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Temperature, health and wellbeing in Australia☆

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ABSTRACT

We examine the effects of temperature on general health and subjective wellbeing. We combine daily temperature data with 19 waves of panel data from the Household, Income and Labour Dynamics in Australia Survey. We find evidence of an inverted U-shaped relationship between temperature and general health. However, the effect of temperature on subjective wellbeing is less robust. We examine whether the adoption of air conditioning technology moderates the observed relationship between temperature and health. Our results show that there is no robust evidence for the role of air conditioning in moderating the relationship between temperature and health/wellbeing. Further, we conducted a mediation analysis to examine whether sleep quality serves as a channel through which the effect of temperature transmits to health. We find little evidence in support of sleep quality as a mechanism.

1. Introduction

The recent COVID-19 global pandemic has been a poignant reminder of how threats to our health and wellbeing have serious implications for human lives, livelihoods, and economic performance. Research that seeks to understand threats to health and wellbeing is pertinent to enable more informed planning and enforce appropriate preventive measures. Climate and weather changes have long been touted as one such key threat to health and wellbeing (Fritze et al., 2008; McMichael et al., 2003; McMichael et al., 2006; Mullins & White, 2019; Mullins & White, 2020). As the average temperature of the world gradually becomes warmer, research on climate change and atmospheric conditions and how they impact on various outcomes has garnered growing interest (Awaworyi Churchill et al., 2023; McMichael et al., 2006). A related body of literature focuses on the impact of weather and temperature, both of which are more short-run phenomena compared to climate change (Dell et al., 2012, 2014). Anecdotally, we know that the weather and daily temperature have important consequences for our daily activities, the clothing we wear and how much time we spend outdoors or indoors. But do temperature and weather changes affect our health and wellbeing?

Although there seems to be a general consensus in the literature that extreme temperature changes and climate events have negative impacts on health and wellbeing, evidence on the effects of daily and seasonal temperature changes on health and wellbeing remain mixed (Barreca et al., 2016; Lucas & Lawless, 2013; McMichael et al., 2006). Some research finds little or no effect, while those studies that do find effects show mixed and contrasting results (Dell et al., 2014; Deschenes, 2014; Frijters et al., 2020; Lucas & Lawless, 2013). Importantly, there is very little evidence on the channels through which short-run changes in temperature affect subjective health and wellbeing, which is a significant shortcoming in the existing literature given the growing tendency among policymakers to use subjective indicators of health and wellbeing to monitor human progress and the impact of policy (Fujiwara & Campbell, 2011; Sachs et al., 2016).

We examine the impact of temperature on self-reported general health and wellbeing, and the channels through which the effect of temperature transmits to health. To do so, we use 19 waves of Australian

☆ This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper are those of the authors and should not be attributed to the DSS or the Melbourne Institute.

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panel data from the Household, Income and Labour Dynamics in Australia (HILDA) survey covering the period 2001 to 2019, and daily temperature data from the Australian Bureau of Meteorology. We measure self-reported general health using the general health subscales of the Short Form 36 (SF-36) and wellbeing using the overall life satisfaction scale.

We find robust evidence for the negative effects of cold and hot temperatures on general health and weak evidence for the effect on subjective wellbeing. Specifically, our results show that changes in temperature lead to a significant negative effect on general health if it is colder than 40 °F (4.4 °C) and hotter than 90 °F (32.2 °C). This general finding is robust to a suite of checks. We find that air conditioning (AC) penetration does not alter the effect of temperature on health and wellbeing. We examine sleep quality as a potential mechanism through which the effect of temperature transmits to general health and find no evidence in support of this.

We contribute to several strands of literature. The first is the growing body of literature that has examined the effects of temperature and other weather conditions on outcomes other than health including agriculture, economic growth, mortality and crime, among others (see, e.g., Auffhammer et al., 2013; Awaworyi Churchill et al., 2022; Barreca & Shimshack, 2012; Dell et al., 2012; Deschênes & Greenstone, 2007; Field, 1992; Jacob et al., 2007; Levy & Galili, 2008; Trinh et al., 2022; Welch et al., 2010). Our study also contributes to the related body of literature that has examined the impact of climate change (see, e.g., Auffhammer et al., 2012; Deschênes & Greenstone, 2007; Hamilton & Tol, 2007; Hoegh-Guldberg & Bruno, 2010; Mall et al., 2006; Tol, 2009, 2018).

Our study also relates to those that examine the impact of sleep quality on health and wellbeing (see, e.g., Blair & Morris, 2009; Hale et al., 2013; Hallal et al., 2006; Miles, 2007; Powell et al., 2011; Vuillemin et al., 2005; Warburton & Bredin, 2016), as well as those that examine the direct effects of weather conditions on sleep quality (Chan et al., 2006; Lan et al., 2017). Our study differs from these studies given that we focus on sleep quality as a mediator in the temperature-wellbeing relationship.

Our main contribution is to literature examining the impact of temperature on health outcomes (see, e.g., Deschenes, 2014; Li et al., 2020; McMichael et al., 2006; Mullins & White, 2019; O'Neill & Ebi, 2009; Xu et al., 2012). Within this literature, our study is closely related to those that have examined the effects of weather and temperature on self-reported indicators of health and wellbeing (Connolly, 2013; Frijters et al., 2020; Li et al., 2020; Mullins & White, 2019). Evidence from most of these studies is based on cross-sectional data and focuses on the United States (US). Connolly (2013) provides evidence for the impact of weather on subjective happiness, while Mullins and White (2019) and Li et al. (2020) provide evidence for the impact of temperature on mental health. The closest study in the literature to ours in terms of the outcomes we examine is Frijters et al. (2020), which examines the impact of temperature on self-reported general health and life satisfaction using cross-sectional data from the US. We differ from Frijters et al. (2020) in that we use 19 years of longitudinal data and present evidence for a country other than the US. Unless indicators of time-invariant personality traits are included as additional regressors in subjective health or wellbeing regressions, it is generally difficult to control for unobserved heterogeneity using cross-sectional data (Awaworyi Churchill et al., 2020).

By using 19 years of household panel data, we effectively control for unobserved factors and the influence of time-invariant unobserved individual and seasonal fixed effects. Through our focus on Australia, we build on the existing literature by providing evidence on a country that offers a unique climatic context to study the dynamics of how weather influences health and wellbeing. Given that Australia is in the southern hemisphere, its weather conditions differ significantly from those of countries (like the US) in the northern hemisphere. Winters are generally milder, but Australia experiences various seasonal abnormalities especially during the summer season, including extensive droughts, dust storms and heatwaves often accompanied by bush fires (Collins et al., 2000; Deo et al., 2007). Additionally, unlike Frijters et al. (2020), we also examine the channels through which temperature influences health and wellbeing. Specifically, we examine sleep quality as a channel through which temperature transmits to general health.

The remainder of the paper is structured as follows. The next section provides further discussions on the literature related to our study. Section 3 describes the data and empirical strategy. Section 4 presents and discusses the results. Section 5 concludes.

2. Related literature

Temperature can have direct and indirect effects on general health and wellbeing. In this section, we present discussions on the direct as well as indirect effects. We discuss how temperature is linked to health and wellbeing drawing on evidence from the literature. We also present discussions on sleep quality as a mediator linking temperature to health and wellbeing.

2.1. *Direct effects*

Temperature directly affects health by inducing physiological effects on the body and its normal functioning that result in increased morbidity (Deschenes, 2014). Extreme hot temperatures that occur during heatwaves can result in heat stress, heat shocks and heat strokes, while extreme cold temperatures can result in cold-related deaths as the body's natural thermoregulation is unable to cope with extreme weather changes (Hajat et al., 2006; McMichael et al., 2006). Very hot and cold temperatures result in increased hospital admissions for cardiovascular and respiratory problems (Deschenes, 2014; McMichael et al., 2006; O'Neill & Ebi, 2009), as well as problems associated with the nervous system, digestion, breathing, and general discomfort with various vital organs (Xiong et al., 2017). Although there is little research on hospitalization for non-fatal temperature-related illnesses, empirical evidence has linked different temperature conditions with health. For example, Deschênes and Greenstone (2011) find that there is a U-shaped non-linear relationship between temperature and mortality, with significant increases at the extremes of the temperature distribution.

The physiological effects of extreme temperatures and related deaths are more likely among vulnerable population groups such as the aged, women, children and infants, people with existing chronic diseases and mental illness, the homeless and those living in houses with poor insulation against extreme heat or cold (Deschênes & Greenstone, 2011; Kovats & Hajat, 2008). For instance, in utero exposure to extreme temperatures has been associated with low birth weight (Deschênes et al., 2009), while the prevalence of stroke and cardiovascular diseases induced by extreme temperatures is higher among people aged 60 years and above (Ebi et al., 2004; Morabito et al., 2005). Extreme weather conditions also increase the vulnerability of children and infants to infectious diseases, such as malaria, hand, foot and mouth disease, as well as respiratory, renal and gastrointestinal diseases (Xu et al., 2012).

