The impact of cold waves and heat waves on mortality: Evidence from a lower middle-income country

Cuong Viet Nguyen, Manh Hung Nguyen, Toan Nguyen

Received: 13 May 2022 | Revised: 31 January 2023 | Accepted: 1 February 2023

DOI: 10.1002/hec.4663

RESEARCH ARTICLE

Health Economics WILEY

The impact of cold waves and heat waves on mortality: Evidence from a lower middle-income country

Cuong Viet Nguyen[1,2] | **Manh-Hung Nguyen**[3] | **Toan Truong Nguyen**[4]

[1]International School, Vietnam National University, Hanoi, Vietnam

[2]Mekong Development Research Institute (MDRI), Hanoi, Vietnam

[3]Toulouse School of Economics, INRAE, University of Toulouse Capitole, Toulouse, France

[4]Crawford School of Public Policy, Australian National University, Canberra, Australian Capital Territory, Australia

Correspondence
Toan Truong Nguyen
Email: Truongtoan.bk.cs@gmail.com

Funding information
Agence Nationale de la Recherche, Grant/Award Number: ANR-17-EURO-0010; Institut de Recherche pour le Développement, Grant/Award Number: GEMMES Vietnam

Abstract

We estimate the impact of temperature extremes on mortality in Vietnam, using daily data on temperatures and monthly data on mortality during the 2000–2018 period. We find that both cold and heat waves cause higher mortality, particularly among older people and those living in the hot regions in Southern Vietnam. This effect on mortality tends to be smaller in provinces with higher rates of air-conditioning and emigration, and provinces with higher public spending on health. Finally, we estimate economic cost of cold and heat waves using a framework of willingness to pay to avoid deaths, then project the cost to the year 2100 under different Representative Concentration Pathway scenarios.

KEYWORDS
health, mortality, Vietnam, weather extremes

JEL CLASSIFICATION
I10, Q54, O15, R23

1 | INTRODUCTION

There is widespread agreement that extreme weather and climate change have been and will continue to be the greatest threat to humankind (Stern, 2008). The link between climate change and extreme weather, especially heat waves, is well documented (Luber & McGeehin, 2008). Although adaptation and medical advances have mitigated the adverse health effects of extreme events, climate change could reverse this trend (Ebi et al., 2021). As extreme weather events occur more frequently, the number of people affected will increase. A recent estimate from Zhao et al. (2021) indicates that non-optimal temperatures are linked with around 5 million deaths worldwide per year, accounting for 9.43% of all deaths, of which 8.52% are cold-related and 0.91% are heat-related. Understanding the effects of extreme weather on health is extremely important for the design of policies that adapt for climate change.

In this study, we examine the effect of temperatures on the monthly province-level rate of mortality in Vietnam during the 2000–2018 period. By exploring a number of ways to measure temperature distribution, we uncover several interesting findings on how temperatures affect mortality. While large literature consider the mortality impact of increases in average temperature measured by bins, we focus on more complex relationships between the duration and extend of extreme weather events. We begin with examining non-linear relationship between mortality and temperature. Using the number of days (within a month) in 3-degree (or 2-degree) temperature bins to capture the non-linear relationship between temperature and mortality, we do not find significant effects of low and high temperature bins relative to the reference temperature bin (21–24°C). However, if a medium temperature from 15 to 30°C is used as the reference bin, we find a significant effect of high but not low temperatures. An additional day with a mean temperature over 30°C relative to a 15–30°C day increases the monthly mortality rate by 0.78%.

Measuring the temperature effect using absolute temperature can be associated with bias since local people have the capacity to adapt to steady temperatures, whether high or low. Therefore, we use temperature shocks, which are measured by the number of days with a daily mean temperature below the fifth percentile or above the 95^{th} percentile of the province-specific temperature distribution during the past 20 years. We find significant effects from both low and high temperature extremes. An additional day with a mean temperature at or below the fifth percentile of the temperature distribution relative to a day within the fifth-95^{th} percentile range, increases the monthly mortality rate by 0.5%. The corresponding figure for the effect of a high temperature extreme is 0.73%. A problem with recording the number of days with temperature extremes is that this does not capture the duration of these extremes. Thus, we define a heat wave as three or more consecutive days with a daily mean temperature at or higher than the 95^{th} percentile of the province-specific temperature distribution, and a cold wave as at least three consecutive days with a daily mean temperature at or below the fifth percentile of the province-specific temperature distribution. We find that a cold wave longer by one additional day within a month increases the monthly mortality rate by 0.6%. The corresponding figure for an additional day in a heat wave is 0.7%. Our estimates are robust for different definitions of cold and heat waves as well as different specification and placebo tests.

The findings concerning the smaller effect of temperature bins but higher effect of cold and heat waves suggest that people living in cold or hot areas may be acclimatized or able to adapt to low or high temperatures, but are more vulnerable to temperature shocks, especially when these shocks are prolonged. Cold and heat waves put a strain on human cardiovascular and respiratory systems and as a result, the number of deaths caused by these waves is higher than the number due to excessive temperatures alone. Furthermore, we find a heterogeneous effect from cold waves on mortality across provinces with different adaptive strategies. The effect of cold waves on mortality tends to be lower in provinces with a higher level of air-conditioning and in provinces with higher public spending on health. Cold waves also push people to migrate from their provinces, and provinces with higher emigration rates are less affected by cold waves. Our study confirms the adverse effect of extreme weather on health and suggests the important role of adaptation and coping strategies to reduce this effect.

Using the estimated effect of cold and heat waves on monthly mortality rate, we predict the number of deaths caused by the cold and heat waves over time. It is estimated that cold and heat waves account for 1.42% of all deaths in Vietnam during the 2003–2017 period (cold and heat waves account for 53% and 47% respectively). We project the economic cost of mortality caused by cold and heat waves by multiplying the number of deaths with a statistical life value of 0.342 million USD (Viscusi & Masterman, 2017). The cost that we are willing to pay to avoid the mortality of 2468 people is estimated at 0.84 billion USD (at constant 2015 prices) in 2017, equivalently 0.44% of GDP in that year.

Finally, we use projected daily data for Vietnam to forecast cold and heat waves in the 2020–2100 timeframe using several Representative Concentration Pathway (RCP) scenarios. The number of days with cold waves is expected to drop rapidly, approaching zero in the 2050s. On the other side, the number of days with heat waves grows dramatically, peaking in about 2060. The RCP 6.0 scenario has the most heat waves, whereas the RCP 2.6 scenario has the fewest. Heat-related deaths are expected to rise in the future, reaching a peak around 2060. These findings raise severe concerns regarding the health repercussions of future heat-related events in Vietnam.

Our study contributes to the related literature in several ways. Firstly, it provides recent empirical evidence on the effect of temperature on mortality in a lower middle-income country. Located in South East Asia, Vietnam is ranked as one of the top five countries most likely to be affected by climate change (World Bank and Asian Development Bank, 2020). According to MONRE (2009), the average surface temperature in Vietnam is predicted to rise by 1.1–3.6°C this century. While the effect of temperature on mortality has been well documented in high-income countries (e.g., Anderson & Bell, 2011; Barreca, 2012; Barreca et al., 2016; Deschenes & Greenstone, 2011; Deschênes & Moretti, 2009; Karlsson & Ziebarth, 2018; Mullins & White, 2020), there is less evidence concerning this effect in low- and middle-income countries (e.g., see a review from Dimitrova et al., 2021). The effect of temperature on health and mortality tends to be greater in lower-income countries (Basu, 2009; Burgess et al., 2017; Carleton et al., 2020; Lee & Li, 2021), partly because of their limited coping and adaptive capacities.

Burgess et al. (2017) show a higher effect from high temperatures on mortality in India than in the US. Recently, Cohen and Dechezleprêtre (2019) estimate that suboptimal temperatures, mainly cold, cause nearly 4% of all deaths in Mexico. Lin et al. (2021) find that drought increases infant mortality and reduces birth weight of children in China. Existing studies show a wide diversity of empirical results, a situation which calls for more empirical findings to better understand the effect of temperature on mortality.[1] Using Russian data, Otrachshenko et al. (2017) present evidence that mortality will be increased because of both hot and cold days. However, extremely cold events (below − 30°C) may reduce mortality because of risk aversion behaviors. Related to cold waves, Otrachshenko et al. (2018) find that single cold days do not have a significant effect on mortality in Russia, but a spell of at least 3 cold consecutive day increases mortality. The method used in this paper is similar to that was used by Otrachshenko et al. (2018) and our results complement to their findings.

The second contribution of this study is to confirm the short-term effect of cold and heat waves on mortality. A challenge in studying the temperature-mortality relationship is to understand the channels through which temperatures can cause mortality. A direct effect of extreme temperature fluctuations is a deterioration in people's health. Hot temperatures can have direct, short-term effects on mortality by increasing the risks of cardiovascular, respiratory, cerebrovascular and blood cholesterol problems, especially in children and older people (see review by Basu & Samet, 2002; Xu et al., 2012). Extreme temperatures can have a medium-term effect on mortality through increasing the risk of contracting disease. Climate variability can affect the survival rate and transmission of viruses and bacteria. Temperature and precipitation are found to strongly affect the spread of dengue, cholera, malaria, diarrhea, and several infectious diseases (e.g., Jahani & Ahmadnezhad, 2011; Levy et al., 2016).

Another indirect mechanism through which extreme temperatures cause deteriorating health is their negative effect on income. High temperatures increase discomfort and tiredness, resulting in reduced labor productivity (e.g., Deryugina & Hsiang, 2014; Somanathan et al., 2021). Several studies document the negative effect of extreme temperatures on agricultural production and economic growth (e.g., Deschênes & Greenstone, 2007; Dell et al., 2009; Miller et al., 2021; Otrachshenko & Popova, 2022). Our study shows that cold and heat waves have only a short-term effect on monthly mortality in Vietnam. There are no significant lagged effects of cold and heat waves on mortality. In addition, we do not find significant effects of cold and heat waves on income. These findings suggest that cold and heat waves cause deaths by increasing people's health problems directly.

Recent studies focus on the heterogeneous effects of climate change and adaptation strategies to mitigate the effects of temperature on mortality (e.g., Banerjee & Maharaj, 2020; Barreca et al., 2016; Burgess et al., 2017; Cohen & Dechezleprêtre, 2019; Heutel et al., 2020; Mullins & White, 2020). Several studies find that greater access to air-conditioning mitigates the adverse effect of heat waves (e.g., Barreca et al., 2016; Heutel et al., 2020). Cohen and Dechezleprêtre (2019) investigate the link between temperature and mortality in Mexico and discover that enrollment in Mexico's national health insurance scheme reduces the impact of a cold day on mortality by 35%. On the other hand, Mullins and White (2020) find that access to primary care services mitigates the harmful effects of heat but not cold in the US. Our study supplements related studies by showing that provinces with a higher number of air-conditioners and higher public spending on health are less affected by cold waves.[2] Moreover, we find that people are more likely to emigrated from provinces with more cold waves and as a result, emigration tends to mitigate the effects of cold waves on mortality.

The remainder of the paper is structured as follows. The second section discusses the data sets used in this study and provides a descriptive analysis of mortality in relation to temperatures in Vietnam. The third and fourth sections present the method of estimation and the effect of temperature on mortality, respectively. The fifth section estimates the number of deaths caused by cold and heat waves and projects the number of deaths under different temperature scenarios in the coming years. Finally, the sixth section offers a concluding summary.

2 | DATA SETS AND DESCRIPTIVE ANALYSIS

This study relies on the two main data sets. The first is the monthly mortality rate of provinces during the 2000–2018 period, provided by General Statistics Office of Vietnam (GSO). The mortality rate is computed from the Population Change and Family Planning Surveys, which have been conducted annually by the GSO since 2000. The sample size of these surveys is representative at the provincial level. Monthly mortality rates can be estimated separately for males and females and for different age groups.

Together with economic growth, Vietnam has experienced improvement in health. Life expectancy has increased from 73 to 75 from 2000 to 2018 (World Bank, 2020). However, the crude mortality rate has not declined during this period. Estimates from the Population and Planning Surveys show that the raw mortality rate for all ages was around 5 deaths per 1000 people during the 2000–2018 period (see Figure A.1 in the Appendix). A major reason why the mortality rate has not decreased during the past 2 decades is the decline in the fertility rate. The government has recommended family planning with a limit of two children per family since 1988. The dramatic decline in birth rates is the most important reason for population aging in Vietnam.[3] When the mortality rate is computed for different age groups, we can see a decline in the mortality rate, especially for children under 5 and people aged 60 and older (Figure A.1 in the Appendix).

The second data set comprises weather data. Temperature and precipitation measurements are sourced from the Vietnam Institute of Meteorology, Hydrology and Climate Change. This data set is an administrative source covering data from all 172 weather stations in Vietnam (as shown in Figure A.2 in the Appendix) and provides daily precipitation, and daily minimum, mean and maximum temperatures. Our data on mortality is taken from the province-by-month mortality rate. Thus, we need to link the weather data from the stations to the provincial-level data. Currently, Vietnam has 63 provinces covering 705 districts.

