ 330 million) in 2016 to about IDR 28 trillion (US$ 2 billion) in 2019 (Deloitte Indonesia, 2019; Prabhakaran et al., 2019).

The remainder of this paper is organized as follows. In Section 2, I briefly summarize the physiological mechanisms of how heat impacts human health and review the relevant epidemiological and economic literature. Section 3 presents the health and weather data. In Section 4, I outline the empirical strategy. Section 5 presents the results including a detailed robustness and heterogeneity analysis. In Section 6, I provide simple back-of-the-envelope calculations of the expected costs for the Indonesian health care system and Section 7 concludes.

2 The heat-morbidity relation

The thermoregulatory function allows the human body to maintain its core temperature despite greatly varying external temperatures. Through sweating, decreasing heat production and vasodilation of the skin blood vessels, the body cools down when outside temperature is high. Vice versa, if outside temperature is low, the body regulates its temperature through heat production by the metabolic system, piloerection (erection of body hair) and vasoconstriction (narrowing) of the skin vessels (Hall and Hall, 2020). Yet, despite these physiological adjustments, the body can only limitedly cope with too high (or too low) temperatures. While the normal body temperature fluctuates around 36°C, the human comfort zone of ambient temperature typically ranges from 22°C to 27°C, depending on humidity levels. Adverse health effects of heat can be observed at levels of ambient temperature that surpass this range in one or the other direction, though only few studies identify an absolute threshold (Kovats et al., 2004; Lin et al., 2009).

Elevated temperatures severely affect the cardiovascular system by causing an accelerated blood circulation and heart rate and decreased blood pressure levels. The resulting cardiac output is insufficient to fulfill the thermoregulatory needs of the human body and this in turn can lead to heat exhaustion, dehydration and heat stroke (Epstein and Yanovich, 2019). Green et al. (2010), for example, investigate CVD hospital admissions in California over a six-year time span (1999-2005) and find that per 10°F (5.5°C) increase in mean apparent temperature the risk of dehydration increases by 10.8%, the risk for heat stroke even by 404%. White (2017) also assesses the heat-morbidity relationship in California using hospitalization rates from 2005-2014 and finds a relative increase of the risk of being hospitalized on a day with a temperature above 80°F (26.6°C) compared to a reference temperature of 60°F-65°F (15.5°C-18.3°C). He finds the largest relative risk for what he labels "Fluid and Electrolyte imbalances" which are driven by dehydration. Schwartz et al. (2004) find similar increases for several cities throughout the US. The study of Karlsson and Ziebarth (2018) supports the US findings also for the German population. Using data covering the years 1999-2006 and information on 170 million hospital admissions, they find that the risk of being hospitalized with a CVD-related diagnosis on a hot day (>30°C) is between 2% and 10% higher compared to a non-hot day. Surprisingly, they find that the risk of being hospitalized is higher for younger than older age groups, while it is reversed when the authors investigate CVD mortality. In contrast, several other studies find no or even a tendentious negative effect of heat on CVD hospital admissions in London (Kovats et al., 2004), Madrid (Linares and Diaz, 2008) and twelve other European cities (Michelozzi et al., 2009). This highlights the context specificity of the heat-morbidity relationship and hence requires to assess the relationship specifically in less developed countries, which face weaker health care systems as well as a different exposure to current temperatures.

Heat exposure also affects respiratory disease morbidity. The literature has documented the link between high ambient temperature and increases in respiratory hospital admissions, yet the underlying physiological mechanism is less clear. Potential pathways are increases in air pollutants and allergens through heat (Åström et al., 2013) as well as breathing hot air which exacerbates chronic respiratory conditions (Michelozzi et al., 2009; Anderson et al., 2013). While the effect on mortality has been largely covered in the economic literature (Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011; Barreca, 2012; Barreca et al., 2016), the evidence for the effect on morbidity is scarcer and relies largely on epidemiological studies (Ye et al., 2001; Kovats et al., 2004; Linares and Diaz, 2008; Lin et al., 2009; Michelozzi et al., 2009; Green et al., 2010). The study results are again quite context-specific and range from no effect of heat on respiratory hospital admissions in Tokyo (Ye et al., 2001) to an increased risk of 10.4% for elderly in London (Kovats et al., 2004). However, all studies are in line with the conclusion that the impact is most severe for the elderly population above the age of 75.

Evidence for the link between heat and diabetes morbidity relies largely on descriptive case studies (Semenza et al., 1999; Knowlton et al., 2009). A notable exception is the study by Green et al. (2010), who find that the risk of being hospitalized with the diagnosis of diabetes in California increases by 3.1% for each 10°F (5.5°C) increase in temperature. Given the rising prevalence rates of diabetes worldwide and the fact that 80% of the affected individuals live in low- and middle-income countries, this aspect requires more attention (International Diabetes Federation, 2013). Individuals suffering from diabetes face a greater risk of heat-related illnesses as their capacity to dissipate heat is compromised. Increases in ambient temperature impair the skin blood flow as well as the sweating process which can have detrimental consequences for an individual's glycemic control (Kenny et al., 2016). Paired with the fact that more than 50% of individuals with diabetes remain undiagnosed in low- and middle-income countries (Manne-Goehler et al., 2019), the relationship between temperature and diabetes needs to be carefully assessed in this context so that health care systems can adequately respond. For Indonesia, the country with the 7^{th} highest number of individuals with diabetes worldwide (International Diabetes Federation, 2013), investigating this link is of special importance.

Heat-induced illness does not only come with individual health-related consequences but also imposes cost on the economy through losses in productivity as well as on the health care systems being confronted with increased costs for acute and longer-term care.

Karlsson and Ziebarth (2018) estimate for Germany that the monetized cost for one additional hot day ranges from €6 million to €43 million (including the cost of hospital services, the monetized cost of quality adjusted life years and the loss in productivity), and from €30 million to €212 million for the US. Cheng et al. (2018) assess the monetary health cost of heat waves for several Australian cities and calculate that a single heat wave over several days can cost in the extreme case up to US$ 21 million for a single city, including monetized deaths. Both studies, however, only assess the cost for severe health consquence on higher health care level, namely for emergency cases and deaths. Hence, the results do neither allow to extract from the total costs those costs that arise on the side of health insurances nor to extract cost for less acute health impacts. To fill this gap, I estimate the heat-induced cost on the primary health care level, which are imposed on the Indonesian health insurance agency, for an additional hot day.

3 Data

3.1 BPJS insurance data & health visits data

The outcomes of interest in this study are the number of all-cause, diabetes, cardiovascular and chronic respiratory disease visits per day per 100,000 insurance members. The data source I use is a nationally representative administrative dataset on health insurance status and health visits, published only in 2019 by the Indonesian Social Health Security Agency (*Badan Penyelenggara Jaminan Sosial Kesehatan - BPJS*). To the best of my knowledge, this is the first study using this data set for a rigorous analysis of (NCD-related) health care visits.

The dataset contains information for a 1% sample of all families and their respective family members that were enrolled in the Indonesian national health insurance scheme *Jaminan Kesehatan Nasional* (JKN) by the end of 2016. The insurance scheme was launched in 2014 with the goal to achieve universal health insurance by 2019 and is hitherto one of the world's largest single-payer and most ambitious health insurance programs with around 223 million members by April 2021 (Prabhakaran et al., 2019; BPJS Kesehatan, 2021). The insurance scheme works to a large extent through a capitation-based payment structure. Each insurance member is registered with a single primary health care facility, which works as the "gatekeeper" to the insurance system. Services at higher level facilities and specialists are only granted when a primary health care facility that is registered with BPJS was approached at first. A gatekeeper is either a *Puskesmas* (community health clinics), a primary clinic or a general practitioner. Every facility receives a monthly capitation payment from BPJS which is calculated on the basis of the number of insurance members registered with the respective facility and an approximation of visits per member. For a primary facility that caters for on average 10,000 to 20,000 members, the capitation payments from BPJS are about US$ 5,000 to 10,000 per month, which is equal to 70% to 90% of total funds (KOMPAK, 2017; Prabhakaran et al., 2019). Certain health services are not covered through this capitation scheme, but the facility needs to claim reimbursement payments directly from BPJS based on the provided services. Non-capitation-based services include mainly obstetric and neonatal services, child delivery and services for family planning programs, but also drugs and treatments for chronic care, such as diabetes (World Health Organization, 2017; Prabhakaran et al., 2019). However, in any case, the service is supposed to be free for the insured patient and entirely covered by the insurance.

The families included in the data set were selected based on a stratified sampling procedure. Within each of the 22,024[2] primary health care facilities functioning as gatekeeper, families were stratified into three categories: (i) families that had not yet utilized any health care services, (ii) families that had utilized only primary health care services and (iii) families that had utilized primary health care services and were referred to higher health facilities. From each of the three strata, ten families were randomly selected and data on all family members were included in the sample.[3] This procedure led to a sample of 1,697,452 individuals from 586,969 selected families. The dataset consists of five distinct data files. The first one includes administrative membership and demographic data, such as an individual insurance number, age, gender, marital status, working status, class of insurance, province and district of residence, the type and location of their gatekeeping health facility, as well as a sampling weight to ensure representativeness for all insurance members. The second file contains information about all inpatient and outpatient primary health care visits conducted by the sampled individuals in the years 2015 and 2016. Due to the sampling procedure at least one primary health care visit was recorded for about 27% of the individuals (465,017). However, this share drops to 18.3% if sampling weights are applied. The third file contains complementary information about non-capitation-based services for the visits recorded in the second file. File four and five include data for referred cases towards higher health care facilities, i.e. district and province hospitals. All data files cover the two-year observation window 2015-2016.

In the analysis, I use the administrative file and the capitation and non-capitation service files and extract demographic characteristics and information on all primary health

[2]This was the number of primary health care facilities by the time of the sampling procedure. As by now this number has increased to 22,717 (April, 2021).

