Received: 3 January 2022 | Revised: 8 August 2022 | Accepted: 9 August 2022

DOI: 10.1002/hec.4590

RESEARCH ARTICLE

Health Economics WILEY

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

Manuela Fritz[1,2]

[1]School of Business, Economics and Information Systems, University of Passau, Passau, Germany

[2]Department of Economics, Econometrics and Finance, University of Groningen, Groningen, The Netherlands

Correspondence
Manuela Fritz, School of Business, Economics and Information Systems, Chair of Development Economics, University of Passau, Passau 94032, Germany.
Email: manuela.fritz@uni-passau.de

Funding information
Horizon 2020 Framework Programme, Grant/Award Number: 825026
Open access funding enabled and organized by Projekt DEAL.

Abstract

Climate change induced rising temperatures will pose a detrimental threat to decent health in the coming decades. Especially at risk are individuals with chronic diseases, since heat can exacerbate a variety of health conditions. In this article, I examine the heat-morbidity relationship in the context of Indonesia, focusing on chronic, non-communicable diseases, namely diabetes, cardiovascular and respiratory diseases. Using a novel dataset from the Indonesian national health insurance scheme Jaminan Kesehatan Nasional/Badan Penyelenggara Jaminan Sosial (BPJS) and linking it with meteorological data on the daily-district level, I estimate the causal effect of high temperatures on the daily number of primary health care visits. The results show that on a hot day all-cause visits and visits with a diagnosis of diabetes and cardiovascular diseases increase by 8%, 25% and 14%, respectively. These increases are permanent and not offset by visit displacement or 'harvesting'. Visits related to respiratory diseases seem not to be affected by high temperatures. I use several climate change scenarios to predict the increase in visits and costs by the end of the century, which all forecast a substantial financial burden for the health care system. These results might have relevance for other middle-income countries with similar climatic conditions.

KEYWORDS
climate change, health, Indonesia, JKN/BPJS kesehatan, non-communicable diseases, temperature

JEL CLASSIFICATION
I10, I13, I18, Q50, Q51, Q54

1 | INTRODUCTION

Climate change will pose a detrimental threat to decent health in the coming decades, with low- and middle-income countries being the most severely affected (Costello et al., 2009). Scientific consensus affirms that, without substantial efforts to constrain greenhouse gas emissions, global average temperatures will rise between 2.1°C and 5.7°C by 2100 (Intergovernmental Panel on Climate Change, 2022). Moreover, heat waves are predicted to occur about twice as often in the coming decades compared to the number at the end of the 20th century (Lhotka et al., 2018). The rise in average and extreme temperatures can deteriorate people's livelihoods, nutrition, physical and even mental health (Ahern et al., 2005; Kovats et al., 2003; McMichael et al., 2006; Mullins & White, 2019; Stanke et al., 2013; White, 2017). Additionally, it can accelerate the spread of infectious diseases, as warmer temperatures enhance the transmission of water-, food- and vector-borne diseases (Bowen & Ebi, 2017; Pandey & Costello, 2019; Wang et al., 2009). More directly, climate change and hot temperatures can worsen all-cause and disease-specific morbidity through deteriorations in physical conditions. Extreme temperatures trigger heat stress and heat strokes; in the most severe cases, they even lead to death (Epstein & Yanovich, 2019).

Individuals with chronic, non-communicable diseases (NCDs), namely cardiovascular diseases, chronic respiratory diseases and diabetes, are especially susceptible to suffering through this channel. Extreme temperatures exacerbate a variety of chronic health symptoms, and hence pose a disproportional health risk to people suffering from or at risk of NCDs (Friel et al., 2011). While NCDs were for a long time uniquely a rich-country problem, nowadays 80% of all NCD-related deaths occur in low- and middle-income countries (Grosskurth, 2019; Islam et al., 2014; WHO, 2018). However, economic research on NCDs in these countries has received only little attention (Behrman et al., 2009). Additionally, 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). This triple burden of surging NCDs, limited health care system capacities and impending climate change make low- and middle-income countries especially vulnerable. Yet until now, there has only been limited scientific evidence of how these factors interplay in this context.

In this article, I assess the effects of temperature on NCD-related morbidity, proxied by primary health care visits, in the middle-income country Indonesia. Specifically, I study how the daily mean temperature affects the number of daily all-cause and NCD-specific health visits, focusing on diabetes, cardiovascular diseases and chronic respiratory diseases. The data consists of a representative sample of 1.7 million individuals covered by the Indonesian national health insurance scheme *Jaminan Kesehatan Nasional* (JKN) and contains information on all primary health care visits during the 2-year observation window of 2015–2016. I relate the daily number of visits within a given district to the local daily mean temperature and include a series of fixed-effects to identify the causal effect of local variations in temperature on health care visits. Finally, I use several climate change scenarios to predict the increase in health visits and related costs by the end of the century.

Whereas the link between temperature and mortality has already been extensively explored in the literature,[1] the effects on morbidity have received comparably little attention, with almost no studies being conducted for low- and middle-income countries (Campbell et al., 2018). Hence, this study makes three contributions. First, I add to the small but growing economic literature that assesses the effect of temperature on morbidity (Agarwal et al., 2021; Karlsson and Ziehbart, 2018; Lee & Li, 2021; Mullins & White, 2019; White, 2017).[2] These studies primarily investigate how temperature relates to emergency department visits and hospitalization rates. The main argument is that emergency visits are not scheduled (as opposed to, e.g., surgeries) and are consequently representative of acute health issues resulting from excessive temperatures (Mullins & White, 2019; White, 2017). Yet this approach most likely only captures visits due to very severe health problems and misses less acute cases, with the latter forming a much higher proportion of all visits. These less acute cases are the focus of this study. I use an alternative approach of focusing on health visits below the hospital level. More specifically, I use data of health visits to Indonesian primary health care facilities, that is, community health clinics (*Puskesmas*), 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 temperature and visits occurring on the same day. Focusing on primary health care visits instead of hospitalization rates and emergency visits can provide important 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 represents not only one of the largest countries in the world, but also comes from a middle-income country. Generally, only few studies assess the health impacts of heat in non-western and low- and middle-income countries (Campbell et al., 2018; Green et al., 2019), of which the major share looks again on mortality (e.g., Burgess et al., 2017, for India). 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 as well as poorer health system capacities, has not yet been investigated in detail.

Third, I explore the cost of temperature increases for the newly established Indonesian national health insurance scheme, JKN, thereby contributing to the literature on the financial burden of climate change (e.g., Auffhammer, 2018; Carleton et al., 2020; Diaz & Moore, 2017). This information is especially relevant for policymakers who are concerned with the financial sustainability of this immense insurance program, which, since its implementation, has suffered from annual deficits from Rp3.3 trillion in 2015 (US$0.24 billion) up to Rp17 trillion in 2019 (US$1.3 billion) (Aidha & Chrisnahutama, 2020; BPJS, 2015, 2016, 2019; Prabhakaran et al., 2019).

The remainder of this paper is organized as follows. Section 2 briefly summarizes the physiological mechanisms of how heat impacts human health and reviews the relevant epidemiological and economic literature. Section 3 presents the health and weather data. Section 4 outlines the empirical strategy. Section 5 presents the results, including a detailed robustness and heterogeneity analysis. Section 6 provides predictions of future increases in health visits and related costs using various climate change scenarios 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's blood vessels, the body cools down when the outside temperature is high. Vice versa, if the outside temperature is low, the body increases its temperature through heat production by the metabolic system, piloerection (erection of body hair) and vasoconstriction (narrowing) of the skin vessels (Hall & Hall, 2020). Yet despite these physiological adjustments, the body has only limited ability to cope with too high (or too low) temperatures. While 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 ambient temperature levels that surpass this range in either direction, though few studies identify an absolute threshold (Kovats et al., 2004; Lin et al., 2009).

Elevated temperatures severely affect the cardiovascular system by causing 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 & Yanovich, 2019). Green et al. (2010), for example, investigated cardiovascular disease hospital admissions in California over a 6-year time span (1999–2005) and found that per 10°F (5.5°C) increase in mean apparent temperature the risk of dehydration increased by 10.8%, the risk for heat stroke by as much as 404%. White (2017) also assessed the heat-morbidity relationship in California using hospitalization rates from 2005 to 2014 and found a relative increase in 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 found the largest relative risk for what he labeled ‘fluid and electrolyte imbalances’ which are driven by dehydration. Schwartz et al. (2004) found similar increases for several cities throughout the US. The study by Karlsson and Ziehbart (2018) supports these US findings in the German context; using data covering the years 1999–2006 and information on 170 million hospital admissions, they found that the risk of being hospitalized with a cardiovascular disease-related diagnosis on a hot day (>30°C) was between 2% and 10% higher compared to a non-hot day. In contrast, several other studies found no or even a negative effect of heat on cardiovascular disease hospital admissions in London (Kovats et al., 2004), Madrid (Linares & Diaz, 2008) and 12 other European cities (Michelozzi et al., 2009) and argue that heat deteriorates the cardiovascular function so tremendously that patients die as opposed to being hospitalized.

Heat exposure also affects the respiratory tract and lungs. 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 (Anderson et al., 2013; Michelozzi et al., 2009). While the effect on mortality has been largely covered in the economic literature (Barreca, 2012; Barreca et al., 2016; Deschênes & Greenstone, 2011; Deschênes & Moretti, 2009), evidence for the effect on morbidity is scarcer and relies largely on epidemiological studies (Green et al., 2010; Kovats et al., 2004; Lin et al., 2009; Linares & Diaz, 2008; Michelozzi et al., 2009; Ye et al., 2001). 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 the elderly in London (Kovats et al., 2004). However, all these 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 (Knowlton et al., 2009; Semenza et al., 1999). A notable exception is the study by Green et al. (2010) who found that the risk of being hospitalized with a 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 will require more attention (International Diabetes Federation, 2021). Individuals suffering from diabetes face a greater risk of heat-related illnesses as their capacity to dissipate heat is compromised. Specifically, the skin's blood flow and the sweating response of individuals with diabetes are lower compared to that of healthy individuals during heat-exposure, 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 fifth highest estimated number of individuals with diabetes (both diagnosed and undiagnosed) and the third highest number of individuals with undiagnosed diabetes, investigating this link is of special importance (International Diabetes Federation, 2021).

3 | DATA

3.1 | BPJS insurance & health visits data

The outcomes of interest in this study are the number of visits related to diabetes, cardiovascular and chronic respiratory diseases per day per 100,000 insurance members. For the sake of completeness and comparison, I also investigate the number of total (‘all-cause’) visits. The data comes from a representative administrative dataset on health insurance status and health visits published in 2019 by the Indonesian Social Health Security Agency (*Badan Penyelenggara Jaminan Sosial Kesehatan–BPJS Kesehatan*).