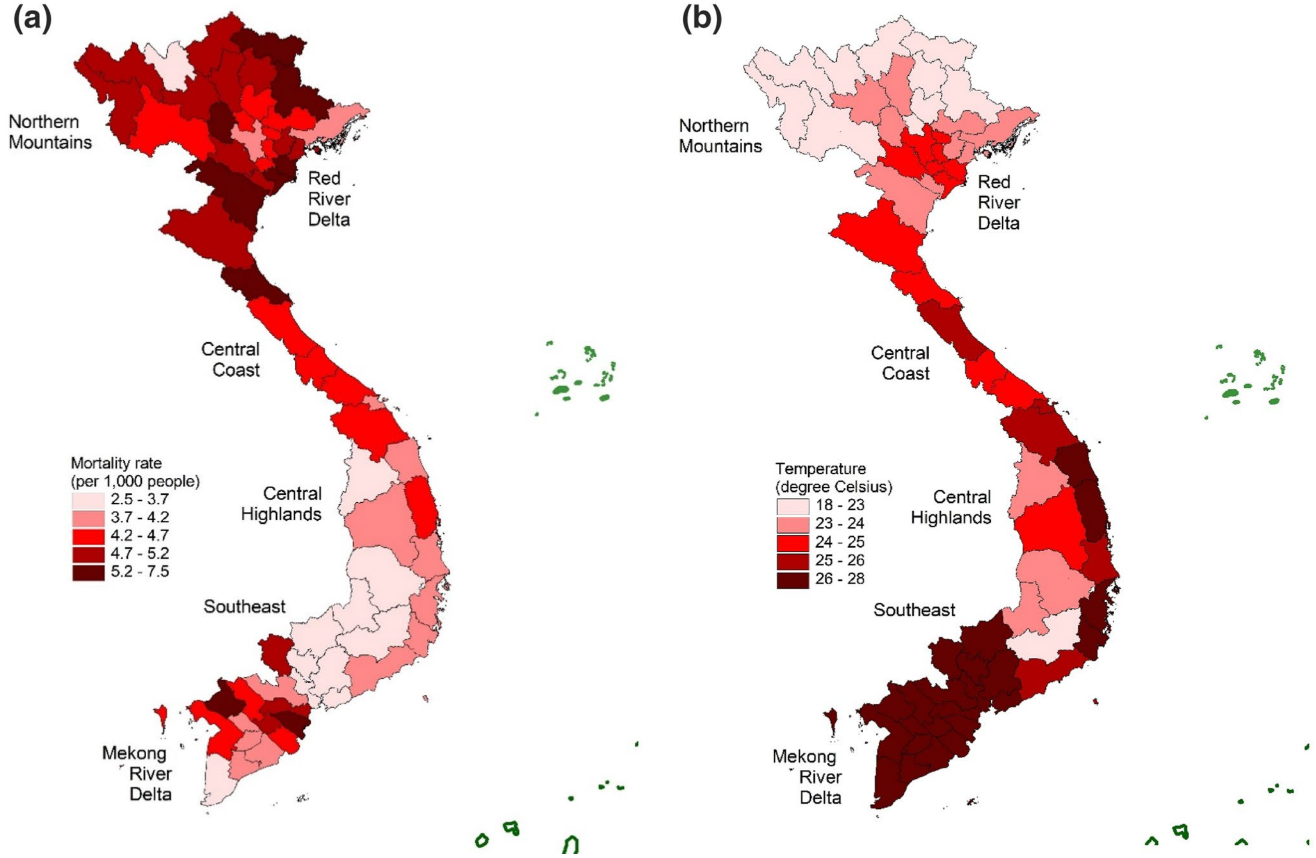

FIGURE 1 Mortality rate and temperatures. (a) Mortality rate (per 1000 people). (b) Average daily temperature (degrees Celsius). (a) presents the crude death rate of each province in a year, measured by the number of deaths per 1000 of the population. The map shows the mortality averaged over the 2000–2018 period. (b) presents the average of the daily mean temperature of each province over the same period.

We first match each district with the nearest weather station (the shortest distance from the district's centroid to the station). The temperature and precipitation at a weather station are used for the temperature and precipitation of a matched (nearest) district. Next, we estimate temperature and precipitation for a province by the average weighted temperature and precipitation of districts in the province with weight equal to district area.[4]

Vietnam is a tropical country with two areas with different climates. North Vietnam has four seasons and winter has significantly lower temperatures and less precipitation than summer. On the other hand, South Vietnam has two seasons, the dry season from November to April and the rainy season from May to October. Compared with the North, temperatures in the South show lower 12-month variation. The average daily temperature for the whole country is around 25°C. This average is computed from the daily provincial average and reflects the variation across provinces and the 12-month variation. The average temperature remained very stable during the 2000–2018 period (See Figure A.3 in the Appendix).

Vietnam's 63 provinces are grouped into 6 geographic regions: the Red River Delta, Northern Midlands and Mountains, the Central Coast in the North and the Central Highlands, and the Southeast and Mekong River Delta in the South (see Figure A.3 in the Appendix for the average daily regional temperature from 2000 to 2018). The Southeast and Mekong River Delta have the highest average daily temperature at around 27°C, while the Northern Midlands and Mountains have the lowest average daily temperature at around 22°C. Figures A.4 and A.5 in the Appendix present the average daily temperature across months in six regions. The hottest month is June in the North and April in the South. January and December are the coldest months in all regions.

Figure 1 presents the geographic maps of the mortality rate and temperatures (averaged over the 2000–2018 period).[5] The mortality rate and the average temperature were fairly similar between provinces within a region. The maps show that the mortality rate was higher in the North, which has a lower average temperature, than in the South. It suggests a negative correlation between temperature and mortality. This is because northern regions which are located in mountains and have lower temperature have lower living standards, while southern regions, especially Southeast region, have high temperature but also higher living standards (Lanjouw et al., 2017). Thus, the correlation between mortality and temperature might be caused by other factors, and this correlation does not reflect the causal effect of temperature on mortality.

As mentioned earlier, the main objective of this study is to examine the effect of weather extremes on mortality. Thus, we follow previous studies on the effect of temperature on mortality (e.g., Barreca et al., 2016; Deschenes & Greenstone, 2011; Mullins & White, 2020) and construct seven temperature bins according to the number of days per month and daily mean temperatures. The seven bins are comprised of the following temperature groupings, in degrees Celsius: 0–15; 15–18; 18–21; 21–24; 24–27; 27–30; 30+.[6] We use 15°C instead of 12°C to define the lowest temperature bin, since daily mean temperatures fall below 12°C in only 1% of the number of the province-by-day observations. Similarly, 30°C instead of 33°C is selected to define the highest temperature bin because there are only a few province-by-day observations with the daily mean temperatures above 33°C (accounting for around 0.08%). Moreover, the WHO (2018) suggests that the range of minimum risk for higher temperatures is about 15–30°C. Temperatures lower than 16°C (61°F) with humidity above 65% were associated with respiratory hazards. The average number of days per year with daily mean temperatures falling into seven bins for the 2000–2018 period is presented in Figure A.7 in the Appendix.

We focus on the effect of weather extremes, which are measured by cold and heat waves occurring within a month. Although there is no universal definition of a heat wave (Meehl & Tebaldi, 2004), it is often measured by a period of abnormally warm weather. There are two issues in defining a heat wave: selection of a temperature threshold and definition of the number of consecutive days of prolonged heat. Most studies use a threshold of a given percentile such as the 90th, 95th or 98th percentile of the temperature distribution of a specific location (e.g., see the review by Perkins & Alexander, 2013; and Perkins, 2015). Several studies use an absolute temperature threshold, such as 30–35°C. However, using a common temperature threshold may not be appropriate in a country with varying climates (Anderson & Bell, 2009; Kent et al., 2014). More important, this definition does not capture exogenous weather shocks for local people. People in warm areas are familiar with high temperatures and have adapted to them. The effect of a 30°C temperature can be very different for people in the Southeast compared with those living in the Central Highlands. Similarly, temperatures below 15°C may be harmful for people in the Southeast and the Mekong River Delta but not for people in the Red River Delta and Northern Midlands and Mountains.

Another issue in measuring heat waves is whether excessively warm periods define a specific season, such as summertime, or the entire year (Perkins & Alexander, 2013). In this study, the threshold for a heat wave is set for all seasons of the year, not just summer or winter. Certainly, heat waves are more likely to happen in summer. The definition of heat waves in winter where there are daily temperatures above the 95th percentile of the winter distribution is not appropriate for the purpose of measuring the effect of heat waves on health. Warmer days in winter are not harmful for health.

The second issue in defining a heat wave is the duration of consecutive days equal to or above the temperature threshold. Exposure to hot weather over several consecutive days has a more detrimental effect on health than exposure to a few hot days occurring separately. For example, Otrachshenko et al. (2018) show that single cold days do not matter to mortality in Russia, but cold waves with at least 3 cold consecutive day increase mortality. A heat wave is often defined as at least 3 or 5 consecutive days with daily temperatures above a given threshold (e.g., see review Perkins & Alexander, 2013; and Perkins, 2015).

In this study, we define a heat wave as 3 or more consecutive days with a daily mean temperature at or above the 95th percentile of the province-specific temperature distribution during the past 20 years. Similarly, we define a cold wave as occurring when the daily mean temperature over at least 3 consecutive days is equal to or below the fifth percentile of the province-specific temperature distribution. For robust analysis, we also define heat waves (and cold waves) as at least 5, 7, and 9 consecutive days when the daily mean temperature is at or above the 95th percentile (and at or below the fifth percentile) of the province-specific temperature distribution. We also consider thresholds at the 10th and 90th percentiles of the temperature distribution. The regression results using these thresholds are very similar to those using the thresholds at the 5th and 95th percentiles.

Figure 2a presents the average number of days per year of cold and heat waves, defined on the basis of the 5th and 95th percentiles of the province-specific temperature distribution. The numbers are computed as the annual average across the province. For example, the first bar in Figure 2a indicates that the annual provincial average number of consecutive days in cold waves, defined as at least 3 consecutive cold days, is 14. The average number of consecutive days in cold waves, defined as at least 9 consecutive cold days, is only 5.2. It should be noted that this average is below 9, since there are a number of provinces which do not experience a cold wave at all in some years. The average number of consecutive days in heat waves is lower. For example, the average number of consecutive days in heat waves, defined as at least 3 and 9 consecutive hot days, is 10.4 and 2.4, respectively. Figure A.8 in the Appendix shows the fluctuation in the average number of consecutive days in cold and heat waves per year from 2000 to 2018.

Figure 2b presents the average percentage of months in which at least one cold or heat wave occurred during 2000–2018. A month is considered to have a cold/heat wave if there is at least one day of a cold/heat wave in the month. The percentage is averaged across provinces. It shows that on average, 16.7% of months in 2000–2018 experienced at least one cold wave, defined as at least 3 consecutive cold days. For heat waves, the average percentage of months which experienced at least one heat wave

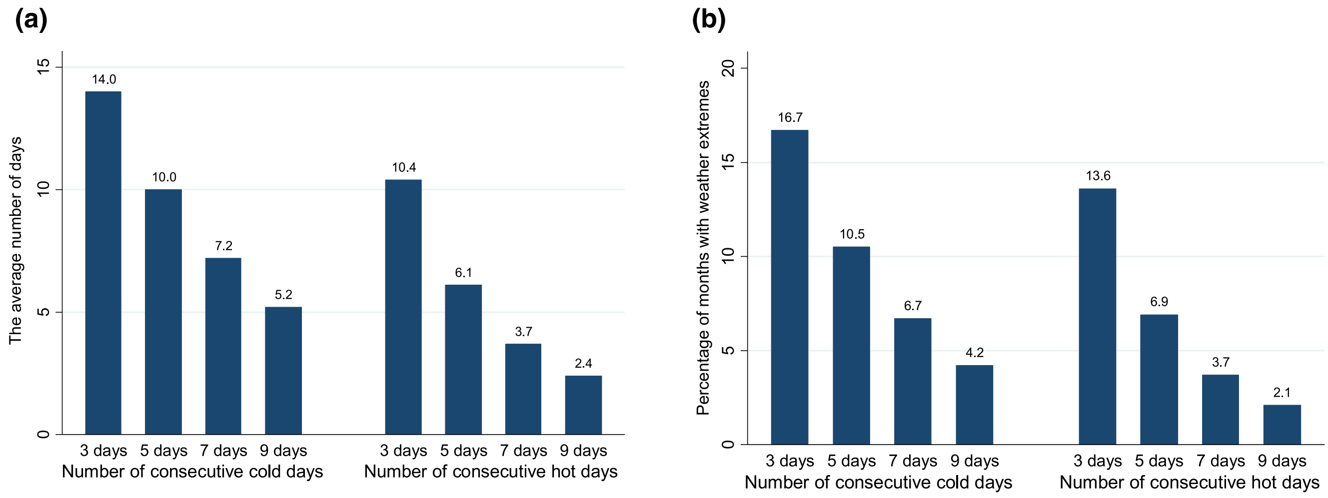

FIGURE 2 Cold and heat waves. (a) The average number of consecutive days in cold and heat waves. (b) The percentage of months with cold and heat waves. (a) presents the average number of days per year in cold and heat waves, defined based on the 5th and 95th percentiles of the province-specific temperature distribution and varying durations of consecutive days. (b) presents the average percentage of months in which at least one cold or heat wave (defined on the basis of varying durations of consecutive days) occurred during the 2000–2018 period.

with 3 or more consecutive hot days, is 13.6%. When cold/heat waves are defined as of longer duration (at least 5, 7, and 9 consecutive days), the percentage of months with at least one cold/heat wave is smaller.

3 | ESTIMATION METHODS

3.1 | Effects of cold and heat waves on mortality

We start with the estimation of the non-linear effect of temperature on mortality. A popular approach to estimate the climate effect is to define the distribution of temperatures by different bins, for example, the number of days with certain temperature levels within a time period (e.g., Deschenes & Greenstone, 2011; Dell et al., 2009; and Deryugina & Hsiang, 2017).[7] Our regression model is expressed as follows:

$$\log\left(y_{pmt}\right) = \alpha_1 + \sum_{j=1}^{7} \beta_j \mathrm{Temp}_{pmt} + X_{pmt}\theta_1 + P_{pm} + M_{mt} + T_p\delta_{1p} + \varepsilon_{pmt}, \tag{1}$$

where y_p is the mortality rate of province p in month m of year t (per 100,000). We use both the mortality rate and the log of the mortality rate as the dependent variables. Temp_{pmt} denotes variables indicating the number of days in a province-year-month where the daily mean temperature falls into one of seven temperature bins, as defined in Figure A.7 in the Appendix. Thus the 21–24°C bin is used as the reference, and we assume the zero effect of this temperature range on mortality. According to the WHO (1990), comfortable indoor temperatures are between 18 and 24°C (64–75°F). The coefficient of a temperature bin in the regression is interpreted as the effect of an additional day in this bin on the mortality rate relative to the effect of a day in the 21–24°C bin.