[3]If there were less than ten families in one stratum, all families were automatically included in the sample.

care visits. The two latter files contain the essential information on 1,733,759 documented visits.[4] For each visit, the following information is recorded: the respective insurance member and visit ID, the date, the location of the facility, the ICD-10-code and name of the primary diagnosis, whether it was an outpatient service or inpatient admission, as well as the information whether a patient received a referral to a higher level facility. Moreover, for the non-capitation health services the amount requested as reimbursement payment by the facility and the amount finally granted from BPJS are recorded. This rich data source allows me to extract the number of disease-specific visits per day within each of the 514 Indonesian districts. To assure comparability across districts and to maintain the representativeness for all members of JKN, I calculate the number of weighted disease-specific visits per 100,000 insured members. Moreover, for the subsequent heterogeneity analysis I differentiate all health visits by gender and age categories.

I consider the following ICD-10-codes for the respective visit category: E10-E14 for diabetes-related visits, I00-I99 for visits with the diagnosis of cardiovascular diseases and J30-J99 for visits with a diagnosis related to chronic respiratory diseases.

3.2 Weather data

The main explanatory variable in my analysis is the mean ambient temperature per district that was observed on each day within the two-year time span. This data was obtained from the SA-OBS dataset (Version 2.0), which is a gridded daily meteorological data set for the entire Southeast Asian region. It is provided by the Southeast Asian Climate Assessment & Dataset project (SACA&D) and combines data from 3,914 meteorological stations throughout Southeast Asia (Van Den Besselaar et al., 2017). Each grid covers an area of $0.25° \times 0.25°$, which corresponds to approximately 27.7 km $\times$ 27.7 km (770 km^2) at the equator. I merge each of these grids to the respective Indonesian district whenever a grid-point falls directly into the district borders and average the temperature over all grids per day and district. For 88 of the 514 districts (mainly smaller cities[5]), there are no grid-points that fall directly within the respective borders. In these cases, I use inverse distance weighting and assign the weighted temperature of the three nearest grid-points towards the district (for more details see Appendix A). For the analysis, I make use of the daily mean temperature as continuous variable and as categorized variable, using eight 1.5° Celsius temperature bins.

[4] After applying population weights, the number of visits amounts to 135,082,178. This is lower than the numbers of total primary health care visits reported from BPJS for the years 2015 and 2016, which sum up to 220 million (BPJS Kesehatan, 2015, 2016). Thus, all of the values and estimates reported in this paper should be interpreted as lower bounds.

[5] Districts in Indonesia are the second administrative level and are either regencies (*kabupaten*) or cities (*kotas*).

Not only ambient temperature but also other weather conditions can affect human health. Especially humidity and precipitation have been shown to have an impact on morbidity and mortality (Maccini and Yang, 2009; Barreca, 2012). Consequently, I include daily humidity measures and precipitation levels as control variables. Data on both variables are collected from the Goddard Earth Sciences Data and Information Services Center (GES DISC). The two respective datasets are also available as a 0.25° × 0.25° gridded data set, with the precipitation data at a daily level and the humidity data at a 3-hourly level, which I aggregate per day. The grid-point to district assignment procedure is analogous to that for the temperature dataset.

The final dataset is a daily panel for each of the 514 Indonesian districts over the two years under study, i.e. 375,734 observations. For five districts, however, no health visit data is available, leaving 372,079 observations (509 districts * 731 days) for the analysis. Panel A of Table 1 summarizes the BPJS health insurance data and Panel B shows the resulting aggregated key variables for the panel data set. Summary statistics for health visits segregated by age categories are shown in Table B1 in Appendix B.

Several findings become apparent already from the summary statistics. First, visits related to cardiovascular diseases account for about 7.7% of the total number of primary health care visits that have been recorded in the years 2015-2016. Visits with the primary diagnosis of hypertension alone even make up for 5.44% of all diagnoses in the two years under study (see Table B2 in Appendix B for a summary of the 20 most frequent diagnoses). To set this share in relation: It is larger than the share recorded for the US, where in 2016 only 3.8% of all visits to physician offices had the primary diagnosis of hypertension (Rui and Okeyode, 2016). Second, only with the exception of chronic respiratory diseases, female individuals have higher numbers for all daily visiting rates than men. For cardiovascular disease visits, this number is even higher by more than 60%. This can result from both, men that in general seek less care or women that suffer more from CVDs. Third, considering that Indonesia is a country with one of the highest smoking rates in the male population worldwide, it is somewhat surprising that the numbers for chronic respiratory diseases do not largely differ between male and female patients, as several of respiratory diseases are caused by tobacco smoking.

The bottom part of Table 1 summarizes the weather data. It reflects the tropical and humid climate of Indonesia. The daily mean temperature is high and varies only little; the days on which the mean temperature fell below 20.5°C account for only 2%. On more than half of the number of days, a mean temperature between 25.5°C and 28.5°C was

Table 1: Summary statistics

	Unweighted		Weighted	
Panel A: BPJS Data				
# of families	586,969			
# of individuals	1,697,452		192,294,875	
# of individuals with at least 1 health visit	465,017		35,266,632	
# of recorded visits (2015-2016)	1,733,759		135,082,178	
	Mean	SD	Min	Max
Panel B: Panel Data Set				
Health Visits				
All				
All-cause	75.14	101.49	0.00	2659.11
Diabetes	1.96	11.66	0.00	774.64
Cardiovascular Diseases	5.81	19.38	0.00	747.09
Respiratory Diseases	1.83	10.33	0.00	625.64
Female				
All-cause	89.48	136.27	0.00	4195.77
Diabetes	2.29	17.00	0.00	1303.34
Cardiovascular Diseases	7.17	29.56	0.00	1303.34
Respiratory Diseases	1.76	13.76	0.00	1016.01
Male				
All-cause	61.45	104.99	0.00	2714.21
Diabetes	1.64	14.84	0.00	1182.82
Cardiovascular Diseases	4.51	22.62	0.00	1291.98
Respiratory Diseases	1.90	14.68	0.00	1038.61
Weather Data				
Mean Temperature (°C)	26.28	2.24	8.70	32.33
Max. Temperature (°C)	30.46	2.38	12.65	37.70
Temperature Bins (°C)				
<20.5°	0.02	0.14		
20.5° - 22°	0.02	0.14		
22° - 23.5°	0.05	0.23		
23.5° - 25°	0.13	0.34		
25° - 26.5°	0.25	0.43		
26.5° - 28°	0.31	0.46		
28° - 29.5°	0.19	0.39		
>29.5°	0.03	0.16		
Rainfall (mm)	5.26	9.68	0.00	166.65
Humidity (grams of water/kg air)	16.25	1.69	4.94	20.77
Number of observations	372,079			

Notes: The data for health visits (Panel B) represent the mean number of daily visits per 100,000 health insurance members per district. Sampling weights are applied. The mean values for the temperature bins represent the percentage of days that fall within the respective temperature range.

recorded. The maximum temperature averages around 30.5°C and achieves a maximum of about 38°. The average rainfall and humidity levels are also expectedly high; on an average day, precipitation levels of 5.26 mm are recorded, with a maximum of 166 mm. Humidity levels are on average 16.25 grams of water per 1 kg air.

4 Empirical approach

4.1 Testing the U-shape

To estimate the causal effect of the daily mean temperature on the number of primary health care visits on the same day, it is essential to control for regional differences in access to care and re-occurring seasonal variation. Consequently, I exploit the panel structure of the data and use a fixed-effects model that allows to control for seasonal and regional effects. Specifically, I include a series of year fixed-effects and month fixed-effects, with the latter controlling for seasonal phenomenon that might confound the number of daily primary health care visits, such as monsoons. Additionally, I include district fixed-effects to capture across-district heterogeneity in terms of health facility density and access to health care, which differs substantially across Indonesian districts.

The literature suggests that the effect of ambient temperature on health outcomes is seldom linear, but rather exhibits a U-shaped relationship (Li et al., 2014; White, 2017; Song et al., 2018; Lin et al., 2019), i.e. adverse health effects occur at very low and very high temperature levels. I consequently start with an investigation of whether a U-shaped functional form is also appropriately depicturing the temperature-morbidity relationship in a tropical climate context where cold temperatures only sparsely occur. Specifically, I estimate the following quadratic model

$$V_{kd} = \beta_1 Temp_{kd} + \beta_2 Temp_{kd}^2 + \gamma \mathbf{X'}_{kd} + \delta_y + \sigma_m + \theta_k + \mu DOW + \varepsilon_{kd} \tag{1}$$

where V_{kd} is the number of primary health care visits (differentiated by diagnosis) that occurred on day d in district k. $Temp_{kd}$ and $Temp_{kd}^2$ are the mean temperature realization on day d in district k and its respective squared term. β_1 and β_2 are, hence, the main coefficients of interest. δ_y, σ_m and θ_k are the year, month and district fixed-effects, respectively. Moreover, I include day-of-the-week fixed-effects (DOW) to account for less health visits during weekends. The error term ε_{kd} is clustered at the district level to account for the possibility that the errors might be correlated within districts over time. The vector of controls $\mathbf{X'}$ contains other weather conditions that might simultaneously affect the outcome variable. As mentioned above, I include the daily rainfall and humidity levels, both in a logarithmic scale to smooth the skewness of the distributions.

4.2 Main specification

I next allow for a quasi-semi-parametric relation between temperature and the amount of daily health visits and estimate a temperature bin model. This semi-parametric specification allows for a more flexible relationship between temperature and health visits. I herewith follow an approach that has been widely adopted in the economic health and climate literature (e.g. Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011; Barreca, 2012; White, 2017; Karlsson and Ziebarth, 2018). In this model, temperature does not enter the regression as a continuous variable but instead, I specify eight temperature bin dummies that are equal to one whenever the temperature on a specific day fell in the respective temperature range. The eight bins each cover a 1.5° temperature range (from below 20.5° to above 29° C) and are chosen such that even at the lower and higher margin at least 2% of the days fall within these two temperature bins. The full model specification reads

$$V_{kd} = \sum_{i=1}^{8} \beta_i Temp^i_{kd} + \sum_{l=1}^{7}\sum_{i=1}^{8} \vartheta_{il} Temp^i_{k,d-l} + \gamma \mathbf{X'}_{kd} + \delta_y + \sigma_m + \theta_k + \mu DOW + \varepsilon_{kd}. \quad (2)$$

The coefficients of interest are now the seven temperature coefficients $\sum_{i=1}^{8} \beta_i$; the bin for the mean temperature 25°-26.5°C is omitted and serves as reference category. The coefficients of interest therefore represent the effect of a day on which the temperature falls in the respective bin compared to the reference category, and hence can be interpreted as the effect of when the temperature exceeds the human temperature comfort zone. I additionally include seven lags for each of the temperature bin (as well as for the rainfall and humidity controls, where they are included) to account for serial correlation in weather realizations. While this inclusion might bias the main coefficients, by construction, due to high collinearity in the regressors, a non-inclusion might similarly bias the results if lagged temperature realizations play an important role in the number of visits on a specific day. Moreover, the bias due to correlation declines at a rate $1/T$ (Nickell (1981); with T as the number of observations within a group), hence, it can be safe to argue that the panel is sufficiently long ($T = 731$) for this bias to approach a neglectable size. I nevertheless present results with and without the inclusion of lags.