On a positive note, more recently, increases in temperature have been linked to a slightly reduced rate of COVID-19 infection (Ozyigit, 2020). Extreme hot temperatures can also reduce winter-related diseases and deaths and also slow mosquito reproduction in places where high temperature disrupts rainfall patterns (McMichael et al., 2006). Except for a few instances of positive effects of temperature documented in the literature, overall, existing research tends to suggest that high temperature has a predominantly negative effect on health. However, the research mostly focuses on the effects of extreme temperature and weather events, and also tends to use indicators relating to mortality and morbidity as measures of health (Deschenes, 2014; McMichael et al., 2006).

2.2. *Indirect effects*

Temperature indirectly impacts health by creating an enabling environment that increases morbidity (Deschenes, 2014). The effects of temperature on subjective wellbeing are often indirect. Intuitively, we can expect that people will dislike extremely cold and hot weathers, and this can affect their dispositions and subsequently life satisfaction. On the one hand, an increase in average temperature is related to improved life satisfaction as sunny days tend to promote positive mood compared to cold and wet days (Klimstra et al., 2011; Schwarz & Clore, 1983). Cold and wet weather has been shown to increase self-reported poor mental health and depression, and lower life satisfaction (Hansen et al., 1991; Rosenthal et al., 1984). On the other hand, the opposite effect has been observed in other contexts where higher temperatures have been found to increase negative emotions and fatigue (Connolly, 2013; Noelke et al., 2016). High temperatures have thus been related to an increased incidence of self-reported poor mental health, increases in emergency admissions for mental illness and higher cases of distress and suicide (Carleton, 2017; Li et al., 2020; Mullins & White, 2019).

The observed heterogenous effects of temperature on wellbeing appear to be seasonal, as increases in temperature during (or immediately after) cold weather has a more positive impact on wellbeing and vice versa. For example, using a panel of 67 countries, Rehdanz and Maddison (2005) found that average temperature increases during winter months had a more positive impact on wellbeing, whereas average temperature increases during summer months had a negative effect on wellbeing. Keller et al. (2005) also found that increased temperature during spring was related to better disposition, memory and cognitive function, but this was not the case during other seasons. Thus, while average temperature increase appears to have a negative impact on wellbeing, it may also be beneficial depending on the extent of increase relative to the season or prior average temperature.

Temperature can also influence health and wellbeing via its effect on sleep. Sleep is essential for the body's optimal functioning and recuperation, and thus good quality and sufficient sleep has many important health and wellbeing benefits. Insufficient sleep impairs cognitive functioning, causes stress and poor mental wellbeing, and weakens the body's immune system, making it more susceptible to illness and infections (Besedovsky et al., 2012; Bryant et al., 2004). Limited sleep and lack of quality sleep have been linked with a higher risk of obesity, diabetes and heart diseases (Obradovich et al., 2017). However, temperature is known to impact on sleep quality and duration (Franco et al., 2000; Obradovich et al., 2017; Pan et al., 2012). Temperature is fundamental to people's ability to fall and stay asleep given that sleep is dependent on the intersectional effects of body temperature and ambient temperature; increases in either can adversely affect sleep quality. Increases in temperature are associated with insufficient sleep during summer (Obradovich et al., 2017), while cold temperatures are associated with insomnia during winter (Johnsen et al., 2012). Several prominent studies also document evidence on the negative effect on health of loss of hours due to observing daylight savings (Barnes and Wanger, 2009; Jin and Ziebarth, 2020; Smith, 2016) and social jetlag (Giuntella and Mazzonna, 2019). Along these lines, a recent study by Costa-Font et al., and Pagan (2021) suggests that daylight saving time changes in Spring leads to a decline in life satisfaction due to sleep deprivation, which in turn negatively impacts physical and emotional health.

3. Data and empirical strategy

3.1. Data

We use data from two main sources. Individual- and household-level information is drawn from Release 19 of the HILDA longitudinal survey. The HILDA survey, which Watson and Wooden (2012) describe in more detail, is a nationally representative household longitudinal study that provides information on family, work, income, wealth, health and socioeconomic variables for Australians.

HILDA conducts interviews annually across multiple months. For Wave 1, interviews began in August 2001 and all but a few interviews were completed by December of the same year. However, the fieldwork was extended by several months from wave 2 onwards. Fig. A1 shows the proportion of individual interviews conducted by calendar month. As demonstrated, individual interviews are spread across several months between July and March, with the largest proportion in August, September and October. There are also variations in the distribution of interviews over time. For example, the proportion of interviews conducted in July sharply increased from Wave 9 onwards, while those in September and October declined. Fig. A2 shows the distribution of individual interviews with reference to the anniversary of the prior wave's interview. The figure shows that significant variations across the period of individual interviews relative to the previous interview months. As shown in Fig. A2, while most respondents were interviewed within 30 days of the anniversary of the previous interview, approximately 4% were conducted three or more months before or after the anniversary of the interview in the previous wave. These variations across interview dates are important for identification in our empirical analysis.

Air temperature data are taken from the Australian Bureau of Meteorology. Air temperature captures the average molecular thermal energy in the air, where higher temperature indicates higher energy of the molecules. The Bureau of Meteorology provides daily measures of minimum and maximum temperatures according to weather stations throughout Australia. The highest temperature over the previous 24 h is recorded as the maximum temperature for the day on which the observation was made and the lowest temperature in the past 24 h is recorded as the minimum temperature for the day. The mean temperature for the day is given as the average of the two temperatures. We collect daily temperature data from over 850 weather stations across all states and territories in Australia and use daily data on average temperature, maximum temperature, and minimum temperature. We merge the weather data with the HILDA dataset using postcode information available in the restricted release of the HILDA survey. Postcodes are associated with temperature reported for weather stations using the minimum Euclidean distance from the weather station to the postcode based on the geographic coordinates (latitudes and longitudes) of weather stations and postcodes. Thus, using postcode information from the restricted release of HILDA, daily temperature for each postcode is determined as the temperature recorded for the nearest weather station.

3.1.1. General health

We follow the literature in using the transformed sub-scale of the SF-36 as an indicator of general health (see, e.g., Awaworyi et al., 2021; Bobak et al., 1998; Drydakis, 2015; Hailemariam et al., 2021; Hosseinpoor et al., 2012; Shields & Shooshtari, 2001). The SF-36 is an internationally accepted diagnostic tool for assessing functional health and wellbeing status (Ware et al., 2000). It is constructed from the responses to various questions in a five-item health survey that captures information on relative measures of self-assessed health. The first dimension is based on the HILDA question: "In general, would you say your health is: excellent, very good, good, fair or poor". We reverse code the responses as "1=Poor, 2=Fair, 3=Good, 4=Very good, and 5=Excellent". The other dimensions of the general health sub-scale include information from respondents to the HILDA questions: (1) "I get sick a little easier than other people"; (2) "I am as healthy as anybody I know"; (3) "I expect my health to get worse"; and (4) "My health is excellent". The scores for the responses to these questions range between 1 and 5, where 1 is for "Definitely true" and 5 indicates "Definitely false". The responses to questions (2) and (4) are reverse-coded such that lower values represent poor general health and higher values represent better general health. In line with the scoring rules suggested in Ware et al. (2000), the general health sub-scale is constructed based on the five dimensions and transformed to a 0–100 index, where 0 represents "poor general health" and 100 indicates "the best possible general health".

3.1.2. Subjective wellbeing

Our main measure of subjective wellbeing is consistent with the large body of literature that has used indicators of life satisfaction to measure wellbeing (see, e.g., Appau et al., 2019; Awaworyi et al., 2017; Awaworyi et al., 2019; Buddelmeyer & Powdthavee, 2016; Chua et al., 2020; Powdthavee & Wooden, 2015; Prakash et al., 2020; Yin et al., 2023). We measure subjective wellbeing using information from the responses to the HILDA survey question: "All things considered, how satisfied are you with your life?" Responses are coded on a 0 to 10 scale, where 0 means "Totally dissatisfied" and 10 means "Totally satisfied".

3.1.3. Air conditioning (AC) technology as a moderator

We collect historical data on AC penetration rate defined as the proportion of Australian households with at least one air conditioner from the Energy Efficient Strategies Technical Papers (Energy Efficient Strategies, 2006, 2008). Our choice of AC penetration as a modifying factor for the relationship between temperature and health is consistent with Mullins and White (2019). Data on AC are available only at the state level and are time-varying at yearly levels.

3.1.4. Mechanisms: sleep quality

We examine if sleep quality is a channel through which temperature influences general health. We measure sleep quality using information on self-rated sleep quality, available in waves 13 and 17 only. HILDA asks respondents to rate their sleep quality on a four-point scale where "1=Very good, 2=Fairly good, 3=Fairly bad, and 4=Very bad". We reverse code the ratings so that a higher sleep quality rating corresponds with a higher number.

Table A1 presents a description and summary statistics of variables included in the study.

