Measuring temperature-related mortality using endogenously determined thresholds

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Abstract

Heat-related mortality tends to be associated with heatwaves that do not allow for sufficient acclimatisation to hot weather. In contrast, damage functions and most heatwave emergency response plans do not account for acclimatisation. Using an excess heat measure that accounts for acclimatisation, this paper produces estimates of temperature-related mortality for the five largest Australian capital cities. Fixed effects panel threshold regressions are applied to establish the thresholds that coincide with heightened mortality during extreme temperature events. The estimated parameters associated with these thresholds are then used to develop hindcast estimates for cold temperatures, moderate temperatures, hot temperatures and extreme heat. The estimated thresholds coincide with a notable impact of hot weather on mortality, but a limited cold weather impact. This shows that the burden of risk associated with mortality related to future temperatures and climate change within Australia coincides with heatwaves rather than coldwaves. This is in contrast to recent studies that found that cold weather-related mortality within Australian capital cities has and will continue to be notable. These studies also found a net benefit from climate change in Australia due to reduced cold weather deaths.

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1. INTRODUCTION

Temperature-related mortality has been identified as a key detrimental impact of rising temperatures related to climate change (Smith et al. 2014). This is reflected in the inclusion of a temperature-mortality relationship in a widely used damage function (Tol 2002a) that has been integrated into the FUND (Tol 2002b; Tol 2013), ENVISAGE (Roson and Van der Mensbrugghe 2012) and GTAP-E (Bosello et al. 2006) integrated assessment models (IAMs). Amongst the criticisms of this damage function, which was built using a meta-analysis conducted by Martens (1998), is the lack of accounting for the impact of acclimatisation on the temperature-mortality relationship and the invalidity of applying a uniform V-shaped temperature-mortality relationship across a range of regions (Ackerman and Stanton 2008; Huber et al. 2017). A major issue with the V-shaped relationship developed in Martens (1998) and utilised in Tol (2002a) is that it has been found to be biased towards cold-related mortality and that this is likely to have led to bias towards finding a net reduction in mortality associated with climate change (Huber et al. 2017). As previous studies have found different shapes for the temperature-mortality relationship depending upon the city/climate focused upon (Analitis et al. 2008; Gasparrini et al. 2015; Gasparrini et al. 2017; Gosling et al. 2009; Gronlund et al. 2016; Guo et al. 2014); it is likely that the application of a cold-biased temperature-mortality relationship to tropic, sub-tropic and temperate regions with warm summers will be problematic. The importance of assessing the nature of the temperature-mortality relationship using different techniques and data from a range of climatic regions is important as previous studies, which includes Guo et al. (2016) and Gasparrini et al. (2017), have found net benefits of climate change that are associated with decreased cold-related deaths in regions that are subject to extremely warm temperatures.

In light of this, this paper estimates temperature-related mortality thresholds that account for a lack of acclimatisation to extreme weather while also making an adjustment for short-term mortality displacement. These thresholds capture levels of temperature where the temperature-related mortality relationship differs. Fixed effects panel threshold regressions are used to endogenously determine the thresholds that coincide with heightened mortality during and after heatwave and coldwave events. The analysis utilises daily temperature and mortality data from the five largest Australian capital cities for the period between 2001 and 2015. These five capital cities are the focus of this paper as they encompass climates that are sub-tropical or temperate with warm summers. Once differences across regions, seasons and climate variability are accounted for, these regions are found to coincide with a temperature-mortality relationship that has a minor or negative coldwave element and a notable heatwave element. Some of the reasons that this temperature-mortality relationship is different to that found in previous studies, such as Gasparrini et al. (2015), Guo et al. (2016) and Gasparrini et al. (2017), are how seasonality is accounted for, the use of a temperature measure that accounts for prevailing temperatures in that region, and the use of a fixed effects model to allow for the number of deaths that occur on any given day.

One of the aims of this research is to show that it is possible to use endogenously determined thresholds and the associated model estimates to develop damage functions or forecasts of temperature-related mortality in Australia and analogue regions. This approach is important as there is no need for assumptions about the shape of the temperature-mortality relationship or exogenous threshold temperatures. However, rather than assessing the impact of these estimates within a damage function or applying these estimates to different analogue regions; in this paper, these estimates are used to produce hindcasts that assess whether the risk of mortality for these five cities coincides with cold weather and/or hot weather. This will be assessed by separating the hindcasts produced into the mortality associated with low, moderate, high and extremely high temperatures. Note that these four groups are those captured by the endogenously determined thresholds and were not predetermined.

Kinney et al. (2008) identified a set of challenges for forecasting the future health consequences of higher temperatures. These challenges were to utilise a historical exposure function that is built for a specific city/region or an analogue climate; to utilise an appropriate minimum mortality threshold that allows for differences in acclimatisation/adaptation; and the allowance for moderators (such as access to air conditioning). In addition to being important for long term assessments of climate change damages and forecasting; these issues are also relevant to the present day as existing heatwave response plans rarely account for region specific thresholds and acclimatisation (Yardley et al. 2011). Note that recent research has found that the impact of heatwaves and coldwaves on health service utilisation differs between urban and rural areas (Jegasothy et al. 2017).

2. METHODOLOGY AND DATA

2.1 Methodology

2.1.1 Specification of extreme heat and extreme cold events

The temperature measure used in this study is an Excess Heat Index that accounts for acclimatisation and is part of the Excess Heat Factor (EHF) produced by the Australian Bureau of Meteorology (BOM) (Nairn and Fawcett 2015; Nairn et al. 2013). The EHF measure uses the conditional multiplication of two indices that account for the significance of the event (EHI_S) and the level of acclimatisation to warmer temperatures (EHI_A). The focus on the EHI_A measure is based on previous research, including Langlois et al. (2013), Scalley et al. (2015), Hatvani-Kovacs et al. (2016), Loridan et al. (2016) and Jegasothy et al. (2017), that found that the EHF is a superior measure of the impact of heat on mortality and health service utilisation. Note that only the EHI_A part of the EHF measure is used in this paper as it can be readily applied within fixed effects panel threshold regressions. As there is no need for an exogenous threshold (as would be the case for the EHI_S component of the EHF measure), the interpretation of the endogenously determined threshold is straightforward and is in units of degrees Celsius. The specification of the EHI_A measure is presented in equation one, with DAT denoting the daily average temperature (calculated using the maximum temperature and minimum temperature) and ThrDAT the three-daily average temperature. The subscript *t* denotes each day during this period for each geographic area, *i*. The EHI_A measure captures the impact of prolonged periods of heat and cold. This is reflected in the use of a two indices measure for both heatwaves (i.e. the EHF) and coldwaves (i.e. the Excess Cold Factor (ECF) has an excess cold index that is computed in the same way as the EHI_A) (Nairn et al. 2013). The ECF has been used in a range of recent papers and these include Wang et al. (2016), Jegasothy et al. (2017) and Piticar et al. (2018).

$$EHI\_A_{it} = ThrDAT_{it} - (DAT_{it-1} + \cdots + DAT_{it-30})/30 \tag{1}$$

As the EHI_A is a measure that captures whether three daily average temperatures are notably different to the thirty-day average it accounts for the level of acclimatisation to warmer temperatures using historical data specific to that region. A lack of acclimatisation is an issue due to the physiological impact on thermoregulation, as well as, the likelihood that people are prepared for and adapt to extreme heat events. Note that it will be important to distinguish between physiological acclimatisation, behavioural adaptation, and planned adaptation, such as subsidies of air conditioning installations and heat health warning systems (Gosling et al. 2016). This paper does not make this distinction and solely accounts for acclimatisation by estimating the impact of heat using the EHI_A measure.

2.1.2 Specification of the threshold model

To determine the temperature thresholds that coincide with temperature-related mortality, this paper utilises fixed effects panel threshold regressions to identify the range of temperatures that have a notable impact on mortality. This estimation procedure was initially proposed in Hansen (1999) and has been implemented in Stata as the 'xthreg' command (refer to Wang (2015) for further details of this approach and its implementation in Stata). A simple description of the approach is that threshold regressions are used to separate the observations of a variable into classes (or regimes) that are distinguished from each other by different coefficient estimates of a given dependent variable. In this case, the dependent variable is the EHI_A measure.

This study utilises a three threshold model due to the expectation that the relationship between temperature and mortality will be different at low, moderate, high and extremely high temperatures. Using a three threshold model produces a temperature-related mortality curve that has different slopes for four distinct ranges of temperatures. This formulation is flexible and can capture the U- shaped, V- shaped or J-shaped temperature-mortality response that have been found (or discussed) in a range of studies. These studies include Martens (1998), Davis et al. (2003), Baccini et al. (2008), Anderson and Bell (2009), Gasparrini et al. (2015) Dang et al. (2016) and Gasparrini et al. (2017). Confirmation of the number of thresholds to use in the models has also been assessed using a threshold effect F-test produced by the 'xthreg' command, as well as, the overall model fit via the Akaike information criterion (AIC). While a four threshold model is possible, I have not assessed it as this command is limited to three thresholds. The model for three thresholds is specified as:

$$M_{it} = \begin{cases} (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_1) + \boldsymbol{Z}_{it}\boldsymbol{\alpha} + u_i + e_{it}, \boldsymbol{EHI\_A}_{it} < \gamma_1 \\ (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_2) + \boldsymbol{Z}_{it}\boldsymbol{\alpha} + u_i + e_{it}, \gamma_1 \leq \boldsymbol{EHI\_A}_{it} < \gamma_2 \\ (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_3) + \boldsymbol{Z}_{it}\boldsymbol{\alpha} + u_i + e_{it}, \gamma_2 \leq \boldsymbol{EHI\_A}_{it} < \gamma_3 \\ (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_4) + \boldsymbol{Z}_{it}\boldsymbol{\alpha} + u_i + e_{it}, \boldsymbol{EHI\_A}_{it} \geq \gamma_3 \end{cases} \tag{2}$$

where M_{it} is the level of mortality on that day, EHI_A_{it} is a column vector of order sixteen and captures the heat measure used in the model (including a contemporaneous and 15 lagged variables) and Z_{it} is a column vector of explanatory variables. Mortality will be specified as the number of deaths per region and the number of deaths per 100,000 people. The daily data used to estimate the threshold models encompasses the period between February 2001 and December 2015. Estimating the threshold model produces estimates for $\beta_{1,2,3,4}$, which are row vector of coefficients for the temperature measure, and α, a row vector of coefficients for the other explanatory variables. $\gamma_{1,2,3}$ are the estimated thresholds and the error terms are u and e. It is important to note that the γ

estimates are endogenously determined as they are the values that minimise the residual sum of squares (RSS) using a sequential estimation procedure. The use of fixed effects captures unobserved differences in mortality across regions that are correlated with the explanatory variables in the model.