The detailed administrative insurance data allow for a separation of the number of visits per day by gender and age categories. Consequently, I run the model for age and gender-specific daily visiting rates (always per 100,000 in that group) to assess whether the temperature-health relation differs with these characteristics.

4.3 Does "harvesting" exist on the primary health care level?

Studies that investigate the heat effect on mortality often also explore the dynamic temperature effect (Braga et al., 2001; Schwartz et al., 2004; Anderson and Bell, 2009; Deschênes and Moretti, 2009; Basu and Malig, 2011; Bi et al., 2011; Karlsson and Ziebarth, 2018). This means concretely that they investigate whether "harvesting" or mortality displacement occurs, i.e. whether individuals dying due to extreme temperatures would have died anyway in the course of the following days. If mortality displacement is occurring, temporary increases in death rates due to extreme heat are followed by days that see decreased numbers of death cases, sometimes resulting in a zero net-effect. The majority of the aforementioned studies conclude that this harvesting phenomenon is especially present for hot temperatures and heat waves, but less so for spells of cold temperatures. Hence, the question arises whether the same phenomenon exists for the temperature-morbidity context also on lower health care levels, i.e. whether primary health visits increase on a day of extreme heat but decrease in the days afterwards. Green et al. (2010) confirm that harvesting exists for emergency hospital admissions in California. Mullins and White (2019) as well as White (2017), on the other hand, contradict these findings and conclude that the evidence for harvesting (similarly in California and on hospital admissions) is lacking. Situations without harvesting are of major concern, as this means that increases in health visits are not offset but persistent.

To advance the discussion on harvesting with respect to heat-morbidity, I assess the dynamic effect of temperature on the current number of primary health visits to explore whether harvesting at this level exists. To do so, I analyze the lag structure of Equation 2 in detail and assess the cumulative effects of extreme temperatures.

5 Results

5.1 Main results

Table 2 presents the results for the quadratic model in Equation 1 for each of the four outcomes of interest (all-cause, diabetes, CVD, and respiratory primary health care visits). Panel A shows the regression coefficients; Panel B shows the result of the F-test for joint significance of the linear and squared term and the turning point. It additionally presents marginal effects at different temperature realizations.

Column (1) suggests that the temperature-morbidity relationship with respect to all-cause visits follows a non-linear shape. Both the linear and squared term of the temperature variable are – on their own as well as jointly – statistically significant at the 1%

level and show the expected signs. The turning point lies at 25.5°C which is below the average mean temperature of 26.2°C and clearly within the range of temperature realizations, indicating the well-known U-shape. Thus, a daily mean temperature above 25.5°C results in an increase in the same-day health visits at the primary health care level, with increasing marginal effects. The size is also economically non-negligible – an increase of 1°C from 27° to 28°C, all else equal, is associated with a same-day increase of 0.46 all-cause visits per 100,000 individuals. A marginal increase at the top of the mean temperature distribution even causes the number of visits to increase by 1.61 per 100,000. Scaling-up these numbers to the national level for a population of around 260 million Indonesians, a single day with a temporary increase of 1°C from 31° to 32° corresponds to around 4,200 more all-cause primary health care visits, an increase of 2.1%.

Column (2) at first suggests that a non-linear effect similarly exists for visits with the diagnosis of diabetes. The joint effect for the linear and squared term is significant at the 1% level and the marginal effects are positive and economically and statistically significant already at a temperature of 25°C. Yet, the turning point is located around 21.5°C, which is below the 4^{th} percentile of the temperature range in the data. This suggests that the functional form rather follows a J-shape or a linearly increasing trend and negative health effects related to diabetes begin to set in at low temperature levels. The marginal effects are obviously smaller in absolute numbers compared to all-cause visits, but the percentage increase is substantially higher. A 1°C increase at 27° and 31° result in 0.065 and 0.113 more visits per 100,000 respectively, the latter corresponding to roughly 300 diabetes visits more per day for the whole country - an increase of 5.7%.

The functional form for cardiovascular disease morbidity, shown in Column (3), seems less clear. The linear and squared temperature terms are on their own as well as jointly insignificant, while the marginal effects at higher temperature levels above 27°C are statistically significant. Moreover, when I instead include only the linear term, it is significant at the 10% significance level. Taken together, a U-shaped functional form for cardiovascular diseases in the tropical and humid context of Indonesia does not seem to exist, but heat effects seem to set in linearly at higher temperature levels. For respiratory disease visits, the two coefficients for temperature are insignificant on their own, but jointly significant at the 5% level. Yet, the signs are reversed; the number of visits with a diagnosis related to respiratory diseases seems to decrease with an increase in ambient temperature, contradicting the hypothesis that hot temperatures affect respiratory health. While other studies have indeed also found evidence that cold temperatures are more severely affecting the lungs and respiratory tract than hot temperatures (Deschênes and Moretti, 2009; Son et al., 2014; White, 2017), I refrain from interpreting my results as a "cold-effect".

Table 2: Results - Testing the U-shape of the temperature-morbidity relation

	(1) All-cause	(2) Diabetes	(3) CVD	(4) Respiratory
Panel A				
Temperature	-7.279***	-0.258**	-0.365	0.110
	(1.416)	(0.117)	(0.256)	(0.114)
Temperature^2	0.143***	0.006**	0.008	-0.003
	(0.028)	(0.002)	(0.005)	(0.002)
Log Rainfall	-0.823***	0.008	-0.038	-0.026
	(0.160)	(0.019)	(0.031)	(0.020)
Log Humidity	10.498***	0.595*	0.997*	0.350
	(3.319)	(0.348)	(0.539)	(0.284)
Constant	52.877***	0.443	0.134	-1.912
	(19.904)	(1.748)	(3.615)	(1.639)
Observations	372,069	372,069	372,069	372,069
R-squared	0.134	0.006	0.018	0.005
Number of Districts	509	509	509	509
District Fixed-Effects	Yes	Yes	Yes	Yes
Month Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed-Effects	Yes	Yes	Yes	Yes
Panel B				
Turning Point	25.45°C	21.5°C	22.81°C	18.33°C
F-statistic ($\beta_1 = \beta_2 = 0$)	13.23	5.13	2.09	3.20
P-value	0.000	0.006	0.125	0.042
Marginal effect at ...				
25°	-0.110	0.041**	0.046	-0.039**
	(0.155)	(0.017)	(0.032)	(0.016)
27°	0.463**	0.065***	0.079**	-0.051**
	(0.191)	(0.021)	(0.040)	(0.021)
29°	1.037***	0.089***	0.112**	-0.063**
	(0.273)	(0.028)	(0.055)	(0.028)
31°	1.610***	0.113***	0.145**	-0.075**
	(0.371)	(0.036)	(0.073)	(0.036)

Notes: Table 2 presents the results for the quadratic model, with health visits differentiated by diagnosis. Panel A displays the regression results and Panel B contains further functional explorations. Standard errors (in parentheses) are robust and clustered on district level. ***p<0.01, **p<0.05, *p<0.1.

Indonesia has a tropical climate and the lowest mean temperature in the data is equal to 8°C, which is still higher than the temperature thresholds used to define a "cold day" in the aforementioned studies, which are commonly chosen around the freezing point. It rather points to a linearly decreasing relation, supported by the fact that the coefficient of the linear term entered alone is negative and significant at the 5% level.

Before I turn to the results of the temperature bin model, I briefly discuss the effects for rain and humidity. An increase in the specific humidity leads to an increase in the number of all-cause primary health care visits and has thereby a similar effect as temperature. The effect, however, is less strong for NCD visits, suggesting that the humidity effect in all-cause visits might be driven rather by infectious diseases, such as bacterial or viral infarcts, which both flourish in humid environments. This is well in line with studies by Barreca (2012) and Chowdhury et al. (2018), which show that high levels of humidity are associated with higher rates of infectious diseases but do less affect non-communicable diseases such as CVDs or cancer. Rainfall levels negatively affect the same-day number of all-cause health visits, but are not significant for any of the NCD visits.

Table 3 below presents the results for the temperature bin model. After having concluded that the temperature-morbidity nexus with respect to NCDs is not U-shaped, but rather J-shaped or linear for diabetes and cardiovascular diseases, and negatively sloped for respiratory diseases, the semi-parametric approach allows a more detailed and flexible analysis. For each of the four outcomes I apply three different models. The first column shows the most parsimonious model, including only the temperature bins and all fixed-effects. In the next column, I add seven lags for each of the temperature bins. The third column for each outcome displays the results of the main specification, including the controls for current and lagged rainfall and humidity. The main coefficients of interests in each model are the coefficients for the three temperature bins representing temperatures above the average. They display the absolute increase in (disease-specific) primary health care visits per day per 100,000 individuals. For the ease of interpretation, I calculate the corresponding percentage increase for the top bin relative to the mean of the outcome variable.