3.2. Empirical Strategy

To estimate the effects of temperature on the outcome variables, consistent with the literature, we adopt a binned model specification to allow for nonparametric responses of health and wellbeing to temperature changes (see, e.g., Barreca et al., 2016; Baylis, 2020; Dell et al., 2014; Deschênes & Greenstone, 2007; Hsiang, 2016; Mullins & Bharadwaj, 2021; Mullins & White, 2019; Mullins & White, 2020). As with the approach outlined in Dell et al. (2014), we transform the temperature variable into a number of temperature bins, which are defined as the number of days in a particular month for which the maximum daily temperature or average daily temperature falls within that bin. The temperature bin for Australian weather consists of seven categories in 10°F interval, ranging from <40°F to >90°F with the 60°F–70°F bin omitted to serve as the reference category.[1] The advantage of the binned method is that it accounts for non-linearities in a non-parametric fashion without the risk of model misspecifications. In addition, the interpretations of the effect of one additional day of temperature relative to a day of reference temperature is straightforward.

We use an empirical specification of the form:

$$y_{ijt} = \alpha + \sum\nolimits_{n=1}^{N} \beta_n T_{n,jt} + X_{ijt}\phi + Z_{jt}\psi + \delta_i + \gamma_m + \tau_y + \eta_p + \pi_{sy} + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} is the outcome variable (i.e., general health and subjective wellbeing) for individual i in neighborhood (i.e., postcode) j at the time t; $T_{n,jt}$ denotes the number of days in a month that fall into 10 °F interval of the maximum daily temperature bin, n; and β_n is the coefficient of interest. X_{ijt} denotes individual-level control variables, including age, income, education, marital status, unemployment and number of dependents. Z_{jt} represents postcode-level factors, including local area unemployment rate and population. We also control a range of fixed effects, including individual fixed effect (δ_i), month fixed effect (γ_m), postcode fixed effect (η_p), year fixed effect (τ_y) and state-by-year fixed effects (π_{sy}). The last term in Eq. (1), ε_{ijt}, is the individual-specific error term. Standard errors are clustered at postcode levels in all regressions to allow for arbitrary within-postcode serial correlation. As a robustness check, we also adopt an alternative binned specification of Eq. (1) using bins of maximum daily temperature, as well as average temperature and minimum temperatures where T_{jt} in Eq. (1) denotes an indicator variable equal to one if it falls in the given bin, n, and zero otherwise.

An important issue regarding identification in the estimation of Eq. (1) is that both local area temperature and the state of wellbeing exhibit substantial seasonality that may bias the estimates if the issue of seasonality is not properly addressed.[2] To address this issue, we include month of year fixed effects so that the estimated coefficients represent a weighted average of the differences in the health and wellbeing on hot days versus cold days within a particular postal area and month. In addition, we include year fixed effects to account for potentially correlated trends in health/wellbeing and temperature in the sample.

Moreover, accounting for cross-sectional variations in health and wellbeing is important in estimating β_n. For example, individuals with higher incomes tend to have higher levels of life satisfaction and can afford to move to states or postal areas with more pleasant weather or climate conditions (Easterlin, 2001). Failure to account for the potential correlation between this variation across postcodes or states and differences in local area weather could result in biased estimates. To account for this issue, we include postcode fixed effects (η_p) and state-by-year fixed effects (π_{sy}) in the model. Consistent with the common practice in the climate literature (e.g., Dell et al., 2014; Mullins & White, 2019), our identification strategy relies on a combination of these fixed effects under the assumption that deviations in temperature are as good as random after accounting for unobserved variation by postcode, month, year and state-by-year fixed effects.

Following the literature, we estimate Eq. (1) at the individual level controlling for a set of baseline covariates, as well as postcode-level factors. In addition to establishing the relationship between temperature and measures of health and wellbeing, we also examine the moderating effects of adaptation to climate change. Specifically, we examine whether the adoption of AC technology moderates the relationship between temperature changes and health and wellbeing outcomes. To do so, we modify Eq. (1) by including an interaction term between temperature and AC penetration rate. The resulting equation is given as:

$$y_{ijt} = \alpha + \sum\nolimits_{n=1}^{N} \beta_n T_{n,jt} + \sum\nolimits_{n=1}^{N} \varepsilon_n \left(T_{n,jt} \times AC_{st}\right) + \lambda AC_{st} + X_{ijt}\phi + Z_{jt}\psi + \delta_i + \gamma_m + \tau_y + \eta_p + \pi_{sy} + \varepsilon_{ijt} \quad (2)$$

where AC_{st} is the measure of AC penetration rate in state, s, at time t, while $(T_{n,jt} \times AC_{st})$ is its interaction with the temperature bins. Other variables are as defined in Eq. (1).

Θ_n in Eq. (2) captures the role that access to residential AC plays in mitigating the observed relationship between temperature and health. If the estimated coefficient of the interaction term, Θ_n, is statistically different from zero, this implies that access to residential AC system modifies the relationship between temperature and health/wellbeing outcomes.

To examine if and to what extent the effect of a temperature (T) on

[1] The Bureau of Meteorology (BOM) reports temperature data in °C. For ease of comparison with the literature we convert it into °F.

[2] Following suggestions made by an anonymous referee, we also use season fixed effects as an alternative way of controlling for seasonality by grouping the calendar months into four seasons. In Australia, these four seasons include: Spring - the three transition months of September, October and November; Summer - the three hottest months including December, January and February; Autumn - the transition months of March, April and May; and Winter - the three coldest months including June, July and August. The majority of respondents are interviewed between July and August and no fieldwork was conducted in April, May or June.

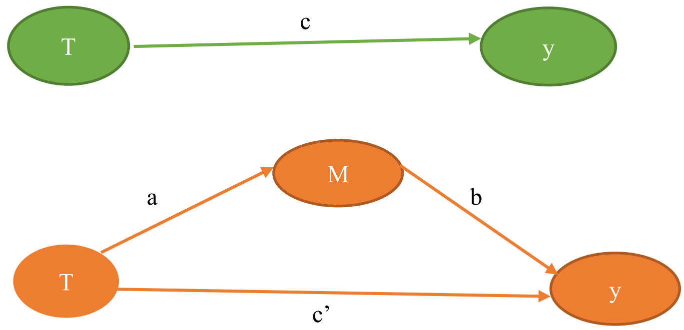

Exhibit 1. Path diagram.

the outcome variable (y) is mediated through a mediating variable (M) (such as sleep), we follow the classical approach of Baron and Kenny (1986). Exhibit 1 presents the path diagram that illustrates the mediation analysis. The upper panel of Exhibit 1 shows the link between temperature and the outcome variable without mediation, as in Eq. (1). The lower panel of Exhibit 1 depicts a model for a causal chain in the three-variable system where there are two paths feeding into the outcome variable: the link from the temperature variable to the mediator (Path a), the impact of the mediator variable (Path b), and the direct impact of the temperature variable (Path c').

To present this using a more formal approach, consider the model for the mediator variable:

$$M_{ijt} = \alpha_1 + aT_{jt} + controls + e_{ijt} \tag{3}$$

and the model for the outcome variable:

$$y_{ijt} = \alpha_1 + c^{'}T_{jt} + \ bM_{ijt} + controls + v_{ijt} \tag{4}$$

where *controls* include all covariates and fixed effects included in the right hand side of Eq. (1) and T_{jt} here denotes a particular bin only for simplicity. From Eqs. (3) and (4), the direct effect of temperature on the outcome variable is given by c′, whereas the indirect effect is captured by the product $a\ x\ b$. Therefore, the total effect of temperature on the outcome variable is $c\ = c^{'} + ab$.

4. Results

4.1. Main results

Fig. 1 presents the estimated effects of maximum and mean temperatures on general health. We started our analysis by presenting baseline pooled estimates, which are reported in Panel A of Fig. 1, while Panel B presents estimates from the panel fixed effect model. Across both panels, the left column of the figure presents the effect of maximum temperature on general health whereas the right reports the effect of mean temperature on general health. The baseline estimates from the pooled regressions show that the relationship between temperature and general health is non-linear. Specifically, we find that lower temperatures, or the temperature bins for the lower temperatures, are negatively associated with general health; however, the magnitude of the coefficient increases with higher temperatures. These results are consistent with the fixed effects estimates in Panel B, although the estimates are relatively larger in magnitude and more significant. Specifically, the results from Panel B show that the relationship between temperature and general health exhibits an inverted U shape. These results are consistent with the findings of a recent study by Baylis (2020). Specifically, our results suggest that colder temperature (less than 40°F) and hotter temperature (above 90°F) have significant negative effects on general health. More precisely, from Panel B, the estimates suggest that an additional colder day (below 40°F) reduces general health score by 0.11 while an additional hotter day (above 90°F) reduces general health by 0.05 points on a 100-point general health scale.

Comparing the pooled and panel fixed effect estimates, we observe that at higher temperatures estimates from the pooled regressions suggest a positive correlation between temperature and general health. However, this turns negative in the panel fixed effect regressions. The differences in results can be attributed to the presence of unobserved individual effects, which are not captured in the pooled regressions. Further, these findings could be an indication that people with better general health live in relatively hot areas but within individual general health is lower during very hot periods.