The dataset contains information on a representative 1% sample of all families and their respective family members who were enrolled in the Indonesian national health insurance scheme *JKN* by the end of 2016 (172 million individuals, representing 66% of the Indonesian population). This insurance scheme was launched in 2014 and all other prior insurance schemes (e.g., Jamkesmas, Askes, Jamsostek) were incorporated into it to form a single scheme for the entire country. By October 2021, it had become one of the world's largest and most ambitious single-payer health insurance programs, with around 225 million members and is expected to achieve universal cover in the next few years (BPJS Kesehatan, 2021; Prabhakaran et al., 2019).

For primary health care services, the insurance scheme works largely 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 if a primary health care facility that is registered with BPJS was approached first. A gatekeeper is either a *Puskesmas* (the Indonesian community health clinics), a *Klinik Pertama* (clinics that provide primary health care) 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 performance-based indicators (such as contact rate, referral rate and services offered). For each registered insurance member, the facilities receive between Rp6,000 and Rp10,000 per month (about US$0.50–0.80).[3] Hence, for a primary facility that caters to an average 10,000–20,000 members, the capitation payments from BPJS are about US$5000 to US$10,000 per month, which equals approximately 70%–90% of primary facilities' total funds (KOMPAK, 2017; Prabhakaran et al., 2019). Certain health services are not covered by this capitation scheme (primarily services related to delivery, postpartum care and contraceptive management). For these services, the facility needs to claim reimbursement payments directly from BPJS based on the provided services. In all circumstances, the service is supposed to be free for the insured patient and entirely covered by the insurance.

The families included in the sample were selected based on a stratified sampling procedure, leading to 1,697,452 individuals from 586,969 sampled families. Additional details on the sampling procedure and a more detailed description of the data are provided in Appendix A. There, I also present details on how the sample population compared to the general Indonesian population in 2015–2016; with the main fact that a certain social group–the non-poor informal working class–was largely not covered by the insurance in its early years.

In total 1,733,759 visits were documented for the sampled individuals over the 2-year observation window. The following information was recorded for each visit: the respective insurance member and visit ID, the date, the location of the facility, the ICD-10-code (International Classification of Diseases) of the primary diagnosis, whether it was an outpatient service or inpatient admission, as well as information about whether a patient received a referral to a higher-level facility. Furthermore, for the non-capitation health services, the amount requested as reimbursement payment by the facility and the amount finally granted from BPJS were recorded. This rich data source allows for an extraction of the number of disease-specific visits per day within each of the 514 Indonesian districts. To ensure comparability across districts and to maintain representativeness for all JKN members, I calculate the number of disease-specific visits per 100,000 insured individuals, using the sampling weights provided in the data. The member counts underlying this calculation reflect the enrollment status at the end of 2016.[4] The ICD-10-codes included in the respective disease categories are shown in Table A1 in Appendix A, the 20 most frequent diagnoses in the data sample are presented in Table A3.

A drawback of the data is, that it does not allow for a differentiation between a first-time diagnosis and continued treatment of a given diagnosis that happened before 2015. This means that, for example, a patient who was already diagnosed with diabetes prior to the period available in the data and visits a health center because of health issues (whether related to heat or not) will be similarly counted as someone who visits a health center (e.g., due to not feeling well on a day with high temperatures) and is diagnosed with diabetes for the first time. Moreover, if, for example, someone with diabetes suffers from heat exhaustion and seeks health care, such a visit will be coded as a cardiovascular disease diagnosis. This implies that the data will not allow for inference regarding initial versus ongoing treatments of these conditions, and that I cannot comment on whether high temperatures are more dangerous for undiagnosed or already diagnosed individuals.

3.2 | Weather data

Temperature data is obtained from the SA-OBS dataset (Version 2.0), a gridded daily meteorological dataset for the entire Southeast Asian region. It is provided by the Southeast Asian Climate Assessment & Dataset Project (SACA&D) and combines data from 3914 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 27.7×27.7 km (770 km^2) at the equator. I merge each of these grids with the respective Indonesian district whenever a grid-point falls directly within the district borders, and average the temperature over all grids per day and district. For 88 of the 514 districts (mainly smaller cities[5]), no grid-points fall directly within the respective borders. In these cases, I use inverse distance weighting and assign the weighted temperature of the four nearest grid-points to the district (for more details see Appendix B).

Other meteorological conditions such as humidity and precipitation also have been shown to affect human health (Barreca, 2012; Maccini & Yang, 2009). Moreover, wind speed can affect the perceived temperature and thereby weather-related morbidity. Consequently, I control for daily humidity measures, precipitation levels and wind speed to identify the pure temperature effect. Data on daily humidity and precipitation levels and wind speed are obtained from the GLDAS Noah Land Surface Model (Beaudoing and Rodell, 2020). Additionally, I control for the amount of sulfur dioxide (SO_2), sulfate particulate matter (SO_4), and black carbon in the air as measures of air pollution, which can also affect health conditions (Liu & Ao, 2021). Data on air pollution is obtained from the Merra 2 Aerosol Diagnostics data provided by the Global Modeling and Assimilation Office (GMAO, 2015). All variables are available as gridded data with a spatial resolution between $0.25° \times 0.25°$ and $0.5° \times 0.625°$. The grid-point to district assignment procedure is analogous to that for the temperature dataset.

The aggregated dataset is a daily panel for the 514 Indonesian districts over the two years under study, that is, 375,734 observations. No health visit data is available for five districts, leaving 372,079 observations (509 districts $\times$ 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 dataset. Summary statistics for health visits by age categories are shown in Table A2 in Appendix A.

The bottom part of Table 1 summarizes the weather data. The temperature variable is specified as a continuous variable and as temperature bins, that is, a set of dummy variables that are equal to one whenever the mean temperature on a given day falls within the specified 1.5°C temperature range (<21°C, 21–22.5°C, …, 28.5°C–30°C, >30°C). Reflecting the tropical climate of Indonesia, the daily mean temperature is high and varies little; the days on which the mean temperature fell below 21°C account for only 1.4% of all days measured. As expected, the average rainfall and humidity levels are also high. On an average day, precipitation levels of 6.49 mm were recorded, with a maximum of 87 mm. Specific humidity levels were on average 16.25 g of water per 1 kg air.

4 | EMPIRICAL APPROACH

4.1 | Main specification

The literature suggests that the effect of ambient temperature on health outcomes often exhibits a U- or J-shaped relationship (Li et al., 2014; Lin et al., 2019; Song et al., 2018; White, 2017), that is, adverse health effects occur at very low and very high temperature levels. I therefore use a semi-parametric specification that allows for a flexible relationship between temperature and health visits; this approach has been widely adopted in the economic health and climate literature (e.g., Barreca, 2012; Deschênes & Greenstone, 2011; Deschênes & Moretti, 2009; Karlsson and Ziehbart, 2018; White, 2017). I specify eight temperature bins which each cover a 1.5°C temperature range and derive eight binary variables that are equal to one whenever the temperature on a given day fell within the respective temperature range. Further, I exploit the panel structure of the data and use a fixed-effects model that allows me to control for re-occurring seasonal variation, for example, rain seasons, and regional, across-district heterogeneity in terms of health facility density and access to health care. Specifically, I include a series of year, month, day-of-the-week as well as district fixed-effects, resulting in the following specification

TABLE 1 Summary statistics

Panel A: BPJS data				
# of families			586,969	
# of individuals			1,697,452	
# of individuals with at least 1 health visit			465,017	
# of recorded primary health care visits (2015–2016)			1,733,759	
Panel B: Panel dataset	**Mean**	**SD**	**Min**	**Max**
Health visits				
All				
All-cause	96.42	97.34	0.00	2659.11
Diabetes	2.50	9.54	0.00	774.64
Cardiovascular diseases	7.22	16.62	0.00	747.09
Respiratory diseases	2.22	8.70	0.00	625.64
Female				
All-cause	115.65	128.21	0.00	4195.77
Diabetes	3.07	14.25	0.00	1303.34
Cardiovascular diseases	9.07	25.48	0.00	1303.34
Respiratory diseases	2.21	11.93	0.00	1016.01
Male				
All-cause	78.01	95.61	0.00	2714.21
Diabetes	1.96	11.40	0.00	1182.82
Cardiovascular diseases	5.44	18.75	0.00	1291.98
Respiratory diseases	2.23	11.89	0.00	1038.61
Weather data				
Mean temperature (°C)	26.76	2.10	8.70	32.33
Temperature bins (°C)				
<21°	0.01	0.12		
21°–22.5°	0.02	0.15		
22.5°–24°	0.06	0.23		
24°–25.5°	0.14	0.34		
25.5°–27°	0.25	0.43		
27°–28.5°	0.32	0.47		
28.5°–30°	0.18	0.38		
>30°	0.02	0.14		
Rainfall (mm/day)	6.79	7.99	0.00	87.09
Specific humidity (grams of water/kg air)	16.09	1.67	5.59	20.77
Wind speed (m/s)	2.08	0.97	0.33	12.00
Sulfur dioxide (SO_2) (μg/m^3)	10.54	13.45	0.00	129.13
Sulfate particulate matter (SO_4) (μg/m^3)	5.04	6.80	0.01	374.46
Black carbon (μg/m^3)	1.90	1.72	0.00	71.83

Note: The data for health visits (Panel B) represents the number of daily visits per 100,000 health insurance members per district. Summary statistics are weighted by the population of insured individuals per district. The mean values for the temperature bins represent the share of district-day observations that fall within the respective temperature range.

$$Visits_{kd} = \alpha + \sum_{i=1, i\neq 5}^{8} \beta_i Temp^i_{kd} + \sum_{l=1}^{7} \sum_{i=1, i\neq 5}^{8} \vartheta_{il} Temp^i_{k,d-l} + \gamma \boldsymbol{X'_{kd}} + \delta_y + \sigma_m + \theta_k + \mu_w + \varepsilon_{kd}, \tag{1}$$

where $Visits_{kd}$ is the number of primary health care visits (differentiated by diagnosis) that occurred on day d in district k. $Temp^i_{kd}$ denotes the binary temperature variables; the bin for the mean temperature 25.5°C–27°C is omitted and serves as a reference category. The coefficients therefore represent the effect of a day on which the temperature falls in the respective bin compared to the reference category. I additionally include seven lags for each of the temperature bins to account for serial correlation in weather realizations.[6] The use of such a finite distributed lag model also allows me to investigate the dynamic effect of visit displacement or 'harvesting', which I address in the following section. δ_y, σ_m, θ_k and μ_w are the year, month, district and day-of-the-week fixed-effects, respectively. The error term ε_{kd} is clustered at the district level to account for the possibility that the errors are correlated within districts over time. The vector of controls $\boldsymbol{X'_{kd}}$ contains daily rainfall and humidity levels, wind speed, all three air pollution measures as well as a dummy variable reflecting whether the current day falls within the fasting month of Ramadan.

4.2 | Does 'harvesting' exist at the primary health care level?