The explanatory variables are grouped into six types of variables and these include dummy variables for the days of the week, months of the year, the calendar year and days with low mortality. Table 1A in the appendix lists the explanatory variables included in the threshold model estimation and provides summary statistics for these variables for the whole sample (using the capital city geography). The low and very low mortality dummy variables capture outlier days that have a number of deaths lower than 25% and between 25% and 50% of the monthly average. Seasonality is accounted for using the months of the year as it is important to capture differences in the level of mortality during winter and summer. It is expected that increases in deaths during winter months are associated with the influenza season and related pneumonia deaths. Note that previous research on coldwaves controlled for influenza as a separate cause of death (Díaz et al. 2015; Montero et al. 2010). The proportion of elderly people (i.e. over 75 years old) within the population is an important variable capturing the risk-exposure to temperature-related mortality that differs across the regions and is correlated with the fixed effect component of the model.

2.1.3 Accounting for mortality displacement

To account for mortality displacement fifteen lags of the EHI_A extreme heat measure are included in the model. The aggregated estimates from all sixteen coefficients will be referred to as short-term mortality displacement. For further background on short-term mortality displacement refer to Box 1A in the appendix. Accordingly, displacement is limited to a maximum of 15 days after the extreme heat event. Otherwise, the usual level of morbidity is captured in the daily and seasonal variables, as well as the fixed effect term for each capital city. As the EHI_A_{it} measure is included with numerous lags, the model is specified as a finite distributed lag model with one contemporaneous and fifteen lags of the EHI_A measure. These lags are included as regime-dependent variables in the threshold model and are accounted for in the determination of $\gamma_{1,2,3}$. Similar distributed lag models have been used to account for mortality displacement in numerous studies (Allen and Sheridan 2018; Armstrong et al. 2017; Qiao et al. 2015). In accordance with this approach, the estimates associated with EHI_A should be interpreted as temperature-related mortality that is adjusted for a short-term displacement period of 16 days. It is expected that the lag variables will capture displacement via negative parameter estimates associated with the EHI_A measure. These estimates and forecasts are the temperature-related deaths that would not otherwise have happened for another reason during the day of and fifteen days after the extreme heat event. At times, the sum of the estimates associated with the contemporaneous and lagged EHI_A variables will be referred to as short-term displacement adjusted temperature-related mortality. Note that the use of lags is also important due to research that found that high temperature-related mortality tends to occur no more than three days after the extreme heat event (Gosling et al. 2009; Guo et al. 2014; Langlois et al. 2013).

2.1.4 Calculating hindcast estimates of temperature-related mortality

Equation three specifies how the temperature-related mortality hindcasts (shown as a column vector, *HM*) are derived using the EHI_A measure. Equation three combines the mortality estimates per 100,000 people with data on the population (*Pop*) of these capital cities between 2001 and 2015. Note that Pop is specified as the population of these cities in hundreds of thousands to match the mortality estimates.

$$\boldsymbol{HM}_{it} = \begin{cases} (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_1)(Pop_{it}), \boldsymbol{EHI\_A}_{it} < \gamma_1 \\ (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_2)(Pop_{it}), \gamma_1 \leq \boldsymbol{EHI\_A}_{it} < \gamma_2 \\ (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_3)(Pop_{it}), \gamma_2 \leq \boldsymbol{EHI\_A}_{it} < \gamma_3 \\ (\boldsymbol{EHI\_A}_{it})(\boldsymbol{\beta}_4)(Pop_{it}), \boldsymbol{EHI\_A}_{it} \geq \gamma_3 \end{cases} \tag{3}$$

2.2 Data

Daily temperature data has been accessed from the BOM website for 21 different weather stations. These weather stations and how they map to the capital city regions is shown in Table 2A within the appendix. The data sourced from the BOM website are the daily maximum temperature and the daily minimum temperature for the 24 hour period leading up to 9am. As the BOM temperature data corresponds to the 24 hours leading up to 9am, the daily maximum temperature data has been adjusted so that it is associated with the day that the mortality occurred. A contemporaneous match between the daily maximum temperature and the mortality variables occurs with this adjustment as the observations of the daily maximum temperature have been moved backwards by one day[1]. This

[1] This means that the daily maximum temperature data reported by the BOM for January 1 becomes the observation for December 31.

adjustment has not been made for the daily minimum temperature data as this variable will capture the temperature of the night preceding mortality and is consistent with research that specified a similar variable to capture the impact of a hot night due to a lack of recovery from heat-stress (Bouchama 2004; D'Ippoliti et al. 2010).

The daily all-cause of death mortality data has been provided by the Australian Bureau of Statistics (ABS) as part of a customised data request from their catalogue of death statistics (Cat. No. 3302.0) that are sourced from Registries of Births, Deaths and Marriages in the relevant regions (ABS 2016). This data has been provided for each major Australian capital city (i.e. Sydney, Melbourne, Brisbane, Adelaide and Perth) and 15 sub-city areas within these capital cities. Note that these cities have a large geographic spread and on the same day there can be notable differences in temperatures between coastal and inland areas. The capital city data is provided at the ABS Greater Capital City Statistical Division (GCCSD) level and the sub-city areas are amalgamations of Level 4 ABS Statistical Areas. Further details and maps of these geographic areas can be accessed from ABS (2010). Note that the sub-city regions have tended to be split based on groupings that coincide with eastern/western or coastal/inland regions. Table 2A in the appendix contains the matching of the 20 regions to the BOM weather stations used as the source of the temperature data. Population data from the ABS was used to create mortality per 100,000 people variables for both regional aggregations (ABS 2018) and to specify the Pop variable in equation 3.

Table 1 contains summary statistics on mortality (both measures) and the EHI_A measure for each geographic region. Note that a balanced panel has been created by replacing a small number of missing values from individual weather stations with data from another weather station in that capital city (i.e. those matched to the GCCSD areas). Between 2001 and 2015, Melbourne and Adelaide were the cities with the highest EHI_A levels. This corresponds with extreme heatwaves in South East Australia during 2009, 2014 and 2015.

3. RESULTS

The estimation results from the threshold model estimation that uses the All Capital Cities (i.e. ABS GCCSD) and All City Areas (i.e. the amalgamations of ABS Statistical Area) geographic specifications are shown in the appendix. Before focusing on these estimation results, it should be noted that estimations were also conducted using an extreme heat measure that does not account for acclimatisation (i.e. ThrDAT); however, the thresholds associated with this measure did not produce a temperature-related mortality curve with the expected temperature-mortality response that has been found in previous studies. Accordingly, these estimation results are not presented in this paper. The appropriateness of a three threshold model has been confirmed using AIC statistics and the threshold effect F-test produced by the 'xthreg' command. These statistics and an accompanying discussion are provided within the appendix in Table 3A.

Overall, the estimation results of the four models shown in Tables 4A and 5A are similar. The highest threshold for the All Capital Cities and All City Areas geographic specifications are quite close to each other. The highest EHI_A threshold values are 7.26 and 7.98 for the mortality per region regressions. These values are 7.26 and 6.71 for the mortality per 100,000 people regressions. For the All Capital Cities specification, the largest increase in mortality that is associated with the EHI_A measure occurs on the second day after the extreme heat event. This is consistent with the findings of Langlois et al. (2013) that found that an "elevation in Excess Heat Factor values preceded the increase in heat-related deaths by 2–3 days" (Langlois et al. 2013). The oscillation in negative and positive estimates that are associated with the EHI_A measure for different thresholds and different numbers of lags is evidence that mortality displacement has been occurring. Mortality displacement is particularly evident in the All City Areas mortality per region regression with statistically significant negative coefficients for the highest threshold occurring four, ten and fourteen days after the extreme heat event. Mortality displacement occurs in all regressions as statistical significant negative coefficients tend to coincide with the highest threshold one or two days after a statistically significant positive coefficient occurs.

As part of sensitivity testing of the model, estimations with six lags of the EHI_A measure have been estimated and these results are shown in Tables 6A and 7A. Consistent results are found as the EHI_A threshold values for these reduced models are 7.26, 7.98, 7.26 and 7.98. These values are very close matches to the thresholds presented in Tables 4A and 5A. In all cases, the largest increase in mortality occurs on the second day after the extreme heat event, irrespective of whether 15 or 6 lags are used.

To assist with the interpretation of the relationship between the EHI_A measure and mortality, Figure 1 contains the accumulated sixteen day temperature-related mortality that is associated with values of EHI_A between -12 and 12. These accumulated sixteen day estimates incorporate all of the contemporaneous and lagged parameters associated with the EHI_A measure. Across all four model specifications there is a notable impact of extreme heat that coincides with a EHI_A greater than 6.71. In all cases, there is a high impact of extreme heat, a moderate impact of high heat, a low or negative impact of moderate temperatures and a low or negative impact of low/cold temperatures. Note that all of these temperature-mortality functions are dissimilar to those found in Martens (1998), Gasparrini et al. (2015), Guo et al. (2016) and Gasparrini et al. (2017). While Guo et al. (2016) forecasted temperature-related mortality for three Australian capital cities, it should be noted that Adelaide, a city that was harshly impacted by severe heatwaves in 2009, was not included within their analysis. Also, the control of long-term trends and seasonality in Gasparrini et al. (2015), Guo et al. (2016) and Gasparrini et al. (2017) was conducted using a smooth non-linear functional form in a time-series model that is notably different from the approach used in this paper. Martens (1998) imposed a V-shaped relationship rather than endogenously determining the shape of the temperature-mortality relationship as done in this paper.

As there are between 2 to 6 sub-city regions within a capital city, differences in the size of reference region explains why the imputed deaths for the two geographic specifications differ even though the thresholds are so similar. Adjustment for the size of the at-risk population should be made when these estimates are applied to produce hindcasts/forecasts for the city level (as specified in equation 3). This approach should be used when applying these results to other analogue regions.

Another important issue is that three cities have had notably high exposures to heatwave events. Based on the historical statistics of the EHI_A measure from 2001 to 2015, these cities are Melbourne, Adelaide and Perth. This evident in Table 1c as Melbourne, Adelaide and Perth are those cities that had EHI_A values above 9 during the 2001 to 2015 period. This is also evident in Figure 2a, which shows the hindcasts for the All Capital Cities model with the dependent variable specified as mortality per 100,000 people. These same three cities have had higher mortality per 100,000 people than the two more northern cities (which are closer to the equator and typically warmer). This reflects the importance of a lack of acclimatisation in the temperature-mortality relationship.