One issue in estimating the temperature bins is the assumption that the effect of temperature on the mortality rate is constant within each bin. To examine this assumption, we also try 2-degree temperature bins (i.e., below 14°C; 14–16; 16–18; 18–20; 20–22; 22–24; 24–26; 26–30; 30–32; 32+°C); the results are very similar. For interpretation, we use the results from 3-degree temperature bins.

X_{pmt} is a vector of control variables. Our main control variables include the yearly temperature average, which is calculated by averaging the daily mean temperatures in the province, and total annual precipitation. We do not control for the monthly temperature since it can be affected by the temperature bins. The control variables should not be affected by the treatment variables (Angrist & Pischke, 2008; Heckman et al., 1999). Our main purpose is to estimate the total instead of the partial effect of temperature on mortality (Duflo et al., 2007). For sensitivity analysis, we try different models, which vary the number of control variables. Specifically, we try to control for the monthly mean temperature and monthly precipitation in addition to the annual mean temperature and total annual precipitation. We also try to control for the bins of monthly precipitation. Another explanatory variable is the humidity level, which might be correlated with temperature and health. However, in our case this variable is not statistically significant in regression of mortality. Regressions using different specification are reported in the Appendix. Overall, the effect of temperatures is very similar in these models.

We also control for the province-by-month fixed effects, P_{pm}, and year-month fixed-effects M_{mt}. The monthly province fixed effects control not only for the time-invariant characteristics of a province (including observed time-invariant variables, such as geography, and unobserved time-invariant variables, such as historical culture) but also local seasonality. In addition, we include the province-specific time trend, T_p, which allows for province-specific time trends in the mortality rate. However, controlling for these time trends might absorb the effect of temperature and bias its effect (Baum-Snow & Lutz, 2011; Wolfers, 2006). Thus, for sensitivity analysis, we also try the model without the province-specific time trend. Several studies also control for quadratic time trends. In our study, a large number of province-specific quadratic time trends are not statistically significant at conventional levels. Moreover, including area-specific quadratic time trends might increase bias in the estimate of the effect of the treatment variable (Wolfers, 2006). In the Appendix, we also report the estimated effects of temperature from models, including the province-specific quadratic time trends. The results are very similar to those from models using only province-specific linear time trends. For interpretation in the main text, we will use results from models with only province-specific linear time trends.

In the second model, we estimate the effect of cold and heat waves on mortality using the same specification as (1):

$$\log\left(y_{pmt}\right) = \alpha_2 + \beta_{2c}\text{Cold}_{pmt} + \beta_{2H}\text{Heat}_{pmt} + X_{pmt}\theta_2 + P_{pm} + M_{mt} + T_p\delta_{2p} + u_{pmt}, \quad (2)$$

where Cold_{pmt} is the number of consecutive days in a cold wave and Heat_{pmt} is the number of consecutive days in heat waves in province p in month m of year t. Cold and heat waves are defined in the previous section. A cold wave is defined as at least a given number of consecutive days (3, 5, 7 and 9 days) with a daily mean temperature at or below the fifth percentile of the province-specific temperature distribution, while a heat wave is defined as at least a given number of consecutive days (3, 5, 7 and 9 days) with daily mean temperatures at or above the 95$^{\text{th}}$ percentile of the temperature distribution. The reference group is days without cold/heat waves (days with temperature falling within the fifth-95$^{\text{th}}$ percentile temperature range). A heat wave (or cold wave) can span over 2 consecutive months, and we still count the number of heat (or cold wave) happening in each month. For example, in a 5-day heat wave in a given province, there can be 2 days in June and 3 days in the following July. Then, the variable heat wave, Heat_{pmt}, is equal to 2 for June and 3 for July. In addition to measuring the variables "cold/heat waves" by the number of consecutive days in the waves, we also use dummy variables indicating whether a cold or heat wave occurs within a month.

The panel data on provinces suggest that the error terms can be correlated within provinces over time. Thus, standard errors should be clustered at the provincial level. In addition, there can be a seasonal effect on mortality. Although we control for year-month fixed effects, the error terms can still be spatially correlated between provinces within a month. We adopt the multi-way clustering technique of Cameron et al. (2011), which allows us to deal simultaneously with the correlation of error within provinces over time and between provinces within a month. For sensitivity analysis, we also try one-way clusters at the provincial level and find that the results are very similar. For interpretation, we use results from two-way clustered standard errors.

Another issue is whether to apply weights to the regression of Equations (1) and (2). When using area-level data to estimate the effect of temperature on area mortality, most studies apply weighted regression, where weights are equal to the square root of a province's population (e.g., Barreca et al., 2016; Deschenes & Greenstone, 2011; Deschênes & Moretti, 2009; Mullins & White, 2020). Applying weights can partially address the issue of heteroscedasticity and obtain the effect of temperature on the average person instead of the average province (Barreca et al., 2016; Deschênes & Moretti, 2009). In this study, we use three weighting schemes: no weighting, weighting by the current population of a province, and weighting by a province's population in 1999 (i.e., the population before the 2000–2018 period of analysis). Weather extremes can cause inter-provincial migration in Vietnam (Nguyen, 2021). Using the 1999 population can avoid the effect of temperature on the population of provinces during the 2000–2018 period. The estimated coefficients of cold and heat waves are insensitive to different weighting schemes. For interpretation, we use the results employing weighting by a province's population in 1999. Results without weighting and those using current population weights are reported in the Appendix.

3.2 | Heterogeneous effects and adaption strategies

Next, we examine the heterogeneous effect of cold and heat waves on mortality across several provincial characteristics. We include interactions between a variable of interest (denoted by I_{pt}), such as a province's per capita income, and cold and heat waves in regression:

$$\log(y_{pmt}) = \alpha_3 + \beta_{3c}\text{Cold}_{pmt} + \beta_{3H}\text{Heat}_{pmt} + \mu_c\text{Cold}_{pmt}I_{pt} + \mu_H\text{Heat}_{pmt}I_{pt} + I_{pt}\pi + X_{pmt}\theta_3 + P_{pm} + M_{mt} + T_p\delta_{3p} + \upsilon_{pmt}. \quad (3)$$

The interaction variables include the proportion of adults with tertiary education, the log of per capita income, the number of households with air conditioners, population density, emigration and immigration rates, government spending on health, and the number of hospitals in the provinces. The variables of air-conditioning, migration and the health care system reflect the adaptation strategies of inhabitants and the local government to cope with weather extremes. The interaction variables are measured annually instead of monthly. A problem with these variables is that they can be affected by temperatures. To mitigate this problem, we use 1-year lags of these variables instead of their values in the current year.

It should be noted that we do not estimate Equation (3) using the interactions between temperature extremes and all the interaction variables at the same time, since using many interactions makes it difficult to interpret the results and might cause a multicollinearity problem. For each regression, we include only interactions between one interaction variable, such as per capita income or population density, and cold/heat waves. In addition, there can be an endogeneity problem of interacted variables, and in this study we are not able to estimate the causal effect of the interacted variables as well as the interaction terms. As a result, the estimates of the interaction variables should be interpreted as an association estimate instead of the causal effect.

The control variables in Equation (3) are the same as those in Equation (2) and include annual average temperature (in degrees Celsius), annual precipitation (mm), province-specific time trends, monthly provincial fixed effects, and year-by-month fixed effects. Standard errors are also clustered at the province and year-by-month levels.

3.3 | Estimation of deaths caused by cold and heat waves

We can examine the cost of cold and heat waves by predicting the number of deaths they cause in a province in a given month. In the counterfactual scenario in which there are no cold or heat waves, the expected mortality rate is estimated using Equation (2) as follows:

$$\log\left(\widehat{y_{pmt\_0}}\right) = \widehat{\alpha}_2 + X_{pmt}\widehat{\theta}_2 + P_{pm} + M_{mt} + T_p\widehat{\delta_{2p}} + \widehat{u_{pmt}} = \log\left(y_{pmt}\right) - \widehat{\beta_{2c}}\text{Cold}_{pmt} - \widehat{\beta_{2H}}\text{Heat}_{pmt}, \tag{4}$$

where $\widehat{y_{pmt\_0}}$ is the predicted mortality rate in the absence of cold/heat waves in a province in month m of year t, while y_{pmt} is the observed mortality rate in the province in that month. The observed mortality rate is the mortality rate with cold/heat waves that has already occurred. Cold_{pmt} and Heat_{pmt} are the number of days in the cold/heat waves occurring during the month. We use the definition of cold or heat waves of at least 3 consecutive days for estimating the cost of cold/heat waves. Parameters with the elongated circumflex denote estimates from regressions of Equation (2). The mortality rate in the absence of cold or heat waves is then:

$$\widehat{y_{pmt}} = exp\left[\log\left(y_{pmt}\right) - \widehat{\beta_{2c}}\text{Cold}_{pmt} - \widehat{\beta_{2H}}\text{Heat}_{pmt}\right]. \tag{5}$$

The number of deaths caused by the cold or heat waves in a province within a month is the difference in the observed mortality rate and the counterfactual mortality rate multiplied by the population of the province:

$$\widehat{\tau_{pmt}} = \left(y_{pmt} - \widehat{y_{pmt}}\right)Pop_{pmt} = \left\{y_{pmt} - \exp\left[\log\left(y_{pmt}\right) - \widehat{\beta_{2c}}\text{Cold}_{pmt} - \widehat{\beta_{2H}}\text{Heat}_{pmt}\right]\right\}\text{Pop}_{pmt}, \tag{6}$$

where Pop_{pmt} is the population of province p in month m in year t. We compute the total number of deaths due to cold or heat waves for the whole country in a given year t by taking the sum of Equation (6) across months (m) and provinces (p):

$$\widehat{\tau}_t = \sum_{m,p}\left\{y_{pmt} - \exp\left[\log\left(y_{pmt}\right) - \widehat{\beta_{2c}}\text{Cold}_{pmt} - \widehat{\beta_{2H}}\text{Heat}_{pmt}\right]\right\}\text{Pop}_{pmt}. \tag{7}$$

We can use Equation (7) to estimate the number of deaths caused by cold or heat waves separately.

Finally, we estimate the economic cost of mortality caused by cold or heat waves by multiplying the number of deaths with a value of a statistical life (VSL). In this study, we use a VSL of 0.342 million USD. This estimate for Vietnam is taken from Viscusi and Masterman (2017) and is very similar to a VSL estimate for Southeast Asia of 0.359 million USD (Saluja et al., 2020).

4 | EMPIRICAL RESULTS

4.1 | Effect of weather events on mortality

Table 1 reports the effect of temperature on mortality using the regression models specified in Equations (1) and (2). The control variables include the average of yearly temperature, total annual precipitation, provincial monthly fixed effects, year-month fixed effects, and the province-specific time trend. The effects of the temperature bins on the mortality rate and the mortality rate log are reported in columns 1 and 2 of Table 1. The 21–24°C bin is used as the reference. The coefficients of the temperature bins measure the estimated effect of one additional day in these bins on the mortality rate (and the log of the mortality

TABLE 1 Regressions of mortality rates for all ages on climate variables.

	Dependent variables					
	Mortality rate (deaths per 100,000 people)	Log of mortality rate	Mortality rate (deaths per 100,000 people)	Log of mortality rate	Mortality rate (deaths per 100,000 people)	Log of mortality rate
Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Number of days 0–15°C	0.2500**	0.0047	0.1976	0.0032		
	(0.1197)	(0.0032)	(0.1264)	(0.0032)		
Number of days 15–18°C	0.1004	0.0026				
	(0.0868)	(0.0028)				
Number of days 18–21°C	0.0859	0.0018				
	(0.0706)	(0.0022)				
Number of days 21–24°C	0	0				
Number of days 24–27°C	−0.0645	−0.0025				
	(0.0450)	(0.0017)				
Number of days 27–30°C	−0.0589	−0.0027				
	(0.0586)	(0.0023)				
Number of days 30°C +	0.0855	0.0036	0.1774**	0.0078**		
	(0.0989)	(0.0042)	(0.0753)	(0.0036)		
Number of days below the 5th percentile of daily temperature					0.1675**	0.0050**
					(0.0809)	(0.0025)
Number of days above the 95th percentile of daily temperature					0.1288**	0.0073**
					(0.0626)	0.0029)
Annual average temperature (°C)	0.7554**	0.0273***	0.6631**	0.0253**	0.6751**	0.0260**
	(0.2981)	(0.0097)	(0.3015)	(0.0101)	(0.3024)	(0.0102)
Annual precipitation (mm)	0.2320*	0.0078	0.2503*	0.0081	0.2534*	0.0081
	(0.1339)	(0.0053)	(0.1347)	(0.0053)	(0.1353)	(0.0053)
Province-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	21.0210***	3.0228***	22.3605***	3.0273***	22.0299***	3.0040***
	(7.2461)	(0.2292)	(7.6248)	(0.2527)	(7.6658)	(0.2573)
Observations	12,639	12,639	12,639	12,639	12,639	12,639
R-squared	0.334	0.306	0.335	0.310	0.335	0.311

Note: This table reports the regression of the mortality rate and the log of the mortality rate on the number of days in different temperature bins in a month, as well as other control variables. Robust standard errors in parentheses. Standard errors are clustered at the province and year-by-month levels.

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

rate) relative to a day in the reference bin. In the regression of the mortality rate, only the number of days in the 0–15°C bin is statistically significant at the 5% level. However, when the log of the mortality rate is used as the dependent variable, none of the temperature bins are statistically significant at the conventional level.