Studies that investigate the heat effect on mortality often also explore the dynamic temperature effect (Anderson & Bell, 2009; Basu & Malig, 2011; Bi et al., 2011; Braga et al., 2001; Deschênes & Moretti, 2009; Karlsson and Ziehbart, 2018; Schwartz et al., 2004). In other words, they investigate whether 'harvesting' or mortality displacement occurs, that is, whether individuals dying on days with extreme temperatures would have died anyway in the course of the following days or weeks. If mortality displacement is occurring, temporary increases in death rates due to extreme heat are followed by days or weeks that see decreased numbers of deaths, sometimes resulting in a zero net-effect. The majority of the aforementioned studies conclude that this harvesting phenomenon is especially present during hot temperatures and heat waves, but less so during cold temperature spells. Hence, the question arises whether the same phenomenon exists for the temperature-morbidity context and at lower health care levels, that is, whether primary health care visits increase on days of extreme heat but decrease in the days afterward.

The underlying mechanisms would be as follows. If increasing temperatures lead to a worsening of an already existing health issue, but the respective individual would have sought health care irrespective of the heat event a couple of days or weeks later, then visits would peak during heat events but would be reduced on the days afterwards. In contrast, if high temperatures lead to newly occurring health issues (i.e., they are caused by hot temperatures), then one would observe a spike in visits on a day with hot temperatures, but no reduction during the following days. Situations without harvesting are of major concern as they imply increases in health visits that are not offset over time 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 and investigate the lag structure of the main model specification in more detail. Specifically, I test whether there are significantly *negative* lagged effects of a day with a temperature in the top bin (<30°C) and whether the cumulative effect remains significantly *positive* after a period of 1–4 weeks, respectively. This cumulative effect is simply derived by summing the coefficients of the highest temperature bin and its respective lags, for example, $\beta_8 + \sum_{l=1}^{7} \vartheta_{8,d-l}$ for the 1-week cumulative effect. This effect can be interpreted either as the effect of a hot day 1 week ago on today's cumulative number of visits or similarly as the effect that a current hot day will have on the cumulative health visits in a week, given that $\frac{\partial\, visits_d}{\partial\, temperature_{d-l}} = \frac{\partial\, visits_{d+l}}{\partial\, temperature_d}$, assuming that on all other days the reference category temperature prevails. To estimate the effect over a period longer than 1 week, the number of lags in the model is increased to the reflect the period of interest (e.g., 21 lags for the 3-week cumulative effect).

5 | RESULTS

5.1 | Main results

Table 2 presents the results for the semi-parametric temperature bin model. 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 the full set of fixed-effects. In the next column, I add seven lags for each of the temperature bins. The third column displays the results of the preferred specification for each outcome, including all fixed-effects, temperature lags and current and lagged control variables. The coefficients of the temperature bins display the absolute increase, respectively decrease, in (disease-specific) primary health care visits per day per 100,000 insured individuals in comparison to a day with a mean temperature of between 25.5°C and 27°C. For the ease of interpretation, I calculate the corresponding percentage increase for the top bin relative to the mean of the outcome variable in the reference bin, shown on the bottom part of the table.

My preferred specification suggests that on a day with an average temperature realization of above 30°C, the number of all-cause primary health care visits is higher by 7.6 per 100,000 or 8.44% compared to a day with a temperature in the reference category. Columns (1)–(3) clearly reject a U-shaped relationship between temperature and all-cause primary health care visits in favor of a linear relation, with negative effects for the four lower temperature bins. The effects for the top three bins are consistently positive and significant. Controlling for serial correlation in temperature in Column (2) slightly increases the absolute size of the coefficients in comparison to the most parsimonious model in Column (1), while they are again slightly reduced as soon as I control for other weather conditions in Column (3). When upscaled to the insured population in 2016 (172 million individuals), the effect estimated in Column (3) translates to about 13,000 more visits per day.

Columns (4)–(6) also support the linear relationship between temperature and diabetes morbidity. Though the negative effects at lower temperatures are not statistically significant, the coefficients for the upper bins are significantly positive across all three specifications. Quantitatively these effects are sizable. On a very hot day, above 30°C, the number of diabetes visits increases between 20.9% and 24.7% (the latter corresponding to an absolute increase of about 1000 visits by the insured population). Even at relatively moderate temperatures between 27°C and 28.5°C, visits increase by 7.2% in comparison to a day with a mean temperature between 25.5°C and 27°C.

The effect of temperature on cardiovascular disease visits, shown in Columns (7)–(9), is also statistically and economically significant. The effects are robust across the three specifications and clearly reject the idea of a U-shaped functional form in favor of a linear relationship, with null or significant negative effects for lower temperature realization and large positive effects for high temperatures. The relative increase is somewhat lower than for diabetes (10.73%–14.77%), yet higher than for all-cause visits. This implies that diabetes and cardiovascular disease morbidity increase disproportionally at high temperatures compared to other diseases.

However, Columns (10)–(12) show that there seems to be no positive relationship between heat and respiratory disease visits. If at all, there is a small negative effect for very high temperatures that reduces the number of respiratory disease visits. Yet this effect is not robust across the three specifications and overall the coefficients are not distinguishable from zero.

Conclusively, high temperatures increase the number of primary health care visits and this relationship is linear rather than U-shaped. When differentiated by diagnosis, the effect remains large and significant for diabetes and cardiovascular diseases, while there is no effect on the number of respiratory disease visits.

5.2 | Robustness checks

In the following, I conduct a series of robustness checks. I start with re-running the main regression with interacted month × district fixed-effects instead of including district and month effects separately to test whether the main results are driven by district-specific time trends in health care visits. The results, shown in Table C1 in Appendix C, are robust to this change in the specification and the coefficients remain similar in significance and size to those in Table 2.

Next, I re-run the main regressions using a single 'hot day' indicator instead of the eight temperature bins. This binary variable is equal to one whenever the temperature is higher than the 90th percentile of the mean temperature distribution (averaged over all district-day observations). The results are shown in Table C2 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 on a hot day for all-causes, diabetes and cardiovascular diseases increase by 4, 0.22 and 0.45 per 100,000 respectively; the coefficient for respiratory visits is negative but insignificant. Similar results are obtained when the mean temperature variable enters the specification in a basic linear form (results shown in Table C3, Appendix C).

I also re-estimate the main specification using a Tobit model to account for the fact that the outcomes are zero-censored variables (i.e., for some district-day observations there are no visits recorded in the sample). The results are shown in Table C4 (regression coefficients) and Table C5 (conditional marginal effects) and are in line with the main results. For all-cause, diabetes and cardiovascular disease visits, the coefficients associated with temperature bins above the mean are significantly positive, and those associated with lower bins are either insignificant or significantly negative. There is again no significant relation between temperature and respiratory disease visits.

TABLE 2 Results–Temperature effects on all and by cause visits per 100,000 insurance members

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All-cause			**Diabetes**			**Cardiovascular diseases**			**Respiratory diseases**		
<21°C	−4.393 (3.652)	−8.652*** (2.551)	−7.825*** (2.623)	0.141 (0.159)	−0.055 (0.201)	−0.074 (0.210)	−0.846** (0.330)	−0.843*** (0.291)	−0.771** (0.305)	0.034 (0.192)	−0.068 (0.198)	−0.045 (0.206)
21°C–22.5°C	−1.612 (2.594)	−7.346*** (1.691)	−6.682*** (1.738)	−0.033 (0.176)	−0.189 (0.192)	−0.206 (0.195)	−0.759** (0.354)	−0.862*** (0.310)	−0.798** (0.316)	0.174 (0.136)	0.145 (0.144)	0.158 (0.147)
22.5°C–24°C	−0.400 (1.328)	−5.299*** (1.210)	−4.795*** (1.214)	0.063 (0.096)	−0.054 (0.100)	−0.060 (0.103)	−0.011 (0.202)	−0.350* (0.206)	−0.306 (0.209)	−0.038 (0.103)	−0.037 (0.120)	−0.025 (0.121)
24°C–25.5°C	−0.784 (0.640)	−3.215*** (0.605)	−2.916*** (0.601)	−0.023 (0.061)	−0.090 (0.060)	−0.093 (0.060)	−0.020 (0.105)	−0.283** (0.117)	−0.261** (0.117)	0.028 (0.066)	0.008 (0.074)	0.014 (0.075)
25.5°C–27°C	Ref.	Ref.	Ref.	Ref. Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
27°C–28.5°C	2.412*** (0.629)	3.920*** (0.571)	3.735*** (0.582)	0.09 (0.061)	0.165*** (0.063)	0.170*** (0.063)	0.212** (0.093)	0.391*** (0.110)	0.380*** (0.109)	−0.030 (0.056)	−0.004 (0.059)	−0.010 (0.060)
28.5°C–30°C	3.535*** (0.971)	5.998*** (0.850)	5.533*** (0.878)	0.151** (0.073)	0.284*** (0.084)	0.295*** (0.088)	0.291** (0.128)	0.581*** (0.161)	0.559*** (0.167)	−0.236*** (0.088)	−0.161* (0.091)	−0.176* (0.094)
>30°C	4.974*** (1.557)	8.475*** (1.451)	7.609*** (1.547)	0.494*** (0.164)	0.582*** (0.200)	0.584*** (0.199)	0.750** (0.300)	1.033*** (0.297)	1.001*** (0.299)	−0.499** (0.196)	−0.250 (0.239)	−0.280 (0.247)
Mean of dep. Variable in reference bin	90.16	90.16	90.16	2.36	2.36	2.36	6.99	6.99	6.99	2.13	2.13	2.13
Percentage change (top bin relative to reference bin)[a]	5.51%	9.39%	8.44%	20.93%	24.66%	24.74%	10.73%	14.77%	14.32%	−23.42%	−11.73%	−13.14%
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	0.464	0.464	0.469	0.102	0.102	0.103	0.134	0.134	0.135	0.042	0.042	0.042
Number of districts	509	509	509	509	509	509	509	509	509	509	509	509
Full set of fixed-effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lags		✓	✓		✓	✓		✓	✓		✓	✓
Controls			✓			✓			✓			✓

Note: Table 2 shows the regression results for the temperature bin model. Robust standard errors (in parentheses) are clustered at the district level. All regressions are weighted by district-populations of insured individuals.

[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 mean number of visits on a day with a temperature in the reference category.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

I also assess whether the results are robust to compositional changes in the sample. Specifically, two aspects need to be considered. First, due to the fast expansion of the insurance scheme in the early years, an aggregation of the visits might lead to non-comparable units over time. Second, mortality can lead to a transition out of the sample. Since mortality can also be related to heat, not accounting for the fact that some individuals in the sample died over the course of the study period might introduce bias. To address these concerns, I re-calculate the number of daily visits only for those individuals that have at least one family member with a reported visit in 2015 (assuming that families with the first visit in 2016 might not have been enrolled yet in 2015) and second, I drop all individuals from the sample that died in the period under study. The results are shown in Tables C6 and C7. Both compositional changes in the sample do not alter the results.

In Figure C1 in Appendix C, I also present details and the results from a randomization inference test, which consolidates that the main results reflect a true causal relationship and are not just the consequence of statistical coincidence.

Lastly, I conduct a falsification test to confirm that the number of daily NCD visits does indeed rise due to higher temperatures and not as a result of other factors inherent to these days. To do so, I use the number of health care visits, which should reasonably not be affected by temperature and weather realizations, namely, 'contraceptive management', 'dental caries' (e.g., tooth decay) and 'other soft tissue disorder' (e.g., pain in limbs or muscles). The results are shown in Table C8 in Appendix C. All three specifications do not show significant changes in the number of visits with rising temperatures.