Figure 2b contains hindcasts that have been upscaled using the city-level population data from the ABS (as specified in equation 3). These hindcasts have been produced using the relationship in Figure 2a (based on the All Capital Cities estimations in Table 5A) to show the differences in the impact per city based on the size of their at-risk population. In this case, Melbourne stands out as it is a large city that has had a notable number of deaths per 100,000 people. The number of deaths in Sydney is also high and this is due to the size of the at-risk population as Sydney is the most populous city in Australia. Adelaide and Perth have relatively high numbers of deaths with respect to the size of their populations. Brisbane (which is the city closest to the equator and in a region classed as sub-tropical) has had the lower number of temperature-related deaths based on these results, which use the EHI_A measure. Whether this occurs using other measures will be of interest in future research.

The highest number of heat-related deaths coincided with the years 2009, 2011, 2014 and 2015. 2009 is the year of a severe heatwave that impacted South East Australia and occurred in two stages between 27-31 January and 6-8 February. During that period Adelaide had its warmest night on record with a minimum of 33.9°C on the morning of January 29 and the city also equalled a 1908 record of six consecutive days with a temperature above 40°C (BOM 2009). During the period between the 27th and 30th January, Adelaide had the highest EHI_A values in the dataset with four days of EHI_A values above 10. This included two days with levels of EHI_A above 12.5. For the period between January 27 and February 5, Langlois et al. (2013) identified 58 deaths in Adelaide that were "reported to the Coroner in which exposure to high ambient temperature was regarded to have caused or significantly contributed to the death" (Langlois et al. 2013). In 2014, Melbourne experienced temperatures above 41ºC on all days between January 14 and 17. This period was associated with 167 excess deaths in a report by the Victorian Department of Health (Vict. Dept. of Health 2014). The end of 2015 was also an extremely hot period for Adelaide and Melbourne (Australian Associated Press 2015; Wahlquist 2015), which is captured in the hindcasts for 2015 as the EHI_A measure for this period is above 8 for both cities.

4. DISCUSSION

The estimates presented in this paper are the number of deaths related to extreme temperatures that would not have otherwise occurred in the next fifteen days and are not associated with seasonality. Upon interpreting the results of this paper it should be noted that many of these regions implemented heatwave emergency response plans after 2009. While a study has evaluated the effectiveness of a heat warning system in Adelaide (Nitschke et al. 2016), whether these policy interventions have been successful and reduced the rate of heat-related deaths in other Australian capital cities will be the subject of future research. Reviewing the annual dummy variables shows an increase in mortality in later years; however, little can be said about the impact of the heatwave emergency response plans implemented after 2009 as controlling for a range of issues, such as the prevailing weather extremes, would need to occur. The hindcasts in this paper should be treated as the exposure to temperature-related mortality based on the relationship and the practices in place in these cities between 2001 and 2015. Changes in adaptation occur and this is a separate issue from acclimatisation that is based on thermoregulatory disfunction and the other drivers of these results.

Five year hindcast estimates for four categories of temperatures are shown in Table 2. Consistent with the thresholds estimated, the large majority of deaths were associated with high and extremely high temperature events. There is a negative impact of extremely low temperatures across all of the cities and this suggests that the burden of risk from future weather events in Australian capital cities will be associated with heat events rather than cold weather events. Brisbane has had less deadly heatwave events in comparison to the other major Australian capital cities and this corresponds with the patterns across cities captured in the 2001-2015 estimates (shown in Figure 2a and Table 1c).

Based on these results, the downward trend in temperature-related mortality found for Melbourne in Guo et al. (2016) for the period between 2000 and 2100 will not be replicated as a historical U- or V-shaped relationship is not found in this study. Guo et al. (2016) also found that climate change will decrease temperature-related deaths in Melbourne, which is a city located in a temperate climate that has warm summers and has been impacted by extreme temperatures. Therefore, the validity of the V-shaped relationship imposed in Martens (1998) is cast in greater doubt and this has implications for damage functions built using these relationships in Huber et al. (2017). The difference in these results to previous studies has relevance to the discussion on damage functions. These differences are likely to be related to the use of fixed effects estimation, monthly dummy variables to capture seasonality, and a measure that accounts for acclimatisation. Future research should assess whether finding a U- or V- shaped relationship in other regions occurs using the threshold model specifications applied in this paper.

5. CONCLUSION

Within this paper, fixed effect threshold regressions have been utilised to determine the threshold temperatures that are related with heightened mortality during and after extreme heat events. These thresholds have been computed to display a method for estimating a region-specific temperature-mortality relationship that can be used to develop region-specific damage functions that account for acclimatisation and mortality displacement. This method requires no prior assumption for the shape of the temperature-mortality relationship nor does it require an exogenous threshold to define a heatwave/coldwave event. As there is a limited impact of cold weather on mortality within these estimates, the temperature-mortality relationship estimated is dissimilar to the V-shaped relationship found in Martens (1998) and applied to climate damages in the literature stemming from Tol (2002a). It is also dissimilar to the U-shaped relationship estimated in Gasparrini et al. (2015), Guo et al. (2016) and Gasparrini et al. (2017) for Australian capital cities.

This paper finds that there is little association between coldwaves and mortality for five Australian capital cities that span temperate (with warm summers) and sub-tropical climates. A lower impact of cold weather events is explained by differences in the regression models used. For example, seasonality is accounted for in a different manner, the heat measure used is specified in relation to recent temperatures and a fixed effects model is applied. The major difference is that the temperature-mortality relationship is endogenously determined by the historical relationship in the data rather than an assumed functional form. These results cast doubt on the reductions in mortality associated with future temperatures and climate change that were estimated in Guo et al. (2016) for Melbourne. It should be noted that Melbourne and Adelaide are the major Australian capital cities that have been severely impacted by notable heat-related mortality events in the past.

The results presented in this paper are also notably different to those found in Gasparrini et al. (2015) where the attributable mortality associated with cold temperatures was 6.50% and 0.45% for heat. These results were established for Australia using data from three capital cities (i.e. Melbourne, Sydney and Brisbane). In a follow up paper, Gasparrini et al. (2017), the temperature mortality relationships found in Gasparrini et al. (2015) were applied to Global Climate Model (GCM) projections to assess the impact of climate change on mortality. Note that Gasparrini et al. (2017) finds a net reduction in deaths due to climate change (even for a high emission RCP 8.5 scenario).

Further applications of this approach and the EHF/EHI_A measures to other regions will assist with the assessment of whether heatwave measures and their trigger thresholds should account for recent temperatures and a lack of acclimatisation. In the interim, the results of this paper suggest that a wider use of heatwave measures that account for acclimatisation and regional differences should be encouraged. Assessments of how a temperature-mortality function that adjusts for mortality displacement and acclimatisation differs across regions and countries will be of direct relevance to damage functions applied within global IAMs. Whether the thresholds that were estimated for Australian capital cities using the EHI_A measure are similar to those that would be estimated using data from other areas (such as Europe and the United States) will be important contributions of future research with great relevance to heatwave emergency response plans, forecasting temperature-related mortality and assessments of the impact of climate change using damage functions or projections from GCMs.

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Table 1 – Summary statistics – Mortality and EHI_A

a) Mortality

Region		min	1st perc.	5th perc.	50th perc.	Mean	95th perc.	99th perc.	max	N
Sydney		15	48	54	71	72	93	103	118	5417
	East, City and Inner West	0	5	6	12	12	19	22	27	5417
	North	0	5	8	14	14	21	24	33	5417
	South	3	5	7	13	13	20	23	30	5417
	West	0	5	7	12	13	20	23	30	5417
	Outer West	0	4	6	12	12	19	22	31	5417
	Central Coast	0	3	4	8	8	13	16	20	5417
Melbourne		19	42	48	64	64	81	89	150	5417
	Inner	3	11	14	22	22	31	35	58	5417
	North and West	5	9	11	19	19	28	32	76	5417
	East and Mornington	6	12	15	23	23	33	37	50	5417
Brisbane		5	18	21	31	32	43	49	59	5417
	Brisbane City	3	9	11	18	18	26	29	39	5417
	Ipswich, Logan and Morten Bay	3	5	7	13	14	21	25	35	5417
Adelaide		5	14	17	25	26	35	40	52	5417
	North, Central and Hills	0	5	7	13	13	20	23	29	5417
	West and South	3	5	7	12	12	19	22	31	5417
Perth		10	14	17	26	26	37	42	50	5417
	West	3	7	9	16	16	24	28	38	5417
	East	3	3	5	10	10	16	19	24	5417