For all-cause visits, Column (1) re-confirms the U-shaped relationship with increases in the number of visits for both higher and lower temperatures than the reference category. Yet, only the higher temperature bins are statistically significant. As soon as a I control for serial correlation in temperature in Columns (2) and (3) the effects for lower temperature bins completely vanish or even turn negative. Including rainfall and humidity somewhat reduces the size of the coefficients but the heat effect is still large and significant. Specifically, on a day with an average temperature realization of above 29.5° compared to a day with a temperature in the reference category, the number of all-cause primary health care visits is higher by 9.47 or 12%. Nationwide, this translates into almost 25,000 visits.

Columns (4) – (6) support the rather linear relation between temperature and diabetes morbidity. All coefficients for lower bins are non-distinguishable from zero or negative and upper bins are significantly positive across all three specifications. Quantitatively these effects are very large. On a very hot day, above 29.5°C, the number of diabetes visits increases between 20% and 29% (corresponding to absolute increases of about 1,000 and 1,500 nationwide, respectively). And even at temperatures between 26.5° and 28°C, the relative increase amounts up to 6.5%. These results also show that assuming a U-shape, as in Table 2, would lead to a substantial underestimation of the actual increase in diabetes morbidity. This becomes even clearer when evaluating the results in Columns (7) – (9) for cardiovascular disease morbidity. While the former results in Table 2 revealed only small temperature effects, the increase in CVD morbidity in the semi-parametric model is large and significant. The effect is robust across the three specifications and also clearly rejects the idea of a U-shape, with null or negative effects for lower temperature realizations. The percentage increase is somewhat lower than for diabetes (11%-19%), but higher than for all-cause visits. This implies that diabetes and CVD morbidity, compared to other diseases, increase disproportionally at high temperatures and are likely to follow this trend under future global warming if not counteracted.

Columns (10) – (12) show that the prior suggested negative relation between temperature and respiratory disease visits disappears in the more sophisticated models. Essentially, I cannot reject the hypothesis that – as soon as I account for serial correlation and other weather conditions – the effect of heat on respiratory morbidity is non-existent in the given setting.

Table 3: Results of the semi-paramatric model - Temperature effects on all and by cause visits

	All-cause			Diabetes			Cardiovascular Diseases			Respiratory Diseases		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<20.5°	3.046	-1.388	-0.656	0.112	-0.043	-0.032	-0.406	-0.673	-0.662	0.178	0.074	0.087
	(2.495)	(2.192)	(2.207)	(0.262)	(0.416)	(0.419)	(0.396)	(0.431)	(0.436)	(0.148)	(0.191)	(0.192)
20.5° - 22°	2.133	-1.236	-0.614	-0.219*	-0.382***	-0.370***	-0.809**	-0.881**	-0.862**	0.085	0.019	0.031
	(1.761)	(1.706)	(1.707)	(0.129)	(0.140)	(0.139)	(0.332)	(0.358)	(0.363)	(0.134)	(0.158)	(0.160)
22° - 23.5°	0.325	-2.622***	-2.160**	-0.036	-0.184	-0.176	-0.052	-0.184	-0.168	-0.006	-0.029	-0.020
	(0.920)	(0.850)	(0.856)	(0.113)	(0.125)	(0.126)	(0.208)	(0.220)	(0.224)	(0.080)	(0.095)	(0.097)
23.5° - 25°	0.485	-1.254**	-1.003*	-0.010	-0.082	-0.078	-0.010	-0.149	-0.141	0.028	0.038	0.043
	(0.566)	(0.546)	(0.547)	(0.060)	(0.064)	(0.064)	(0.108)	(0.116)	(0.114)	(0.061)	(0.075)	(0.076)
25° - 26.5°	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
26.5° - 28°	1.647***	2.932***	2.658***	0.111*	0.131**	0.129**	0.193**	0.322***	0.312***	0.038	0.056	0.050
	(0.484)	(0.456)	(0.460)	(0.060)	(0.061)	(0.061)	(0.097)	(0.108)	(0.110)	(0.053)	(0.054)	(0.055)
28° - 29.5°	2.038***	4.484***	3.918***	0.155**	0.221***	0.220***	0.213	0.514***	0.494***	-0.106	-0.064	-0.077
	(0.655)	(0.621)	(0.654)	(0.068)	(0.076)	(0.075)	(0.133)	(0.144)	(0.148)	(0.075)	(0.079)	(0.081)
>29.5°	5.021***	10.222***	9.476***	0.401***	0.569***	0.576***	0.651**	1.112***	1.087***	-0.344***	-0.151	-0.171
	(1.378)	(1.483)	(1.501)	(0.151)	(0.191)	(0.201)	(0.256)	(0.308)	(0.312)	(0.124)	(0.147)	(0.150)
Log Rainfall			-0.957***			-0.008			-0.049			-0.029
			(0.150)			(0.020)			(0.031)			(0.020)
Log Humidity			8.512**			0.471			0.624			0.283
			(3.361)			(0.424)			(0.832)			(0.430)
Constant	-10.915***	-10.739***	-45.304***	-0.553***	-0.623***	-1.683	-1.033***	-0.960***	-2.039	-0.116	-0.098	-0.733
	(2.870)	(2.926)	(16.140)	(0.185)	(0.196)	(1.563)	(0.334)	(0.336)	(2.293)	(0.108)	(0.114)	(1.154)
Mean of dep. variable	75.14	75.14	75.14	1.96	1.96	1.96	5.81	5.81	5.81	1.83	1.83	1.83
Percentage change (top bin)[a]	6.68%	13.60%	12.11%	20.41%	29.03%	29.38%	11.20%	19.13%	18.71%	-18.79%	-8.25%	-9.34%
Observations	372,069	372,023	372,023	372,069	372,023	372,023	372,069	372,023	372,023	372,069	372,023	372,023
R-squared	0.134	0.134	0.135	0.006	0.006	0.006	0.018	0.019	0.019	0.005	0.006	0.006
Number of Districts	509	509	509	509	509	509	509	509	509	509	509	509
District Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lags	0	7	7	0	7	7	0	7	7	0	7	7
Rainfall & Humidity (+ lags)	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Table 3 shows the regression results for the temperature bin model. Robust standard errors (in parentheses) are clustered at the districts level. [a]The percentage change is shown for the top bin and indicates the percentage increase in daily primary health care visits for a day with a temperature in the top bin compared to a day with a temperature in the reference category. *** p<0.01, ** p<0.05, * p<0.1

5.2 Robustness checks

I conduct a series of robustness checks to test whether the results hold under different specifications. I start with re-running the regressions using a single "Hot Day" indicator instead of the eight temperature bins. This binary variable is equal to one whenever the temperature is larger than 29.5°C and zero otherwise, corresponding to the 98$^{\text{th}}$ percentile of the mean temperature distribution. The results are shown in Table C1 in Appendix C. The coefficients are smaller in size compared to the main results, but still economically large and statistically significant. The numbers of visits for all-cause, diabetes and CVDs increase by 5.6, 0.37 and 0.59 per 100,000 on a hot day, respectively, the coefficient for respiratory visits is negative but insignificant. When up-scaled to the national level, these numbers correspond to 14,500 visits more per day in Indonesia for a single hot day, of which about 1,000 and 1,500 are attributed to diabetes and CVDs, respectively.

Secondly, I re-estimate the main specification but use instead a Tobit model to account for the fact that the outcomes of interest are zero-censored variables (i.e. for some days there are no visits recorded in the sample). The results are shown in Table C2 (regression coefficients) and TableC3 (conditional marginal effects) and are in line with the main results. For all-cause, diabetes and CVD visits, all three bins with temperatures above the mean are significant, while there is no significant relation between temperature and respiratory disease visits. The marginal effects are somewhat smaller than those from the original model, but the difference is marginal.

In another specification, I use the daily maximum temperature as my main explanatory variable instead of the daily mean temperature. Again, I divide the temperature realizations into eight temperature bins with a range of 1.5°C each, with the bottom bin corresponding to temperatures below 24°C and the top bin to temperatures above 33°C. Table C4 displays the results and reveals some interesting findings; while the effects are not substantially different (though somewhat smaller) for all-cause, diabetes and CVD, the relation between the maximum temperature and the number of visits related to respiratory diseases now shows the well-known U-shape. Both, the coefficients below and above the reference category are positive and marginally significant. It seems that while diabetes and CVD visits do constantly increase with higher temperatures, respiratory disease symptoms only deteriorate when temperatures spike in the highest possible realizations.

Next, I conduct a placebo permutation test; I randomly assign the number of daily visits to temperature observations (permuting within a given district but keeping the day constant across district[6]) and re-estimate the semi-parametric model, using 100 replications for each outcome. To confirm that the main results are valid and not occur by simple statistical coincidence, the coefficients for the upper temperature bins in the placebo test should be indistinguishable from zero, but statistically different from the estimates in the main model. This is indeed the case; Figure C1 in Appendix C shows the kernel density plots for the estimates of the three bins above the reference temperature for each of the four outcomes. The straight line in each of the graphs represents the point estimate from the original model. The placebo estimates are with no exception not distinguishable from zero. Moreover, for all-cause, diabetes and CVD visits, I can in every case reject the hypothesis that the point estimates for the different temperature bins obtained in the main results are equal to the estimate distribution obtained from the permuted data. Not surprisingly, the null-effects for respiratory diseases from the main regression overlap with the distribution of the placebo estimates. Hence, the permutation test suggests that my main results show indeed a true relationship between temperature and primary health care visits and are not only significant by chance.

In a second placebo test, I use as outcome the number of health care visits with the diagnosis "contraceptive management", which should reasonably not be affected by temperature and weather realizations. The results are shown in Table C5 in Appendix C. All three specifications support the hypothesis that visits concerning contraceptive management are not affected by temperature and thereby support the validity of the main results.

5.3 Heterogeneity

I next turn to assessing the temperature-health effects separately for men and women and by age categories. Figure 1 shows that for each of the three significant outcomes in the pooled sample – all-cause, diabetes and CVD visits – the impact on health care visits are consistently larger for women, represented by the red lines. The red line always lies above the blue line (representing men's visits) and the confidence intervals do never include zero. For male patients, the picture is slightly different; mean temperatures above 26.5° increase all-cause and CVD visits. Yet, I cannot reject that there is no increase for men with respect to diabetes visits below temperatures of 29.5°C. Only at the very top of the temperature distribution the effect becomes significant. Thus, women may suffer more from hot temperatures in general and in particular when it comes to diabetes. It could of course also reflect a difference in health care seeking behavior. Respiratory visits,

[6]For example, the number of visits on the 2nd of June are randomly assigned to the temperature realizations on the 24th of September for each district.

contrarily, do not increase with temperature for neither gender.