5.3 | Heterogeneity

Thus far, the results have characterized the temperature-morbidity relation for both genders and all ages jointly. In the following, I assess the effects separately for men and women and by age categories.

Figure 1 shows that for all-cause and cardiovascular disease visits, the impact of high temperatures, that is, of the top three bins, is consistently greater in absolute terms for women, represented by the blue lines. While for cardiovascular disease visits, the effects are too imprecisely measured to conclude that they are statistically different from each other, for all-cause visits, this difference is statistically significant for the temperature bins 27°–28.5° and 28.5°–30° (see Table D1 in Appendix D). Granted, this greater effect could also arise from women simply seeking care more often than men, yet when I asses the heat effect on visit severity, proxied by whether the patient was referred to a hospital or higher health care level, I also find these effects to be greater for women (see Table D2 in Appendix D). This indicates that women are indeed also more severely affected at the intensive margin with respect to all-cause and cardiovascular diseases. For diabetes visits, the effects for men and women are almost identical in size and significance (and also not statistically different from each other); yet interestingly, men are more often referred to a higher health care level, indicating that at the intensive margin, men are more severely affected with respect to diabetes. Respiratory disease visits, contrarily, do not increase with temperature for either gender.

Figure 2 shows the temperature effect separately for adults between the ages of 15 and 65 and for persons older than 65 years (regression results are presented in Table D3 in Appendix D). The findings are well in line with previous studies that concluded that elderly are most severely affected by high temperatures (e.g., Agarwal et al., 2021; Karlsson and Ziehbart, 2018). Especially for cardiovascular diseases, the number of visits for the elderly spikes remarkably. Nevertheless, also for adults between 15 and 65 the effect for all-cause, diabetes and cardiovascular disease visits is large and significant; and for diabetes and cardiovascular disease visits (for temperatures between 27°C and 30°C) the point estimates are very similar for both age groups. Of course, increasing morbidity is reason for concern at all ages, but if the adult working population is likewise severely affected by increases in temperature with respect to cardiovascular diseases and diabetes, it may imply a potentially large productivity loss for the Indonesian economy in the coming decades.

5.4 | Harvesting

As discussed in Section 4.2, I assess the dynamic effect of temperature to investigate whether harvesting also exists for visits at the primary health care level or whether the increases found in the main results can be interpreted as permanent increases. Specifically, I test whether a day with a temperature in the top bin (<30°C) leads to a significant *decrease* in visits on the days after the heat event. Moreover, I test whether the cumulative effect remains significant for a period of up to 4 weeks.

Figure 3 presents the results graphically for each of the four disease categories. The circles in each graph indicate the point estimates of a hot day on the number of visits on the same day and for 7 days in the future. The four red squares on the right in every graph depict the cumulative effect after 1−4 weeks, respectively.

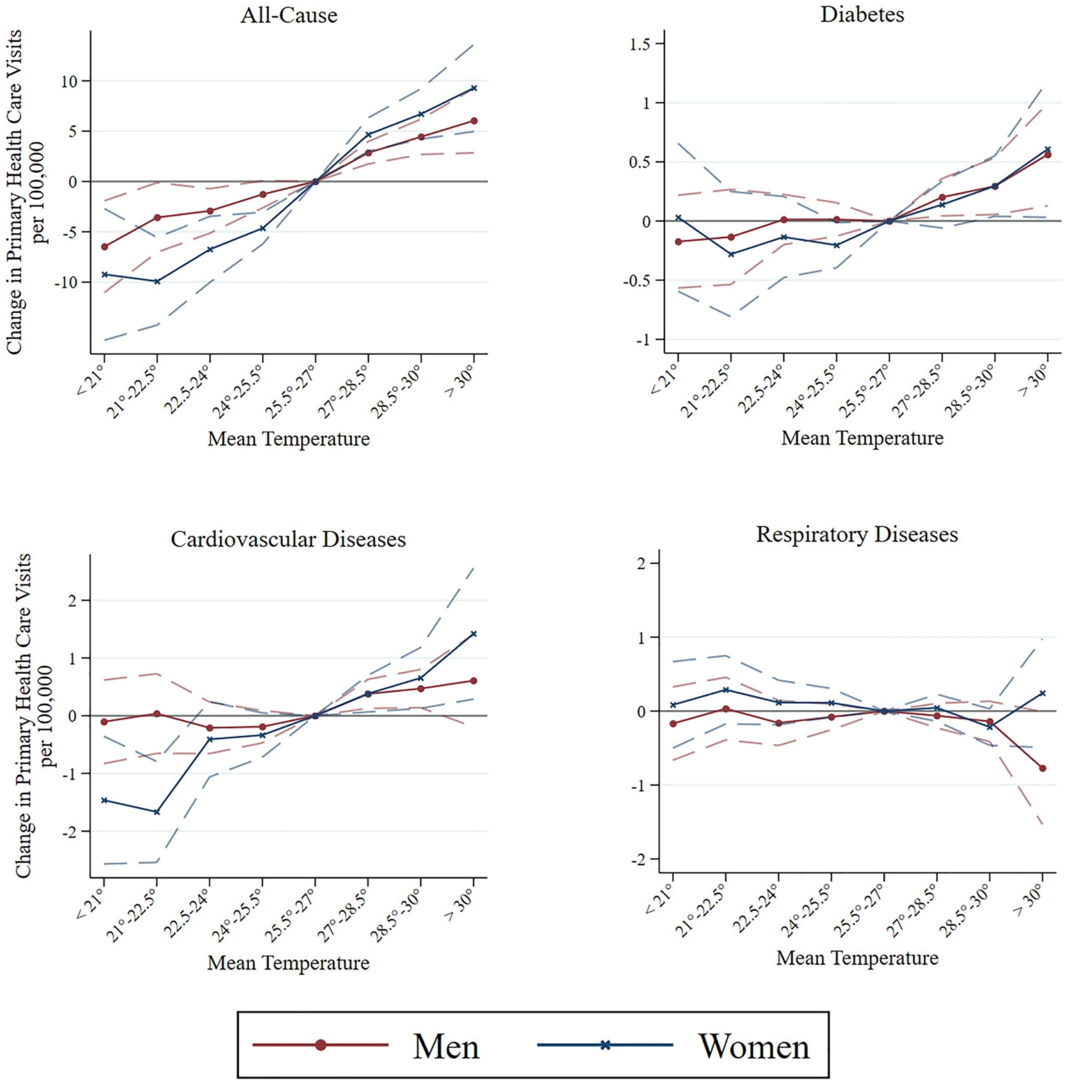

FIGURE 1 Gender heterogeneity. Figure 1 presents the temperature effects separately for men and women for each of the four outcome variables. Blue lines represent the female effect, red lines the male effect. Solid lines display the point estimates while the dashed lines represent the upper and lower 95% confidence interval [Colour figure can be viewed at wileyonlinelibrary.com]

Overall, the harvesting hypothesis can be rejected. With a single exception ($t + 2$ for all-cause visits), none of the lagged effects for any of the disease types is significantly negative, while the cumulative effects of a single hot day above 30°C remain significant up to 3 weeks for all-causes and cardiovascular diseases and even up to 4 weeks for diabetes. For respiratory diseases, in contrast, the cumulative effects confirm the findings above, that is, a decreasing impact of high temperatures for this specific disease category.

Conclusively, the findings speak strongly against the harvesting hypothesis for all-cause, diabetes and cardiovascular disease visits; the increase in primary health care visits is permanent and not offset by visit displacement.

6 | VISIT AND COST PREDICTIONS UNDER VARIOUS CLIMATE CHANGE SCENARIOS

Heat-induced illness comes not only with individual health-related consequences but also imposes costs on the economy through losses in productivity, as well as impacting the health care system due to increased costs for acute and long-term care. Several studies have assessed the cost of heat waves for the overall economy (e.g., Cheng et al., 2018; Karlsson and Ziehbart, 2018) or, taking on the insurer perspective, heat-related costs for hospitalization rates (Agarwal et al., 2021). I expand these estimates to

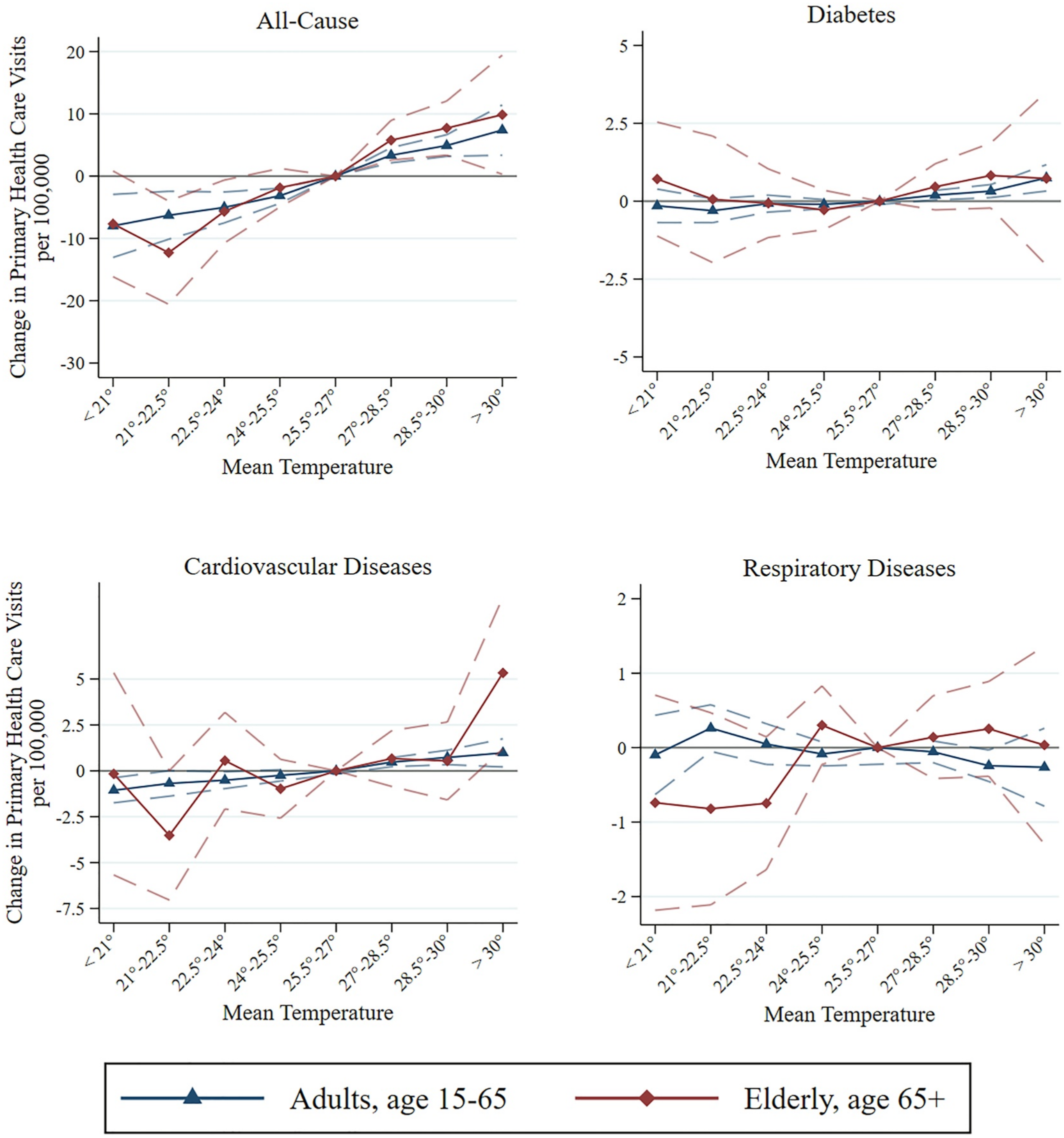

FIGURE 2 Age heterogeneity. Figure 2 presents the temperature effects separately for two age categories for each of the four outcome variables. Blue lines represent the effect for adults (age 15–65), red lines the effect for elderly (65+ years). Solid lines display the point estimates while the dashed lines represent the upper and lower 95% confidence interval [Colour figure can be viewed at wileyonlinelibrary.com]

the costs that occur for less acute health consequences at the primary health care level and calculate the yearly financial burden for the Indonesian health insurance scheme that might occur under various climate change scenarios by the end of the century.