Figure A.9 in the Appendix presents the point estimates and the 95% confidence intervals of the effect of the temperature bins on the mortality rate and the log of the mortality rate. The figures show a U-shaped relation between the temperature and the mortality rate. The estimates of the low- and high-temperature bins are positive but not statistically significant at the conventional level. In Table A.1 in the Appendix, we use the 2-degree temperature bins, with the 22–24°C bin as the reference. Most coefficients of the temperature bins are not statistically significant.

In columns 3 and 4 of Table 1, we only include the number of days below 15°C and those above 30°C. This means that a temperature range between 15 and 30°C is used as the reference. The coefficients of the number of days above 30°C are positive and statistically significant at the 5% level. Thus, when middle temperature bins are combined and used as the reference, we find significant effects from high temperatures. An additional day with a mean temperature over 30°C (relative to a day between 15 and 30°C) leads to an increase in the monthly mortality rate of 0.1774 deaths per 100,000 (column 3 of Table 1). When the dependent variable is a log of the mortality rate, the estimated effect is 0.0078. This means that an additional day with a mean temperature over 30°C increases the monthly mortality rate by 0.78% (column 4 of Table 1). This point estimate is larger than the point estimate that Deschenes and Greenstone (2011) found for the US. They report that an additional day with a mean temperature above 90°F (around 32°C) results in an increase in the annual mortality rate of about 0.11%. The effect on the mortality rate for Vietnam is quite similar to the approximately 0.7% effect of high temperatures on the mortality rate that Burgess et al. (2017) found for India. The two countries are at similar economic levels, and this may explain the similar effect of temperature on mortality in these countries.

We can compute the elasticity of the mortality rate with respect to the number of days with a mean temperature above 30°C to gain insight into the magnitude of the effect of high temperatures. The average number of days with a mean temperature above 30°C within a month across province-by-year observations is only 0.97. At 3.87 days, June is the month with the highest average number of days above 30°C. An additional hot day (above 30°C) means 26% of the average number of hot days occur in June. Roughly speaking, if the number of hot days in June increases by 26%, the mortality rate increases by 0.78%. This implies that the elasticity of the mortality rate to the number of hot days in June is equal to 0.03.

The last two columns in Table 1 show the effect of the number of days with temperature extremes. Days of high temperature extremes are defined as days when the daily mean temperature is at or higher than the 95th percentile of the province-specific temperature distribution during the past 20 years. Days of low temperature extremes are days when the daily mean temperature is equal to or below the fifth percentile of the province-specific temperature distribution. The results show that both low and high temperature extremes increase the monthly mortality rate. An additional day with a mean temperature at or below the fifth percentile of the temperature distribution, relative to a day within the fifth-95th percentile range, results in an increase in the monthly mortality rate of 0.5%. The corresponding figure for the effect of high temperature extremes is 0.73. The point estimate of the effect of high temperature extremes is higher than that of low temperature extremes, but the difference is not statistically significant at conventional levels.

Table 1 shows a positive and significant correlation between annual mean temperature and the mortality rate. According to column (2), a 1°C increase in the annual average temperature is associated with a 2.73% increase in the monthly mortality rate. Annual precipitation is statistically significant at the 10% level in regressions of the mortality rate but not in regressions of the log of the mortality rate.

4.2 | Effects of cold and heat waves on mortality

The effects of cold and heat waves on mortality are summarized in Figure 3. In this figure, we graph the point estimate and the 95% confidence interval of the effects of cold and heat waves on the monthly mortality rate (panels A and B of the figure) and the log of the monthly mortality rate (panels C and D of the figure). The full regression results are reported in Tables A.2 and A.3 in the Appendix. The estimated effects of cold and heat waves on the mortality rate and the log of the mortality rate are very similar. For interpretation, we use the results from the effects on the log of the mortality rate.

Consistent with previous studies on cold and heat waves such as Anderson and Bell (2011), Son et al. (2012), Azhar et al. (2014), Otrachshenko et al. (2017), Otrachshenko et al. (2018), we find an increasing effect of both cold and heat waves on mortality in Vietnam. Panel C plots the estimated coefficients of occurrence of at least one cold or heat wave within a month. All the coefficients of the cold and heat waves are positive, indicating a higher risk of mortality during weather extremes. The effect of cold waves as well as heat waves tends to increase when they last longer. A cold wave with at least 5 consecutive cold days increases the monthly mortality rate by around 4.9% (significant at the 10% level), while a cold wave with at least 9 consecutive cold days increases the mortality rate by 6.5% (significant at the 5% level). Compared with a cold wave, the effect

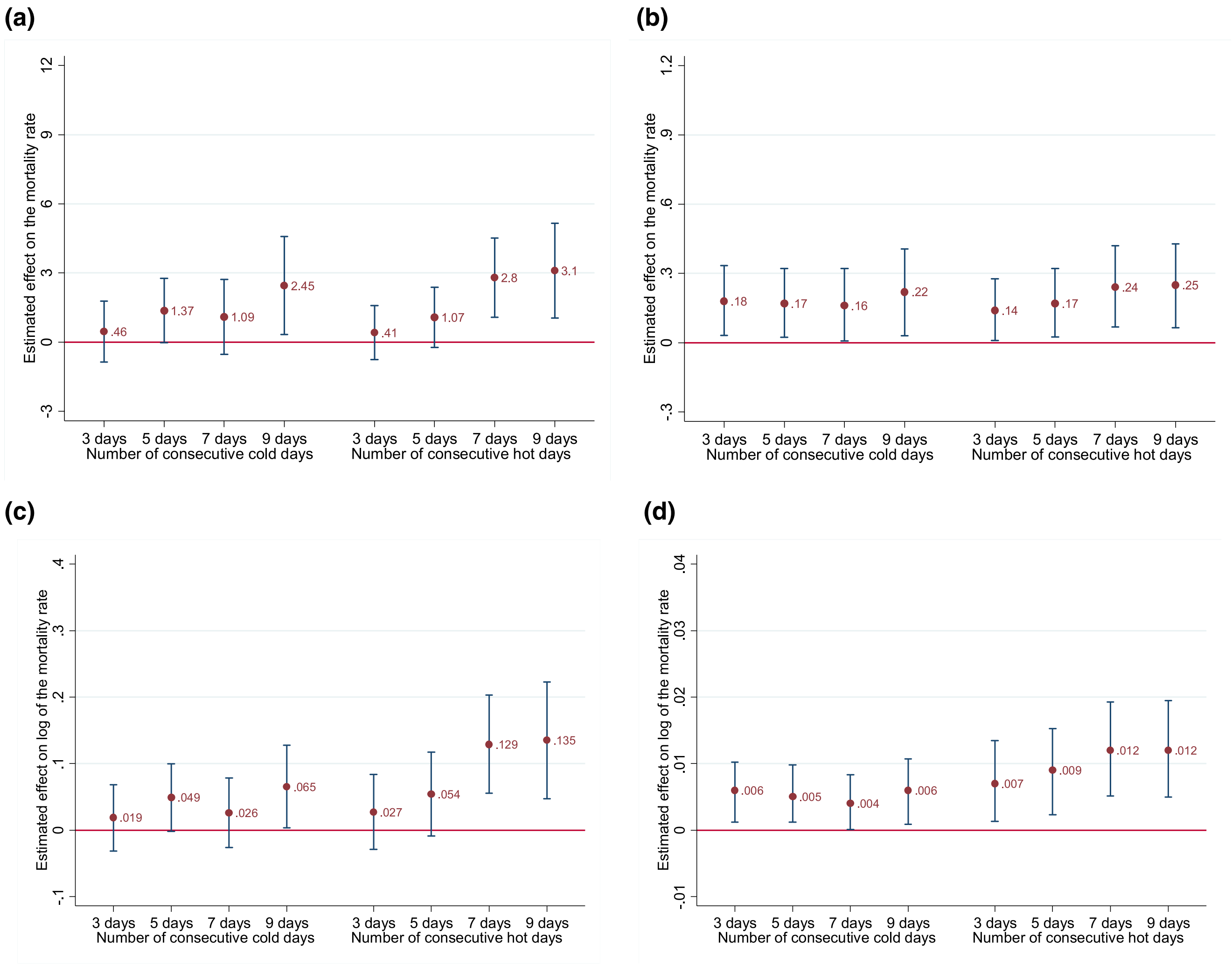

FIGURE 3 Estimated effects (and 95% confidence interval) of cold and heat waves on the mortality rate for all ages. (a) Estimated effect on the mortality rate of cold and heat waves. (b) Estimated effect on the mortality rate of the number of days in cold and heat waves. (c) Estimated effects of cold and heat waves on the log of the mortality rate. (d) Estimated effects of the number of days in cold and heat waves on the log of the mortality rate. This figure reports the estimated effects and their 95% confidence interval of cold and heat waves on the mortality rate (measured by the number of deaths per 100,000 people in a month) and the log of the mortality rate in the provinces. A cold (heat) wave is defined as at least k (3, 5, 7, and 9) consecutive days with a daily mean temperature at or below the fifth percentile (at or above the 95th percentile) of the temperature distribution of a specific province. The control variables include the annual average temperature (in degrees Celsius), annual precipitation (mm), province-specific time trend, province-by-month fixed effects, and year-by-month fixed effects. The full regression models are presented in Tables A.2 and A.3 in the Appendix.

of a heat wave on the mortality rate is greater and more significant. The mortality rate in a month increases by 13.5% if there is a heat wave of at least 9 consecutive days in the month, indicating the substantial effect of a prolonged severe heat wave. However, a heat wave of at least 9 consecutive days rarely occurs. During the 2000–2018 period, the average percentage of months in which a heat wave of at least 9 consecutive hot days occurred was only 2.1% (Figure 2).

Figure 2d depicts the estimated coefficients of the number of consecutive days in cold and heat waves on the log of mortality rates. When cold and heat waves are measured by the number of consecutive days, their effect estimates are statistically more significant. All the estimates are positive and statistically significant at the 5% level. The point estimate of the effect of a hot day is greater than that of a cold day, but the difference is not statistically significant. An additional day in a cold wave lasting at least 3 consecutive days (relative to a day within the fifth-95th percentile temperature range) leads to an increase in the mortality rate of 0.6%. The corresponding figure for an additional day during a heat wave is 0.7%. During a cold or heat wave, defined as at least 9 consecutive days, an additional day increases the mortality rate by 0.6% and 1.2%, respectively.

Deschênes and Moretti (2009) suggest that there is a so-called harvesting effect of temperature extremes. If temperature extremes mainly affected people with very poor health, mortality will increase in the first few days following a cold or heat wave but then tend to decrease. It means that cold and heat waves can have a large and positive effect on mortality in the short term but then a negative effect in the medium or long term. In our study, we do not have data on daily mortality to test the harvesting effects exactly according to the approach of Deschênes and Moretti (2009). However, we try to include 1-month and 2-month lagged variables of cold and heat waves to examine the lagged effects of cold and heat waves (reported in Table A.4 in the Appendix). Most lagged variables of cold and heat waves are not statistically significant, implying that there is no supportive evidence on the harvesting effects in our study.

The effect of cold or heat waves might depend on the temperature of the proceeding days. For example, there can be some warm days that are not considered too extreme as a heat wave happen just before a heat wave. The effect of heat waves might be stronger because the human bodies are exhausted because of relatively long and hot temperatures. We examine this issue by measuring the cold and heat waves using the thresholds of the 10^{th} and 90^{th} percentiles of temperature distribution instead of the 5^{th} and 95^{th} percentiles. The effect estimates of cold and heat waves using lower thresholds are reported in Table A.5 in the Appendix. Comparing Tables A.3 and A.5, we do not see evidence that cold/heat waves with lower thresholds but longer duration (e.g., a 7-day cold defined at the 10^{th} percentile) have a higher effect on mortality than cold/heat waves with higher threshold but shorter duration (e.g., a 5-day cold defined at the fifth percentile). We further examine this issue by using an approach from Otrachshenko et al. (2018), which combine the number of days in both temperature bins and cold/heat waves in one regression of mortality. The results are reported in Table A.6 in the Appendix. Overall, the results are similar to those from separate regressions of the mortality rate (and log of the mortality rate) on temperature bins and cold/heat waves. Temperature bin variables are not statistically significant, while most variables of cold/heat waves are positive and statistically significant.

Another issue is influence that the daily spread between minimum and maximum temperature might have on the impact of mortality. It is possible that during heat waves, the lower the nighttime temperature, the better the body can cope with higher daytime temperatures. To examine this issue, we compute the average of daily minimum temperature of heat waves within a month. For example, if there were two 3-day heat waves in a given month, we compute the average of daily minimum temperature of these days (6 days) in the two heat waves. Then, we include an interaction between this average daily minimum temperature of heat waves and the number of heat wave days in the regression. Similarly, we control for the average of the daily maximum temperature of cold waves and included an interaction between this variable and the number of cold wave days in the regression. The regression results are reported in Table A.7 in the Appendix. All the interactions are not statistically significant, indicating that there are no heterogenous effects of cold/heat waves across the daily maximum/minimum temperature of the cold/heat waves.

Finally, we argue that cold and heat waves cause mortality mainly through the adverse effect on health, for two reasons. Firstly, cold and heat waves have only short-term effects on mortality. As mentioned in the previous paragraph, Table A.4 in the Appendix indicates that cold and heat waves do not have medium- or long-term effects on mortality. Secondly, we do not find a significant effect of cold and heat waves on income (see Table A.26 in the Appendix). Thus, income is not a means through which cold and heat waves increase mortality.

4.3 | Robustness analysis

In this section, we conduct a series of robustness checks to examine the interval validity of our estimated effect of weather extremes on mortality. Firstly, we try different measures of the dependent variable. For interpretation, we use the crude mortality rate and the log of the crude mortality rate as the dependent variables in regressions. An issue with the crude mortality rate is that it depends on the age distribution of the population. The effect of weather extremes on the mortality rate may depend on the makeup of the population rather than the risk of death.