Fig. 2 presents the effect of maximum and mean temperatures on subjective wellbeing. Consistent with Fig. 1, Panel A presents baseline estimates from pooled regressions, while Panel B presents fixed effects estimates. Across both panels we find consistent results for hot temperatures although the pooled estimates are not significant. From Panel B, we find that colder temperature has no significant effect on subjective wellbeing while hot temperature has a negative effect, despite the negligible magnitude of the estimated coefficient (0.003). The results in Panel B of Fig. 2 show that an additional day with a temperature value of above 90 °F (32 °C) leads to a decrease in the score of subjective wellbeing approximately by 0.003. For the mean temperature, the effect becomes significant, and the magnitude is larger for additional days with temperatures recorded above 80 °F.

We examine the heterogenous effects of temperature on health and wellbeing considering various several socioeconomic dimensions. Table 1 reports the heterogeneous effects of temperature on health and wellbeing by labor force status. We find that the negative effect of cold and hot temperatures on general health is severe for those who are employed. Specifically, an additional day of temperature value below 40 °F is associated with a decrease in general health by 1.95 points in a 100-point scale, whereas an additional day with a temperature value of 90 °F leads to a decline in the index of general health by 0.43 points. Colder temperature also reduces life satisfaction of employed persons while the effect of hot temperature is insignificant (Table 2). This is plausible given that many jobs, such as those within construction and mining sectors (among Australia's largest sectors), are mostly performed outdoors. Our findings have important and broader policy implications given the negative impact of cold and hot temperatures on employed persons has far-reaching consequences and could adversely affect productivity and economic performance.

Table 2 presents the heterogeneous effect of temperature on health and wellbeing by gender. Interestingly, the results show that the general health of men is more sensitive to temperature on hot days, while women's health tends to be negatively affected on cold days. The effect on subjective wellbeing is statistically insignificant for both men and women at 1% and 5% significance levels. Although the HILDA data are nationally representative, measures of health indicators are largely based on self-report. In addition, unobserved confounders could be a potential threat to causal identification. Therefore, our results should be interpreted with caution considering these limitations.

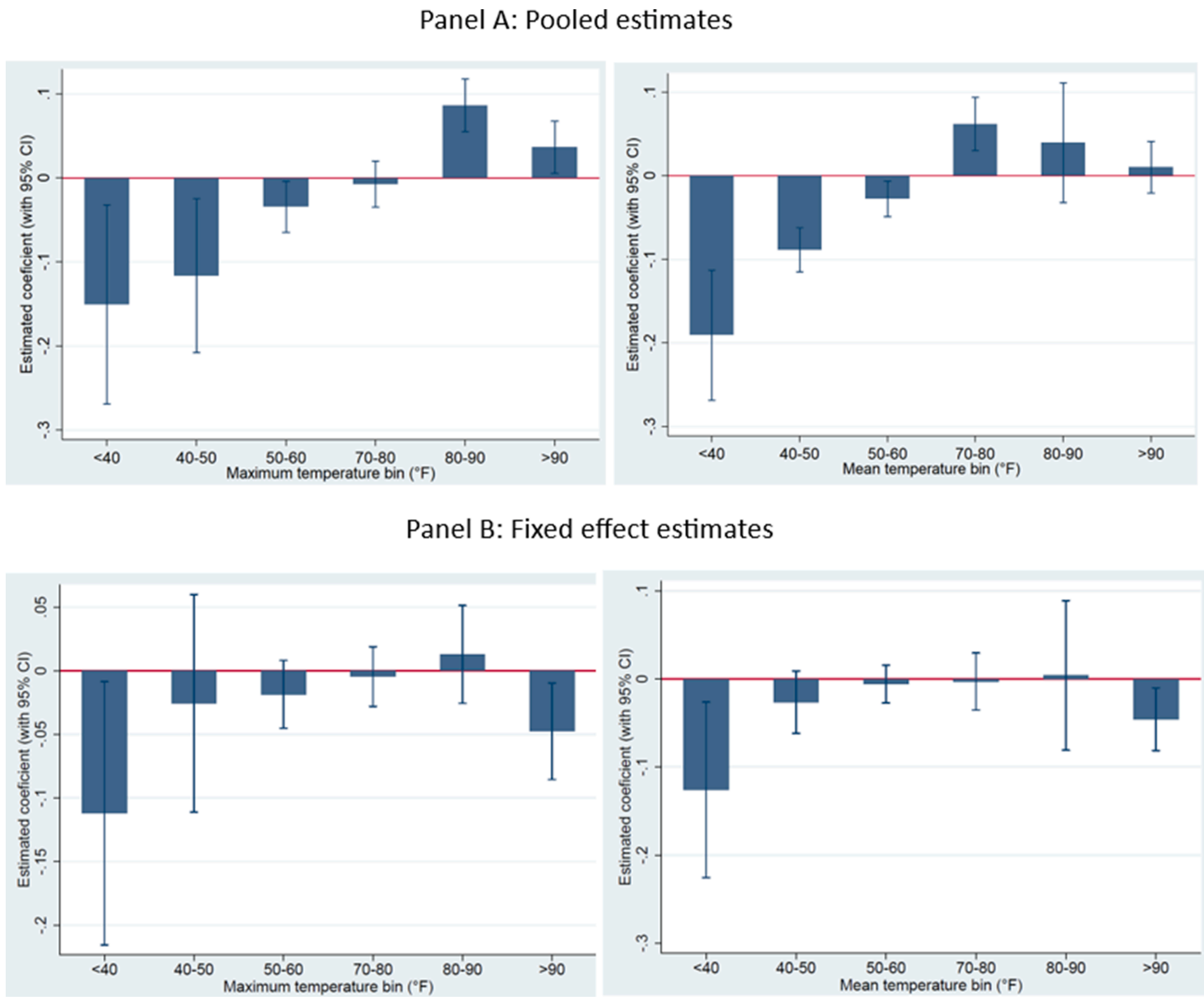

Fig. 1. The effect of maximum and mean temperatures on general health (SF-36 scale).
Notes: The vertical bars represent the estimated coefficients whereas the vertical lines represent the associated 95% confidence intervals (CI). The regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

4.2. Robustness checks

In our main analysis, we use a binned specification where the temperature bin denotes the number of days that fall in a particular bin during the month. An important question might be whether it is the maximum temperature that matters during very hot days or the minimum temperature that matters during very cold days. To address this, we also estimate Eq. (1) using bins of daily mean temperature and minimum temperatures. We examine if findings are sensitive to the use of daily temperature as opposed to temperature over the month of interview. To check the robustness of our results, we estimate an alternative binned specification using bins of maximum daily temperature, as well as average and minimum temperatures. In this case, T_{jt} in Eq. (1) is an indicator variable equal to one if it falls in the given bin, b, and zero otherwise.

Fig. 3 shows the results from the estimations of the effect of maximum and mean temperatures on general health using the alternative binned specification with bins of maximum and mean daily temperatures. The results confirm the robustness of the findings that colder and hotter temperatures have a significant negative effect on general health. Interestingly, the estimated coefficients are quantitatively larger than the estimates reported in Fig. 1, suggesting that daily maximum and mean temperatures matter the most for general health.[3] Fig. 3 confirms that the effects of daily mean temperature on general health are similar to the effect of daily maximum temperature on general health, albeit with differences in the magnitude of the estimated coefficients. However, we find that daily minimum temperature has a statistically indistinguishable effect on general health of Australians (See Table 3A). Therefore, the evidence corroborates that the maximum and mean temperatures matter most for health and wellbeing. Consistent with this, Baylis (2020) also used maximum temperature bins to examine the effect of temperature on temperament in the US.

However, for subjective wellbeing, we find no robust evidence of

[3] We also estimated the effect of minimum temperature on health and wellbeing using both alternative binned specifications. The results are statistically indistinguishable from zero as shown in Table A3.