Since the implementation of JKN, the managing social security agency (BPJS) has faced substantial financial deficits, primarily due to member contribution rates that are too low to cover the costs arising from comprehensive benefit packages (Aidha and Chrisnahutama, 2020; Prabhakaran et al., 2019). Primary health care services should be entirely free for insured members, with health services paid for by BPJS–either indirectly via capitation payments or directly via reimbursement payments. Given that payments are determined by the number and type of visits a facility manages and given that the current height of the capitation rate is already considered to be substantially too low to finance the actually demanded health services, increases in visits will further lead to increases in the required payments (Jo & Setiawan, 2019; Nugraheni et al., 2020). This, in turn, will further deteriorate the financial sustainability of the scheme, assuming that the financial burden is not transferred into higher member contribution rates.

To shed light on the extent of potential additional costs caused by increasing temperatures, I simulate the increases in the number of primary health care visits up to the end of the current century (2060–2080), applying various climate change scenarios and relate these predictions to official cost estimates per visit. Data on climate change predictions are drawn from the CNRM-CM6-1 model, provided by the National Center for Meteorological Research (Voldoire, 2018).[7] It is one of nine models

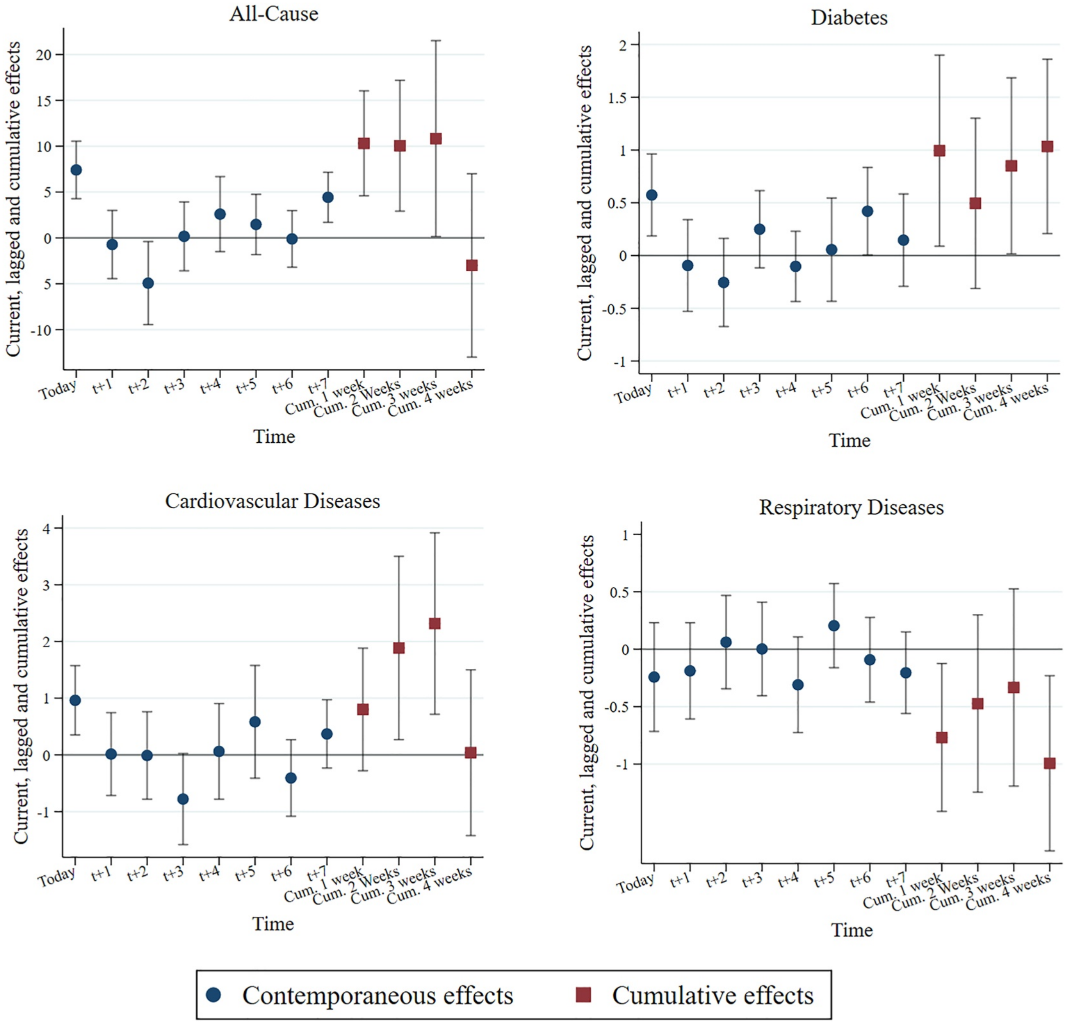

FIGURE 3 Harvesting. The circle point estimates represent the effect of a day with a temperature in the top bin (<30°C) relative to the reference bin (25.5°C–27°C) on the number of daily visits today and up to seven days in the future. The squares show the cumulative effects after 1–4 weeks, respectively. Whiskers represent the 95% confidence interval. To estimate the effect over a period longer than 1 week, the number of lags in the model presented in Equation (1) is increased to the reflect the period of interest (e.g., 21 lags for the 3-week cumulative effect) [Colour figure can be viewed at wileyonlinelibrary.com]

that are used within the World Climate Research Program's Coupled Model Intercomparison Project Phase 6, which is the database on which the Intergovernmental Panel on Climate Change builds its regular climate assessment reports. The predictions are provided as monthly means for 20-year averages, with a spatial resolution of about 18.5 × 18.5 km and for several Shared Socioeconomic Pathways (SSPs, previously Representative Concentration Pathways), that is, climate change scenarios. From the available year-averages and emission scenarios, I use the 2060–2080 monthly average with an intermediate (SSP2-4.5) and high-emission (SSP5-8.5) scenario. The former describes a scenario in which CO_2 emissions stagnate at current levels until 2050 and the global mean temperature increases by about 2.7°C by the end of the century compared to the pre-industrial level. The latter describes a scenario in which CO_2 emissions continue to rise and the global mean temperature increases by about 4.4°C (IPCC, 2022).

I transform the temperature predictions to temperature bins at the daily-district level by adding the predicted difference in monthly-district means to the current daily temperature realizations, thereby keeping the variation at the daily level. Figure E1 in Appendix E presents the population-weighted yearly temperature bin distribution resulting from this procedure for the 2015/2016 data and the two climate change scenarios. While in 2015/2016 on average only seven days per year experienced a temperature above 30°C, by the end of the century this number is predicted to climb to 32 and 108 under the intermediate and high-emission scenario, respectively. In both climate scenarios, the number of days falling into temperature bins below 28.5°C is substantially reduced and only the upper two bins with temperatures above 28.5°C experience increases in the number of days per year.

Simulating the increase in primary health care visits and the corresponding costs is then a simple back-of-the-envelope calculation exercise and similar to the linear combination method used in comparable studies (e.g., Agarwal et al., 2021; White, 2017): I calculate the change in the population-weighted number of days per year that fall in each bin and multiply this change with the respective coefficient that was estimated in the main model, that is, $\sum_i \beta_i * \Delta Temp_i$. Since this depicts the additional yearly visit per 100,000 insured individuals, I further upscale these numbers to the national level, using the current population size of 270 million Indonesians and assuming that the goal of universal insurance coverage will be reached in the coming years and thereby the whole population should be enrolled by 2060.

In an additional prediction model, I also consider population growth jointly with population aging and the resulting changing age structure in Indonesia. In this model, I predict the visit increases and related costs by using the estimated age-specific coefficients and upscale them with the predicted Indonesian population size and age distributions for 2060–2080 which I derive from the United Nations World Population Prospects (United Nations - Department of Economic and Social Affairs, Population Division, 2019).

The final additional visits per year can then be related to the unit cost per visit. To be precise, capitation payments from BPJS to *Puskesmas* are in the short term independent of the number of visits that are made by a single patient. Hence, the assumption underlying the following calculations is that capitation payments have to be adjusted in the long run to finance increases in health care visits. The respective unit costs are derived from an evaluation and costing study that was conducted by the BPJS Health Research & Development Group (Kurniawan et al., 2016) to calculate the average unit cost per *Puskesmas* visit.[8] Based on a random sample of 400 *Puskesmas* from 20 districts, the study calculated an average unit cost of Rp120,000 (US$8.90[9]).

Table 3 shows the resulting visit and cost predictions under both climate change scenarios in the second half of the current century (2060–2080). In contrast to former studies (e.g., Agarwal et al., 2021; White, 2017), I find the increases in visits to be statistically and economically significant–again with the exception of respiratory diseases.

Under the intermediate-emission scenario, the Indonesian health care system is likely to face one million additional primary health care visits a year and a corresponding additional financial burden of US$9.68 million. Under the high-emission scenario, these numbers increase to 2.8 million additional yearly visits and an additional financial burden of US$25 million. In both scenarios, primary health care visits related to diabetes or cardiovascular diseases together account for about 17% of the increase in visits and costs. If population growth and the shift in the population structure toward an older population are considered, this share climbs by another 5% points to 22%. This indicates that the shift in the population-age structure will also lead to a shift in the disease-burden structure, with a higher burden due to NCDs. The related yearly costs under this scenario amount to US$32 million.