To examine this issue, we use age-adjusted mortality rates, which rely on a fixed age distribution over years and across provinces. An age-adjusted mortality rate for province p in year t is computed as a weighted average of age-specific mortality rates for the province, with weights equal to the proportion of the population of the corresponding 5-year age group in a baseline year (e.g., see the formula in Mullins & White, 2020). In this study, we divide the population into 5-year age groups, drawing on the 1999 Vietnam Population and Census. These weights are applied for all provinces in all years. Table A.8 presents regressions of the age-adjusted mortality rate and the log of the age-adjusted mortality rate on cold and heat waves using the same model specifications as Tables A.2 and A.3. The estimated effects of cold and heat waves on the age-adjusted mortality rate are very similar to the estimated effects on the crude mortality rate, implying that the effect of cold and heat waves on the crude mortality rate is not the result of age distribution.

Secondly, we use different measures of temperature and weather extremes. As presented in Table 1 and Table A.1, we use different temperature bins to examine the non-linear effects of temperature on mortality. We define cold and heat waves according to duration — 3, 5, 7, and 9 consecutive days. In regressions, cold and heat waves are measured by both dummy variables, which indicate the occurrence of the cold and heat waves, and the number of consecutive days in these waves. In addition to using the 5th and 95th percentiles to define a cold or heat wave, we also use the thresholds of the 10th and 90th percentiles. Regressions of the mortality rate on these weather extreme variables are reported in Table A.5 in the Appendix. Overall, cold and heat waves, which are defined based on the 10th and 90th percentiles of the temperature distribution, also increase the mortality rate, but their effects are smaller than the effects of cold and heat waves, which are defined based on the 5th and 95th percentiles of the temperature distribution (Table A.3 in the Appendix).

Thirdly, we examine the sensitivity of estimates of the impact of cold and heat waves to different model specifications. In previous regressions, we control for the average of yearly instead of monthly temperatures and rainfall to avoid the effect of cold and heat waves on the control variables. In Tables A.9 and A.10 in the Appendix, we control for monthly temperatures and month rainfall and note that controlling for these variables does not change the coefficients appreciably. We also classify monthly rainfall into different bins, that is, the number of months with different precipitation level of 0–50 mm; 50–100 mm; 100–200 mm; 200–300 mm; 300–400 mm; 400–500 mm; and 500+ mm. The results are reported in Table A.11 in the Appendix. All these bins are not statistically significant. Regarding the estimates of cold and heat waves, they are very similar to those reported in Figure 3.

Figure A.5 shows a difference in the variation in the daily temperature between regions. To capture this issue, we compute the standard deviation of the daily (mean) temperature within a month and the standard deviation of the daily (mean) temperature within a year for all provinces, and control for these variables in regressions. Table A.12 in the Appendix show that the effect of cold and heat waves on mortality stay unchanged when we control for the standard deviation of the daily temperature. We also control for the average humidity of months in the model. Table A.13 in the Appendix shows that this variable is not statistically significant, and the effect estimates of cold and heat waves on mortality are almost the same as those in model without controlling for humidity.

Next, Tables A.14 to A.16 report different model specifications which differ in the number of control variables. More specifically, Table A.14 reports regressions without controlling for annual mean temperature and rainfall. We also exclude province-specific time trends, since controlling for them might absorb the effect of temperature and bias its effect (Baum-Snow & Lutz, 2011; Wolfers, 2006). In Table A.15, on the other hand, we include both the province-specific time trend and province-specific time trend squared. Regressions presented in Table A.16 feature additional control variables, including number of hospitals, population density, and the proportion of the urban population. The effect estimates of cold and heat waves in Tables A.14 to A.16 are very similar to those from the main models that are used for interpretation in the previous section.

Fourthly, we examine whether the estimates are sensitive to the use of weighting schemes. Table A.17 in the Appendix reports regressions without population weights, and Table A.18 in the Appendix presents regressions which use the weights of the current population instead of the population in 1999. As we can see, different weighting schemes do not affect estimates of the effect of cold and heat waves.

Finally, we conduct a placebo test by running a regression of the mortality rate on the 1-month and 2-month leads of cold and heat waves. We use both the mortality rate and the log of the mortality rate as the dependent variables. The cold and heat waves are measured by both dummy variables and the number of consecutive days of cold or heat. The regression results are presented in Tables A.19 to A.22 in the Appendix. There are 32 regressions in total. Almost none of the coefficients of cold and heat waves are statistically significant at conventional levels. Among 64 estimated coefficients of cold and heat waves, there is only one estimated coefficient which is statistically at the 10% level. This placebo test suggests that cold and heat waves are exogenous and can be regarded as random in the mortality equation.

4.4 | Heterogeneous effects and adaptions

This section explores whether the effect of cold and heat waves varies across different population groups and provinces with different characteristics. Children and older people are more vulnerable to weather extremes than others (e.g., see Basu, 2009; Arbuthnott & Hajat, 2017; Geruso & Spears, 2018). Table 2 presents the coefficients of the number of days in cold and heat waves in regressions of the mortality rate for different age groups. There are 32 regressions in total, and the table presents only the estimated coefficients of the number of days in cold and heat waves for each regression. The regression specifications are the same as those in Table A.3 in the Appendix.

The results suggest that only older people, especially those over 80, are affected by weather extremes. Almost no coefficients of cold and heat waves are statistically significant for people below 40. For people aged over 40, all the estimated coefficients of cold and heat waves are positive, indicating an adverse effect on health for this group. The effect on the mortality rate of people over 80 is notably higher than it is for younger people.

It should be noted that we use the mortality rate instead of the log of the mortality rate as the dependent variable, since the monthly mortality rate for some population subgroups in some provinces is equal to zero. We apply the inverse hyperbolic sine

TABLE 2 Regression of mortality rates for different population groups.

	Dependent variables							
	Mortality rate of people aged 0–4 (deaths per 100,000 people)	Mortality rate of people aged 5–15 (deaths per 100,000 people)	Mortality rate of people aged 16–39 (deaths per 100,000 people)	Mortality rate of people aged 40–59 (deaths per 100,000 people)	Mortality rate of people aged 60–79 (deaths per 100,000 people)	Mortality rate of people aged 80+ (deaths per 100,000 people)	Mortality rate of males (deaths per 100,000 people)	Mortality rate of females (deaths per 100,000 people)
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# days with at least 3 consecutive days below the 5th percentile of temperature	0.0891	0.0409	−0.0401	0.1513*	0.8443	5.2655***	0.2940**	0.0743
	(0.1421)	(0.0267)	(0.0587)	(0.0760)	(0.5369)	(1.9113)	(0.1190)	(0.0768)
# days with at least 3 consecutive days above the 95th percentile of temperature	−0.0294	−0.0002	−0.0512	0.2518**	0.4004	4.5024**	0.1193	0.1647*
	(0.1517)	(0.0382)	(0.0537)	(0.1224)	(0.4869)	(2.0700)	(0.1044)	(0.0832)
# days with at least 5 consecutive days below the 5th percentile of temperature	0.1617	0.0318	−0.0122	0.1558*	0.8126	4.3609**	0.2737**	0.0752
	(0.1482)	(0.0224)	(0.0519)	(0.0785)	(0.4943)	(2.0221)	(0.1127)	(0.0706)
# days with at least 5 consecutive days above the 95th percentile of temperature	−0.1212	0.0264	−0.0254	0.2554*	0.5119	4.5884*	0.1525	0.1924*
	(0.1499)	(0.0430)	(0.0627)	(0.1342)	(0.4683)	(2.3812)	(0.1035)	(0.1090)
# days with at least 7 consecutive days below the 5th percentile of temperature	0.1671	0.0555*	−0.0505	0.1288*	0.9184	4.0651*	0.2349**	0.0972
	(0.1580)	(0.0326)	(0.0544)	(0.0749)	(0.5677)	(2.0609)	(0.1161)	(0.0729)
# days with at least 7 consecutive days above the 95th percentile of temperature	−0.0297	−0.0143	−0.0439	0.2302	1.0251*	6.9202***	0.1975*	0.2851**
	(0.1548)	(0.0438)	(0.0616)	(0.1649)	(0.5177)	(2.4346)	(0.1082)	(0.1290)
# days with at least 9 consecutive days below the 5th percentile of temperature	0.1640	0.0485	−0.0298	0.1810*	1.3919**	4.1322**	0.3063**	0.1342*
	(0.1717)	(0.0299)	(0.0634)	(0.1007)	(0.6492)	(2.0547)	(0.1296)	(0.0767)
# days with at least 9 consecutive days above the 95th percentile of temperature	0.0282	−0.0018	−0.0748	0.2076	0.8034*	8.6812***	0.2171**	0.2716**
	(0.1683)	(0.0494)	(0.0680)	(0.1813)	(0.4470)	(2.4793)	(0.1055)	(0.1313)
Observations	12,639	12,639	12,639	12,639	12,639	12,639	12,639	12,639

Note: This table reports the coefficients of the number of days in cold and heat waves in regressions of the mortality rate for different age groups. A cold (heat) wave is defined as at least k (3, 5, 7, and 9) consecutive days, where the daily mean temperature is at or below the 5th percentile (at or above the 95th percentile) of the temperature distribution for a specific province. There are 32 regressions in total. The regression specifications are the same as those in Table A.3 in the Appendix. The control variables include annual average temperature (in degrees Celsius), annual precipitation (mm), province-specific time trend, province-by-month fixed effects, and year-by-month fixed effects. Robust standard errors in parentheses. Standard errors are clustered at the province and year-by-month levels.

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

transformation ($\text{arsinh}(x) = \ln(x + \sqrt{1 + x^2})$), which has a similar interpretation as the log function but can avoid a zero value of the dependent variable.[8] Regressions of arsinh (the mortality rate) are presented in Table A.23 in the Appendix. The effect of cold and heat waves is greater for older people, especially those over 80. An additional day in cold and heat waves leads to an increase in the monthly mortality rate of people over 80 by 0.0246% and 0.0396%, respectively.[9]

Several studies suggest gender differences in the impact of climate change of health, and empirical findings are mixed (see a review of Gender & Alliance, 2016). For example, a higher effect of heat waves on mortality of men is found in Russia (Otrachshenko et al., 2018) and Australia (Coates et al., 2014), while a large effect on mortality of women is found in India (Azhar et al., 2014) and Korea (Son et al., 2012). In Table 2, we also explore the difference in the effect of cold and heat waves on the mortality of men compared with women. Overall, we find a significant effect of cold waves (measured by 3 and 5 consecutive cold days) on the mortality rate of men and a significant effect of heat waves (measured by 3 and 5 consecutive hot days) on the mortality of women. Data limitation does not allow us to explore the possible reason for the gender differences in the impact of temperature extremes. However, according to WHO (2014), the gender differences might be due to differences in health status, exposure to weather extremes and access to health care and adaption measures. It should be noted that when we measure the cold and heat waves at least 9 consecutive days with temperature extremes, we find that both women and men are affected by both cold and heat waves. It means that both men and women cannot resist longer spells of temperature extremes.

We also estimate the effect of cold and heat waves on mortality for different regions: North (Red River Delta & Northern Midlands and Mountain Areas), Central (Central Coast & Central Highland and South (Southeast & Mekong River Delta). Table A.25 in the Appendix shows that cold and heat waves have no significant effects on mortality in the North. On the other hand, both cold and heat waves increase mortality in the South, which is the hottest region in Vietnam. For the Central, heat waves have positive and significant effects on mortality. This finding indicates that if the global temperature continues to increase, people in the hot areas will be more strongly affected.

Next, we examine the adaption issue by estimating the heterogeneous effect of weather extremes across different province characteristics, using the regression specified in Equation (3). We select the characteristics that reflect the different strategies that people adopt to adapt to temperature fluctuations. Specifically, eight variables that interact with the number of days in cold and heat waves include education level, per capita income, air-conditioning, population density, emigration and immigration rates, government spending on health care, and the number of hospitals in a province. As mentioned in Section 4.2, to avoid the problem that the interaction variables are also affected by temperature, we use 1-year lags of these variables instead of their values in the current year.

Table 3 reports the estimated coefficients on interactions between the number of days in cold and heat waves (measured by 3, 5, 7 or 9 consecutive days with temperature extremes) and interaction variables in regressions of the log of the mortality rate for all ages. There are 32 regressions in total. The control variables include annual average temperature (in degrees Celsius), annual precipitation (mm), province-specific time trends, province-by-month fixed effects, year-by-month fixed effects, and the interaction variables (the same regression specifications as Table A.3 in the Appendix).

The effect of temperature on health tends to be greater in lower income countries (Basu, 2009; Burgess et al., 2017; Carleton et al., 2020). However, in our study almost none of the interactions between weather extremes, education level, and per capita income of the provinces are statistically significant (columns 1 and 2 of Table 3). Possibly, average income does not capture the income distribution for people within a province. Higher per capita income in a province does not mean higher income for most people in it. To explore this issue further, we regress the log of per capita income on cold and heat waves using the province-by-year data level (there are no monthly data on per capita income). Cold and heat waves are also determined for a year rather than for a month, as in previous regressions.[10] Compared with a regression using province-by-month observations, a regression using province-by-year observations naturally has larger standard errors because of the smaller sample. Table A.26 in the Appendix shows that cold and heat waves have no significant effect on per capita income or on education level.

We expect that higher access to air-conditioning can mitigate the adverse effect of heat waves (e.g., Barreca et al., 2016; Heutel et al., 2020). However, we do not find a significant effect from the interactions between heat waves and the number of households with air-conditioners (column 3 of Table 3). On the other hand, coefficients on the interaction between cold waves and the air-conditioning variable are negative and significant. This suggests that the effect of cold waves on mortality is smaller in provinces where there is more air-conditioning.