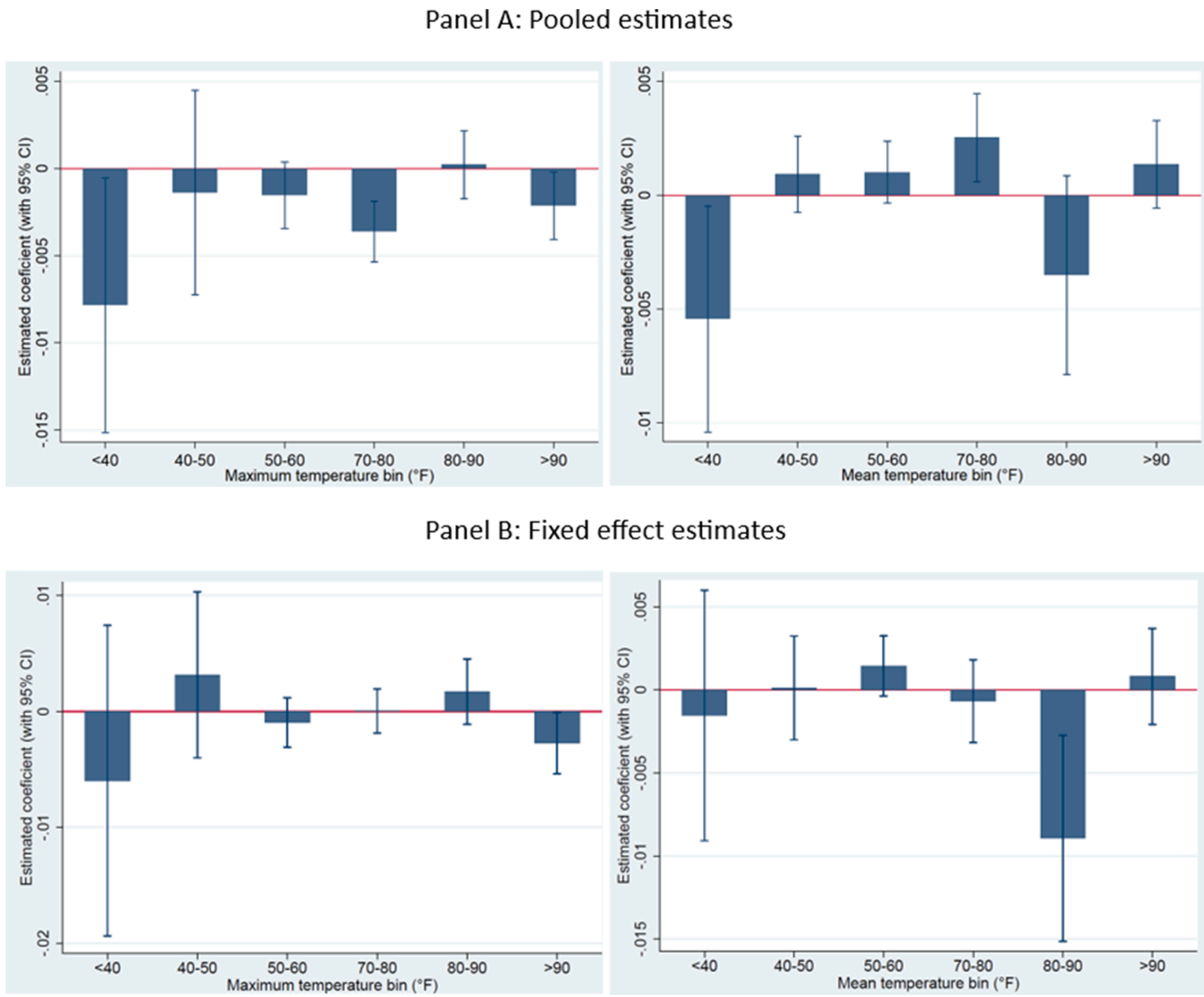

Fig. 2. The effect of maximum and mean temperatures on subjective wellbeing.

Notes: The vertical bars represent the estimated coefficients whereas the vertical lines represent the associated 95% confidence intervals (CI). The regressions include individual-level control variables, including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

Table 1
Heterogeneous effect of maximum temperature on health by labour force status.

	Panel A: General health (SF-36 scale)		Panel B: Subjective wellbeing	
	Employed	Unemployed	Employed	Unemployed
Bin1 (<40°F)	−1.947***	−0.648	−0.193**	−0.119
	(0.737)	(8.783)	(0.094)	(0.485)
Bin2 (40–50°F)	−0.755	−3.702	−0.091**	−0.530**
	(0.549)	(3.960)	(0.046)	(0.250)
Bin3 (50–60°F)	0.054	−0.780	0.008	0.033
	(0.154)	(0.736)	(0.010)	(0.075)
Bin5 (70–80°F)	0.160	0.629	0.007	0.033
	(0.134)	(0.620)	(0.010)	(0.057)
Bin6 (80–90°F)	0.421**	−0.605	0.000	0.038
	(0.189)	(0.939)	(0.014)	(0.084)
Bin7 (>90°F)	−0.426*	−0.821	−0.022	0.046
	(0.248)	(1.353)	(0.020)	(0.105)
Controls	Yes	Yes	Yes	Yes
Observations	68,276	6533	75,779	7315

Note: Robust standard errors in parentheses and are clustered at postcode levels. *$p< 0.1$, **$p < 0.05$, ***$p< 0.01$.
All regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

Table 2
Heterogeneous effect of temperature on health by gender.

	Panel A: General health (SF-36 scale)		Panel B: Subjective wellbeing	
	Male	Female	Male	Female
Bin1 (<40°F)	0.448	−4.447**	−0.205*	−0.238*
	(1.055)	(1.770)	(0.119)	(0.124)
Bin2 (40–50°F)	0.312	−1.006**	−0.015	−0.049
	(0.640)	(0.513)	(0.050)	(0.055)
Bin3 (50–60°F)	0.218	−0.279*	−0.004	0.010
	(0.180)	(0.169)	(0.014)	(0.014)
Bin5 (70–80°F)	0.056	0.107	0.003	0.006
	(0.151)	(0.140)	(0.013)	(0.012)
Bin6 (80–90°F)	0.312	0.159	0.006	0.001
	(0.227)	(0.214)	(0.017)	(0.018)
Bin7 (>90°F)	−0.845***	−0.469	0.023	−0.040*
	(0.300)	(0.320)	(0.024)	(0.024)
Observations	46,167	51,797	51,782	57,213

Note: Robust standard errors in parentheses and are clustered at postcode levels. *$p< 0.1$, **$p < 0.05$, ***$p< 0.01$.
All regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

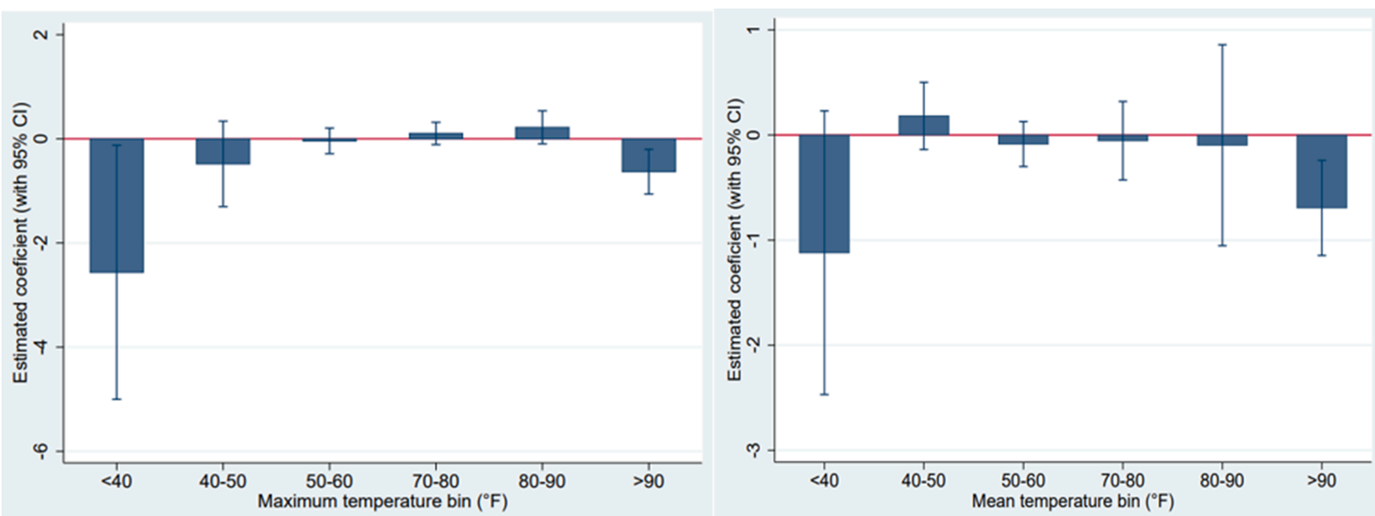

Fig. 3. Robustness check on the effect of maximum and mean temperatures on general health (SF-36 scale) using alternative binned specification.
Notes: Unlike the case in Figs. 1 and 2 (where the bins contain the count of days in a month), the binned specification here is based on an indicator variable that takes value of one if the temperature measure falls in the given bin, b, on the day of interview and zero otherwise. The vertical bars represent the estimated coefficients whereas the vertical lines represent the associated 95% confidence intervals (CI). The regressions include individual level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

negative effects of maximum daily temperature on life satisfaction (Fig. 4). This result is consistent with the findings of earlier studies (see e.g., Connolly, 2013;Frijters et al., 2020; Lucas & Lawless, 2013). These studies find that there is no robust evidence on the effect of temperature on subjective wellebeing after the inclusions of fixed effects. Along these lines, Lucas and Lawless (2013) examine the link between daily weather conditions and life satisfaction scores in the US using state-level survey data from the Behavioral Risk Factor Surveillance System for the period from 2005 to 2009. They find that daily weather conditions have little effect on life satisfaction.

We also use season fixed effects as an alternative way of controlling for seasonality by grouping the calendar months into the four seasons. The results reported in Figs. A3 and A4 confirm the robustness of the main findings.

4.3. *Moderating factors*

Next, we examine whether access to residential AC technology mitigates the harmful effect of hot weather and modifies the underlying relationship between higher temperatures and health. To do so, we estimate Eq. (2), where the bins of temperature are interacted with the AC ownership penetration rate.