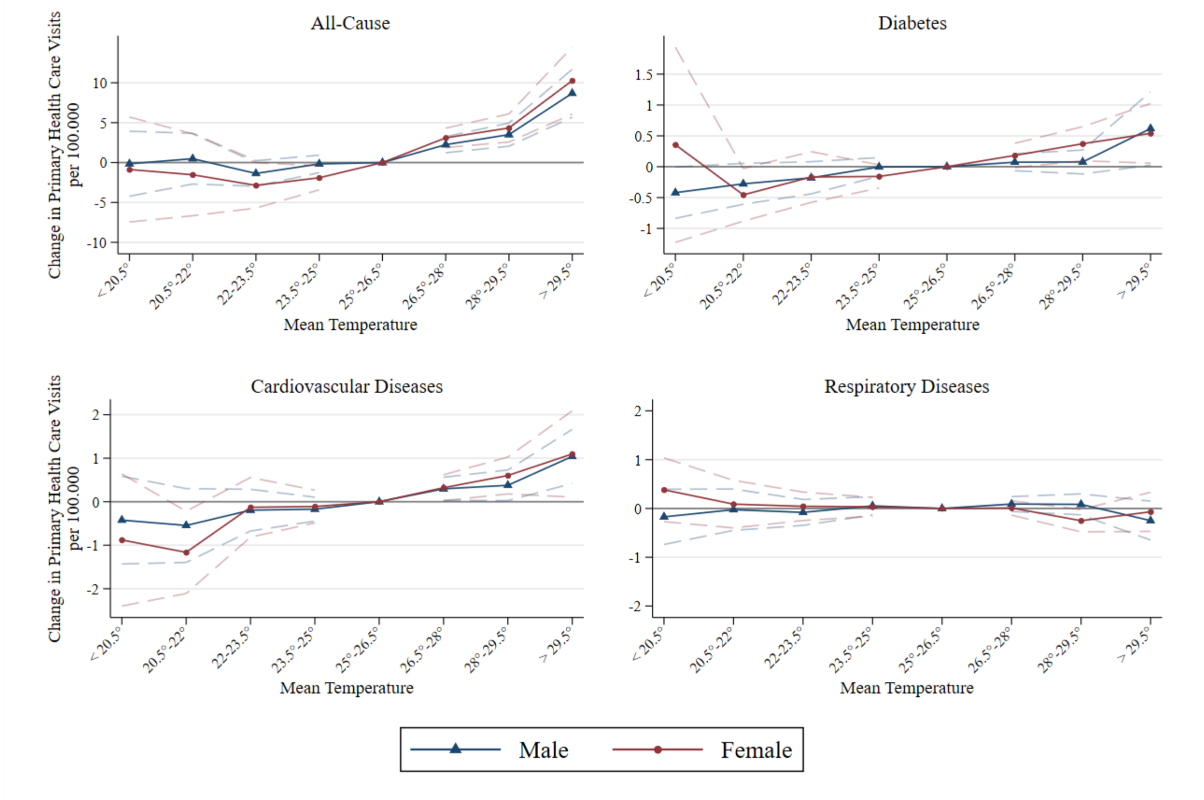

Figure 1: Gender heterogeneity. *Notes:* Figure 1 presents the temperature effects separately for men (blue lines) and women (red lines) for each of the four outcome variables. Dashed lines represent the 95% confidence interval.

The heterogeneity assessment with respect to the age distribution (see Figure D1 in Appendix D) shows, as does most of the literature, that elderly suffer most from hot temperatures. This holds for all-cause and CVD visits. The point estimates for elderly, meaning 65 years older, are consistently larger (and significant) than for children and adults, with numbers that are up to four times larger than for adults. Yet, when it comes to diabetes, the large confidence intervals do not allow me to conclude that there is an effect for elderly persons, while the effect is significant for adults between 15 and 65. Of course, increasing morbidity is reason to concern at all ages, but if the adult working population will be more severely affected by increases in temperature, at least with respect to diabetes, it may imply a potentially large productivity loss.

5.4 Harvesting

Increases in the number of daily primary health care visits due to hot temperatures impose a substantial burden on the health care system, both financially as well as for staff members working in the respective health centers. Yet, this burden could at least partially be offset if high increases on a particular day are followed by one or more days with significantly lower visits. To test whether this “harvesting” phenomenon – which is often observed for heat strokes and deaths – does also occur for primary health care visits, I assess the lag structure of the main model specification. Specifically, I test whether the effect of a day with a temperature in the top bin (< 29.5°C) persists as well in the following seven days. Figure 2 presents the results graphically. The circles indicate the effect of a hot day on the number of visits on the same day and for seven days in the future, whereas the last two squares on the right in every graph depict the cumulative effect after one week and two weeks, respectively.

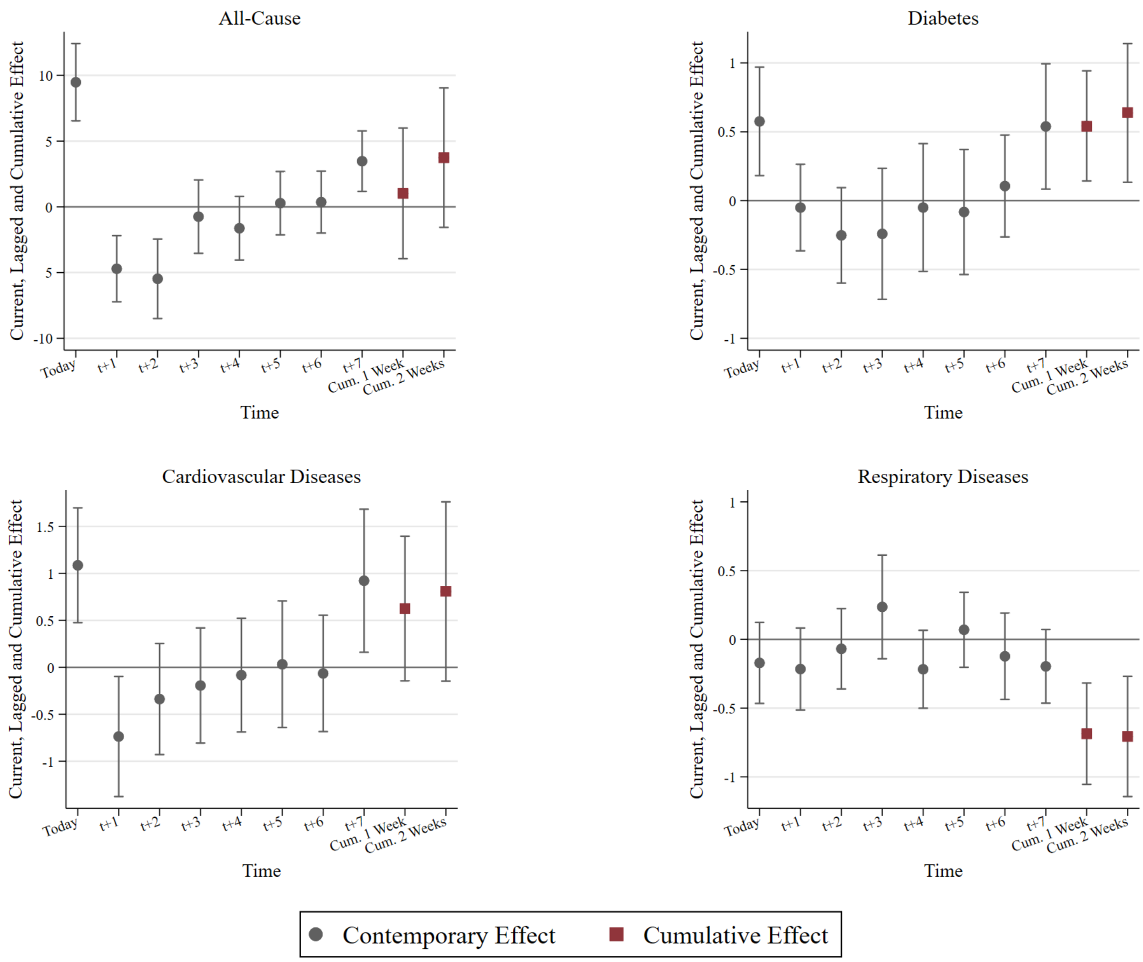

Figure 2: Assessment of visit displacement. *Notes:* The circle point estimates represent the effect of a day with a temperature in the top bin (< 29°C) relative to the reference bin (25°-26.5°C) on the number of daily visits today and up to seven days in the future. The squares show the cumulative effects after one and two weeks, respectively. The lines represent the 95% confidence interval.

The results differ between all-cause visits and the three NCD-outcomes. For all-cause visits, a high spike on the current day is followed by a significant decrease in the number of visits in the next two days. Afterwards the effect returns to zero. Likewise, the cumulative effects after one and two weeks are not significantly different from zero. This suggests that for all-cause visits some form of harvesting indeed occurs and the spike in daily visits is only temporary. A similar but less strong pattern is observed for cardiovascular diseases. The high increase in daily visits is partly offset by a slight decrease in the following day. Yet, the cumulative effects after one and two weeks are positive and significant at the 10% level, contradicting the harvesting hypothesis. For diabetes, there is clearly no displacement in the primary health care visits; for none of the following days the heat effect is statistically significant and the cumulative effects after one and two weeks remain large and statistically significant.

Interestingly, while none of the day-by-day effects for respiratory diseases is on its own significant, the cumulative effects show a significant negative impact. This could, on the one hand, indicate that hot temperatures in tropical climates somewhat reduce morbidity from respiratory diseases. It could, however, also signal that respiratory diseases become more severe and need advanced treatment at a higher health care level. Indeed, when I instead use the number of respiratory visits that received a referral as outcome variable, the temperature bins above the average mean temperature show a positive sign. However, this is rather speculative and requires a more detailed analysis to be confirmed. Conclusively, while the harvesting phenomenon occurs on the primary health care level when all visits are jointly assessed, the findings speak strongly against visit displacement for diabetes and, somewhat less strong, also for cardiovascular diseases.