b) Mortality per 100,000 people

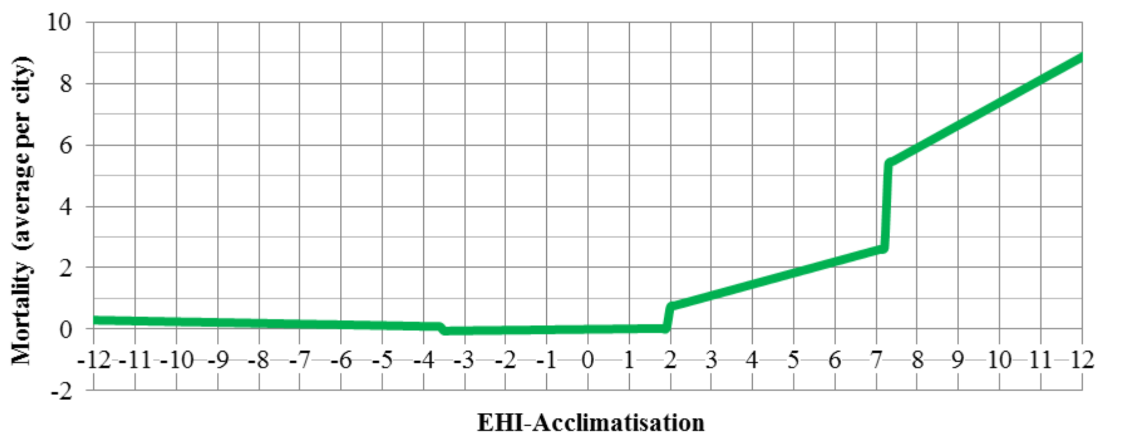
Region		min	1st perc.	5th perc.	50th perc.	Mean	95th perc.	99th perc.	max	N
Sydney		0.30	1.09	1.22	1.61	2.07	2.10	2.32	2.68	5417
	East, City and Inner West	0.00	0.58	0.81	1.53	1.56	2.45	2.94	3.83	5417
	North	0.00	0.67	0.94	1.72	1.75	2.68	3.13	4.43	5417
	South	0.37	0.68	0.96	1.70	1.76	2.67	3.09	4.22	5417
	West	0.00	0.54	0.75	1.39	1.41	2.14	2.50	3.62	5417
	Outer West	0.00	0.47	0.70	1.32	1.34	2.07	2.38	3.15	5417
	Central Coast	0.00	0.92	1.22	2.53	2.61	4.29	5.27	6.31	5417
Melbourne		0.41	1.07	1.24	1.62	1.63	2.06	2.26	3.72	5417
	Inner	0.21	0.86	1.11	1.75	1.78	2.56	2.89	4.60	5417
	North and West	0.31	0.69	0.88	1.43	1.44	2.05	2.38	5.63	5417
	East and Mornington	0.38	0.85	1.07	1.65	1.66	2.28	2.56	3.52	5417
Brisbane		0.22	0.91	1.07	1.56	1.58	2.13	2.41	3.01	5417
	Brisbane City	0.24	0.79	1.00	1.63	1.65	2.37	2.72	3.92	5417
	Ipswich, Logan and Morten Bay	0.28	0.61	0.83	1.45	1.49	2.23	2.64	3.30	5417
Adelaide		0.38	1.13	1.39	2.07	2.09	2.87	3.27	3.96	5417
	North, Central and Hills	0.00	0.93	1.30	2.31	2.36	3.54	4.10	5.41	5417
	West and South	0.42	0.71	1.01	1.83	1.87	2.86	3.35	4.53	5417
Perth		0.65	0.86	1.03	1.54	1.55	2.10	2.39	3.44	5417
	West	0.35	0.74	0.98	1.65	1.67	2.44	2.79	4.54	5417
	East	0.35	0.47	0.68	1.37	1.38	2.18	2.59	3.12	5417

c) Excess Heat Index – Acclimatisation (EHI_A)

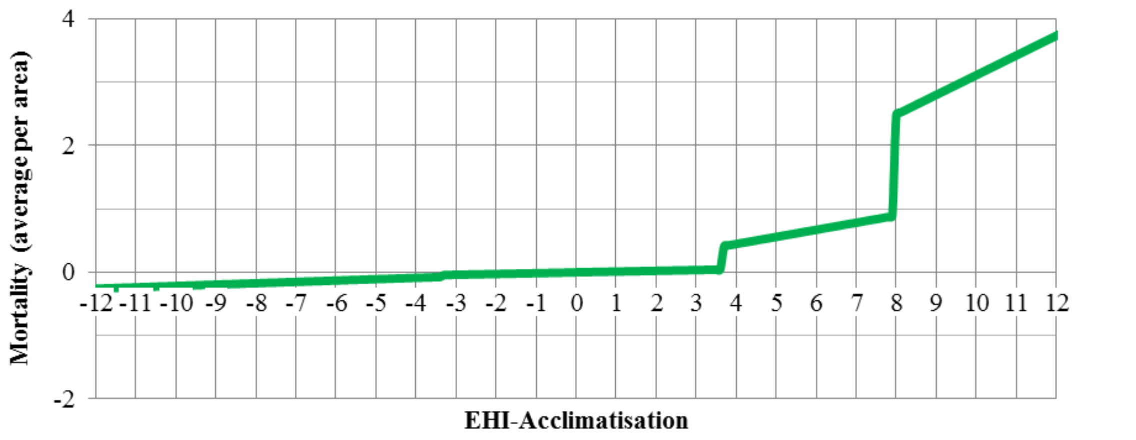
Region		min	1st perc.	5th perc.	50th perc.	Mean	95th perc.	99th perc.	max	N
Sydney		-5.03	-3.74	-2.80	-0.07	0.00	3.16	4.77	8.68	5417
	East, City and Inner West	-5.03	-3.74	-2.80	-0.07	0.00	3.16	4.77	8.68	5417
	North	-6.02	-4.08	-3.11	-0.10	0.00	3.53	5.39	9.55	5417
	South	-5.90	-4.01	-3.09	-0.09	0.00	3.45	4.90	7.56	5417
	West	-7.58	-4.14	-3.17	-0.11	0.00	3.59	5.28	8.47	5417
	Outer West	-7.01	-4.46	-3.38	-0.08	0.00	3.67	5.33	8.21	5417
	Central Coast	-6.03	-4.07	-3.07	-0.10	0.00	3.41	5.08	8.16	5417
Melbourne		-7.39	-4.73	-3.57	-0.18	0.00	4.04	6.27	12.00	5417
	Inner	-7.32	-5.11	-3.65	-0.12	0.00	3.95	6.14	12.38	5417
	North and West	-7.52	-4.94	-3.64	-0.16	0.00	4.17	6.33	12.51	5417
	East and Mornington	-6.60	-4.51	-3.41	-0.13	0.00	3.90	6.15	11.34	5417
Brisbane		-5.37	-3.73	-2.71	-0.02	0.00	2.70	3.82	6.82	5417
	Brisbane City	-5.45	-3.76	-2.57	-0.06	0.00	2.80	4.02	6.79	5417
	Ipswich, Logan and Morten Bay	-6.28	-4.57	-3.28	-0.12	0.00	3.54	5.27	8.44	5417
Adelaide		-9.92	-5.80	-4.14	-0.19	0.00	5.03	7.85	12.52	5417
	North, Central and Hills	-9.91	-5.85	-4.28	-0.15	0.00	5.02	7.89	12.11	5417
	West and South	-8.99	-5.28	-3.74	-0.19	0.00	4.39	7.37	11.68	5417
Perth		-9.90	-5.53	-3.99	0.00	-0.01	4.06	6.23	9.61	5417
	West	-7.66	-4.64	-3.47	-0.03	-0.01	3.65	6.14	9.59	5417
	East	-8.86	-5.35	-3.94	-0.03	-0.01	4.13	6.41	10.70	5417

Figure 1 – Model estimates of the accumulated sixteen day temperature-related mortality

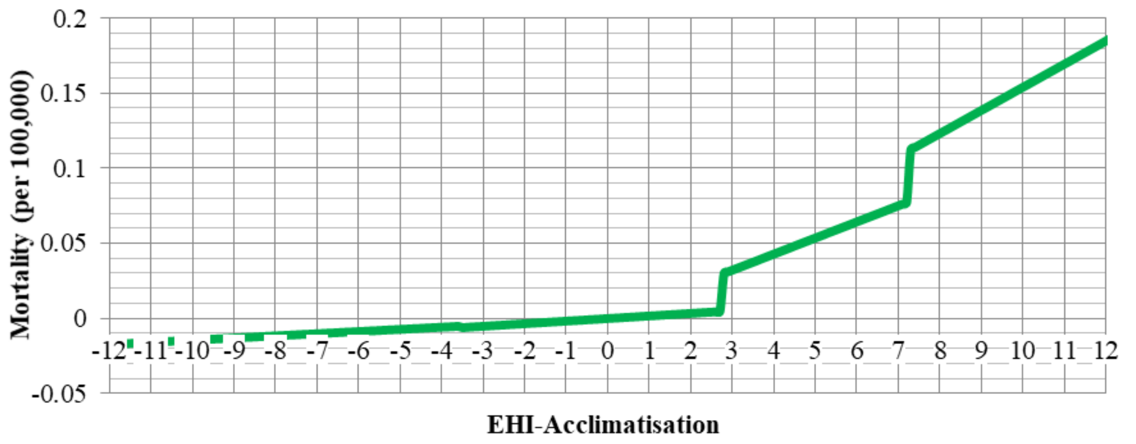
a) All Capital Cities – Number of deaths



b) All City Areas – Number of deaths



c) All Capital Cities – Deaths per 100,000 people



d) All City Areas – Deaths per 100,000 people

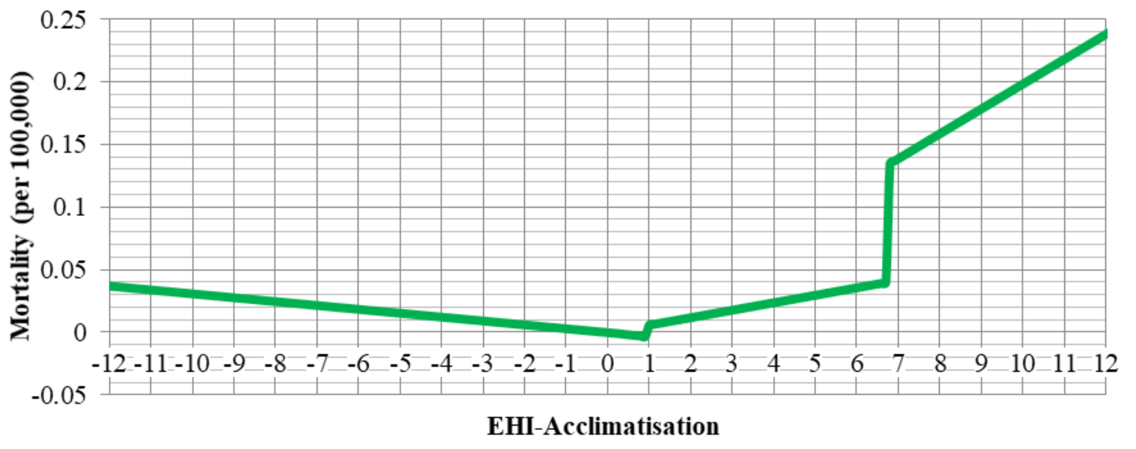
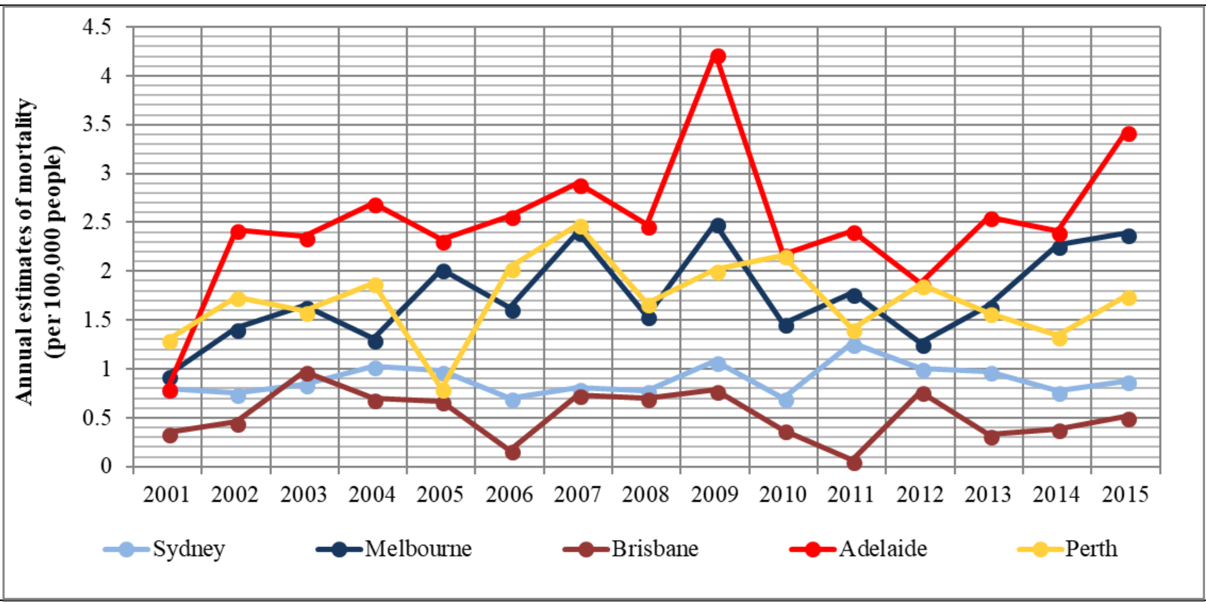