Table 3 reports our estimates from Eq. (2). Our results shown in Columns (1) and (2) indicate that adoption of AC technology does not moderate the effect of higher temperature on health/wellbeing. Given that air conditioning is measured at the state-year level we also estimate the model by double-clustering the standard errors accordingly. The results reported in Columns (3) and (4) generally confirm the finding of no moderating effect of air conditioning. This result lends support to the

Table 3
The moderating role of air conditioning (AC) technology.

	(1) General health (SF-36 scale)	(2) Subjective wellbeing	(3) General health (SF-36 scale)	(4) Subjective wellbeing
Bin1 (<40°F)	−0.036	−0.000	−0.178	−0.010
	(0.062)	(0.004)	(0.128)	(0.010)
Bin2 (40–50°F)	−0.025	0.005	−0.070	−0.000
	(0.060)	(0.004)	(0.053)	(0.005)
Bin3 (50–60°F)	−0.017	0.001	−0.019	0.001
	(0.015)	(0.001)	(0.014)	(0.001)
Bin5 (70–80°F)	−0.003	−0.001	−0.001	−0.000
	(0.011)	(0.001)	(0.011)	(0.001)
Bin6 (80–90°F)	0.012	0.000	0.009	0.001
	(0.016)	(0.001)	(0.016)	(0.001)
Bin7 (>90°F)	−0.034**	−0.004***	−0.038**	−0.004***
	(0.017)	(0.001)	(0.017)	(0.001)
Air conditioning (AC)	2.440	0.537***	3.997*	0.553***
	(2.456)	(0.182)	(2.051)	(0.165)
Bin1 x AC	−0.186**	−0.002	−0.281	−0.011
	(0.092)	(0.007)	(0.200)	(0.016)
Bin2 x AC	−0.113	−0.002	−0.185	−0.011
	(0.124)	(0.007)	(0.125)	(0.011)
Bin3 x AC	−0.071	0.006	−0.058	0.007**
	(0.047)	(0.004)	(0.041)	(0.003)
Bin5 x AC	−0.052	0.000	−0.078	0.000
	(0.053)	(0.004)	(0.049)	(0.004)
Bin6 x AC	0.007	−0.002	−0.009	−0.002
	(0.058)	(0.004)	(0.053)	(0.004)
Bin7 x AC	0.016	−0.004	0.024	−0.004
	(0.073)	(0.005)	(0.064)	(0.005)
Observations	97,959	108,979	97,959	108,979

Note: Robust standard errors in parentheses and are clustered at postcode levels in Column (1) and Column (2) whereas they are double-clustered by state and year in Column (3) and Column (4). $^{**}p < 0.05$, $^{***}p < 0.01$.
All regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects.

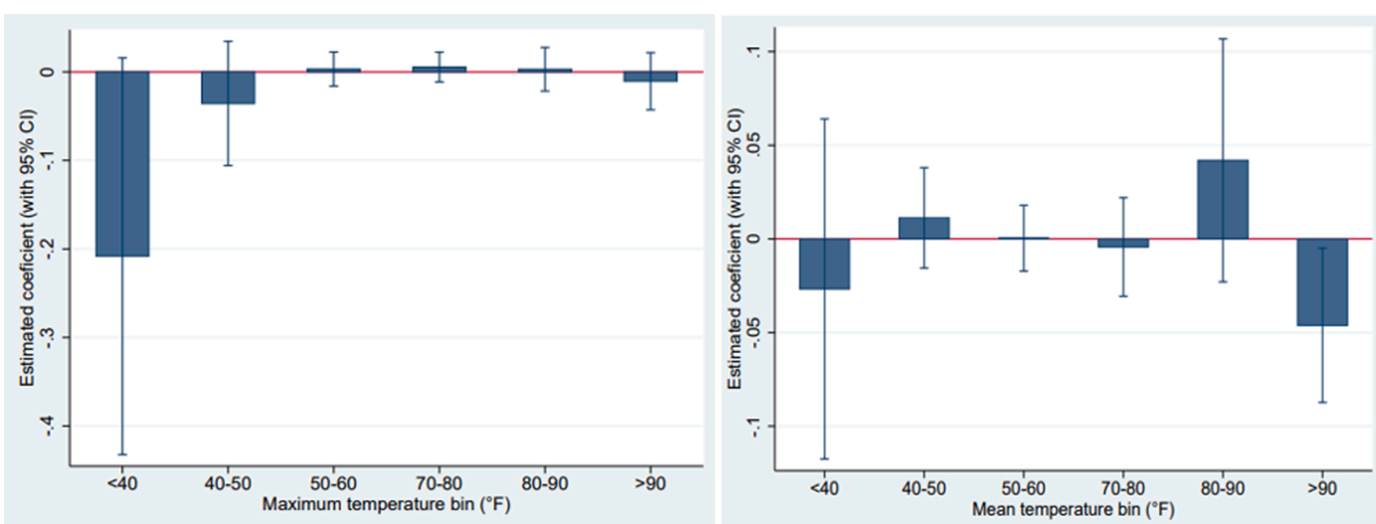

Fig. 4. Robustness check on the effect of maximum and mean temperatures on subjective wellbeing using alternative binned specification.
Notes: The vertical bars represent the estimated coefficients whereas the vertical lines represent the associated 95% confidence intervals (CI). The regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

findings of Mullins and White (2019) that document the absence of evidence on mitigating factors on the temperature-mental health relationship. Although we find no evidence of the moderating effect of AC technology on the relationship between temperature and health, we find a positive and significant unconditional effect of AC ownership on subjective wellbeing.

Table 4
Mediation analysis for general health: Sleep quality.

	Direct	Indirect	Total
Bin1 (<40°F)	−0.004	0.023	0.019
	(0.104)	(0.036)	(0.122)
Bin2 (40–50°F)	−0.187	−0.065*	−0.252
	(0.158)	(0.033)	(0.155)
Bin3 (50–60°F)	−0.066*	0.012	−0.054
	(0.034)	(0.011)	(0.037)
Bin5 (70–80°F)	−0.075**	0.010	−0.065*
	(0.034)	(0.010)	(0.037)
Bin6 (80–90°F)	0.060	0.000	0.060
	(0.038)	(0.011)	(0.039)
Bin7 (>90°F)	−0.083**	0.010	−0.073*
	(0.038)	(0.015)	(0.039)

Note: Robust standard errors in parentheses and are clustered at postcode levels. *$p< 0.1$, **$p < 0.05$.
All regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

4.4. Sleep as a mechanism

We examine the role of sleep quality as a mechanism through which temperature affects general health using the approach developed by Baron and Kenny (1986) described in Section 3.2. Table 4 reports the estimates of the direct, indirect and total effects of temperature on general health, using sleep quality as a mediator. We find that higher temperatures affect general health directly whereas the indirect effect is statistically insignificant. These results suggest that there is no evidence on the mediating role of sleep quality in the relationship between temperature and general health. These results are unsurprising given the high penetration of AC in Australia that can mitigate the impact of temperature on sleep quality (Table A2).

5. Conclusion

We have examined the effect of temperature on self-reported general health and wellbeing in Australia using a nationally representative household panel dataset over the period 2001 to 2019. After controlling for individual- and postcode-level, time-varying covariates as well as a range of fixed effects (month, year, postcode and state-by-year fixed effects), we provide evidence of an inverted U-shaped relationship between temperature and general health suggesting that both cold and hot temperatures have a negative effect on health. Specifically, our results show that temperature leads to a negative effect on general health on days with maximum and minimum temperatures below 40 °F and above 90 °F, respectively. This result is robust to a suite of checks. However, the effect of temperature on subjective wellbeing is not robust. We examine whether sleep quality is a channel through which the effect of temperature transmits to general health. Our results show that there is no evidence supporting sleep quality as a mechanism for linking temperature with health and wellbeing.

Our results are generally consistent with literature examining the impact of temperature on general health, mental health and subjective wellbeing. For instance, Frijters et al. (2020) find no robust evidence on the impact of temperature on life satisfaction. Regarding the health effects of temperature, Mullins and White (2019) find negative effects of temperature on a spectrum of mental health indicators. However, these studies report linear effects of temperature on health; we find a non-linear effect, as in Baylis (2020).

Our research findings join a growing body of research highlighting the precarious relationship between temperature and health and wellbeing. While the negative health effects of high temperature are more readily felt and easily understood, the impact of colder temperatures on general health and wellbeing is less appreciated in practice. In Australia, for example, public announcements usually advise people to drink more water, use sunscreen and stay indoors during hot summer days. However, there is little education advising people about how colder days affect health and wellbeing, or how hot days can dampen mood, increase stress and induce physiological effects that increase morbidity.