6 Cost estimates

What do the previous findings imply regarding the financial consequences for the Indonesian health insurance? The Indonesian national insurance scheme JKN was launched in 2014 and all other prior existing insurance schemes in Indonesia (e.g. Jamkesmas, Askes, Jamsostek) were incorporated into JKN to form a single scheme for the entire country. Since then, the managing agency BPJS faced substantial financial deficits, primarily due to member contribution rates that are too low to cover the costs that arise from comprehensive benefit packages. Primary health care services are ought to be entirely free for insured members and health services are payed for – either indirectly via capitation payments or directly via reimbursement payments – by BPJS. Given that both payments are determined by the number and type of visits a facility manages, increases in (chronic disease) visits will directly lead to increases in the required payments and therefore further deteriorate the financial sustainability of the scheme.

In the following, I calculate the expected costs of one additional day in the highest temperature bin, i.e. the health care cost of one additional day with a mean temperature above 29.5°C, and apply alternative scenarios for the expected occurrence of such hot days. This will provide a rough estimate of the costs that might occur with increased temperatures. However, the numbers have to be interpreted as lower bound cost estimates, as they do neither include monetized cost of emergency cases nor monetized deaths and productivity losses. Moreover, it should be noted that this simple extrapolation method does not account for any form of human adaptation, intensification of climate effects or general equilibrium effects, which are vital to model health effects in the long-run (Dell et al., 2014).

I use two different sources to get an estimate of the cost per visit at a primary health care center. First, I use the results from a monitoring and evaluation study conducted by BPSJ in 2014 and 2015 to examine capitation fund management and utilization (Kurniawan et al., 2016). The study concluded that an average visit (not differentiated by in- or outpatient) costs approximately IDR 78,000 (∼US$ 6) in primary and general practitioner clinics and IDR 120,000 (∼US$ 14) in a Puskesmas. Second, I use the 5$^{\text{th}}$ wave of the Indonesian Family and Life Survey, which is conducted every four to five years in Indonesia and includes an extensive survey module about the service fees and costs within Puskesmas. The cost indicators from this survey are somewhat lower: IDR 12,000 (∼US$ 0.9) for a simple examination or check-up, additional IDR 14,000 (∼US$ 1) for a blood sugar test and IDR 85,000 (∼US$ 6.2) for a regular inpatient visit. For simplicity and to get a single value, I a take a weighted average of these unit cost, using the share of in- and outpatient visits in the BPJS data as weights (the additional costs for a single blood sugar test are considered for diabetes visits only). This results in an average cost of IDR 15,000 (∼US$ 1), which I use as a lower bound estimate.

The projections for the increases in occurrence rates of hot days are derived from the estimates of the Intergovernmental Panel on Climate Change (2015), which uses global circulation models to predict future changes in temperature. Under a low emission scenario (RCP2.6), the mean temperature in Indonesia is predicted to increase by about 0.8°C until 2060, under a high emission scenario (RCP8.5), an increase of 1.4°C until 2060 is likely.

To approximate the increase in the number of days with a mean temperature above 29.5°C, I shift the daily temperature distributions in the original temperature data by 0.8° and 1.4°C, respectively, and calculate the difference in hot days between the original data and the two scenarios. Since the number of hot days varies by district within Indonesia, I take the average number of hot days across districts to get a single estimate for the country. For scenario 1, these back-of-the envelope calculations suggest an increase in the number of hot days from 9.5 per year in 2015/2016 to 34.5 per year in 2060. For the second scenario, the days with a temperature above 29.5° would even climb to 68 per year in 2060.

With these numbers at hand I finalize the cost estimate calculations in Table 4. Column (1) recapitulates the coefficients from the main results in Table 3 for all-cause, diabetes and CVD visits. In Column (2), I up-scale the increases per 100,000 to the national level. Columns (3) and (4) present the lower and upper bound estimates, respectively, for the cost of one more hot day, multiplying the absolute numbers with the unit cost of a single visit as outlined above. Columns (5) and (6) show the final cost estimates for the predicted increases in the number of hot days under scenario 1 and 2 for the upper bound estimates (all monetary values shown in 1,000s of IDR or USD).

Table 4: Costs of one and several additional hot days

	(1) Increase per 100,000	(2) Absolute Increase	(3) Costs/hot day (Lower Bound)	(4) Costs/hot day (Upper Bound)	(5) S1: 25 more hot days in 2060	(6) S2: 58 more hot days in 2060
All-cause	9.476	24,638	IDR 369,570.0	IDR 2,956,560.0	IDR 73,914,000.0	IDR 171,480,480.0
			$ 27.1	$ 344.9	$ 8,623.3	$ 20,006.1
Diabetes	0.576	1,498	IDR 4,3442.0	IDR 179,760.0	IDR 4,494,000.0	IDR 10,426,080.0
			$ 3.2	$ 20.9	$ 524.3	$ 1,216.4
CVD	1.087	2,826	IDR 42,390.0	IDR 339,120.0	IDR 8,478,000.0	IDR 19,668,960.0
			$ 2.9	$ 39.6	$ 989.1	$ 2,294.7

Notes: Table 4 summarizes the cost estimates derived from the main results. Column (1) recapitulates the coefficients from the main results in Table 3, Column (2) up-scales the numbers to the national level, Columns (3) and (4) display the health care cost for an additional hot day at a lower and upper bound (using 15,000 IDR/visit as the lower bound cost and IDR 120,000/visit as the upper bound cost; the lower bound cost for diabetes include the extra cost of a blood sugar test). Columns (5) and (6) extrapolate the upper bound cost per day to the yearly cost in 2060, assuming two different scenarios (S1 and S2) regarding the occurrence of hot days with a temperature above 29.5°C. Currencies are in units of 1,000s.

The monetized cost of a single additional day with a temperature above 29.5°C could cause an additional financial burden for the Indonesian health care system up to IDR 3 billion (US$ 0.34 million). 17% of this financial burden can be attributed to primary health care visits with the primary diagnosis of diabetes or cardiovascular diseases. The extrapolated estimates suggest that the yearly health care cost due to temperature-driven increases in primary health care visits could rise up to IDR 73 billion (US$ 8.6 million) and IDR 171 billion (US$ 20 million) under a low and high emission scenario, respectively.

Again, I do not claim these estimates do be very precise, especially in light of likely adaptation patterns or other factors tight to climate change that may play a role in the longer run. But even the cost of a single additional day at current times would imply an additional burden for the already financially struck Indonesian insurance scheme and would further challenge its financial sustainability.

7 Conclusion

I explored the relationship between high temperatures and non-communicable disease-morbidity in Indonesia. The study results confirm that high temperatures increase the health burden on primary health care level. Even though Indonesia is a country where high temperatures prevail and residents are used to heat and humid weather conditions, the heat-morbidity relationship is a relevant factor in people's health care seeking behavior. Using health and weather data on the day and district level, I show that the numbers of all-cause and NCD-related primary health care visits substantially increase on days where the daily mean temperature exceeds the average mean temperature. Specifically, I find that on days with a mean temperature above 29.5°C compared to a reference day with a mean temperature between 25° and 26.5°, the numbers of daily all-cause, diabetes and cardiovascular disease visits increase by 12%, 29% and 19%, respectively, and these increases are permanent and not offset by visit displacement.

As in any typical low- and middle-income country, the primary health care sector forms the backbone of the health system in Indonesia. The finding that not only emergency departments but also the primary health care sector experiences an increasing burden when temperatures rise has potentially important implications for the management of the health care system. To prevent an overwhelming burden within the primary care sector during heat waves, actions could be taken on the side of the health providers as well as on the side of affected individuals. First, the primary health care sector could establish links with local meteorological services to receive early information and warnings of impending heat events. This would allow a timely response of physicians and general practitioners in the form of increased and disease-specialized staff during days with excessive temperatures. Second, individuals affected by a chronic disease could be sensitized to the risks of heat. Possible interventions could include the provision of educational material or targeted counseling for individuals at risk. Third, individual early warning systems, for example in the form of alerting weather apps, could provide a useful complementary tool for patients to prevent personal exposure to heat. Early notifications of heat waves and hot days would then allow to re-organize necessary outdoor activities and delay them to cooler evening hours. Special attention could be given to women and the elderly, as they seem to be more severely affected by heat.

Given rising temperatures and an increasing occurrence of heat waves, the findings also imply an increasing financial burden for the Indonesian national health insurance agency BPJS. Under a high-emission scenario, representing a mean temperature increase of 1.4°C until 2060, the insurance system could face an additional financial burden of US$ 20 million per year, not yet accounting for emergency costs and more severe health consequences. 17% of this burden can solely be attributed to diabetes and cardiovascular diseases. Increasing rates of NCDs and their risk factors, such as obesity, smoking and high blood-pressure, further jeopardize the system's sustainability. Higher efforts for the prevention and control of such diseases would have to be taken immediately to counteract this trend.

My findings do not only contribute to a better understanding of the relationship between temperature and chronic diseases in Indonesia, but have probably a broader applicability to other low- and middle-income countries with a similar tropical climate. Especially for other Southeast Asian countries, which face a similar surge of non-communicable diseases and comparable meteorological conditions and trends, the results might have similar validity.

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Appendix A Details on gridded weather data

Figure A1 graphically displays the matching of the gridded weather data with the respective district. For districts A and B, there are 4 and 5 grid points, respectively, that fall directly within the borders of the districts. The daily mean temperature for district A is, hence, constructed as the arithmetic mean of the four grids displayed in black, whereas the daily mean temperature for district B is constructed as the arithmetic mean of the five grid points displayed in white.

Due to the small size of District C, no grid points are assorted toward it. The daily mean temperature is consequently derived via inverse distance weighting of the three nearest grid points from the districts' centroid, as shown in the right part of the figure.

