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Weather effects on academic performance: An analysis using administrative data

Abstract

A growing number of studies have examined the impact of temperature and weather extremes on a range of economic outcomes. In this paper we contribute to the evolving literature on the relationship between temperature and educational outcomes given the crucial role of human capital development on economic growth. Specifically, we use national level administrative data on nearly 1 million Australian students to study if their test scores are affected by temperature variations. Overall, our analysis on national data shows a significant negative effect of heat and cold on students' test scores. The effects get exacerbated with heatwaves. The large geographical size and climate variability across Australia also allows us to study spatial heterogeneity in the effects of temperature on student performance. According to our findings, students become resilient to climatic conditions in the region they live, consistent with the adaptation hypothesis. Those living in regions with hot dry or high humid summer are not affected by extreme heat and those living in cool winter or cool temperate weather conditions are not impacted by cold temperatures.

JEL classification: C3, I1, K3

Keywords: climate change; temperature; academic performance; NAPLAN; heatwave; climate zones.

1 Introduction

One of the main threats of climate change stemming from the rising temperature of the Earth's atmosphere is that we will experience more frequent and severe weather risks (Masson-Delmotte et al., 2021). Global warming is expected to have a range of consequences in various aspects of our lives. So far that weather effects are transient, they do not require any policy response. However, with permanently changing weather patterns in the advent of global temperature warming, the effects are mostly expected to be non-transitory requiring policy actions to mitigate any long-term harm.

A growing number of studies have examined the impact of temperature and weather extremes on a range of economic outcomes such as health and wellbeing (Patz et al., 2005; Hsiang et al., 2013; Deschenes, 2014), labour supply and productivity (Deryugina and Hsiang, 2014; Behrer et al., 2021; Somanathan et al., 2021), agricultural yield (Schlenker and Roberts, 2009; Chen et al., 2016), energy demand (Auffhammer and Mansur, 2014; Wenz et al., 2017) and economic activity (Dell et al., 2012; Burke et al., 2015; Diffenbaugh and Burke, 2019; Acevedo et al., 2020). These studies provide crucial insights on the potential impacts of future climate change. Climatic conditions can also potentially affect student learning and performance. High environmental temperature is known to be a natural stressor that influences a number of psychological and physiological responses including increased blood pressure and heart rate (Crandall and Gonzalez-Alonso, 2010; Crandall and Wilson, 2015), decreased cerebral blood flow (e.g., Brothers et al., 2009; Ogoh et al., 2013; Schlader et al., 2016) and increased heat-related fatigue (e.g., McMorris et al., 2006; Robertson and Marino, 2017; Kenny et al., 2018; Ciuha et al., 2019). Laboratory based experiments have shown that cognitive impairment induced by high temperatures negatively affects performance in a variety of tasks; in particular, exposure to high temperatures decreased participants' memory, attention, and accuracy (Cian and Raphel., 2001; Pilcher et al., 2002; Schlader et al., 2015).

How does cumulative heat and cold exposure affect student learning and performance? Prolonged exposure to heat and cold in the classroom may reduce the effectiveness of instructional time through physiological impacts on both students and teachers, thus making it harder for both to focus and accomplish a given set of learning tasks. Other than the direct effects of weather through cognitive performance, student learning can also be disrupted in various other ways. Extreme heat and cold may also result in school closure or early dismissal, reducing the amount of instructional time. Furthermore, learning can be affected through sleep deprivation (e.g., Okamoto-Mizuno and Mizuno, 2012), food poisoning and disease transmission which are not unusual in hot weather (e.g., Bentham and Langford, 2001; Akil et al., 2014), and critical social infrastructure such as transport, electricity and water supply - particularly in less-developed countries (Wilby, 2007)- all of which may indirectly affect their performance at school. Given the crucial role of human capital development on economic growth, it is important to examine to what extent rising temperatures are likely to affect skill formation and whether these effects are temporary or persistent. At the same time, it is also important to find out whether the effects are causal or arise from unobserved heterogeneity. More recent studies in real world formal learning environments (Cho, 2017; Park, 2022) have lent further support to existing lab-based findings by showing a causal effect of temperature on academic achievement.

We contribute to the evolving literature by examining the relationship between temperature and academic performance in Australian children, using national level administrative data. A recent study in Australia that uses a smaller sample of our dataset (and a different time period) that focuses on New South Wales, a state with mostly warm to hot weather conditions, shows that high temperatures in the year prior to the test do not have any significant effect on students' performance (Johnston et al., 2021). Conversely, cold temperatures are found to significantly reduce test scores. In contrast, we use data at a national level which covers almost the entire population of students in Australia and allows us to consider different climatic conditions across the country. Our dataset comprises nearly 1 million students who participated in the National Assessment Program – Literacy and Numeracy (NAPLAN) tests in grade 3, 5, 7 and 9 over the period 2014-19 from approximately

10,000 schools across the entire country.

Overall, our analysis shows a significant negative effect of heat and cold on students' test scores. Relative to a day with an ambient temperature of 20–25°C, an additional colder school day in the last academic year can reduce reading test scores by approximately 0.11% and an additional hot day exceeding 35°C, by 0.39% of a standard deviation. An analysis by grade levels indicates that the effect of high temperature is more pronounced in older students. In direct analogy to class size effects on scores estimated by Fredriksson et al. (2013), a 0.59% standard deviation reduction in the writing score of a grade 9 student is equivalent to increasing class size by about 0.26 student. Ten such hot days will be equivalent to increasing class size by two to three students. We also examine the effects of heatwave which has been on an increasing trend in Australia more recently. We find that an additional heatwave lasting longer than 9 days decreases numeracy test scores by 8.33% of a standard deviation, which is equivalent to increasing class size by three to four students. Lastly, we find that the effect of temperature is cumulative with hot and cold school days two years prior to the assessment day having a worsening effect on scores.