We suggest that more effort is needed in public education to create

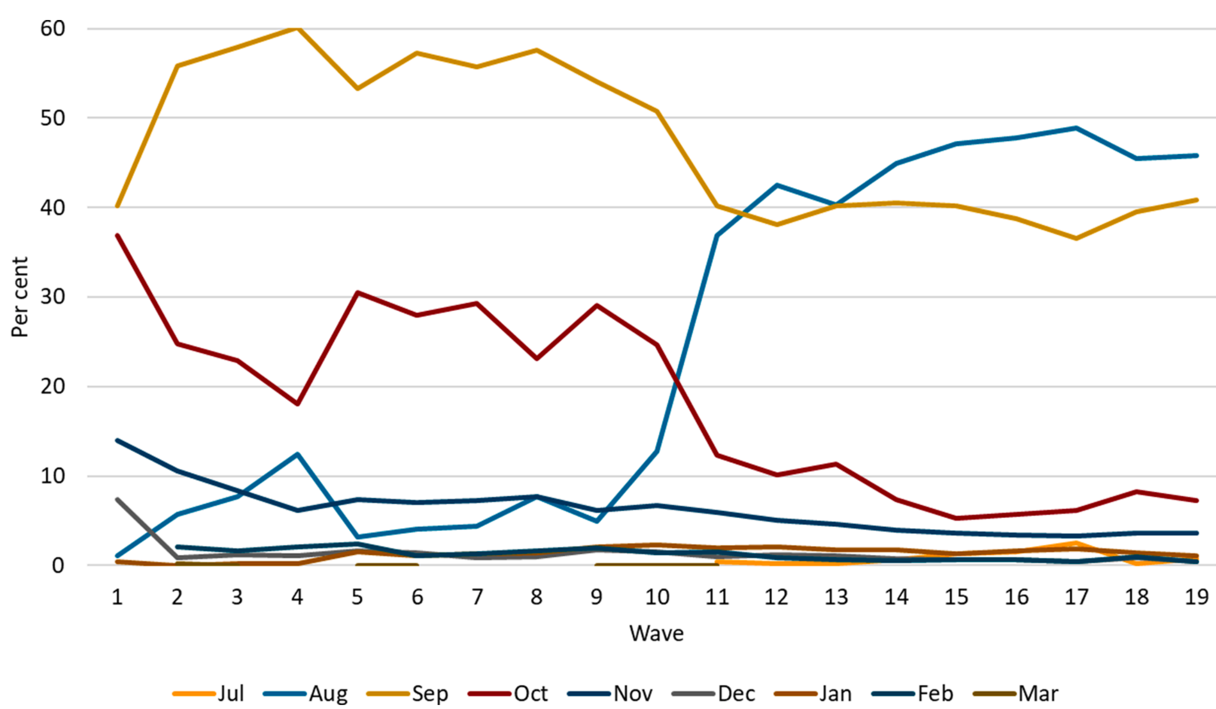

Fig. A1. Monthly distribution of individual interviews by HILDA, waves 1–19.
Source: HILDA survey (2001 to 2019)

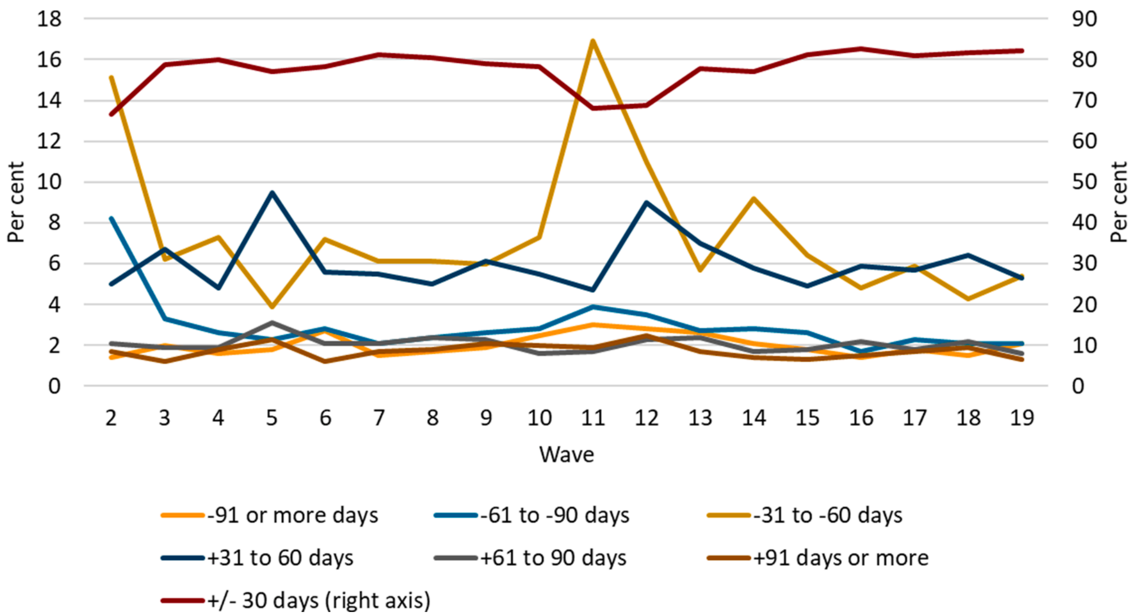

Fig. A2. Monthly distribution of individual interviews by HILDA around the anniversary of the prior wave's interview, waves 2–19.
Source: HILDA survey (2001 to 2019)

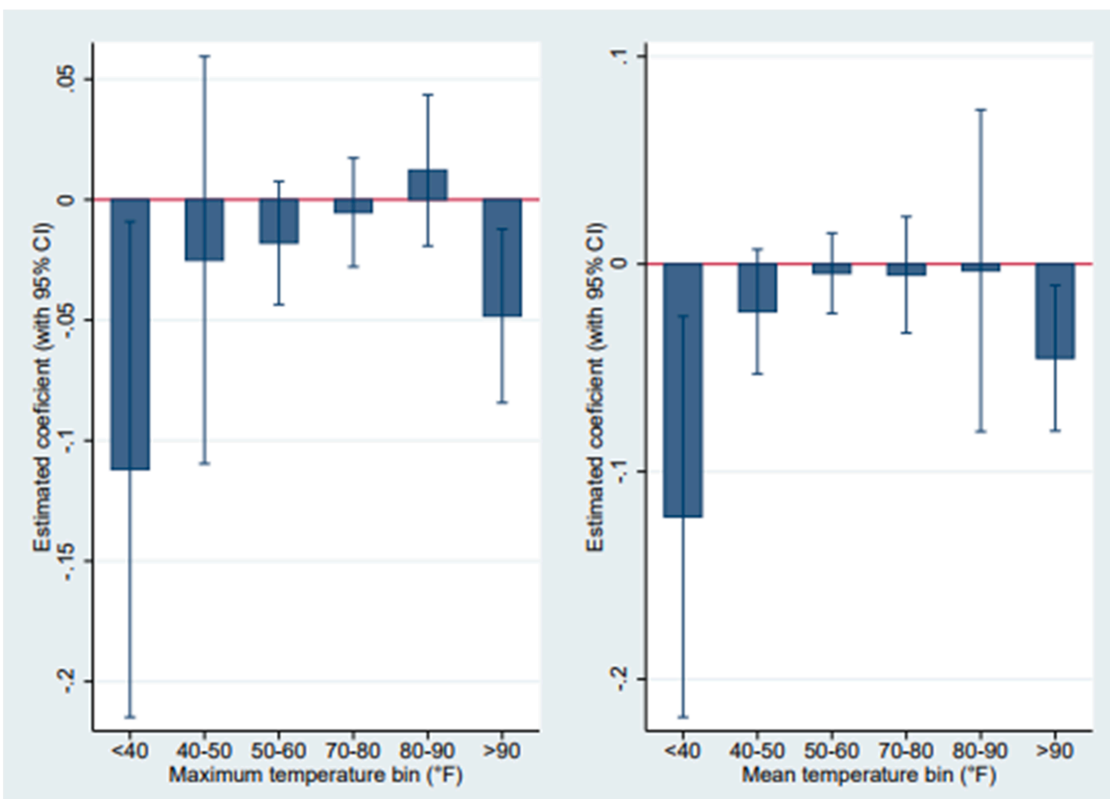

Fig. A3. The effect of maximum and mean temperature on general health, controlling for season effects.
Notes: The vertical bars represent the estimated coefficients whereas the vertical lines represent the associated 95% confidence intervals (CI). The regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including season, postcode, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