Using four instead of three nearest grid points did not cause any significant changes in the results.

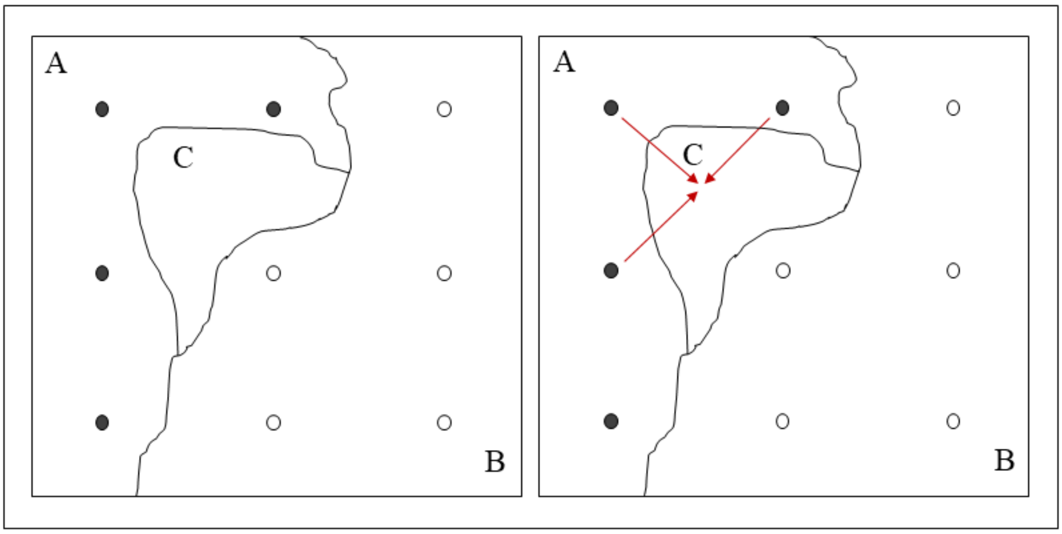

Figure A1: Assignment of gridded weather data to districts.

Appendix B Additional summary statistics (BPJS data)

Table B1: Summary Statistics of PHC visits by age

	Mean	SD	Min	Max
All-Cause				
Total	75.14	101.49	0.00	2659.11
Age <15	69.85	157.29	0.00	5930.57
Age 15-65	75.86	109.57	0.00	4011.96
Age 65+	88.35	316.64	0.00	16584.00
Diabetes				
Total	1.96	11.66	0.00	774.64
Age <15	0.04	3.91	0.00	771.55
Age 15-65	2.18	14.50	0.00	1168.74
Age 65+	5.20	78.87	0.00	6465.48
Cardiovascular Diseases				
Total	5.81	19.38	0.00	747.09
Age <15	0.20	7.74	0.00	1696.80
Age 15-65	5.70	22.37	0.00	1127.18
Age 65+	21.98	147.31	0.00	6738.34
Respiratory Diseases				
Total	1.83	10.33	0.00	625.64
Age <15	1.95	21.74	0.00	1696.80
Age 15-65	1.65	11.72	0.00	811.04
Age 65+	3.23	53.62	0.00	4891.47
Number of Observations 372,079				

N*otes:* Table B1 shows summary statistics for the number of daily primary health care visits by age categories. The values correspond to daily visits per 100,000 individuals within the respective age category.

Table B2: Distribution of diagnoses frequency (ICD-10 Codes) in BPJS insurance data (capitation services)

ICD-10 Code	Diagnosis Name	Sample frequency (weighted)	Population frequency	Percentage
J06	Acute upper respiratory infections of multiple and unspecified sites	179,273.30	13,967,699	10.34%
J00	Acute nasopharyngitis [common cold]	116,893.20	9,107,484	6.74%
I10	Essential (primary) hypertension	94,368.59	7,352,530	5.44%
M79	Other soft tissue disorders, not elsewhere classified	73,117.16	5,696,770	4.22%
K29	Gastritis and duodenitis	69,746.40	5,434,144	4.02%
K30	Functional dyspepsia	55,143.92	4,296,422	3.18%
R50	Fever of other and unknown origin	53,220.84	4,146,590	3.07%
K04	Diseases of pulp and periapical tissues	46,804.05	3,646,639	2.70%
J02	Acute pharyngitis	44,383.06	3,458,012	2.56%
A09	Other gastroenteritis and colitis of infectious and unspecified origin	41,458.42	3,230,145	2.39%
R51	Headache	40,823.80	3,180,700	2.35%
Z30	Contraceptive management	34,914.56	2,720,294	2.01%
E11	Type 2 diabetes mellitus	33,979.08	2,647,409	1.96%
J11	Influenza, virus not identified	33,560.07	2,614,762	1.94%
R05	Cough	25,497.82	1,986,609	1.47%
K02	Dental caries	25,287.31	1,970,207	1.46%
L30	Other dermatitis	21,029.44	1,638,464	1.21%
O80	Single spontaneous delivery	18,987.38	1,479,362	1.10%
L23	Allergic contact dermatitis	17,790.01	1,386,071	1.03%
A01	Typhoid and paratyphoid fevers	17,319.03	1,349,376	1.00%
Total		**1,733,759**	**135,082,178**	**100%**

Notes: Table B2 shows the distribution of the 20 most frequent diagnoses from the BPJS insurance data over the years 2015-2016. The column “sample frequency” shows the weighted distribution in the data; the column “Population Frequency” refers to the frequency upscaled to the national level using the provided population weights in the data sample.

Appendix C Additional tables and figures of robustness checks

Table C1: Robustness checks - Hot day specification

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
Hot Day	5.664***	0.375**	0.583**	-0.130
	(1.341)	(0.188)	(0.265)	(0.124)
Constant	-39.827**	-1.756	-1.780	-0.645
	(16.113)	(1.545)	(2.302)	(1.145)
Observations	372,023	372,023	372,023	372,023
R-squared	0.134	0.006	0.018	0.005
Number of Districts	509	509	509	509
District Fixed-Effects	Yes	Yes	Yes	Yes
Month Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed-Effects	Yes	Yes	Yes	Yes
Lags	7	7	7	7

Notes: Table C1 shows the results for a re-estimation of the main model, in which a single binary variable to indicate a "Hot Day" is used, which is equal to one for temperatures above 29.5°C. Robust standard errors (in parentheses) are clustered at the district level. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C2: Robustness checks - Tobit model, regression coefficients

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<20.5°	-3.019	-0.798	-3.173	2.321
	(4.035)	(7.852)	(3.087)	(3.847)
20.5° - 22°	-0.893	-4.447*	-4.069***	0.652
	(2.635)	(2.317)	(1.488)	(1.936)
22° - 23-5°	-3.014**	-3.189**	-0.792	-0.465
	(1.230)	(1.514)	(0.957)	(1.176)
23.5° - 25°	-1.187	-1.288	-0.827	0.365
	(0.779)	(0.837)	(0.543)	(0.753)
25° - 26.5°	ref.	ref.	ref.	ref.
26.5° - 28°	3.363***	1.085*	1.463***	0.531
	(0.606)	(0.610)	(0.471)	(0.532)
28° -29.5°	4.822***	2.256***	2.115***	-0.332
	(0.804)	(0.769)	(0.584)	(0.716)
>29.5°	11.169***	4.403***	3.937***	-1.169
	(1.699)	(1.293)	(0.958)	(1.169)
Constant	-151.477***	-353.204***	-144.404***	-114.404***
	(21.401)	(30.861)	(11.140)	(12.741)
Observations	372,023	372,023	372,023	372,023
Number of Districts	509	509	509	509
District Fixed-Effects	Yes	Yes	Yes	Yes
Month Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed-Effects	Yes	Yes	Yes	Yes
Lags	7	7	7	7
Pseudo R-squared	0.0649	0.0988	0.0735	0.0669

Notes: Table C2 shows the results for a re-estimation of the main model, using a Tobit model. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Robustness checks - Tobit model, conditional marginal effects

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<20.5°	-1.413	-0.087	-0.550	0.294
	(1.889)	(0.858)	(0.536)	(0.487)
20.5° - 22°	-0.418	-0.486*	-0.706***	0.082
	(1.233)	(0.253)	(0.258)	(0.245)
22° - 23-5°	-1.410**	-0.348**	-0.137	-0.059
	(0.574)	(0.165)	(0.166)	(0.149)
23.5° - 25°	-0.555	-0.141	-0.144	0.046
	(0.364)	(0.091)	(0.094)	(0.095)
25° - 26.5°	ref.	ref.	ref.	ref.
26.5° - 28°	1.574***	0.119*	0.254***	0.067
	(0.281)	(0.067)	(0.081)	(0.067)
28° -29.5°	2.256***	0.246***	0.367***	-0.042
	(0.375)	(0.084)	(0.101)	(0.091)
>29.5°	5.227***	0.481***	0.683***	-0.148
	(0.769)	(0.141)	(0.165)	(0.148)

Notes: Table C3 shows the conditional marginal effects for the Tobit model in Table C2. Marginal effects are calculated at the sample means on uncensored observations. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Robustness checks - Maximum temperature

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<24°C	-1.298	-0.271	-0.033	0.452*
	(2.077)	(0.210)	(0.461)	(0.258)
24° - 25.5°	-2.034	-0.179	-0.510**	0.273
	(1.386)	(0.193)	(0.230)	(0.192)
25.5° - 27°	-1.733*	-0.178	-0.072	0.214**
	(1.026)	(0.112)	(0.192)	(0.101)
27° - 28.5°	-1.071*	-0.014	-0.138	0.093
	(0.551)	(0.077)	(0.126)	(0.081)
28.5° - 30°	ref.	ref.	ref.	ref.
30° - 31.5°	2.075***	0.084	0.276***	0.089*
	(0.495)	(0.055)	(0.106)	(0.052)
31.5° - 33°	3.242***	0.147**	0.312**	0.148*
	(0.597)	(0.070)	(0.140)	(0.083)
>33°	4.865***	0.228**	0.481**	0.177*
	(0.873)	(0.116)	(0.203)	(0.106)
Constant	-41.445***	-1.688	-2.069	-0.634
	(15.988)	(1.550)	(2.277)	(1.125)
Observations	370,990	370,990	370,990	370,990
R-squared	0.135	0.006	0.019	0.006
Number of Districts	509	509	509	509
District Fixed-Effects	Yes	Yes	Yes	Yes
Month Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed-Effects	Yes	Yes	Yes	Yes
Lags	7	7	7	7