Figure 2 – Annual estimates of short-term displacement adjusted temperature-related mortality

a) Hindcasts (per 100,000 people)



b) Hindcasts (total number per city)

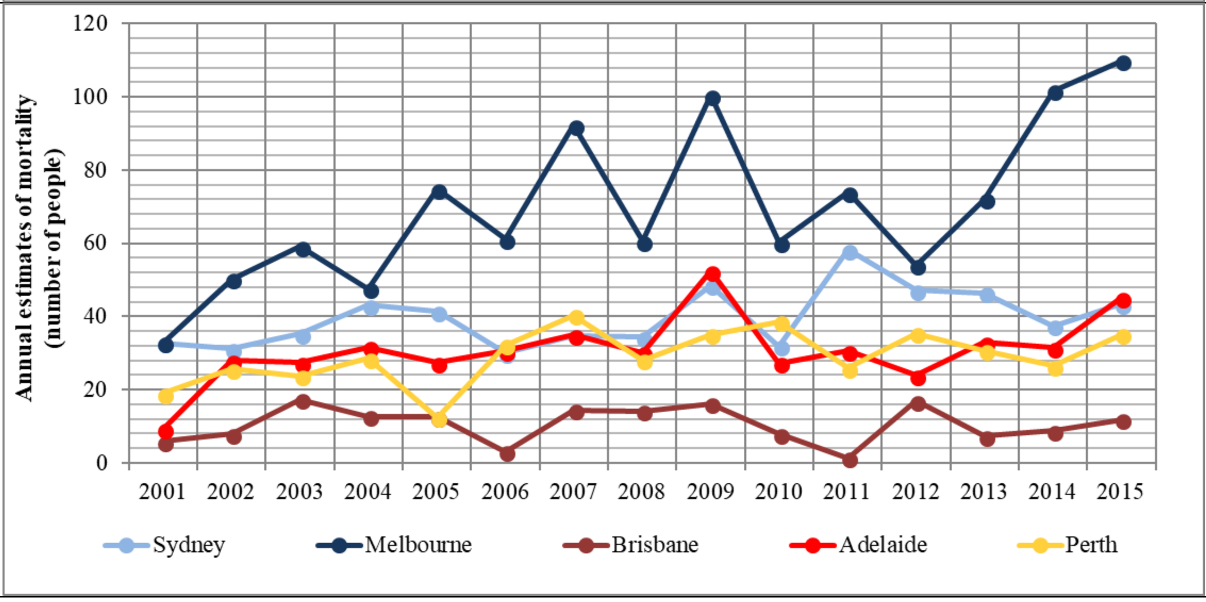


Table 2 – Five yearly hindcasts of short-term displacement adjusted temperature-related mortality between 2001 and 2015 by capital cityand EHI_A threshold

Years	Sydney				
	Low/cold temperatures ($< \gamma_1$)	Moderate temperatures ($\geq \gamma_1$ &$< \gamma_2$)	High heat/hot temperatures ($\geq \gamma_2$ &$< \gamma_3$)	Extreme heat temperatures ($\geq \gamma_3$)	All temperatures
2001-2005	-6	-47	216	20	183
2006-2010	-8	-47	234	0	180
2011-2015	-8	-57	286	12	233
All years	-21	-151	736	32	596
Years	**Melbourne**				
	Low/cold temperatures ($< \gamma_1$)	Moderate temperatures ($\geq \gamma_1$ &$< \gamma_2$)	High heat/hot temperatures ($\geq \gamma_2$ &$< \gamma_3$)	Extreme heat temperatures ($\geq \gamma_3$)	All temperatures
2001-2005	-14	-53	327	5	265
2006-2010	-33	-49	386	72	375
2011-2015	-24	-59	420	75	411
All years	-72	-161	1,132	151	1,051
Years	**Brisbane**				
	Low/cold temperatures ($< \gamma_1$)	Moderate temperatures ($\geq \gamma_1$ &$< \gamma_2$)	High heat/hot temperatures ($\geq \gamma_2$ &$< \gamma_3$)	Extreme heat temperatures ($\geq \gamma_3$)	All temperatures
2001-2005	-3	-17	76	0	56
2006-2010	-2	-19	78	0	56
2011-2015	-4	-16	66	0	46
All years	-9	-52	220	0	159
Years	**Adelaide**				
	Low/cold temperatures ($< \gamma_1$)	Moderate temperatures ($\geq \gamma_1$ &$< \gamma_2$)	High heat/hot temperatures ($\geq \gamma_2$ &$< \gamma_3$)	Extreme heat temperatures ($\geq \gamma_3$)	All temperatures
2001-2005	-9	-16	113	36	124
2006-2010	-15	-16	140	66	175
2011-2015	-13	-17	152	41	164
All years	-37	-49	406	144	463
Years	**Perth**				
	Low/cold temperatures ($< \gamma_1$)	Moderate temperatures ($\geq \gamma_1$ &$< \gamma_2$)	High heat/hot temperatures ($\geq \gamma_2$ &$< \gamma_3$)	Extreme heat temperatures ($\geq \gamma_3$)	All temperatures
2001-2005	-14	-13	131	6	109
2006-2010	-15	-17	167	39	174
2011-2015	-15	-21	180	9	154
All years	-43	-52	478	54	437

Appendix

Table 1A – Specification and summary statistics of the explanatory variables in the threshold models

Type of Variable	Variable description	Variable Type	min	1st perc.	5th perc.	50th perc.	Mean	95th perc.	99th perc.	max	N
Days of the week	Monday	DV	0.00	0.00	0.00	0.00	0.14	1.00	1.00	1.00	27085
	Tuesday	DV	0.00	0.00	0.00	0.00	0.14	1.00	1.00	1.00	27085
	Thursday	DV	0.00	0.00	0.00	0.00	0.14	1.00	1.00	1.00	27085
	Friday	DV	0.00	0.00	0.00	0.00	0.14	1.00	1.00	1.00	27085
	Saturday	DV	0.00	0.00	0.00	0.00	0.14	1.00	1.00	1.00	27085
	Sunday	DV	0.00	0.00	0.00	0.00	0.14	1.00	1.00	1.00	27085
Months	January	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	February	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	March	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	April	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	June	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	July	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	August	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	September	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	October	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	November	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
	December	DV	0.00	0.00	0.00	0.00	0.08	1.00	1.00	1.00	27085
Years	Year 2001	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2002	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2003	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2004	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2005	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2006	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2007	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2008	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2009	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2010	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2011	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2012	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2013	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
	Year 2014	DV	0.00	0.00	0.00	0.00	0.07	1.00	1.00	1.00	27085
Elderly population	Population >75	%	5.09	5.09	5.10	5.86	6.18	7.58	7.60	7.60	27085
Days with low mortality	Low	DV	0.00	0.00	0.00	0.00	0.02	0.00	0.00	1.00	27085
	Very low	DV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	27085
Extreme heat measure	Excess Heat Index - Acclimatisation	°C (3 day average temperature / 30 day average temperature)	-9.92	-5.03	-3.47	-0.08	-0.00	3.79	6.25	12.52	27085

Table 2A – Mapping of ABS mortality data and BOM weather stations

Region		Greater Capital City Statistical Division	Statistical Area (Level 4)	BOM Weather Station
Sydney		1GSYD Greater Sydney		66062 – Observatory Hill
	East, City and Inner West		117 Sydney - City and Inner South; 118 Sydney - Eastern Suburbs; 120 Sydney - Inner West;	66062 – Observatory Hill
	North		121 Sydney - North Sydney and Hornsby; 122 Sydney - Northern Beaches; 126 Sydney - Ryde;	66131 – Lane Cove; 66059 – Terrey Hills AWS
	South		119 Sydney - Inner South West; 128 Sydney - Sutherland	66194 – Canterbury
	West		115 Sydney - Baulkham Hills and Hawkesbury; 116 Sydney - Blacktown; 125 Sydney - Parramatta	67019 – Prospect Dam
	Outer West		127 Sydney - South West; 123 Sydney - Outer South West; 124 Sydney - Outer West and Blue Mountains	68192 – Camden
	Central Coast		102 Central Coast	61087 – Gosford; 61425 – Gosford AWS
Melbourne		2GMEL Greater Melbourne		87031 – Laverton RAAF
	Inner		206 Melbourne - Inner; 207 Melbourne - Inner East; 208 Melbourne - Inner South	86068 – Viewbank
	North and West		209 Melbourne - North East; 210 Melbourne - North West; 213 Melbourne - West	86282 – Melbourne Airport
	East and Mornington		211 Melbourne - Outer East; 212 Melbourne - South East; 214 Mornington Peninsula	86375 – Cranbourne Botanic Gardens
Brisbane		3GBRI Greater Brisbane		40842 – Brisbane Airport
	Brisbane City		301 Brisbane - East; 302 Brisbane - North; 303 Brisbane - South; 304 Brisbane - West; 305 Brisbane Inner City	40913 – Brisbane
	Ipswich, Logan and Morten Bay		310 Ipswich; 311 Logan - Beaudesert; 313 Moreton Bay - North; 314 Moreton Bay - South	40004 – Amberley AMO
Adelaide		4GADE Greater Adelaide		23090 – Adelaide (Kent Town)
	North, Central and Hills		403 Adelaide - South; 404 Adelaide - West	23034 – Adelaide Airport
	West and South		401 Adelaide - Central and Hills; 402 Adelaide - North	23013 – Parafield Airport
Perth		5GPER Greater Perth		9021 – Perth Airport
	West		503 Perth - Inner; 505 Perth - North West; 507 Perth - South West	9215 – Swanbourne
	East		502 Mandurah; 504 Perth - North East; 506 Perth - South East	9106 – Gosnells City