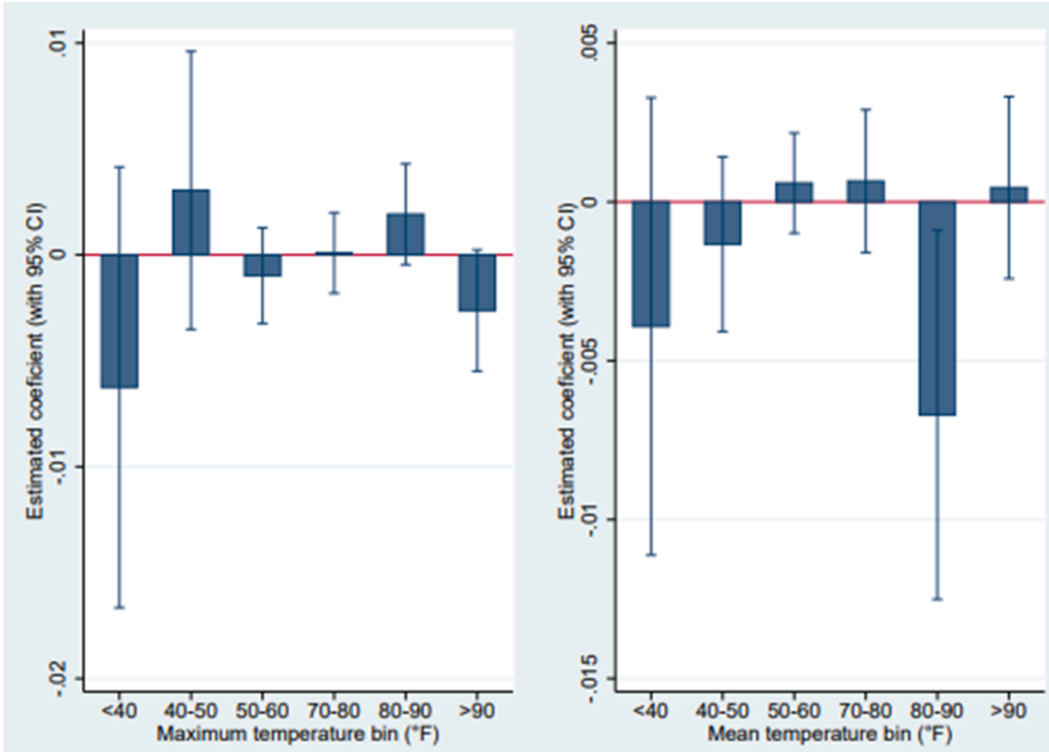

Fig. A4. Temperature and subjective wellbeing, controlling for season effects.
Notes: The vertical bars represent the estimated coefficients whereas the vertical lines represent the associated 95% confidence intervals (CI). The regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, season, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

Table A1
Description and summary statistics of variables.

Variable	Descriptions	Mean	SD
General health-transformed	SF-36 general health - transformed	68.04	20.86
Life satisfaction	"All things considered, how satisfied are you with your life?" Responses are coded on a 0 to 10 scale, where 0 means "totally dissatisfied" and 10 means "totally satisfied"	7.91	1.49
Average temperature	Mean temperature (degree Celsius)	15.33	4.79
Minimum temperature	Minimum temperature (degree Celsius)	9.73	5.06
Bin1 (<40°F)	Number of days in a month that fall into a temperature bin of <40°F	0.08	1.20
Bin2 (40–50°F)	Number of days in a month that fall into a temperature bin of 40-50°F	0.34	1.66
Bin3 (50–60°F)	Number of days in a month that fall into a temperature bin of 50–60°F)	4.89	7.13
Bin5 (70–80°F)	Number of days in a month that fall into a temperature bin of 70–80°F	8.70	7.28
Bin6 (80–90°F)	Number of days in a month that fall into a temperature bin of 80–90°F	3.77	5.51
Bin7 (>90°F)	Number of days in a month that fall into a temperature bin of >90°F	1.91	4.85
Maximum temperature	Maximum temperature (degree Celsius)	20.96	5.66
Age	Age of respondent	36.23	22.66
Separated	Binary variable equals 1 if separated	0.03	0.16
Single	Binary variable equals 1 if single	0.24	0.43
Married/De facto	Binary variable equals 1 if married or in a de facto relationship	0.48	0.50
Income	Log of household income	11.09	0.74
Unemployed	Binary variable equals 1 if unemployed	0.04	0.19
Postgrad	Binary variable equals 1 if highest level of education is masters or doctorate	0.04	0.20
Graduate Diploma	Binary variable equals 1 if highest level of education is graduate diploma or certificate	0.05	0.22
Bachelor	Binary variable equals 1 if highest level of education is bachelor or honours	0.13	0.34
Diploma	Binary variable equals 1 if highest level of education is advanced diploma or diploma	0.09	0.28
Certificate	Binary variable equals 1 if highest level of education is certificate I, II, III or IV	0.21	0.40
Year 12	Binary variable equals 1 if highest level of education is year 12	0.15	0.36
Sleep quality	"How would you rate your sleep overall? 1= very bad, 2= fairly bad, 3=fairly good, and 4=very good"	2.13	0.75
AC	Air conditioning ownership penetration rate	0.865	0.251

Table A2
Estimated results for the full set covariates on the effect of maximum and mean temperatures on health and wellbeing.

	Maximum temperature		Mean temperature	
	General health	Subjective wellbeing	General health	Subjective wellbeing
Bin1(<40°F)	−0.112**	−0.006	−0.126**	−0.002
	(0.053)	(0.007)	(0.051)	(0.004)
Bin2 (40–50°F)	−0.026	0.003	−0.026	0.000
	(0.044)	(0.004)	(0.018)	(0.002)
Bin3 (50–60°F)	−0.019	−0.001	−0.006	0.001
	(0.014)	(0.001)	(0.011)	(0.001)
Bin5 (70–80°F)	−0.005	0.000	−0.003	−0.001
	(0.012)	(0.001)	(0.017)	(0.001)
Bin6 (80–90°F)	0.013	0.002	0.004	−0.009***
	(0.020)	(0.001)	(0.043)	(0.003)
Bin7 (>90°F)	−0.048**	−0.003**	−0.046**	0.001
	(0.019)	(0.001)	(0.018)	(0.001)
Age	0.654***	0.031***	0.656***	0.032***
	(0.135)	(0.011)	(0.135)	(0.011)
Long income	0.096	0.044***	0.095	0.044***
	(0.119)	(0.009)	(0.119)	(0.010)
Unemployed	0.465	−0.140***	0.469	−0.139***
	(0.316)	(0.029)	(0.316)	(0.028)
Postgraduate	2.984***	−0.221***	2.973***	−0.221***
	(0.733)	(0.054)	(0.734)	(0.049)
Bachelor	2.094***	−0.349***	2.093***	−0.350***
	(0.559)	(0.039)	(0.559)	(0.038)
Graduate diploma	1.839**	−0.257***	1.838**	−0.257***
	(0.803)	(0.057)	(0.802)	(0.051)
Diploma	1.544**	−0.270***	1.550**	−0.270***
	(0.723)	(0.055)	(0.723)	(0.053)
Certificate	0.124	−0.291***	0.128	−0.290***
	(0.510)	(0.040)	(0.510)	(0.036)
Year 12	−0.573*	−0.282***	−0.574*	−0.282***
	(0.345)	(0.025)	(0.345)	(0.024)
Married	0.280	0.093***	0.278	0.093***
	(0.259)	(0.023)	(0.259)	(0.021)
Single	−1.025***	−0.176***	−1.026***	−0.176***
	(0.344)	(0.027)	(0.344)	(0.026)
Separated	0.769	−0.372***	0.769	−0.372***
	(0.534)	(0.046)	(0.534)	(0.047)
Number of children	−0.438***	−0.072***	−0.436***	−0.071***
	(0.117)	(0.009)	(0.117)	(0.009)
Local area unemployment	−0.082	−0.006	−0.082	−0.006
	(0.063)	(0.005)	(0.063)	(0.005)
Local area population	0.101	0.008	0.095	0.008
	(0.122)	(0.009)	(0.122)	(0.009)
Observations	97,959	10,8979	97,959	10,8979

Notes: The reference category of control variables are widowed and divorced for marital status, unemployed and those not in the labour force for employment status, year 11 and below for level of education. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3
The effect of daily minimum temperature on health and wellbeing.

	General health	Subjective wellbeing
Bin1(<40°F)	−0.002	0.002
	(0.019)	(0.002)
Bin2 (40–50°F)	−0.005	0.002*
	(0.015)	(0.001)
Bin3 (50–60°F)	0.005	0.001
	(0.013)	(0.001)
Bin4 (70–80°F)	0.068*	−0.002
	(0.036)	(0.002)
Bin6 (80–90°F)	0.192	−0.002
	(0.201)	(0.013)
Bin7 (>90°F)	−0.033	0.001
	(0.020)	(0.001)
Controls	Yes	Yes
N	97,959	108,979

Note: Robust standard errors in parentheses and are clustered at postcode levels. *$p< 0.1$,
All regressions include individual-level control variables including age, education, marital status and number of dependents and postcode-level factors including local area unemployment rate and population as well as a range of fixed effects including postcode, month, year and state-by-year fixed effects. Standard errors are clustered at postcode levels.

awareness and prepare people to anticipate and respond to colder and hotter temperature's negative effect on general health and wellbeing. Possible measures to counteract the negative effects of hot weather on health and wellbeing should include encouraging more indoor physical activity during these periods. Finally, this research echoes the body of research and advocacy calling on policymakers and governments to act more urgently to address global climate change, which manifests in short-run temperature increases year-on-year. Our study provides more evidence that regardless of ideological debates, the impact of increasing temperatures in day-to-day weather is clearly negative for health.

Data availability

The authors do not have permission to share data.

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