TABLE 3 Visit and cost predictions under various climate change and population scenarios

	(1)	(2)	(3)	(4)	(5)	(6)
	Additional yearly visits by 2060-2080			Additional yearly costs by 2060-2080		
Scenario	SSP2-4.5	SSP5-8.5	SSP5-8.5 + population growth and aging	SSP2-4.5	SSP5-8.5	SSP5-8.5 + population growth and aging
All-cause	1,084,433*** (155,002)	2,797,376*** (466,318)	3,569,337*** (47,818)	Rp130.13 billion ($9.69 million)	Rp336.41 billion ($24.98 million)	Rp428.32 billion ($31.88 million)
Diabetes	65,713*** (18,426)	185,178*** (58,302)	270,982*** (83,331)	Rp7.86 billion ($0.59 million)	Rp22.33 billion ($1.65 million)	Rp32.52 billion ($2.42 million)
Cardiovascular diseases	122,270*** (28,057)	338,672*** (86,964)	524,243*** (153,443)	Rp14.67 billion ($1.09 million)	Rp40.99 billion ($3.02 million)	Rp62.91 billion ($4.68 million)
Respiratory diseases	−36,119 (23,245)	−97,153 (73,910)	−88,224 (65,590)	Rp-4.33 billion ($-0.32 million)	Rp-11.85 billion ($-0.88 million)	Rp-10.58 billion ($-0.78 million)

Note: Table 3 displays the predicted increases in yearly primary health care visits (all-cause and by diagnosis) in comparison to the 2015/2016 data. A single visit is assumed to lead to additional costs to the amount of Rp120,000 (US$8.90).

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Compared to BPJS's annual expenditures for primary health care services, which constituted approximately 14% of total expenditures and averaged US$0.72 billion over the period 2015–2017 (Aidha and Chrisnahutama, 2020; Sambodo et al., 2021), this implies an increase between 1.3% and 4.3% for the expenditures allocated to primary health care services.

While this a sizable burden, it most likely captures only a fraction of the total financial burden that might be caused by climate change, since it does not include costs that might arise in hospitals, nor does it include monetized deaths or 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 also vital to comprehensively model health effects in the long run (Dell et al., 2014).

7 | CONCLUSION

This study explored the relationship between high temperatures and NCD-morbidity in Indonesia. The results confirm that high temperatures increase the health burden at the primary health care level as heat-induced morbidity significantly increases health care usage. Hence, even though Indonesia is a country where high temperatures prevail and residents are used to heat and high humidity, the heat-morbidity relationship is a relevant factor in people's health care seeking behavior. Using daily health and weather data at the district level, I show that the number of all-cause and NCD-related primary health care visits substantially increases on days when the daily mean temperature exceeds the average mean temperature. Specifically, I find that on days with a mean temperature above 30°C, the numbers of daily all-cause, diabetes and cardiovascular disease visits increase by 8%, 25% and 14%, respectively, compared to a reference day with a mean temperature between 25.5°C and 27°C. These increases are permanent and not offset by visit displacement or 'harvesting'.

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, the insurance system could face an additional financial burden of US$25 million per year from primary health care services alone, even before accounting for emergency costs and more severe health consequences. Seventeen percent of this burden can be attributed solely 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 made immediately to counteract this trend.

Moreover, to prevent the surge in visits on days with extreme temperatures, action could be taken by health care providers as well as by 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 by 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 patients to re-organize outdoor activities and delay them until cooler evening hours. Special attention could be given to women and the elderly, as they seem to be more severely affected by heat.

As in any typical low- and middle-income country, the primary health care sector forms the backbone of the health care system in Indonesia. The finding that the primary health care sector experiences an increasing burden when temperatures rise also has potentially important implications for the management of the overall health care system. If, for example, the surge in visits in the primary health care sector leads to bottlenecks in human or resource capacities, an efficient and fast interaction between the various health care levels is urgently required to prevent a locally overloaded health care system. What such interactions and synergies could look like is therefore of great interest for future research.

My findings not only contribute to a better understanding of the relationship between temperature and NCDs in Indonesia, but may possibly be more broadly applied to other low- and middle-income countries with a similar tropical climate. Especially for other Southeast Asian countries, which face a similar surge of NCDs and comparable meteorological conditions, the results might be equally applicable.

ACKNOWLEDGMENTS

This paper benefited greatly from the valuable advice provided by Michael Grimm. I also sincerely thank Robert Lensink, Nathalie Luck and Ronja Platz for valuable comments and remarks, Stephan Geschwind for excellent research assistance, Jon Einar Flåtnes and Annika Mueller for their valuable discussions of this paper at the Nordic Conference of Development

Economics 2021 and the University of Groningen PhD Conference 2021, respectively, and participants at the German Development Economics Conference 2021 for their comments and suggestions. I am grateful to BPJS Kesehatan for granting me access to the JKN data sample. I also want to thank two anonymous referees as well as the editor for very constructive comments and valuable advice. This work was supported by the international research consortium SUNI-SEA (Scaling-Up NCD Interventions in Southeast Asia), which received funding from the European Union's Horizon 2020 Research and Innovation Program under grant agreement number 825026.

Open access funding enabled and organized by Projekt DEAL.

[Correction added on 26-August 2022, after first online publication: Projekt DEAL funding statement has been added.]

CONFLICT OF INTEREST

The author declares no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study (health insurance data) are available from BPJS Kesehatan. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at https://bpjs-kesehatan.go.id/bpjs. All other data that support the findings of this study (data on temperature, rainfall, humidity, air pollution, climate change predictions) are openly available. Data on temperature are openly available at the Southeast Asian Climate Assessment and Dataset project database at https://doi.org/10.1175/JCLI-D-16-0575.1 (van den Besselaar et al., 2017). Data on rainfall and humidity are openly available at NASA Earth Data at https://doi.org/10.5067/E7TYRXPJKWOQ (Beaudoing & Rodell, 2020). Data on air pollution are openly available at the Global Modeling and Assimilation Office at https://doi.org/10.5067/FH9A0M-LJPC7N (GMAO, 2015). Data on climate change predictions are openly available at the WorldClim database at https://www.worldclim.org/data/cmip6/cmip6_clim10 m.html (Voldoire, 2018).

ETHICS STATEMENT

This study uses only secondary data; hence no ethical approval was required. The author has received full approval from BPJS Kesehatan to use the JKN data sample that provides anonymized individual health insurance data.

ORCID

Manuela Fritz https://orcid.org/0000-0002-6507-644X

ENDNOTES

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

[2] Studies that also assess the heat-morbidity nexus but take an epidemiological/public health perspective are for example, Kovats et al. (2004), Johnson et al. (2005), Larrieu et al. (2008), Lin et al. (2009), 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), Song et al. (2018), Lin et al. (2019).

[3] The capitation payment per registered insurance member is set by the Indonesian Ministry of Health (see Ministry of Health decrees No. 69, year 2013 (https://peraturan.bpk.go.id/Home/Details/153871/permenkes-no-69-tahun-2013) and No. 52, year 2016 (http://hukor.kemkes.go.id/uploads/produk_hukum/PMK_No._52_Tahun_2016_Tentang_Standar_Tarif_Pelayanan_Kesehatan_Dalam_Penyelenggaraan_JKN_.pdf)). Payments depend on the type of facility, yet are irrespective of whether the insured individual actually makes use of the insurance. If certain performance indicators are not met, BPJS can adjust the payments downward by up to 10% (Functional and Regulatory Review of Strategic Health Purchasing Under JKN, 2018; Sambodo et al., 2021). By the time the capitation rate was set (2014), the US$ - Indonesian Rupiah exchange rate was about 12,000. In 2022, the US$ - Indonesian Rupiah exchange rate is about 14,000.

[4] Using the member counts from the end of the year 2016 might imply an underestimation of the number of visits per 100,000 for any previous point in time, since the member rates increased over time. This means that all results presented in the study should be interpreted as lower-bound estimates. Member counts per district over time are not provided in the data set.

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

[6] 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, that is, whether the heat-effect of today also depends on yesterday's temperature. Moreover, the bias due to correlation declines at a rate $1/T$ (Nickell, 1981; with T being the number of observations within a group). Given a panel length of $T = 731$, the bias is negligible in size.

[7] A downscaled and ready-to-use version of the data is provided at the WorldClim database: https://www.worldclim.org/data/cmip6/cmip6_clim10m.html.

[8] As described in Section 3.1., some of the primary health care visits are not covered by the capitation payments and cost for such visits are reimbursed from BPJS directly. Yet, claims for reimbursements occur at the primary health care level only in a limited number of cases. The major share of primary health care visits is reimbursed via the monthly capitation payments. Overall, only for 4% of the 1.73 million visit observations in the data, a cost claim was made, of which 55% are related to delivery, postpartum care and contraceptive management. Hence, only for a very limited number of visits related NCDs a cost claim was made, which are, however, not representative for the visits that do not result in cost claims. Therefore, the cost per visit was derived from Kurniawan et al. (2016) who estimate the cost for an average visit at Rp120,000. Using the cost claims from the BPJS data would have resulted in a cost per visit of almost three times the amount (Rp317,365) implying a substantial over-estimation of the cost predictions.

[9] Using the 2016 US$-Rp exchange rate with Rp13,436 being equal to US$1.

REFERENCES

Agarwal, S., Qin, Y., Shi, L., Wei, G., & Zhu, H. (2021). Impact of temperature on morbidity: New evidence from China. *Journal of Environmental Economics and Management*, *109*, 102495. https://doi.org/10.1016/j.jeem.2021.102495

Ahern, M., Kovats, R. S., Wilkinson, P., Few, R., & Matthies, F. (2005). Global health impacts of floods: Epidemiologic evidence. *Epidemiologic Reviews*, *27*(1), 36–46. https://doi.org/10.1093/epirev/mxi004

Aidha, C. N., & Chrisnahutama, A. (2020). Deficit of the National Health Insurance (JKN). A proposed alternative for sustainable funding. Prakarsa policy brief. Retrieved July 22, 2022, from https://repository.theprakarsa.org/media/publications/310043-policy-brief-22-deficit-of-the-national-a0ec7204.pdf

Anderson, B. G., & Bell, M. L. (2009). Weather-related mortality: How heat, cold, and heat waves affect mortality in the United States. *Epidemiology*, *20*(2), 205–213. https://doi.org/10.1097/ede.0b013e318190ee08

Anderson, G. B., Dominici, F., Wang, Y., McCormack, M. C., Bell, M. L., & Peng, R. D. (2013). Heat-related emergency hospitalizations for respiratory diseases in the Medicare population. *American Journal of Respiratory and Critical Care Medicine*, *187*(10), 1098–1103. https://doi.org/10.1164/rccm.201211-1969oc

Åström, C., Orru, H., Rocklöv, J., Strandberg, G., Ebi, K. L., & Forsberg, B. (2013). Heat-related respiratory hospital admissions in Europe in a changing climate: A health impact assessment. *BMJ Open*, *3*(1), e001842. https://doi.org/10.1136/bmjopen-2012-001842

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, *32*(4), 33–52. https://doi.org/10.1257/jep.32.4.33

Barreca, A. I. (2012). Climate change, humidity, and mortality in the United States. *Journal of Environmental Economics and Management*, *63*(1), 19–34. https://doi.org/10.1016/j.jeem.2011.07.004