Table 3A – Goodness of fit and threshold statistics from the different threshold models

Dependent variable	Region	Number of thresholds	AIC	Threshold effect F-test	Estimation results shown in:
Number of deaths per region	All Capital Cities	**1**	185133.60	65.48**	
		2	185097.90	54.31***	
		3	185091.70	30.48	Table 4A
		3 (6 lags of EHI_A)	185370.10	21.54	Table 6A
	All City Areas	**1**	446351.00	94.01***	
		2	446340.00	40.50*	
		3	446336.00	34.06	Table 4A
		3 (6 lags of EHI_A)	447078.30	22.23	Table 6A
Number of deaths per 100,000	All Capital Cities	**1**	11806.91	231.75***	
		2	11803.76	233.31***	
		3	11804.05	232.03***	Table 5A
		3 (6 lags of EHI_A)	11798.59	13.23	Table 7A
	All City Areas	**1**	106701.80	1415.68***	
		2	106697.10	1415.88***	
		3	106699.50	1415.24***	Table 5A
		3 (6 lags of EHI_A)	106861.00	13.00	Table 7A

Note: The Threshold effect F-test is run sequentially for each threshold. The null hypothesis is whether a lesser number of thresholds is appropriate. For the three threshold model, the null is whether a model with less than three thresholds is appropriate versus the alternative hypothesis of a three threshold model being appropriate. While the Threshold effect F-test indicates that either two or three thresholds are preferred to one threshold, the AIC statistics indicate that three threshold model produced the better model fit. Statistical Significance is indicated as: * for p<0.01, ** for p<0.05, * for p<0.1.**

Table 4A – Threshold regression model results – Number of deaths per region

Variables	All Capital Cities		All City Areas	
	Coef.	SE	Coef.	SE
Constant	30.59***	4.789	3.612***	0.452
Monday	-0.663***	0.168	-0.199***	0.0496
Tuesday	-0.292*	0.168	-0.0635	0.0495
Thursday	0.231	0.168	0.0623	0.0495
Friday	0.859***	0.168	0.251***	0.0496
Saturday	0.519***	0.168	0.173***	0.0496
Sunday	-0.624***	0.168	-0.196***	0.0496
January	-3.854***	0.246	-1.261***	0.0733
February	-4.078***	0.236	-1.345***	0.0698
March	-3.729***	0.220	-1.221***	0.0650
April	-2.586***	0.218	-0.860***	0.0645
June	2.733***	0.219	0.865***	0.0648
July	5.191***	0.223	1.636***	0.0660
August	5.244***	0.236	1.655***	0.0703
September	2.483***	0.249	0.820***	0.0754
October	-0.360	0.246	-0.128*	0.0739
November	-2.331***	0.251	-0.758***	0.0749
December	-3.228***	0.243	-1.058***	0.0725
Year 2001	-5.428***	0.419	-1.077***	0.0827
Year 2002	-4.550***	0.357	-0.926***	0.0778
Year 2003	-5.323***	0.312	-1.266***	0.0758
Year 2004	-5.566***	0.278	-1.425***	0.0744
Year 2005	-5.999***	0.258	-1.672***	0.0735
Year 2006	-5.219***	0.251	-1.454***	0.0732
Year 2007	-3.752***	0.252	-0.993***	0.0732
Year 2008	-2.804***	0.258	-0.722***	0.0735
Year 2009	-3.188***	0.271	-0.776***	0.0739
Year 2010	-2.760***	0.268	-0.685***	0.0736
Year 2011	-1.728***	0.261	-0.401***	0.0733
Year 2012	-1.222***	0.262	-0.284***	0.0733
Year 2013	-1.220***	0.259	-0.317***	0.0731
Year 2014	0.240	0.250	0.105	0.0729
Population >75	2.805***	0.778	1.952***	0.0694
Low mortality	-16.74***	0.918	-7.284***	0.0811
VLow mortality	-37.61***	4.264	-10.21***	0.446

Temperature thresholds – All Capital Cities
EHI-A (1st Thresh.) = -3.51
EHI-A (2nd Thresh.) = 1.95
EHI-A (3rd Thresh.) = 7.26
Temperature thresholds – All City Areas
EHI-A (1st Thresh.) = -3.36
EHI-A (2nd Thresh.) = 3.61
EHI-A (3rd Thresh.) = 7.98

Variables	No. of lags	All Capital Cities		All City Areas	
		Coef.	SE	Coef.	SE
EHI-A < γ_1	0	0.538*	0.319	0.200**	0.0957
EHI-A ≥ γ_1 & < γ_2		0.103	0.0841	0.0497**	0.0211
EHI-A ≥ γ_2 & < γ_3		0.0512	0.124	-0.0722	0.0554
EHI-A ≥ γ_3		-0.733	0.583	-0.489*	0.291
EHI-A < γ_1	1	-0.810	0.582	-0.198	0.171
EHI-A ≥ γ_1 & < γ_2		0.299**	0.139	0.0685*	0.0352
EHI-A ≥ γ_2 & < γ_3		0.270	0.229	0.156	0.105
EHI-A ≥ γ_3		-2.163*	1.190	-0.628	0.619
EHI-A < γ_1	2	-0.0141	0.574	-0.00951	0.164
EHI-A ≥ γ_1 & < γ_2		0.0174	0.141	0.0458	0.0355
EHI-A ≥ γ_2 & < γ_3		0.471**	0.240	0.0107	0.114
EHI-A ≥ γ_3		6.731***	1.370	2.547***	0.686
EHI-A < γ_1	3	1.249**	0.626	0.271	0.181
EHI-A ≥ γ_1 & < γ_2		-0.431***	0.160	-0.120***	0.0408
EHI-A ≥ γ_2 & < γ_3		-0.336	0.293	0.128	0.143
EHI-A ≥ γ_3		-2.863*	1.717	-0.685	0.765
EHI-A < γ_1	4	-2.086***	0.699	-0.494**	0.205
EHI-A ≥ γ_1 & < γ_2		0.137	0.181	-0.000114	0.0458
EHI-A ≥ γ_2 & < γ_3		-0.395	0.340	-0.0904	0.161
EHI-A ≥ γ_3		-2.250	1.897	-1.998**	0.930
EHI-A < γ_1	5	0.911	0.699	0.117	0.198
EHI-A ≥ γ_1 & < γ_2		0.118	0.180	0.0673	0.0458
EHI-A ≥ γ_2 & < γ_3		0.598*	0.343	-0.215	0.165
EHI-A ≥ γ_3		2.364	2.089	2.155**	0.918
EHI-A < γ_1	6	1.272*	0.699	0.549***	0.204
EHI-A ≥ γ_1 & < γ_2		-0.222	0.187	-0.0866*	0.0478
EHI-A ≥ γ_2 & < γ_3		-0.186	0.365	0.368**	0.172
EHI-A ≥ γ_3		-0.683	2.176	-0.769	0.938
EHI-A < γ_1	7	-1.960***	0.723	-0.693***	0.212
EHI-A ≥ γ_1 & < γ_2		0.0899	0.190	-0.00200	0.0486
EHI-A ≥ γ_2 & < γ_3		-0.457	0.375	-0.116	0.174
EHI-A ≥ γ_3		-0.328	2.008	-0.205	1.109
EHI-A < γ_1	8	0.539	0.728	0.173	0.203
EHI-A ≥ γ_1 & < γ_2		0.0527	0.189	0.0774	0.0486
EHI-A ≥ γ_2 & < γ_3		0.505	0.379	-0.290	0.180
EHI-A ≥ γ_3		0.627	2.316	0.377	1.099
EHI-A < γ_1	9	1.534**	0.712	0.251	0.198
EHI-A ≥ γ_1 & < γ_2		-0.207	0.185	-0.0879*	0.0477
EHI-A ≥ γ_2 & < γ_3		-0.152	0.370	0.308*	0.176
EHI-A ≥ γ_3		1.932	2.246	1.678*	1.008
EHI-A < γ_1	10	-1.753**	0.683	-0.0747	0.196
EHI-A ≥ γ_1 & < γ_2		0.247	0.178	0.0201	0.0457
EHI-A ≥ γ_2 & < γ_3		-0.402	0.361	-0.0287	0.169
EHI-A ≥ γ_3		-2.719	1.796	-2.157**	0.968
EHI-A < γ_1	11	0.268	0.698	-0.137	0.195
EHI-A ≥ γ_1 & < γ_2		-0.0543	0.177	0.0430	0.0457
EHI-A ≥ γ_2 & < γ_3		0.438	0.360	-0.166	0.173
EHI-A ≥ γ_3		-1.529	1.906	-1.034	0.950
EHI-A < γ_1	12	0.646	0.619	0.129	0.173
EHI-A ≥ γ_1 & < γ_2		-0.226	0.157	-0.0762*	0.0406
EHI-A ≥ γ_2 & < γ_3		0.120	0.311	0.162	0.150
EHI-A ≥ γ_3		4.002**	1.668	2.772***	0.800
EHI-A < γ_1	13	-0.293	0.525	0.00813	0.149
EHI-A ≥ γ_1 & < γ_2		0.197	0.137	0.0326	0.0352
EHI-A ≥ γ_2 & < γ_3		-0.190	0.269	0.0958	0.130
EHI-A ≥ γ_3		-1.100	1.430	-1.065	0.680
EHI-A < γ_1	14	-0.200	0.489	-0.0702	0.138
EHI-A ≥ γ_1 & < γ_2		0.0296	0.134	0.0283	0.0349
EHI-A ≥ γ_2 & < γ_3		-0.118	0.266	-0.176	0.130
EHI-A ≥ γ_3		-2.899*	1.493	-1.524**	0.682
EHI-A < γ_1	15	0.137	0.255	-0.00102	0.0742
EHI-A ≥ γ_1 & < γ_2		-0.135*	0.0756	-0.0471**	0.0201
EHI-A ≥ γ_2 & < γ_3		0.151	0.150	0.0384	0.0742
EHI-A ≥ γ_3		2.350***	0.815	1.336***	0.402
Observations		27,085		81,255	
R-squared (within)		0.250		0.201	
R-squared (between)		0.024		0.019	
F stat		91.60***		207.72***	
Number of groups		5		15	