To examine whether people respond to cold waves by purchasing air-conditioners, we regress the number of households with air-conditioning on the number of days in cold and heat waves and other control variables. The regressions use province-by-year observations, since the dependent variables are measured at the provincial level. Cold and heat waves are also defined for a year instead of for a month, as in the previous regressions.[11] Regression results from Table A.26 (column 3) shows that there are no significant effects from cold or heat waves on the number of households with air-conditioning.

Interactions between cold/heat waves, population density, and the immigration rate are not statistically significant, suggesting that the effect of cold/heat waves does not differ across provinces with different population densities and immigration rates. However, coefficients on the interactions between cold waves and the emigration rate are negative and significant (column 5, Table 3). This indicates that provinces with a higher rate of emigration tend to experience a smaller effect from cold waves. People can respond to temperature extremes by migration (e.g., Cattaneo & Peri, 2016; Deschênes & Greenstone, 2007). Table A.26 in the Appendix reports the regression of emigration and immigration rates on cold and heat waves using province-by-year data. It shows that cold waves tend to increase the emigration rate. Cold waves can drive people directly to emigrate from their provinces for health reasons, or indirectly though income pressures by reducing agricultural production (e.g., Deschênes & Greenstone, 2007; Burke et al., 2015). In this paper, we argue that cold waves mainly cause emigration for reasons of health, since there are no significant effects of cold waves on per capita income (column 2 in Table A.26 in the Appendix). In addition, the effect of cold waves on emigration is similar in regression with and without controlling for per capita income (Tables A.26 and A.27 in the Appendix). This implies that income is not an important channel through which cold waves induce migration.

Better provision of health care can be an important factor reducing the adverse effect of temperature on mortality (e.g., Mullins & White, 2020). We examine this issue by including interactions between cold/heat waves and public spending on health and the number of hospitals in the provinces. This approach shows that the effect of cold waves on the mortality rate tends to be smaller in provinces with higher spending on health. Provinces that spend more on health care tend to have better healthcare facilities and staff, helping to mitigate the adverse effect of weather extremes on people's health. According to column 7 of Table 3, if a province's health spending increases by 1%, the magnitude of the effect of a cold wave (measured by

TABLE 3 Heterogeneous effects of cold and heat waves on log of mortality rate for all ages.

	Interaction variables							
	Interaction with proportion of population with college degrees	Interaction with log of per capita income	Interaction with proportion of population with air conditioning	Interaction with log of population density	Interaction with emigration ratio	Interaction with immigration ratio	Interaction with log of government spending on health	Interaction with log of the number of hospitals
Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
# days with at least 3 consecutive days below the 5th percentile of temperature	−0.0589	−0.0002	−0.0328**	−0.0013	−0.2445***	−0.0149	−0.0019**	−0.0002
	(0.0363)	(0.0022)	(0.0149)	(0.0015)	(0.0633)	(0.0933)	(0.0009)	(0.0062)
# days with at least 3 consecutive days above the 95th percentile of temperature	0.0319	0.0043	0.0204	0.0027	0.0916	−0.0029	0.0002	−0.0061
	(0.0510)	(0.0030)	(0.0203)	(0.0018)	(0.1586)	(0.1024)	(0.0021)	(0.0059)
# days with at least 5 consecutive days below the 5th percentile of temperature	−0.0495	−0.0017	−0.0327*	−0.0011	−0.1592**	0.0441	−0.0019**	0.0016
	(0.0445)	(0.0023)	(0.0192)	(0.0016)	(0.0747)	(0.1005)	(0.0009)	(0.0063)
# days with at least 5 consecutive days above the 95th percentile of temperature	0.0833	0.0051	0.0325	0.0036	0.2864	0.0785	0.0013	−0.0132**
	(0.0608)	(0.0032)	(0.0217)	(0.0022)	(0.1785)	(0.1330)	(0.0024)	(0.0065)
# days with at least 7 consecutive days below the 5th percentile of temperature	−0.0367	0.0005	−0.0248	−0.0013	−0.2342***	0.0125	−0.0015	0.0016
	(0.0464)	(0.0027)	(0.0203)	(0.0015)	(0.0475)	(0.0907)	(0.0010)	(0.0064)
# days with at least 7 consecutive days above the 95th percentile of temperature	0.0107	0.0057	0.0083	0.0007	−0.0193	−0.0352	0.0010	−0.0071
	(0.0774)	(0.0040)	(0.0221)	(0.0021)	(0.1422)	(0.1079)	(0.0030)	(0.0069)
# days with at least 9 consecutive days below the 5th percentile of temperature	−0.0730**	0.0002	−0.0371**	−0.0021	−0.2821***	−0.0508	−0.0018*	0.0051
	(0.0352)	(0.0033)	(0.0171)	(0.0015)	(0.0681)	(0.1106)	(0.0011)	(0.0061)
# days with at least 9 consecutive days above the 95th percentile of temperature	0.0133	0.0048	0.0213	0.0013	0.1644	0.0800	0.0041	−0.0063
	(0.0914)	(0.0047)	(0.0242)	(0.0025)	(0.1501)	(0.1088)	(0.0031)	(0.0068)
Observations	11,252	11,252	11,252	12,639	11,387	11,387	11,252	9227

Note: This table reports the estimated coefficients on interactions between the number of days in cold and heat waves and interaction variables in the regression of the log of the mortality rate. A cold (heat) wave is defined as at least k (3, 5, 7, and 9) consecutive days with a daily mean temperature at or below the fifth percentile (at or above the 95th percentile) of the temperature distribution in a specific province. There are 32 regressions in total. The control variables include annual average temperature (degrees Celsius), annual precipitation (mm), province-specific time trend, province-by-month fixed effects, and year-by-month fixed effects, and the interaction variables. Robust standard errors in parentheses. Standard errors are clustered at the province and year-by-month levels.

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

the number of days with at least 3 consecutive days below the fifth percentile of temperature) on the log of the mortality rate decreases by 0.000019 (equal to 0.0019/100). This magnitude is equal to 0.33% of the effect of cold waves on the log of the mortality rate, which is equal to 0.0057 (Figure 3d).

Unlike health spending, the variables "air-conditioning" and "emigration" are not measured in log form. Thus, we cannot directly compare the role of air-conditioning, emigration and health spending in reducing the effect of cold waves on mortality using estimates from Table 3. For comparison, we can compute estimates of interactions corresponding to the percentage change in the air-conditioning rate and the emigration rate. Estimates of the interactions between cold waves (measured by the number of days with at least 3 consecutive days below the fifth percentile of temperature) and the air-conditioning rate and the emigration rate are −0.0328 and −0.2445 (columns 3 and 5 of Table 3), respectively. Using these estimates and the rates of air-conditioning and emigration in the pool sampled, we can compute the percentage changes. If the air-conditioning rate increases by 1%, the magnitude of the effect of cold waves (measured by the number of days with at least 3 consecutive cold days) on the log of the mortality rate decreases by 0.000016. The corresponding figure for the emigration rate is 0.000038. This suggests that emigration has a relatively more important role in reducing the effect of cold waves on mortality than air-conditioning and health spending.

5 | PROJECTION OF MORTALITY CAUSED BY COLD AND HEAT WAVES

5.1 | Mortality caused by cold and heat waves

Table 4 estimates the number of deaths caused by cold and heat waves over time. In this table, a cold/heat wave is defined as at least 3 consecutive days which have a daily mean temperature at or below the fifth percentile (or at or above the 95th percentile) of the temperature distribution for a specific province. Column 1 reports the number of deaths, which is computed directly from the annual population surveys. Columns 2 and 3 estimate the number of deaths in the absence of cold and heat waves,

TABLE 4 Estimation of the number of deaths caused by cold and heat waves.

Year	Observed number of deaths (1)	Number of deaths if no cold waves (2)	Number of deaths if no heat waves (3)	Number of deaths due to cold waves (4) = (1) - (2)	Number of deaths due to heat waves (5) = (1) - (3)	Total number of deaths due to cold and heat waves (6) = (4) + (5)	Percentage of deaths caused by cold and heat waves (7) = (6)/(1)	Percentage of cold wave related deaths (8) = (4)/(6)	Percentage of heat wave related deaths (9) = (5)/(6)
2003	326,319	325,255	325,093	1064	1226	2290	0.70	46.5	53.5
2004	324,901	322,160	323,177	2741	1724	4465	1.37	61.4	38.6
2005	312,682	309,701	311,049	2981	1633	4614	1.48	64.6	35.4
2006	367,523	366,302	366,027	1221	1496	2717	0.74	44.9	55.1
2007	349,754	348,057	347,820	1697	1934	3631	1.04	46.7	53.3
2008	300,264	295,260	300,064	5004	200	5204	1.73	96.2	3.8
2009	283,293	280,652	282,431	2641	862	3503	1.24	75.4	24.6
2010	338,773	338,018	333,329	755	5444	6199	1.83	12.2	87.8
2011	350,934	345,986	350,718	4948	216	5164	1.47	95.8	4.2
2012	368,245	366,201	366,673	2044	1572	3616	0.98	56.5	43.5
2013	394,071	390,140	392,056	3931	2015	5946	1.51	66.1	33.9
2014	375,823	371,507	372,525	4316	3298	7614	2.03	56.7	43.3
2015	355,470	352,482	350,330	2988	5140	8127	2.29	36.8	63.2
2016	373,777	371,649	368,117	2128	5660	7788	2.08	27.3	72.7
2017	335,408	334,791	333,557	617	1851	2468	0.74	25.0	75.0
Total	5,157,237	5,118,161	5,122,966	39,076	34,271	73,346	1.42	53	47

Note: This table estimates the number of deaths caused by cold and heat waves over time. A cold (heat) wave is defined here as at least 3 consecutive days with a daily mean temperature at or below the 5th percentile (at or above the 95th percentile) of the temperature distribution in a specific province. Column 1 reports the number of deaths, computed directly from annual population surveys. Columns 2 and 3 estimate the number of deaths in the absence of cold and heat waves, respectively. The number of deaths caused by cold and heat waves is presented in columns 4 and 5, respectively. The number of deaths due to both cold and heat waves and the corresponding percentage of all deaths are reported in columns 6 ad 7, respectively. The percentage of cold wave and heat wave related deaths in total deaths caused by cold and heat waves are presented in columns 8 and 9, respectively.

respectively. The number of deaths caused by cold and heat waves is presented in columns 4 and 5, respectively. In 2017, it is estimated that cold and heat waves caused 617 and 1851 deaths, respectively. The total number of deaths due to both cold and heat waves (reported in column 6) is estimated at 2468 for 2017, accounting for 0.74% of all deaths in this year (reported in column 7). The number of deaths caused by cold or heat waves in a year depends on the number of cold and heat waves that occur that year. The number of fatalities due to cold or heat waves was highest in 2015 and lowest in 2009.

To compare mortality caused by cold and heat waves, columns 8 and 9 present the number of cold/heat wave related deaths in total deaths caused by both. For the entire 2003–2017 period, cold and heat waves account for 1.42% of all deaths in Vietnam. Among the deaths caused by these waves, cold waves account for 53%, while heat waves account for 47%.

We can estimate the economic cost of mortality caused by cold and heat waves by multiplying the number of deaths with a statistical life value of 0.342 million USD (Viscusi & Masterman, 2017). Table 5 shows that the putative cost of preventing the mortality of 2468 people is estimated at 0.84 billion USD (at constant 2015 prices) in 2017, the equivalent of around 0.44% of GDP in that year.

5.2 | The projection

In this section, we project daily data for Vietnam by adopting different RCP scenarios to predict cold and heat waves in the 50 future years from 2020 to 2070. The RCP is a greenhouse gas concentration trajectory projected for the future. In the IPCC's fifth Assessment Report in 2014, four paths were employed for climate modeling and research. Different climate futures described in the pathways are all considered feasible, depending on the amount of greenhouse gases emitted in the coming years. The RCPs are labeled according to a possible range of radiative forcing values in the year 2070 (2.6, 4.5, 6, and 8.5 W/m2, respectively) (IPCC, 2019).

For simplicity, we assume that people's health status and economic conditions as well as their adaptation to climate changes will remain unmodified in the future. Thus, we use the same 5th and 95th percentiles, defined from the temperature distribution in 2000–2018, to project the cold and heat waves in the 50 years to come, that is, for the 2020–2070 period. Figure 4a,b present the projected number of consecutive days of cold and heat waves under different RCP scenarios. In this graph, a cold (heat) wave is defined as at least 3 consecutive days which have a daily mean temperature at or below the fifth percentile (at or above the 95th percentile) of the temperature distribution for a specific province. Since the average temperature is projected to increase in the coming year, the number of days of cold waves decreases quickly and is close to 0 in the 2050s. On the other

TABLE 5 Estimated economic cost of cold and heat waves.

Year	Number of deaths due to cold and heat waves (1)	WTP to reduce deaths caused by cold and heat waves (constant 2015 US$ billion) (2)	GDP (constant 2015 US$ billion) (3)	WTP as a percentage of GDP (%) (4)
2003	2290	0.78	80.22	0.98
2004	4465	1.53	86.26	1.77
2005	4614	1.58	92.77	1.70
2006	2717	0.93	99.25	0.94
2007	3631	1.24	106.32	1.17
2008	5204	1.78	112.34	1.58
2009	3503	1.20	118.41	1.01
2010	6199	2.12	126.01	1.68
2011	5164	1.77	133.88	1.32
2012	3616	1.24	140.90	0.88
2013	5946	2.03	148.54	1.37
2014	7614	2.60	157.43	1.65
2015	8127	2.78	167.94	1.66
2016	7788	2.66	178.38	1.49
2017	2468	0.84	190.53	0.44

Note: This table estimates at 0.342 million USD the economic cost of mortality caused by cold and heat waves, multiplying the number of deaths by statistical life value (Viscusi & Masterman, 2017). It also reports this cost as a proportion of GDP. The 2018 data contains the data mortality from January to April 2018. Thus we do not present the estimate for the 2018 years.