Barreca, A. I., Clay, K., Deschênes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, *124*(1), 105–159. https://doi.org/10.1086/684582

Bassil, K. L., & Cole, D. C. (2010). Effectiveness of public health interventions in reducing morbidity and mortality during heat episodes: A structured review. *International Journal of Environmental Research and Public Health*, *7*(3), 991–1001. https://doi.org/10.3390/ijerph7030991

Basu, R. (2009). High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. *Environmental Health*, *8*(1), 1–13. https://doi.org/10.1186/1476-069x-8-40

Basu, R., & Malig, B. (2011). High ambient temperature and mortality in California: Exploring the roles of age, disease, and mortality displacement. *Environmental Research*, *111*(8), 1286–1292. https://doi.org/10.1016/j.envres.2011.09.006

Beaudoing, H., & Rodell, M., & NASA/GSFC/HSL. (2020). GLDAS Noah Land surface model L4 3 hourly 0.25 x 0.25 degree V2.1. *Goddard Earth Sciences Data and Information Services Center (GES DISC)*. Greenbelt, Maryland, USA. https://doi.org/10.5067/E7TYRXPJKWOQ

Behrman, J. R., Behrman, J. A., & Perez, N. M. (2009). On what diseases and health conditions should new economic research on health and development focus? *Health Economics*, *18*(S1), S109–S128. https://doi.org/10.1002/hec.1464

Benmarhnia, T., Deguen, S., Kaufman, J. S., & Smargiassi, A. (2015). Vulnerability to heat related mortality: A systematic review, meta-analysis, and meta-regression analysis. *Epidemiology*, *26*(6), 781–793. https://doi.org/10.1097/ede.0000000000000375

Bi, P., Williams, S., Loughnan, M., Lloyd, G., Hansen, A., Kjellstrom, T., Dear, K., & Saniotis, A. (2011). The effects of extreme heat on human mortality and morbidity in Australia: Implications for public health. *Asia Pacific Journal of Public Health*, *23*(2), 27–36. https://doi.org/10.1177/1010539510391644

Bobb, J. F., Obermeyer, Z., Wang, Y., & Dominici, F. (2014). Cause-specific risk of hospital admission related to extreme heat in older adults. *Jama*, *312*(24), 2659–2667. https://doi.org/10.1001/jama.2014.15715

Bowen, K. J., & Ebi, K. L. (2017). Health risks of climate change in the world health organization South-east Asia region. *WHO South-East Asia Journal of Public Health*, *6*(2), 3–8. https://doi.org/10.4103/2224-3151.213789

BPJS Kesehatan. (2015). Laporan Pengeloaan program Tahun 2015 & Lapuran Keuangan Tahun 2015 (Auditan). Retrieved September 15, 2021, from https://bpjs-kesehatan.go.id/bpjs/arsip/view/572

BPJS Kesehatan. (2016). Laporan Pengeloaan program Tahun 2016 & Lapuran Keuangan Tahun 2016 (Auditan). Retrieved September 15, 2021, from https://bpjs-kesehatan.go.id/bpjs/arsip/view/835

BPJS Kesehatan. (2019). Laporan Pengeloaan program Tahun 2019 & Lapuran Keuangan Tahun 2019 (Auditan). Retrieved July 21, 2022, from https://www.bpjs-kesehatan.go.id/bpjs/arsip/view/1520

BPJS Kesehatan. (2021). Jumlah Peserta dan fasilitas kesehatan. Retrieved September 15, 2021, from https://bpjs-kesehatan.go.id/bpjs/jumlahPeserta

Braga, A. L. F., Zanobetti, A., & Schwartz, J. (2001). The time course of weather-related deaths. *Epidemiology*, *12*(6), 662–667. https://doi.org/10.1097/00001648-200111000-00014

Burgess, R., Deschênes, O., Donaldson, D., & Greenstone, M. (2017). Weather, climate change and death in India. Working Paper. Retrieved July 21, 2022, from https://www.lse.ac.uk/economics/Assets/Documents/personal-pages/robin-burgess/weather-climate-change-and-death.pdf

Campbell, S., Remenyi, T. A., White, C. J., & Johnston, F. H. (2018). Heatwave and health impact research: A global review. *Health & Place*, *53*, 210–218. https://doi.org/10.1016/j.healthplace.2018.08.017

Carleton, T. A., Jina, A., Delgado, M. T., Greenstone, M., Houser, T., Hsiang, S. M., … Zhang, A. T. (2020). *Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits*. National Bureau of Economic Research. No. w27599.

Cheng, J., Xu, Z., Bambrick, H., Su, H., Tong, S., & Hu, W. (2018). Heatwave and elderly mortality: An evaluation of death burden and health costs considering short-term mortality displacement. *Environment International*, *115*, 334–342. https://doi.org/10.1016/j.envint.2018.03.041

Costello, A., Abbas, M., Allen, A., Ball, S., Bell, S., Bellamy, R., Friel, S., Groce, N., Johnson, A., Kett, M., Lee, M., Levy, C., Maslin, M., McCoy, D., McGuire, B., Montgomery, H., Napier, D., Pagel, C., Patel, J., & Patterson, C. (2009). Managing the health effects of climate change: Lancet and university college London institute for global health commission. *The Lancet*, *373*(9676), 1693–1733. https://doi.org/10.1016/s0140-6736(09)60935-1

Dans, A., Ng, N., Varghese, C., Tai, E. S., Firestone, R., & Bonita, R. (2011). The rise of chronic non-communicable diseases in Southeast Asia: Time for action. *The Lancet*, *377*(9766), 680–689. https://doi.org/10.1016/s0140-6736(10)61506-1

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, *52*(3), 740–798. https://doi.org/10.1257/jel.52.3.740

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, *3*(4), 152–185. https://doi.org/10.1257/app.3.4.152

Deschênes, O., & Moretti, E. (2009). Extreme weather events, mortality, and migration. *The Review of Economics and Statistics*, *91*(4), 659–681. https://doi.org/10.1162/rest.91.4.659

Diaz, D., & Moore, F. (2017). Quantifying the economic risks of climate change. *Nature Climate Change*, *7*(11), 774–782. https://doi.org/10.1038/nclimate3411

Epstein, Y., & Yanovich, R. (2019). Heatstroke. *New England Journal of Medicine*, *380*(25), 2449–2459. https://doi.org/10.1056/nejmra1810762

Friel, S., Bowen, K., Campbell-Lendrum, D., Frumkin, H., McMichael, A. J., & Rasanathan, K. (2011). Climate change, noncommunicable diseases, and development: The relationships and common policy opportunities. *Annual Review of Public Health*, *32*(1), 133–147. https://doi.org/10.1146/annurev-publhealth-071910-140612

Functional and Regulatory Review of Strategic Health Purchasing Under JKN. (2018). *Overview of strategic Purchasing functions under JKN. JKN policy note*. World Bank Group. Retrieved July 21, 2022, from http://documents.worldbank.org/curated/en/328701534744931433/Functional-and-Regulatory-Review-of-Strategic-Health-Purchasing-Under-JKN-Overview-of-Strategic-Purchasing-Functions-Under-JKN

Global Modeling, & Assimilation Office (GMAO) (2015). MERRA-2 tavgM_2d_aer_Nx: 2d, monthly mean, time-averaged, single-level, assimilation, Aerosol Diagnostics V5.12.4. *Goddard Earth Sciences Data and Information Services Center (GES DISC)*. Greenbelt, MD, USA. https://doi.org/10.5067/FH9A0MLJPC7N

Green, H., Bailey, J., Schwarz, L., Vanos, J., Ebi, K., & Benmarhnia, T. (2019). Impact of heat on mortality and morbidity in low and middle income countries: A review of the epidemiological evidence and considerations for future research. *Environmental Research*, *171*, 80–91. https://doi.org/10.1016/j.envres.2019.01.010

Green, R. S., Basu, R., Malig, B., Broadwin, R., Kim, J. J., & Ostro, B. (2010). The effect of temperature on hospital admissions in nine California counties. *International Journal of Public Health*, *55*(2), 113–121. https://doi.org/10.1007/s00038-009-0076-0

Grosskurth, H. (2019). The burden of non-communicable diseases in low-and middle-income countries. In K. Attkinson & D. Mabey (Eds.), *Revolutionizing tropical medicine: Point-of-Care tests, new imaging technologies and digital health* (pp. 37–80). John Wiley & Sons.

Hall, J. E., & Hall, M. E. (2020). *Guyton and Hall textbook of medical physiology*. E-Book. Elsevier Health Sciences.

Intergovernmental Panel on Climate Change - IPCC. (2022). Summary for policymakers. In Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., & Zhou, B. (Eds.), *Climate change 2022: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*. Cambridge University Press. In Press.

International Diabetes Federation. (2021). *IDF diabetes Atlas* (*10*th ed.). IDF.

Islam, S. M. S., Purnat, T. D., Phuong, N. T. A., Mwingira, U., Schacht, K., & Fröschl, G. (2014). Non-communicable diseases (NCDs) in developing countries: A symposium report. *Globalization and Health*, *10*(1), 1–8. https://doi.org/10.1186/s12992-014-0081-9

Jo, C., & Setiawan, E. (2019). Strengthening JKN system as a strategic purchaser in Indonesia. In *National health insurance service of the Republic of Korea, Ministry of national development planning Indonesia (BAPPENAS), & BPJS kesehatan*. [eds.]. 2018/19 KSP Policy Consultation Report. Supporting Social Health Insurance in Indonesia. Policy Brief. Retrieved July 22, 2022, from https://www.kdevelopedia.org/asset/99202003310152542/1585617881697.pdf

Johnson, H., Kovats, R. S., McGregor, G., Stedman, J., Gibbs, M., Walton, H., … Black, E. (2005). The impact of the 2003 heat wave on mortality and hospital admissions in England. *Health Statistics Quarterly*(25), 6–11.

Karlsson, M., & Ziebarth, N. R. (2018). Population health effects and health-related costs of extreme temperatures: Comprehensive evidence from Germany. *Journal of Environmental Economics and Management*, *91*, 93–117. https://doi.org/10.1016/j.jeem.2018.06.004

Kenny, G. P., Sigal, R. J., & McGinn, R. (2016). Body temperature regulation in diabetes. *Temperature*, *3*(1), 119–145. https://doi.org/10.1080/23328940.2015.1131506

Knowlton, K., Rotkin-Ellman, M., King, G., Margolis, H. G., Smith, D., Solomon, G., Trent, R., & English, P. (2009). The 2006 California heat wave: Impacts on hospitalizations and emergency department visits. *Environmental Health Perspectives*, *117*(1), 61–67. https://doi.org/10.1289/ehp.11594

KOMPAK (2017). Fund interplay in public health centres (Puskesmas). Policy brief. Kolaborasi Masyarakat dan Pelayanan untuk Kesejahteraan (KOMPAK), the government of Indonesia and the Australian government. Retrieved November 26, 2021, from https://www.kompak.or.id/index.php/en/download/68/171219_Policy_Brief_Puskesmas-Funds_Interplay-1-Final1.pdf

Kostova, D., Husain, M. J., Sugerman, D., Hong, Y., Saraiya, M., Keltz, J., & Asma, S. (2017). Synergies between communicable and noncommunicable disease programs to enhance global health security. *Emerging Infectious Diseases*, *23*(Suppl 1), 40–46. https://doi.org/10.3201/eid2313.170581

Kovats, R. S., Bouma, M. J., Hajat, S., Worrall, E., & Haines, A. (2003). El Niño and health. *The Lancet*, *362*(9394), 1481–1489. https://doi.org/10.1016/s0140-6736(03)14695-8

Kovats, R. S., Hajat, S., & Wilkinson, P. (2004). Contrasting patterns of mortality and hospital admissions during hot weather and heat waves in Greater London, UK. *Occupational and Environmental Medicine*, *61*(11), 893–898. https://doi.org/10.1136/oem.2003.012047

Kurniawan, M. F., Siswoyo, B. E., Mansyur, F., Aisyah, W., Revelino, D., & Gadistina, W. (2016). Pengelolaan dan Pemanfaatan Dana Kapitasi (Monitoring dan Evaluasi Jaminan Kesehatan Nasional di Indonesia). *Jurnal Kebijakan Kesehatan Indonesia: JKKI*, *5*(3), 122–131.