Note: Variables for Wednesday, May and the Year 2015 are not included and absorbed into the constant. Statistical Significance is indicated as: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 5A – Threshold regression model results – Number of deaths per 100,000

Variables	All Capital Cities		All City Areas		Variables	No. of lags	All Capital Cities		All City Areas	
	Coef.	SE	Coef.	SE			Coef.	SE	Coef.	SE
Constant	1.303***	0.195	0.223***	0.056	**EHI-A $< \gamma_1$**	0	0.031**	0.013	0.005	0.004
Monday	-0.027***	0.007	-0.022***	0.006	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		0.004	0.003	0.001	0.010
Tuesday	-0.009	0.007	-0.010	0.006	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		0.000	0.006	0.002	0.004
Thursday	0.011*	0.007	0.007	0.006	**EHI-A $\geq \gamma_3$**		-0.023	0.024	-0.025	0.020
Friday	0.031***	0.007	0.029***	0.006	**EHI-A $< \gamma_1$**	1	-0.033	0.024	0.004	0.006
Saturday	0.023***	0.007	0.020***	0.006	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		0.018***	0.005	0.012	0.012
Sunday	-0.017**	0.007	-0.021***	0.006	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		0.002	0.011	0.010	0.006
January	-0.130***	0.010	-0.153***	0.009	**EHI-A $\geq \gamma_3$**		-0.109**	0.049	-0.038	0.042
February	-0.137***	0.010	-0.158***	0.009	**EHI-A $< \gamma_1$**	2	-0.015	0.023	0.005	0.006
March	-0.121***	0.009	-0.146***	0.008	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		-0.006	0.005	-0.021*	0.012
April	-0.093***	0.009	-0.103***	0.008	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		0.026**	0.012	0.012*	0.007
June	0.105***	0.009	0.105***	0.008	**EHI-A $\geq \gamma_3$**		0.241***	0.056	0.140***	0.050
July	0.199***	0.009	0.204***	0.008	**EHI-A $< \gamma_1$**	3	0.073***	0.026	-0.013*	0.007
August	0.212***	0.010	0.205***	0.009	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		-0.013**	0.006	0.018	0.014
September	0.113***	0.010	0.100***	0.009	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		-0.013	0.015	-0.017**	0.008
October	0.011	0.010	-0.013	0.009	**EHI-A $\geq \gamma_3$**		0.010	0.070	-0.045	0.062
November	-0.064***	0.010	-0.088***	0.009	**EHI-A $< \gamma_1$**	4	-0.091***	0.029	-0.004	0.007
December	-0.100***	0.010	-0.119***	0.009	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		0.012*	0.007	-0.005	0.016
Year 2001	0.156***	0.017	0.261***	0.010	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		-0.025	0.018	0.003	0.009
Year 2002	0.164***	0.015	0.262***	0.010	**EHI-A $\geq \gamma_3$**		-0.183**	0.077	-0.048	0.067
Year 2003	0.125***	0.013	0.205***	0.009	**EHI-A $< \gamma_1$**	5	0.018	0.029	0.011	0.007
Year 2004	0.093***	0.011	0.163***	0.009	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		-0.010	0.007	-0.007	0.016
Year 2005	0.070***	0.011	0.116***	0.009	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		0.035*	0.018	-0.001	0.009
Year 2006	0.073***	0.010	0.116***	0.009	**EHI-A $\geq \gamma_3$**		0.007	0.085	0.055	0.068
Year 2007	0.099***	0.010	0.132***	0.009	**EHI-A $< \gamma_1$**	6	0.077***	0.029	-0.009	0.008
Year 2008	0.096***	0.011	0.130***	0.009	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		-0.001	0.007	-0.011	0.016
Year 2009	0.045***	0.011	0.090***	0.009	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		-0.009	0.019	0.004	0.010
Year 2010	0.034***	0.011	0.067***	0.009	**EHI-A $\geq \gamma_3$**		0.164*	0.089	-0.024	0.072
Year 2011	0.038***	0.011	0.071***	0.009	**EHI-A $< \gamma_1$**	7	-0.084***	0.030	-0.007	0.008
Year 2012	0.028***	0.011	0.058***	0.009	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		0.010	0.007	0.031*	0.017
Year 2013	-0.003	0.011	0.020**	0.009	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		-0.027	0.019	-0.005	0.010
Year 2014	0.020*	0.010	0.039***	0.009	**EHI-A $\geq \gamma_3$**		-0.097	0.082	0.007	0.071
Population >75	0.053*	0.032	0.227***	0.009	**EHI-A $< \gamma_1$**	8	0.010	0.030	0.016**	0.008
Low mortality	-0.874***	0.037	-1.032***	0.010	**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		-0.010	0.007	-0.013	0.016
VLow mortality	-1.379***	0.174	-1.680***	0.055	**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		0.017	0.020	-0.000	0.010
					EHI-A $\geq \gamma_3$		-0.036	0.094	-0.005	0.077
					EHI-A $< \gamma_1$	9	0.071**	0.029	-0.009	0.007
					EHI-A $\geq \gamma_1$ & $< \gamma_2$		-0.004	0.007	-0.012	0.016
					EHI-A $\geq \gamma_2$ & $< \gamma_3$		0.013	0.019	-0.005	0.010
					EHI-A $\geq \gamma_3$		0.158*	0.092	0.076	0.077
					EHI-A $< \gamma_1$	10	-0.075***	0.028	-0.003	0.007
					EHI-A $\geq \gamma_1$ & $< \gamma_2$		0.015**	0.007	0.006	0.016
					EHI-A $\geq \gamma_2$ & $< \gamma_3$		-0.029	0.019	0.010	0.009
					EHI-A $\geq \gamma_3$		-0.147**	0.073	-0.101	0.067
					EHI-A $< \gamma_1$	11	0.010	0.028	0.008	0.007
					EHI-A $\geq \gamma_1$ & $< \gamma_2$		-0.011	0.007	0.021	0.016
Temperature thresholds – All Capital Cities					**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		0.009	0.019	-0.007	0.009
EHI-A (1st Thresh.) = -3.51					**EHI-A $\geq \gamma_3$**		-0.064	0.078	-0.066	0.072
EHI-A (2nd Thresh.) = 2.74					**EHI-A $< \gamma_1$**	12	0.033	0.025	-0.009	0.006
EHI-A (3rd Thresh.) = 7.26					**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		-0.005	0.006	-0.023*	0.014
					EHI-A $\geq \gamma_2$ & $< \gamma_3$		0.020	0.016	-0.004	0.008
Temperature thresholds – All City Areas					**EHI-A $\geq \gamma_3$**		0.188***	0.068	0.196***	0.061
EHI-A (1st Thresh.) = 0.33					**EHI-A $< \gamma_1$**	13	-0.031	0.021	-0.000	0.006
EHI-A (2nd Thresh.) = 0.98					**EHI-A $\geq \gamma_1$ & $< \gamma_2$**		0.011**	0.005	-0.005	0.012
EHI-A (3rd Thresh.) = 6.71					**EHI-A $\geq \gamma_2$ & $< \gamma_3$**		-0.013	0.014	0.013*	0.007
					EHI-A $\geq \gamma_3$		-0.084	0.058	-0.083	0.051
					EHI-A $< \gamma_1$	14	0.009	0.020	0.009*	0.005
					EHI-A $\geq \gamma_1$ & $< \gamma_2$		-0.006	0.005	0.014	0.012
					EHI-A $\geq \gamma_2$ & $< \gamma_3$		-0.001	0.014	-0.010	0.007
					EHI-A $\geq \gamma_3$		-0.072	0.061	-0.073	0.053
					EHI-A $< \gamma_1$	15	-0.001	0.010	-0.008***	0.003
					EHI-A $\geq \gamma_1$ & $< \gamma_2$		-0.001	0.003	-0.010	0.007
					EHI-A $\geq \gamma_2$ & $< \gamma_3$		0.005	0.008	0.001	0.004
					EHI-A $\geq \gamma_3$		0.063*	0.033	0.055*	0.030
					Observations		27,085		81,255	
					R-squared (within)		0.194		0.203	
					R-squared (between)		0.920		0.550	
					F stat		66.05***		210.24***	
					Number of groups		5		15	

Note: Variables for Wednesday, May and the Year 2015 are not included and absorbed into the constant. Statistical Significance is indicated as: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 6A – Threshold regression model results – Number of deaths per region – Reduced model

Variables	All Capital Cities		All City Areas	
	Coef.	SE	Coef.	SE
Constant	31.501***	4.774	3.668***	0.451
Monday	-0.652***	0.167	-0.198***	0.049
Tuesday	-0.295*	0.167	-0.064	0.049
Thursday	0.232	0.167	0.059	0.049
Friday	0.855***	0.167	0.246***	0.049
Saturday	0.515***	0.167	0.172***	0.050
Sunday	-0.616***	0.167	-0.195***	0.050
January	-4.027***	0.234	-1.325***	0.070
February	-4.178***	0.228	-1.374***	0.067
March	-3.807***	0.218	-1.239***	0.064
April	-2.610***	0.218	-0.861***	0.064
June	2.707***	0.219	0.862***	0.065
July	5.110***	0.221	1.617***	0.066
August	5.099***	0.228	1.607***	0.068
September	2.310***	0.236	0.738***	0.071
October	-0.540**	0.232	-0.209***	0.069
November	-2.511***	0.236	-0.835***	0.070
December	-3.408***	0.232	-1.129***	0.069
Year 2001	-5.440***	0.417	-1.067***	0.082
Year 2002	-4.588***	0.356	-0.928***	0.078
Year 2003	-5.347***	0.312	-1.266***	0.076
Year 2004	-5.582***	0.278	-1.417***	0.074
Year 2005	-6.011***	0.257	-1.673***	0.074
Year 2006	-5.215***	0.251	-1.448***	0.073
Year 2007	-3.755***	0.252	-0.989***	0.073
Year 2008	-2.815***	0.258	-0.720***	0.073
Year 2009	-3.216***	0.270	-0.774***	0.074
Year 2010	-2.764***	0.268	-0.677***	0.074
Year 2011	-1.741***	0.261	-0.397***	0.073
Year 2012	-1.232***	0.262	-0.285***	0.073
Year 2013	-1.230***	0.259	-0.309***	0.073
Year 2014	0.236	0.250	0.101	0.073
Population >75	2.676***	0.776	1.946***	0.069
Low mortality	-16.925***	0.905	-7.288***	0.081
VLow mortality	-37.408***	4.260	-10.354***	0.446