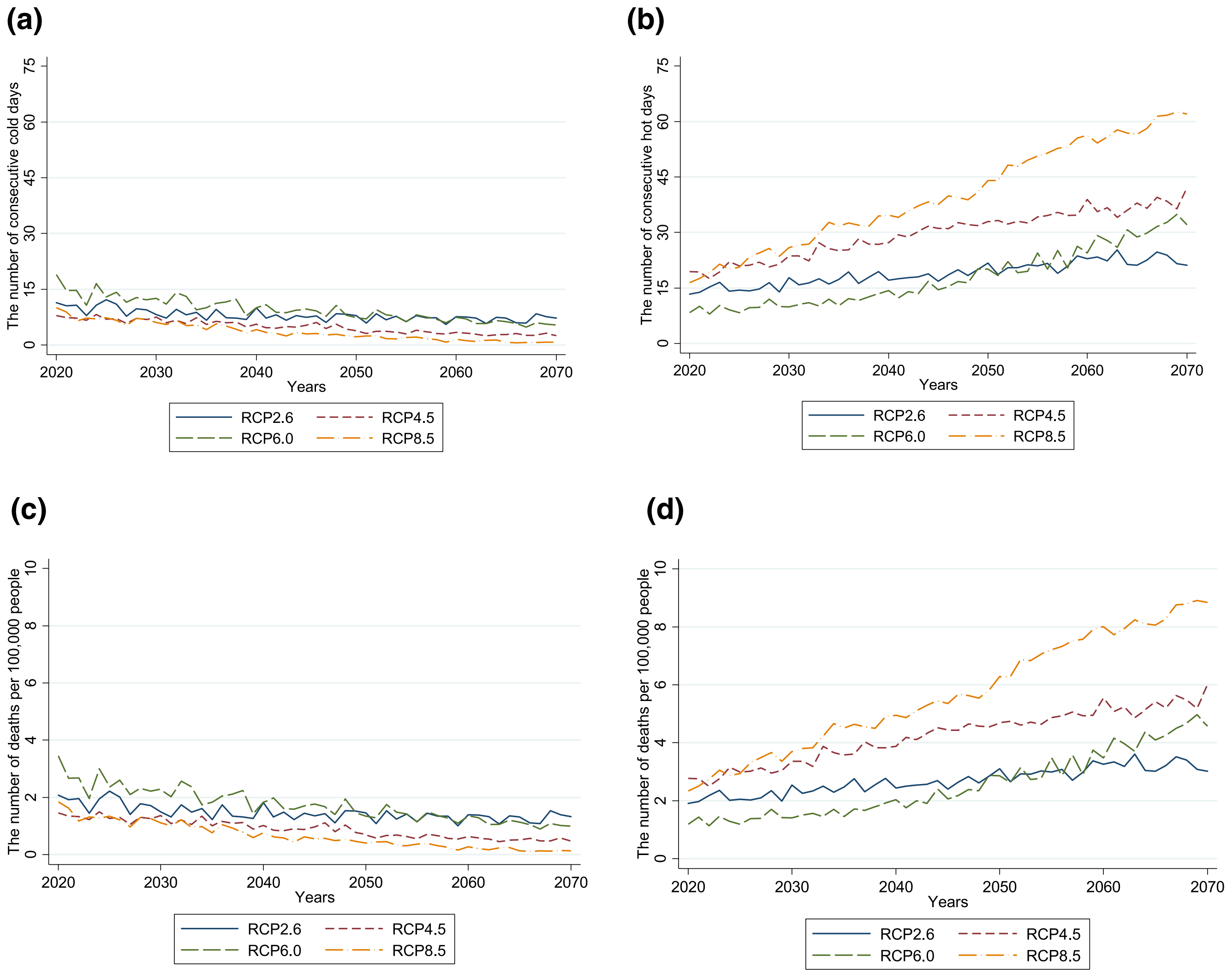

FIGURE 4 The projected number of consecutive days in cold and heat waves and the number of deaths under different Representative Concentration Pathway (RCP) scenarios. (a) The projected number of consecutive days in cold waves. (b) The projected number of consecutive days in heat waves. (c) The projected number of deaths per 100,000 people due to cold waves. (d) The projected number of deaths per 100,000 people due to heat waves. This figure presents the projected number of consecutive days in cold and heat waves according to different RCP scenarios and the estimated number of deaths due to these waves in 50 years from 2020 to 2070. A cold/heat wave is defined as at least 3 consecutive days with a daily mean temperature at or below the fifth percentile (at or above the 95th percentile) of the temperature distribution for a specific province.

hand, the number of days of heat waves increases significantly and reaches a maximum about 2060. The number of heat waves is largest for the RCP 6.0 scenario and smallest for the RCP 2.6 scenario.

We multiply the projected number of days of cold and heat waves by their estimated effect on the mortality rate (0.18 and 0.14 as indicated in Figure 4d) to predict the number of deaths per 100,000 people caused by cold and heat waves in the coming years. It should be noted that we use estimates of the effect of cold and heat waves on the mortality rate instead of on the log of the mortality rate for the projection. The mortality rate is better for measuring the number of deaths caused by temperature extremes in the future. Figure 4 shows that the shape of the number of deaths caused by cold and heat waves (presented in Figure 4c,d) is very similar to that of the cold and heat waves, since we use constant effect estimates of cold or heat waves on mortality. The number of deaths caused by heat waves will increase in the future. These findings raise serious concerns about future heat-related health consequences for Vietnam.

In the Figure 4, the projected figures of RCP6.0 and RCP2.6 intersect. This is consistent with previous studies which also show the pattern of intersection between RCP6.0 and RCP2.6, for example, Chen et al. (2022) and even Martínez-Solanas et al. (2021). It's also worth reminding that this paper used weather data that were developed using insights from the local climate community and were also bias-corrected using the local climate data repository (see Tran-Anh et al. (2022) for more information about the dataset). Tran-Anh et al. (2022) also show that trends of RCP scenarios intersect (Figure 10 in their study). The use of local climate community helps better reflection Vietnam's climate projections, and might contain some differences from that exhibited at the global scale or in other areas - such as Europe as shown in Martínez-Solanas et al. (2021).

6 | CONCLUSION

Understanding the effect of weather extremes on health has received great attention from scholars and practitioners. In this study, we examine the effects of cold and heat waves on mortality in Vietnam during the 2000–2018 period. There are no medium-term effects from cold and heat waves, but we find robust evidence for the short-term effect of cold and heat waves on mortality. An additional day in a cold wave, defined as at least 3 consecutive cold days, increases the mortality rate by 0.6%. The corresponding figure for a day in a heat wave is 0.7%. For cold/heat waves, which are defined as at least 9 consecutive cold/hot days, an additional day in a cold/heat wave increases the mortality rate by 0.6% and 1.2%, respectively. We find heterogenous effects across age, gender and regions. Cold and heat waves have a higher effect on older people, especially those over 80. Overall, male mortality rates are more affected by cold waves, while female mortality rates are more affected by heath waves. By geographical regions, cold and heat waves are more likely to affect mortality of people in South than North. There is a heterogeneous effect from cold waves on mortality across provinces with different adaptation strategies. The effect of cold waves on mortality tends to be lower in provinces with a higher degree of air-conditioning. Cold waves also push people to migrate out of their provinces, and provinces with higher emigration rates are less affected by cold waves. Public spending on health also mitigates the effect of cold waves on mortality.

Indeed, heat- and cold-related events are among the deadliest extreme events, but are underrepresented in the estimated (economic) burden of extreme weather events because they are less visible (being more widespread and resulting in less easily identifiable deaths than those caused by hurricanes, floods or wildfires), seemingly less costly to society (due to their limited impact on insured assets such as infrastructure, cultures, and property), and often affect the most vulnerable segments of the population such as the poor and older people with less economic impact and visibility, both globally and within a specific country. In addition, although only mortality is considered here, a growing body of literature links heat to a wide range of adverse health effects as well as the resulting loss of productivity and work time. Finally, the heat-and cold-related health effects are somewhat preventable, unlike other natural hazards (volcanoes, landslides, tsunamis or earthquakes) or other extreme weather events (hurricanes, floods or wildfires).

Limaye et al. (2020) suggest that the climate change could have a large and negative impact on health if communities are not well prepared for the climate change. Our findings, therefore, suggest several important policy implications. Firstly, not only heat but also cold waves are very harmful for health, particularly for older people in hot areas. In Vietnam, older people over 80 years of age are currently eligible for social pensions and free health insurance.[12] The government should consider lowering the age threshold to 70 years so that more older people can receive assistance to improve their nutrition and health care in the face of weather-related shocks. Secondly, support measures should be tailored to different groups such as males/females and people in different regions because of the heterogenous effect of cold and heat waves. Thirdly, these findings suggest the important role of adaptive and coping strategies from both the government and households to reduce the adverse effect of climate change and weather extremes. Borg et al. (2021) show that climate change can cause more economic loss for low- and middle-income countries and countries with warmer climates. Thus, the government of Vietnam needs to improve the health care system, especially in rural and remote areas, while households can install air-conditioning systems to cope with temperature shocks.

ACKNOWLEDGMENTS

We would like to thank Etienne Espagne, Ngo Duc Thanh, Malcolm Elliot-Hogg, Son Nghiem, Tatyana Deryugina, Lucas Davis, Aditya Goenka, Michael Anderson, Robert Breunig, Mathias Reynaert, Cécile Aubert and participants in GEMMES's workshops for their useful comments on this study. We thank Tuan Nguyen and Thuong Vu Thi for their outstanding research assistance. We also thank Alexis Drogoul and Linh Ha Nguyen (IRD Vietnam) for their supports. Manh-Hung Nguyen acknowledges support from ANR under grant ANR-17-EURO-0010 (Investissesments d'Avenir program).

Open access publishing facilitated by Australian National University, as part of the Wiley - Australian National University agreement via the Council of Australian University Librarians.

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest in connection with the paper. If our paper is accepted, the co-authors and I will provide all the data set and program codes for replication.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Toan Truong Nguyen https://orcid.org/0000-0002-6111-0727

ENDNOTES

[1] Numerous studies show heterogenous effects from climate events on health and infectious diseases (e.g., see review by Jahani & Ahmadnezhad, 2011; Phalkey et al., 2015; Levy et al., 2016).

[2] Although air-conditioners are mainly used to cool air, they can also warm air. Moreover, it can be associated with electric heaters. In our data sets, there are no information on electric heaters. Possibly, people respond to more temperature extremes by purchasing not only air-conditioners but also electric heaters.

[3] Vietnam is among the most rapidly aging countries in the world. According to the GSO (2019), the aging index, which is equal to the ratio of the number of people from 60 to the number of children below 15 (measured in percent), has increased over time. The aging index increased by 13.3 percentage points from 35.5% in 2009% to 48.8% in 2019.

[4] We do not match provinces with the nearest weather stations (using the distance between a province's centroid to the stations) since the weather stations are not located spatially in a random manner (see Figure A.2 in Appendix).

[5] Figure A.6 in the Appendix presents the provincial map of annual rainfall averaged over the 200–2018 period.

[6] In estimating the effect of temperature bins on mortality, we also try 2-degree temperature bins (i.e., below 14°C; 14–16; 16–18; 18–20; 20–22; 22–24; 24–26; 26–30; 30–32; 32+°C). The results are very similar to those obtained by using 3-degree temperature bins. For interpretation, we use the results from 3-degree temperature bins.

[7] For other methods and definitions, see the review by Hsiang (2016) and Kolstad and Moore (2019).

[8] Discussion of the arsinh transformation and its application can be found in several studies, such as those of Pence (2006), and Card and DellaVigna (2020).

[9] Another model which can address the problem of zero values in the dependent variable is the Poisson regression. We tried to estimate by means of the Poisson model, in which the dependent variables are the number of deaths per 100,000. There are no problems with zero inflation in the dependent variables. However, there is an indication of overdispersion; that is, the variance of the dependent variables is remarkably higher than their mean. Therefore, we also used a negative binomial regression. The estimated coefficients on cold and heat waves are very similar to those in the model using the arsinh of the mortality rate. Table A.24 in the Appendix reports the estimates from the negative binomial regression.

[10] The control variables include annual average temperature (in degrees Celsius), annual precipitation (mm), the log of per capita income of provinces, province fixed effects and year fixed effects.

[11] The control variables include annual average temperature (in degrees Celsius), annual precipitation (mm), province fixed effects and year fixed effects.

[12] Decree 20/2021/NĐ-CP "Provisions on social support policies for social protection people" issued by the Government of Vietnam on 15/03/2021. Available at: https://thuvienphapluat.vn/van-ban/Van-hoa-Xa-hoi/Nghi-dinh-20-2021-ND-CP-chinh-sach-tro-giup-xa-hoi-doi-voi-doi-tuong-bao-tro-xa-hoi-467723.aspx.

REFERENCES

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., & Bell, M. L. (2011). Heat waves in the United States: Mortality risk during heat waves and effect modification by heat wave characteristics in 43 US communities. *Environmental Health Perspectives*, *119*(2), 210–218. https://doi.org/10.1289/ehp.1002313

Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arbuthnott, K. G., & Hajat, S. (2017). The health effects of hotter summers and heat waves in the population of the United Kingdom: A review of the evidence. *Environmental Health*, *16*(1), 1–13. https://doi.org/10.1186/s12940-017-0322-5

Azhar, G. S., Mavalankar, D., Nori-Sarma, A., Rajiva, A., Dutta, P., Jaiswal, A., Sheffield, P., Knowlton, K., & Hess, J. J. (2014). Heat-related mortality in India: Excess all-cause mortality associated with the 2010 ahmedabad heat wave. *PLoS One*, *9*(3), e91831. https://doi.org/10.1371/journal.pone.0091831

Banerjee, R., & Maharaj, R. (2020). Heat, infant mortality, and adaptation: Evidence from India. *Journal of Development Economics*, *143*, 102378. https://doi.org/10.1016/j.jdeveco.2019.102378

Barreca, A., Clay, K., Deschenes, 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

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

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., & Samet, J. M. (2002). Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. *Epidemiologic Reviews*, *24*(December), 190–202. https://doi.org/10.1093/epirev/mxf007

Baum-Snow, N., & Lutz, B. F. (2011). School desegregation, school choice, and changes in residential location patterns by race. *The American Economic Review*, *101*(7), 3019–3046. https://doi.org/10.1257/aer.101.7.3019

Becker, G. (2007). Health as human capital: Synthesis and extensions. *Oxford Economic Papers*, *59*(3), 379–410. https://doi.org/10.1093/oep/gpm020

Borg, M. A., Xiang, J., Anikeeva, O., Pisaniello, D., Hansen, A., ZanderDear, K., Sim, D., & Bi, P. (2021). Occupational heat stress and economic burden: A review of global evidence. *Environmental Research*, *195*, 110781. https://doi.org/10.1016/j.envres.2021.110781

Burgess, R., Deschenes, O., Donaldson, D., & Greenstone, M. (2017). *Weather, climate change and death in India*. University of Chicago.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239.