Larrieu, S., Carcaillon, L., Lefranc, A., Helmer, C., Dartigues, J. F., Tavernier, B., Ledrans, M., & Filleul, L. (2008). Factors associated with morbidity during the 2003 heat wave in two population-based cohorts of elderly subjects: PAQUID and three city. *European Journal of Epidemiology*, *23*(4), 295–302. https://doi.org/10.1007/s10654-008-9229-3

Lee, W. S., & Li, B. G. (2021). Extreme weather and mortality: Evidence from two millennia of Chinese elites. *Journal of Health Economics*, *76*, 102401. https://doi.org/10.1016/j.jhealeco.2020.102401

Lhotka, O., Kyselý, J., & Farda, A. (2018). Climate change scenarios of heat waves in Central Europe and their uncertainties. *Theoretical and Applied Climatology*, *131*(3–4), 1043–1054. https://doi.org/10.1007/s00704-016-2031-3

Li, Y., Lan, L., Wang, Y., Yang, C., Tang, W., Cui, G., Luo, S., Cheng, Y., Liu, Y., Liu, J., & Jin, Y. (2014). Extremely cold and hot temperatures increase the risk of diabetes mortality in metropolitan areas of two Chinese cities. *Environmental Research*, *134*, 91–97. https://doi.org/10.1016/j.envres.2014.06.022

Lin, S., Luo, M., Walker, R. J., Liu, X., Hwang, S. A., & Chinery, R. (2009). Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases. *Epidemiology*, *20*(5), 738–746. https://doi.org/10.1097/ede.0b013e3181ad5522

Lin, Y. K., Maharani, A. T., Chang, F. T., & Wang, Y. C. (2019). Mortality and morbidity associated with ambient temperatures in Taiwan. *Science of the Total Environment*, *651*, 210–217. https://doi.org/10.1016/j.scitotenv.2018.09.161

Linares, C., & Diaz, J. (2008). Impact of high temperatures on hospital admissions: Comparative analysis with previous studies about mortality (Madrid). *European Journal of Public Health*, *18*(3), 317–322. https://doi.org/10.1093/eurpub/ckm108

Liu, Y. M., & Ao, C. K. (2021). Effect of air pollution on health care expenditure: Evidence from respiratory diseases. *Health Economics*, *30*(4), 858–875. https://doi.org/10.1002/hec.4221

Maccini, S., & Yang, D. (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, *99*(3), 1006–1026. https://doi.org/10.1257/aer.99.3.1006

Manne-Goehler, J., Geldsetzer, P., Agoudavi, K., Andall-Brereton, G., Aryal, K. K., Bicaba, B. W., Bovet, P., Brian, G., Dorobantu, M., Gathecha, G., Singh Gurung, M., Guwatudde, D., Msaidie, M., Houehanou, C., Houinato, D., Jorgensen, J. M. A., Kagaruki, G. B., Karki, K. B., Labadarios, D., & Jaacks, L. M. (2019). Health system performance for people with diabetes in 28 low-and middle-income countries: A cross-sectional study of nationally representative surveys. *PLoS Medicine*, *16*(3), e1002751. https://doi.org/10.1371/journal.pmed.1002751

McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: Present and future risks. *The Lancet*, *367*(9513), 859–869. https://doi.org/10.1016/s0140-6736(06)68079-3

Michelozzi, P., Accetta, G., De Sario, M., D'Ippoliti, D., Marino, C., Baccini, M., Biggeri, A., Anderson, H. R., Katsouyanni, K., Ballester, F., Bisanti, L., Cadum, E., Forsberg, B., Forastiere, F., Goodman, P. G., Hojs, A., Kirchmayer, U., Medina, S., Paldy, A., & Perucci, C. A. (2009). High temperature and hospitalizations for cardiovascular and respiratory causes in 12 European cities. *American Journal of Respiratory and Critical Care Medicine*, *179*(5), 383–389. https://doi.org/10.1164/rccm.200802-217oc

Mullins, J. T., & White, C. (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of Health Economics*, *68*, 102240. https://doi.org/10.1016/j.jhealeco.2019.102240

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417–1426. https://doi.org/10.2307/1911408

Nitschke, M., Tucker, G. R., Hansen, A. L., Williams, S., Zhang, Y., & Bi, P. (2011). Impact of two recent extreme heat episodes on morbidity and mortality in adelaide, South Australia: A case-series analysis. *Environmental Health*, *10*(1), 1–9. https://doi.org/10.1186/1476-069x-10-42

Nugraheni, W. P., Zahroh, A. H., Hartono, R. K., Nugraha, R. R., & Chun, C. B. (2020). National health insurance deficit in Indonesia: Identification of causes and solutions for resolution. *Global Journal of Health Science*, *12*(13), 1–58. https://doi.org/10.5539/gjhs.v12n13p58

Pandey, B. D., & Costello, A. (2019). The dengue epidemic and climate change in Nepal. *The Lancet*, *394*(10215), 2150–2151. https://doi.org/10.1016/s0140-6736(19)32689-3

Prabhakaran, S., Dutta, A., Fagan, T., & Ginivan, M. (2019). Financial sustainability of Indonesia's Jaminan kesehatan nasional: Performance, Prospects, and policy options. Palladium, Health Policy Plus, and Jakarta, Indonesia: Tim Nasional Percepatan Penanggulangan Kemiskinan (TNP2K).

Sambodo, N. P., Van Doorslaer, E., Pradhan, M., & Sparrow, R. (2021). Does geographic spending variation exacerbate healthcare benefit inequality? A benefit incidence analysis for Indonesia. *Health Policy and Planning*, *36*(7), 1129–1139. https://doi.org/10.1093/heapol/czab015

Schaffer, A., Muscatello, D., Broome, R., Corbett, S., & Smith, W. (2012). Emergency department visits, ambulance calls, and mortality associated with an exceptional heat wave in Sydney, Australia, 2011: A time-series analysis. *Environmental Health*, *11*(1), 1–8. https://doi.org/10.1186/1476-069x-11-3

Schwartz, J., Samet, J. M., & Patz, J. A. (2004). Hospital admissions for heart disease: The effects of temperature and humidity. *Epidemiology*, *15*(6), 755–761. https://doi.org/10.1097/01.ede.0000134875.15919.0f

Semenza, J. C., McCullough, J. E., Flanders, W. D., McGeehin, M. A., & Lumpkin, J. R. (1999). Excess hospital admissions during the July 1995 heat wave in Chicago. *American Journal of Preventive Medicine*, *16*(4), 269–277. https://doi.org/10.1016/s0749-3797(99)00025-2

Song, X., Wang, S., Li, T., Tian, J., Ding, G., Wang, J., & Shang, K. (2018). The impact of heat waves and cold spells on respiratory emergency department visits in Beijing, China. *Science of the Total Environment*, *615*, 1499–1505. https://doi.org/10.1016/j.scitotenv.2017.09.108

Stanke, C., Kerac, M., Prudhomme, C., Medlock, J., & Murray, V. (2013). Health effects of drought: A systematic review of the evidence. *PLoS Currents Disasters*, *5*. https://doi.org/10.1371/currents.dis.7a2cee9e980f91ad7697b570bcc4b004

United Nations, department of economic and social Affairs, population division. (2019). World Population Prospects 2019. Online Edition, Rev. 1. [Data] Retrieved November 26, 2021, from https://population.un.org/wpp/Download/Standard/Population/

van den Besselaar, E. J., Van Der Schrier, G., Cornes, R. C., Iqbal, A. S., & Klein Tank, A. M. (2017). SA-OBS: A daily gridded surface temperature and precipitation dataset for Southeast Asia. *Journal of Climate*, *30*(14), 5151–5165. https://doi.org/10.1175/JCLI-D-16-0575.1

Voldoire, A. (2018). CNRM-CERFACS CNRM-CM6-1 model output prepared for CMIP6 CMIP. *Earth System Grid Federation*. Version 20181203. https://doi.org/10.22033/ESGF/CMIP6.1375

Wang, L., Kanji, S., & Bandyopadhyay, S. (2009). *The health impact of extreme weather events in Sub-Saharan Africa*. The World Bank. Policy Research Working Paper 4979.

White, C. (2017). The dynamic relationship between temperature and morbidity. *Journal of the Association of Environmental and Resource Economists*, *4*(4), 1155–1198. https://doi.org/10.1086/692098

Wichmann, J., Andersen, Z., Ketzel, M., Ellermann, T., & Loft, S. (2011). Apparent temperature and cause-specific emergency hospital admissions in Greater Copenhagen, Denmark. *PLoS One*, *6*(7), e22904. https://doi.org/10.1371/journal.pone.0022904

Williams, S., Nitschke, M., Weinstein, P., Pisaniello, D. L., Parton, K. A., & Bi, P. (2012). The impact of summer temperatures and heatwaves on mortality and morbidity in Perth, Australia 1994–2008. *Environment International*, *40*, 33–38. https://doi.org/10.1016/j.envint.2011.11.011

World Health Organization (WHO). (2018). *Noncommunicable diseases country profiles 2018*. World Health Organization.

Ye, F., Piver, W. T., Ando, M., & Portier, C. J. (2001). Effects of temperature and air pollutants on cardiovascular and respiratory diseases for males and females older than 65 years of age in Tokyo, July and August 1980-1995. *Environmental Health Perspectives*, *109*(4), 355–359. https://doi.org/10.1289/ehp.01109355

Ye, X., Wolff, R., Yu, W., Vaneckova, P., Pan, X., & Tong, S. (2012). Ambient temperature and morbidity: A review of epidemiological evidence. *Environmental Health Perspectives*, *120*(1), 19–28. https://doi.org/10.1289/ehp.1003198

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Fritz, M. (2022). Temperature and non-communicable diseases: Evidence from Indonesia's primary health care system. *Health Economics*, *31*(11), 2445–2464. https://doi.org/10.1002/hec.4590