Variables	No. of lags	All Capital Cities		All City Areas	
		Coef.	SE	Coef.	SE
EHI-A < γ_1	0	0.139	0.310	0.042*	0.023
EHI-A ≥ γ_1 & < γ_2		0.136*	0.077	0.042	0.030
EHI-A ≥ γ_2 & < γ_3		0.037	0.117	-0.230**	0.100
EHI-A ≥ γ_3		-0.853	0.558	-0.530**	0.262
EHI-A < γ_1	1	0.077	0.542	0.080**	0.037
EHI-A ≥ γ_1 & < γ_2		0.254**	0.123	0.058	0.051
EHI-A ≥ γ_2 & < γ_3		0.374*	0.211	0.196	0.190
EHI-A ≥ γ_3		-1.822	1.109	-0.731	0.518
EHI-A < γ_1	2	-0.607	0.540	-0.030	0.037
EHI-A ≥ γ_1 & < γ_2		0.015	0.124	0.117**	0.053
EHI-A ≥ γ_2 & < γ_3		0.350	0.221	0.347	0.213
EHI-A ≥ γ_3		6.330***	1.230	2.569***	0.563
EHI-A < γ_1	3	0.629	0.518	-0.058	0.036
EHI-A ≥ γ_1 & < γ_2		-0.355***	0.124	-0.134**	0.056
EHI-A ≥ γ_2 & < γ_3		-0.390*	0.233	-0.343	0.228
EHI-A ≥ γ_3		-2.732*	1.411	-0.309	0.579
EHI-A < γ_1	4	-0.579	0.492	-0.008	0.036
EHI-A ≥ γ_1 & < γ_2		0.047	0.122	0.015	0.055
EHI-A ≥ γ_2 & < γ_3		-0.099	0.236	0.181	0.218
EHI-A ≥ γ_3		-2.039	1.262	-2.145***	0.536
EHI-A < γ_1	5	0.188	0.494	0.020	0.035
EHI-A ≥ γ_1 & < γ_2		0.115	0.121	0.007	0.054
EHI-A ≥ γ_2 & < γ_3		0.334	0.230	0.053	0.216
EHI-A ≥ γ_3		1.752	1.144	1.424***	0.552
EHI-A < γ_1	6	0.122	0.272	-0.028	0.021
EHI-A ≥ γ_1 & < γ_2		-0.115	0.070	-0.027	0.033
EHI-A ≥ γ_2 & < γ_3		-0.275**	0.134	-0.048	0.131
EHI-A ≥ γ_3		0.052	0.645	0.125	0.315
EHI-A < γ_1	7	N/A – only six lags applied			
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	8				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	9				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	10				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	11				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	12				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	13				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	14				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	15				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
Observations		27,130		81,390	
R-squared (within)		0.249		0.200	
R-squared (between)		0.024		0.019	
F stat		144.37***		327.90***	
Number of groups		5		15	

Temperature thresholds – All Capital Cities
EHI-A (1st Thresh.) = -3.76
EHI-A (2nd Thresh.) = 1.95
EHI-A (3rd Thresh.) = 7.26
Temperature thresholds – All City Areas
EHI-A (1st Thresh.) = 1.21
EHI-A (2nd Thresh.) = 5.34
EHI-A (3rd Thresh.) = 7.98

Note: Variables for Wednesday, May and the Year 2015 are not included and absorbed into the constant. Statistical Significance is indicated as: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 7A – Threshold regression model results – Number of deaths per 100,000 – Reduced model

Variables	All Capital Cities Coef.	All Capital Cities SE	All City Areas Coef.	All City Areas SE
Constant	1.347***	0.195	0.231***	0.056
Monday	-0.026***	0.007	-0.022***	0.006
Tuesday	-0.009	0.007	-0.009	0.006
Thursday	0.012*	0.007	0.008	0.006
Friday	0.031***	0.007	0.030***	0.006
Saturday	0.024***	0.007	0.020***	0.006
Sunday	-0.016**	0.007	-0.021***	0.006
January	-0.137***	0.010	-0.163***	0.009
February	-0.142***	0.009	-0.164***	0.008
March	-0.124***	0.009	-0.151***	0.008
April	-0.093***	0.009	-0.104***	0.008
June	0.105***	0.009	0.103***	0.008
July	0.197***	0.009	0.199***	0.008
August	0.206***	0.009	0.196***	0.008
September	0.105***	0.010	0.090***	0.009
October	0.002	0.009	-0.024***	0.009
November	-0.074***	0.010	-0.099***	0.009
December	-0.108***	0.009	-0.129***	0.009
Year 2001	0.154***	0.017	0.264***	0.010
Year 2002	0.162***	0.015	0.262***	0.010
Year 2003	0.124***	0.013	0.205***	0.009
Year 2004	0.093***	0.011	0.163***	0.009
Year 2005	0.069***	0.011	0.117***	0.009
Year 2006	0.073***	0.010	0.116***	0.009
Year 2007	0.099***	0.010	0.133***	0.009
Year 2008	0.096***	0.011	0.130***	0.009
Year 2009	0.044***	0.011	0.089***	0.009
Year 2010	0.034***	0.011	0.067***	0.009
Year 2011	0.037***	0.011	0.072***	0.009
Year 2012	0.027**	0.011	0.058***	0.009
Year 2013	-0.003	0.011	0.020**	0.009
Year 2014	0.019*	0.010	0.039***	0.009
Population >75	0.046	0.032	0.227***	0.009
Low mortality	-0.878***	0.037	-1.032***	0.010
VLow mortality	-1.364***	0.174	-1.685***	0.055

Variables	No. of lags	All Capital Cities Coef.	All Capital Cities SE	All City Areas Coef.	All City Areas SE
EHI-A < γ_1	0	0.002	0.003	0.006**	0.003
EHI-A ≥ γ_1 & < γ_2		0.013	0.008	0.001	0.004
EHI-A ≥ γ_2 & < γ_3		-0.001	0.006	-0.007	0.024
EHI-A ≥ γ_3		-0.042*	0.023	-0.062*	0.032
EHI-A < γ_1	1	0.014***	0.005	0.006	0.004
EHI-A ≥ γ_1 & < γ_2		0.014	0.015	0.010	0.006
EHI-A ≥ γ_2 & < γ_3		0.008	0.011	-0.037	0.047
EHI-A ≥ γ_3		-0.076*	0.045	-0.060	0.064
EHI-A < γ_1	2	-0.003	0.005	-0.002	0.004
EHI-A ≥ γ_1 & < γ_2		0.004	0.015	0.013**	0.007
EHI-A ≥ γ_2 & < γ_3		0.021*	0.012	0.094*	0.054
EHI-A ≥ γ_3		0.247***	0.050	0.273***	0.070
EHI-A < γ_1	3	-0.010**	0.005	-0.005	0.004
EHI-A ≥ γ_1 & < γ_2		-0.034**	0.016	-0.019***	0.007
EHI-A ≥ γ_2 & < γ_3		-0.016	0.012	-0.048	0.062
EHI-A ≥ γ_3		-0.068	0.058	-0.061	0.072
EHI-A < γ_1	4	0.000	0.005	-0.002	0.004
EHI-A ≥ γ_1 & < γ_2		0.037**	0.016	0.005	0.007
EHI-A ≥ γ_2 & < γ_3		-0.013	0.013	0.027	0.055
EHI-A ≥ γ_3		-0.121**	0.052	-0.217***	0.066
EHI-A < γ_1	5	0.002	0.005	0.002	0.004
EHI-A ≥ γ_1 & < γ_2		-0.018	0.015	-0.001	0.007
EHI-A ≥ γ_2 & < γ_3		0.024**	0.012	0.016	0.051
EHI-A ≥ γ_3		0.072	0.047	0.169**	0.068
EHI-A < γ_1	6	-0.002	0.003	-0.002	0.003
EHI-A ≥ γ_1 & < γ_2		-0.005	0.009	-0.002	0.004
EHI-A ≥ γ_2 & < γ_3		-0.018**	0.007	-0.016	0.033
EHI-A ≥ γ_3		0.014	0.026	-0.017	0.039
EHI-A < γ_1	7	N/A – only six lags applied			
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	8				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	9				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	10				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	11				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	12				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	13				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	14				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
EHI-A < γ_1	15				
EHI-A ≥ γ_1 & < γ_2					
EHI-A ≥ γ_2 & < γ_3					
EHI-A ≥ γ_3					
Observations		27,130		81,390	
R-squared (within)		0.192		0.202	
R-squared (between)		0.920		0.550	
F stat		103.63***		331.85***	
Number of groups		5		15	

Temperature thresholds – All Capital Cities
EHI-A (1st Thresh.) = 2.01
EHI-A (2nd Thresh.) = 2.84
EHI-A (3rd Thresh.) = 7.26
Temperature thresholds – All City Areas
EHI-A (1st Thresh.) = 1.29
EHI-A (2nd Thresh.) = 6.71
EHI-A (3rd Thresh.) = 7.98

Note: Variables for Wednesday, May and the Year 2015 are not included and absorbed into the constant. Statistical Significance is indicated as: *** for p<0.01, ** for p<0.05, * for p<0.1.

Box 1A – Background on short-term mortality displacement

The debate surrounding the magnitude of temperature-related mortality that coincided with certain extreme heat events has led to a range of studies that measure short-term mortality displacement (Benmarhnia et al. 2016; Braga et al. 2001; Hajat et al. 2005; Kaiser et al. 2007; Le Tertre et al. 2006; Toulemon and Barbieri 2008). The key issue being the extent to which temperature-related deaths coincided with people who were likely to die from another cause within a short amount of time. Previous studies have found differing results on the extent to which mortality displacement occurs. A study that utilised data from Brisbane found that heat tended to be related to a short displacement period of between two days and one week (Yu et al. 2011). Saha et al. (2013) utilised a short-term mortality displacement period that was limited to a maximum of 15 days after the extreme heat event and found that mortality displacement varied with the severity of heat events and the city focused upon. A similar time-frame for short-term displacement is used in this paper as it is consistent with the findings of Guo et al. (2014). Guo et al. (2014) found that the duration of cold-related mortality lasted for 10 days after the event and for heat-related mortality it lasted 3 days. Note that distinguishing between short-term and long-term mortality displacement is important as a previous study associated high respiratory, cardiovascular and influenza mortality in winter with lower temperature effects in the following summer (Rocklöv et al. 2009).