Notes: Table C4 shows the results for a re-estimation of the main model, with the maximum temperature instead of the mean temperature used as basis to define the temperature bins. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

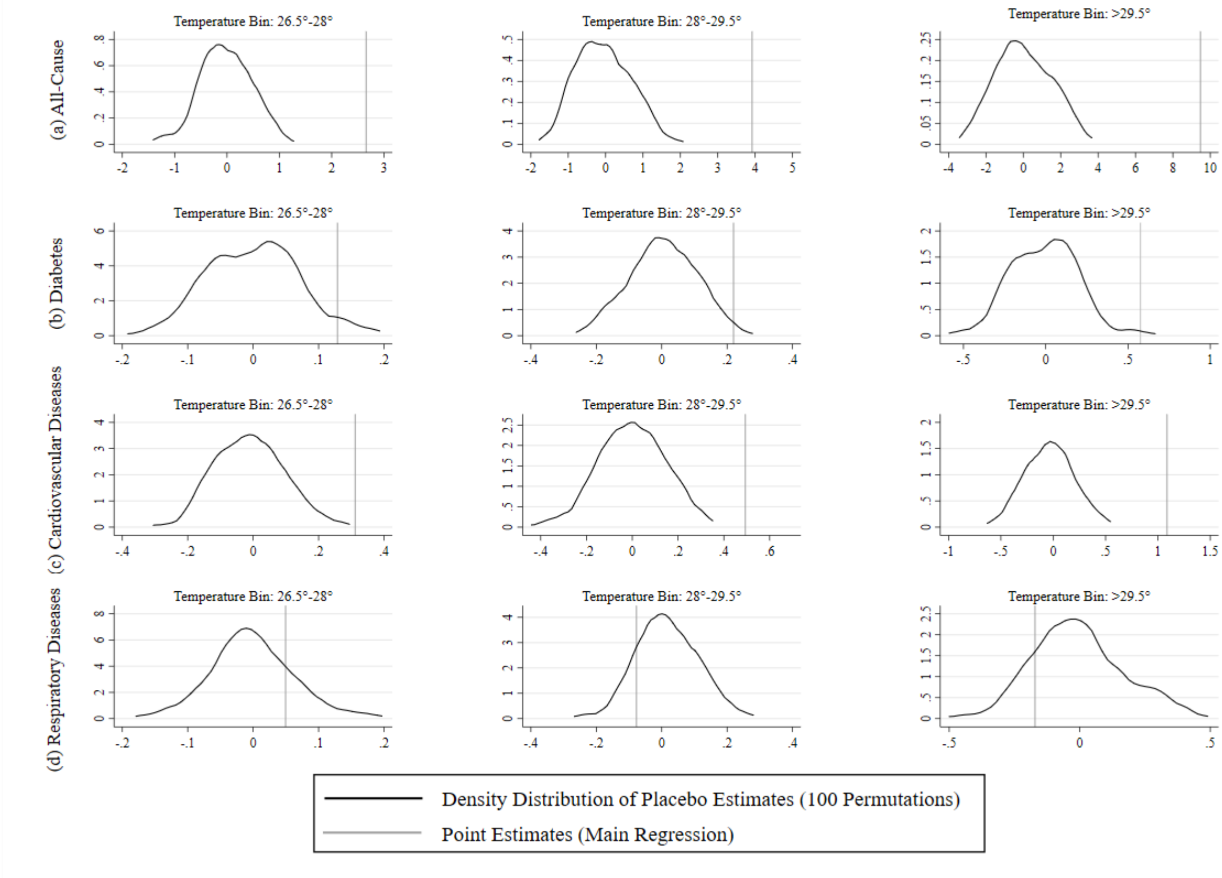

Figure C1: Placebo estimates from permutation tests. *Notes:* Figure C1 shows the kernel density distribution for placebo estimates of the three highest temperature bins for each disease outcome. The placebo estimates are obtained by 100 random permutations of the daily number of visits and temperature realizations and the subsequent re-estimation of the main model. The light-grey straight line displays the point estimate from the main results.

Table C5: Robustness checks - Placebo outcome

	Contraception management		
	(1)	(2)	(3)
<20.5°	0.213	0.074	0.070
	(0.176)	(0.221)	(0.219)
20.5° - 22°	0.085	-0.080	-0.085
	(0.139)	(0.179)	(0.176)
22° - 23-5°	0.069	-0.058	-0.062
	(0.097)	(0.110)	(0.108)
23.5° - 25°	-0.020	-0.052	-0.054
	(0.060)	(0.062)	(0.062)
25° - 26.5°	ref.	ref.	ref.
26.5° - 28°	-0.027	-0.026	-0.023
	(0.054)	(0.056)	(0.057)
28° - 29.5°	-0.137*	-0.097	-0.092
	(0.078)	(0.088)	(0.087)
>29.5°	-0.051	0.050	0.054
	(0.171)	(0.200)	(0.203)
Log Rainfall			0.004
			(0.018)
Log Humidity			-0.155
			(0.379)
Constant	-0.098	-0.110	0.736
	(0.120)	(0.128)	(1.252)
Observations	372,069	372,023	372,023
R-squared	0.004	0.004	0.004
Number of Districts	509	509	509
District Fixed-Effects	Yes	Yes	Yes
Month Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
Day-of-Week Fixed-Effects	Yes	Yes	Yes
Lags	0	7	7
Rainfall & Humidity (+ lags)	No	No	Yes

Notes: Robust standard errors (in parentheses) are clustered at the districts level. *** p<0.01, ** p<0.05, * p<0.1

Appendix D Age heterogeneity

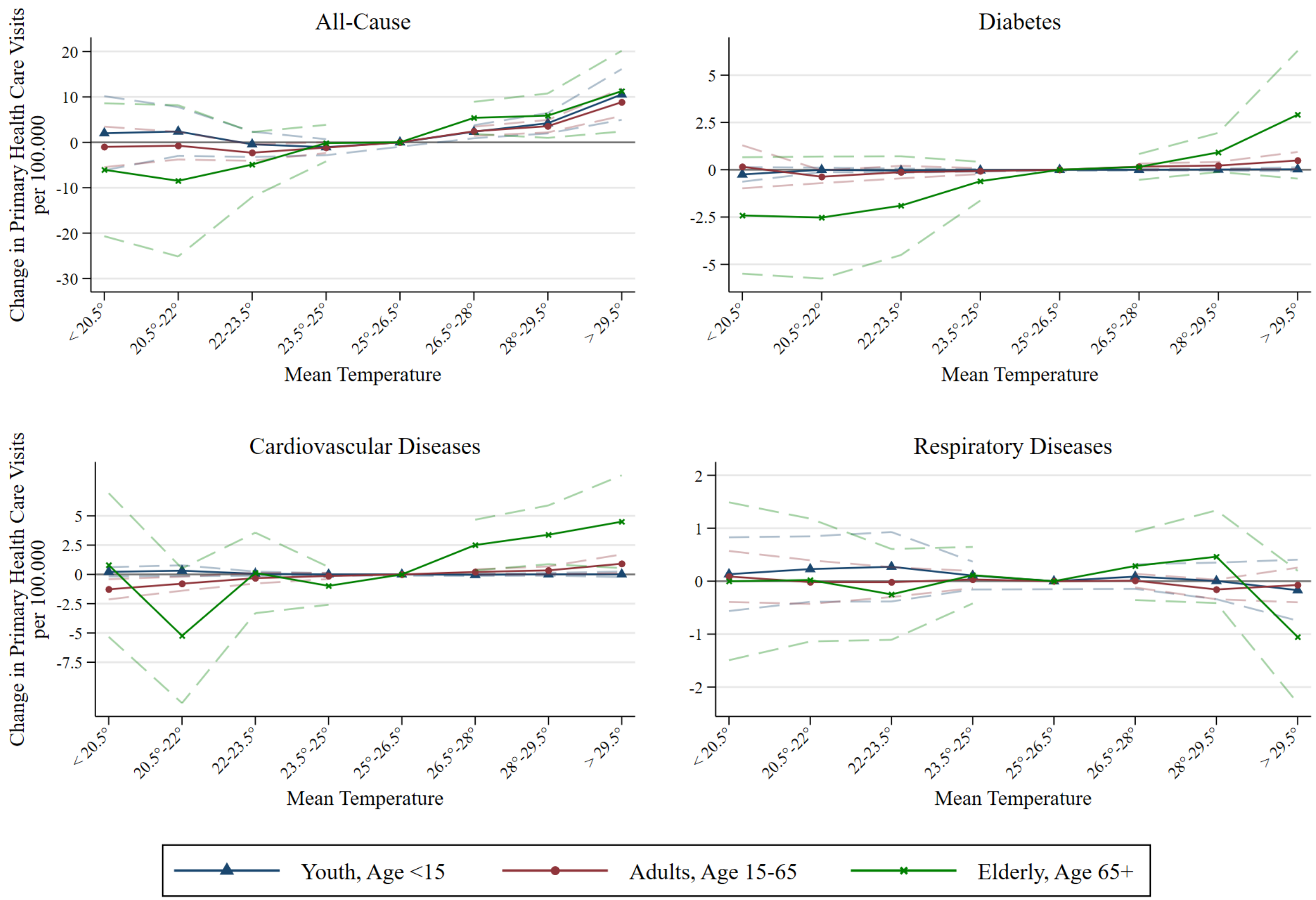

Figure D1: Age heterogeneity. *Notes:* Figure D1 presents the temperature effects separately for three age categories for each of the four outcome variables. Blue lines correspond to youth below the age of 15, red lines to adults between 15 and 65, green lines to elderly above 65 years. Straight lines display the point estimates while the dashed lines represent the upper and lower 95% confidence interval.