Cameron, A. C., Gelbach, J., & Douglas, M. (2011). Robust inference with multi-way clustering. *Journal of Business & Economic Statistics*, *29*(2), 238–249. https://doi.org/10.1198/jbes.2010.07136

Card, D., & DellaVigna, S. (2020). What do editors maximize? Evidence from four economics journals. *The Review of Economics and Statistics*, *102*(1), 195–217. https://doi.org/10.1162/rest_a_00839

Carleton, T. A., Jina, A., Delgado, M. T., Greenstone, M., Houser, T., Hsiang, S. M., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I. B., & Rising, J. (2020). *Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits (No. w27599)*. National Bureau of Economic Research.

Cattaneo, C., & Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, *122*, 127–146. https://doi.org/10.1016/j.jdeveco.2016.05.004

Chen, H., Zhao, L., Cheng, L., Zhang, Y., Wang, H., Gu, K., Bao, J., Yang, J., Liu, Z., Huang, J., Chen, Y., Gao, X., Xu, Y., Wang, C., Cai, W., Gong, P., Luo, Y., Liang, W., & Huang, C. (2022). Projections of heatwave-attributable mortality under climate change and future population scenarios in China. *The Lancet Regional Health-Western Pacific*, *28*, 100582. https://doi.org/10.1016/j.lanwpc.2022.100582

Coates, L., Haynes, K., O'brien, J., McAneney, J., & De Oliveira, F. D. (2014). Exploring 167 years of vulnerability: An examination of extreme heat events in Australia 1844–2010. *Environmental Science & Policy*, *42*, 33–44. https://doi.org/10.1016/j.envsci.2014.05.003

Cohen, F., & Dechezleprêtre, A. (2019). *Mortality, temperature, and public health provision: Evidence from Mexico*. American Economic Journal: Economic Policy.

Cropper, M. L. (1977). Health, investment in health, and occupational choice. *Journal of Political Economy*, *85*(6), 273–1294. https://doi.org/10.1086/260637

Dell, M., Jones, B. F., & Olken, B. A. (2009). Temperature and income: Reconciling new cross-sectional and panel estimates. *The American Economic Review*, *99*(2), 198–204. https://doi.org/10.1257/aer.99.2.198

Deryugina, T., & Hsiang, S. (2017). *The marginal product of climate (No. w24072)*. National Bureau of Economic Research.

Deryugina, T., & Hsiang, S. M. (2014). *Does the environment still matter? Daily temperature and income in the United States (No. w20750)*. National Bureau of Economic Research.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *The American Economic Review*, *97*(1), 354–385. https://doi.org/10.1257/aer.97.1.354

Deschenes, 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

Dimitrova, A., Ingole, V., Basagana, X., Ranzani, O., Mila, C., Ballester, J., & Tonne, C. (2021). Association between ambient temperature and heat waves with mortality in South Asia: Systematic review and meta-analysis. *Environment International*, *146*, 106170. https://doi.org/10.1016/j.envint.2020.106170

Duflo, E., Glennerster, R., & Kremer, M. (2007). Using randomization in development economics research: A toolkit. *Handbook of Development Economics*, *4*, 3895–3962.

Ebi, K. L., Vanos, J., Baldwin, J. W., Bell, J. E., Hondula, D. M., Errett, N. A., Hayes, K., Reid, C. E., Saha, S., Spector, J., & Berry, P. (2021). Extreme weather and climate change: Population health and health system implications. *Annual Review of Public Health*, *42*(1), 293–315. https://doi.org/10.1146/annurev-publhealth-012420-105026

Gender, G., & Alliance, C. (2016). *Gender and climate change: A closer look at existing evidence*. Global Gender and Climate Alliance.

Geruso, M., & Spears, D. (2018). *Heat, humidity, and infant mortality in the developing world (No. w24870)*. National Bureau of Economic Research.

GSO. (2019). *Kết quả Tổng điều tra Dân số và Nhà ở thời điểm 0 giờ ngày 01 tháng 4 năm 2019, Nhà Xuất bản Thống kê, Tháng 12/2019*. Hà Nội.

Heckman, J., Lalonde, R., & Smith, J. (1999). The economics and econometrics of active labor market programs. In A. Ashenfelter & D. Card (Eds.), *1865–2097, Handbook of labor economics* (Vol. 3). Elsevier Science.

Heutel, G., Miller, N. H., & Molitor, D. (2020). Adaptation and the mortality effects of temperature across US climate regions. *The Review of Economics and Statistics*, 1–33. https://doi.org/10.1162/rest_a_00936

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, *8*, 43–75.

IPCC. (2019). Representative concentration pathways (RCPs). Intergovernmental panel on climate change. Retrieved from https://sedac.ciesin.columbia.edu/ddc/ar5_scenario_process/RCPs.html

Jahani, F., & Ahmadnezhad, E. (2011). A systematic review of climate change' impact and infectious disease. *Journal of Epidemiology & Community Health*, *65*(Suppl 1), A445. https://doi.org/10.1136/jech.2011.142976p.34

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

Kent, S. T., McClure, L. A., Zaitchik, B. F., Smith, T. T., & Gohlke, J. M. (2014). Heat waves and health outcomes in Alabama (USA): The importance of heat wave definition. *Environmental Health Perspectives*, *122*(2), 151–158. https://doi.org/10.1289/ehp.1307262

Kolstad, C., & Moore, F. (2019). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*, *14*(1, Winter 2020), 1–24. https://doi.org/10.1093/reep/rez024

Lanjouw, P., Marra, M., & Nguyen, C. (2017). Vietnam's evolving poverty index map: Patterns and implications for policy. *Social Indicators Research*, *133*(1), 93–118. https://doi.org/10.1007/s11205-016-1355-9

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

Levy, K., Woster, A., Goldstein, R., & Carlton, E. (2016). Untangling the impacts of climate change on waterborne diseases: A systematic review of relationships between diarrheal diseases and temperature, rainfall, flooding, and drought. *Environmental Science and Technology*, *50*(10), 4905–4922. https://doi.org/10.1021/acs.est.5b06186

Limaye, V. S., Max, W., Constible, J., & Knowlton, K. (2020). Estimating the Costs of Inaction and the Economic Benefits of Addressing the Health Harms of Climate Change: Commentary describes illuminates the costs of inaction on the climate crisis and the economic savings of addressing this problem. *Health Affairs*, *39*(12), 2098–2104. https://doi.org/10.1377/hlthaff.2020.01109

Lin, Y., Liu, F., & Xu, P. (2021). Effects of drought on infant mortality in China. *Health Economics*, *30*(2), 248–269. https://doi.org/10.1002/hec.4191

Luber, G., & McGeehin, M. (2008). Climate change and extreme heat events. *American Journal of Preventive Medicine*, *35*(5), 429–435. https://doi.org/10.1016/j.amepre.2008.08.021

Martínez-Solanas, È., Quijal-Zamorano, M., Achebak, H., Petrova, D., Robine, J. M., Herrmann, F. R., Rodo, X., & Ballester, J. (2021). Projections of temperature-attributable mortality in Europe: A time series analysis of 147 contiguous regions in 16 countries. *The Lancet Planetary Health*, *5*(7), e446–e454. https://doi.org/10.1016/s2542-5196(21)00150-9

Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science*, *305*(5686), 994–997. https://doi.org/10.1126/science.1098704

Miller, S., Chua, K., Coggins, J., & Mohtadi, H. (2021). Heat waves, climate change, and economic output. *Journal of the European Economic Association*, *15*(5), 2658–2694. https://doi.org/10.1093/jeea/jvab009

MONRE. (2009). *Climate change, sea level rise scenarios for Vietnam*. Ministry of Natural Resources and Environment of Vietnam.

Mullins, J. T., & White, C. (2020). Can access to health care mitigate the effects of temperature on mortality? *Journal of Public Economics*, *191*, 104259. https://doi.org/10.1016/j.jpubeco.2020.104259

Nguyen, C. V. (2021). Do weather extremes induce people to move? Evidence from Vietnam. *Economic Analysis and Policy*, *69*, 118–141. https://doi.org/10.1016/j.eap.2020.11.009

Otrachshenko, V., & Popova, O. (2022). Does weather sharpen income inequality in Russia? *Review of Income and Wealth*, *68*(S1), 193–223. https://doi.org/10.1111/roiw.12532

Otrachshenko, V., Popova, O., & Solomin, P. (2017). Health consequences of the Russian weather. *Ecological Economics*, *132*, 290–306. https://doi.org/10.1016/j.ecolecon.2016.10.021

Otrachshenko, V., Popova, O., & Solomin, P. (2018). Misfortunes never come singly: Consecutive weather shocks and mortality in Russia. *Economics and Human Biology*, *31*, 249–258. https://doi.org/10.1016/j.ehb.2018.08.008

Pence, K. M. (2006). The role of wealth transformations: An application to estimating the effect of tax incentives on saving. *Contributions to Economic Analysis and Policy*, *5*(1), 1–24. https://doi.org/10.2202/1538-0645.1430

Perkins, S. E. (2015). A review on the scientific understanding of heatwaves—Their measurement, driving mechanisms, and changes at the global scale. *Atmospheric Research*, *164*, 242–267. https://doi.org/10.1016/j.atmosres.2015.05.014

Perkins, S. E., & Alexander, L. V. (2013). On the measurement of heat waves. *Journal of Climate*, *26*(13), 4500–4517. https://doi.org/10.1175/jcli-d-12-00383.1

Phalkey, K., Aranda-Jan, C., Marx, S., Höfle, B., & Sauerborn, R. (2015). Systematic review of current efforts to quantify the impacts of climate change on undernutrition. *Proceedings of the National Academy of Sciences*, *112*(33), E4522–E4529. https://doi.org/10.1073/pnas.1409769112

Saluja, S., Rudolfson, N., Massenburg, B. B., Meara, J. G., & Shrime, M. G. (2020). The impact of physician migration on mortality in low and middle-income countries: An economic modelling study. *BMJ Global Health*, *5*(1), e001535.

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy*, *129*(6), 1797–1827. https://doi.org/10.1086/713733

Son, J. Y., Lee, J. T., Anderson, G. B., & Bell, M. L. (2012). The impact of heat waves on mortality in seven major cities in Korea. *Environmental Health Perspectives*, *120*(4), 566–571. https://doi.org/10.1289/ehp.1103759

Stern, N. (2008). The economics of climate change. *The American Economic Review*, *98*(2), 1–37. https://doi.org/10.1257/aer.98.2.1

Tran-Anh, Q., Ngo-Duc, T., Espagne, E., & Trinh-Tuan, L. (2022). A high-resolution projected climate dataset for Vietnam: Construction and preliminary application in assessing future change. *Journal of Water and Climate Change*, *13*(9), 3379–3399. https://doi.org/10.2166/wcc.2022.144

Viscusi, W. K., & Masterman, C. J. (2017). Income elasticities and global values of a statistical life. *Journal of Benefit-Cost Analysis*, *8*(2), 226–250. https://doi.org/10.1017/bca.2017.12

WHO (1990). Environmental health in rural and urban development and housing unit. *Indoor Environment : Health Aspects of Air Quality, Thermal Environment, Light and Noise*, 17.

WHO (2014). Gender, climate change and health world health organization. Available at: https://apps.who.int/iris/bitstream/handle/10665/144781/9789241508186_eng.pdf

WHO (2018). *WHO housing and health guidelines*. World Health Organization.

Wolfers, J. (2006). Did unilateral divorce laws raise divorce rates? A reconciliation and new results. *The American Economic Review*, *96*(5), 1802–1820. https://doi.org/10.1257/aer.96.5.1802

World Bank. (2020). World development indicators, the World Bank. Available at: https://data.worldbank.org/indicator

World Bank and Asian Development Bank. (2020). *Climate risk country profile: Vietnam*. World Bank, Washington and Asian Development Bank.

Xu, Z., Etzel, R. A., Su, H., Huang, C., Guo, Y., & Tong, S. (2012). Impact of ambient temperature on children's health: A systematic review. *Environmental Research*, *117*, 120–131. https://doi.org/10.1016/j.envres.2012.07.002

Zhao, Q., Guo, Y., Ye, T., Gasparrini, A., Tong, S., Overcenco, A., Urban, A., Schneider, A., Entezari, A., Vicedo-Cabrera, A. M., Zanobetti, A., Analitis, A., Zeka, A., Tobias, A., Nunes, B., Alahmad, B., Armstrong, B., Forsberg, B., Pan, S. C., …, & Li, S. (2021). Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: A three-stage modelling study. *The Lancet Planetary Health*, *5*(7), e415–e425. https://doi.org/10.1016/s2542-5196(21)00081-4

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: Nguyen, C. V., Nguyen, M.-H., & Nguyen, T. T. (2023). The impact of cold waves and heat waves on mortality: Evidence from a lower middle-income country. *Health Economics*, 1–24. https://doi.org/10.1002/hec.4663