Due to its large geographical size and location with respect to the equator, Australia is one of the very few countries in the world to span several climate zones, ranging from tropical zone in the north to temperate zones in the south. The northern parts of the country are fairly warmer than areas to the south, with nearly 12-15 °C difference in the average daily maximum temperature, on average (Bureau of Meteorology, 2022). We exploit the variability in temperatures across regions to examine spatial heterogeneity in the effects of temperature on student performance, making a unique contribution to the existing literature. Overall our results are consistent to some extent with adaptation hypothesis, reported in previous studies (Christidis et al., 2010; Korhonen et al., 2018; Folkerts et al., 2020; Johnston et al., 2021). We find that students who live in regions with hot dry or high humid summer are not impacted by hot temperatures but are sensitive to cold weather. Likewise, students living in cool winter or cool temperate weather conditions are not greatly affected by cold temperatures but heat decreases their test scores. Finally, students who live in warm to mild temperate weather conditions are affected by both hot and cold temperatures.

Our study makes an important contribution to the growing debate in Australia and internationally about the importance of thermal comfort in classrooms (Andamon, M., Woo, J. and Rajagopalan, P., 2021; ACSIS, 2021). Recent studies have shown that classroom thermal comfort plays a crucial role in educational achievement (Mendell and Heath, 2005; Park et al., 2020). According to Park et al. (2020), for the average student, school air-conditioning is likely to offset 73% of the learning impact of hot school days. We contend that given the significant impact of temperature on Australian children's academic performance, temperature regulation in schools to mitigate the impact of heat and cold stress can result into better learning and educational outcomes. At large, understanding the influence of temperature on human performance is important for predicting the potential magnitude of climate change externalities.

2 Data

2.1 Weather information

We have daily weather information from 969 weather stations across Australia over the period 2004 to 2019, which we obtain from the Australian Bureau of Meteorology. In particular, from each weather station, we have information on the maximum and minimum temperatures (in degree Celsius) and precipitation (in millimeters) recorded in the last 24 hours. We use this information to create a range of weather variables, including temperature bins, heatwave indicators, and average precipitation, for each weather station.

Our main variable of interest is constructed using maximum daily temperatures recorded at weather stations. To account for the possibility that temperature has non-linear effects on test scores, we use a temperature-bin approach that allows for a more flexible function of temperature (see, for example, Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Deryugina and Hsiang, 2014; Heyes and Saberian, 2019). Specifically, we construct five bins as follows: ≤20°C, (20°C, 25°C], (25°C, 30°C], and (30°C, 35°C] and >35°C. Our temperature shock variable measures the number of days when the daily maximum temperature is within a specific bin over the 13 months prior to the assessment, i.e. between the 1^{st} April of the last year and the 30^{th} April of the current year. In a similar way we construct six temperature bins for minimum daily temperatures as follows: ≤5°C, (5°C, 10°C], (10°C, 15°C], (15°C, 20°C], (20°C, 25°C], and >25°C.

To measure prolonged exposure to abnormal heat for a specific location and day, we create a heatwave index, following the method proposed by Miller et al. (2021). Specifically, we define the heatwave index for day d in year y at weather station w as E_{wyd}:

$$\begin{aligned} &E_{wy0} = 0 \\ &E_{wyd} = max\{0, E_{wyd-1} + I(T_{wyd} \geq t_{wd}) - I(T_{wyd} < t_{wd}) \times \infty\} \end{aligned} \tag{1}$$

where T_{wyd} is the maximum temperature of day d in year y recorded at weather station w; t_{wd} is the threshold of "abnormally hot" on day d at weather station w; and $I(\theta)$ is an indicator function such that $I(\theta) = 1$ if θ is true, 0 otherwise. In this way, E_{wyd} is an evolving index which goes up by one if an additional (consecutive) day of temperature above the location-day-specific threshold for "abnormal" heat and goes back to zero otherwise. Therefore, events with several abnormally hot days in a row will drive the index above zero for several days, reaching its highest level as the length of the heatwave at the end of the heatwave spell. During the period of normal or abnormally cold days, the index remains at zero. On sporadic hot days, the index will be pushed up briefly and moderately over zero. Put simply, this index generally tracks the number of consecutive days that the maximum temperature is higher than the threshold for a particular day at a particular location. With respect to the threshold t_{wd}, following the spirit of Miller et al. (2021), we set it as

$$t_{wd} = max\{\mu_{wd} + 1.5\sigma_{wd}, 30\}, \tag{2}$$

where μ_{wd} and σ_{wd} are the mean and standard deviation, respectively, of the daily maximum temperature over the window covering 15 days before to 15 days after day d across all years, at weather station w. By definition, "abnormally hot" on day d at weather station w is either a temperature of 1.5 standard deviation above average for the location and day (i.e. hotter than normal), or 30°C (i.e. hot in intuitive sense), whichever is higher. Using the heatwave index, we construct the heatwave variables which measure the number of days in the 13 months prior to the assessment when the heatwave index is higher than 3, 6, and 9. Essentially, we count the number of days when a heatwave longer than 3 days, 6 days, and 9 days is experienced. Other than the temperature variables, we construct another variable to measure the average precipitation rate over the 13 months prior to the assessment, for each weather station.

Finally, in order to link the weather variables to our test score data, we calculate the distance between a school and a weather station by using the coordinate of the weather station and the coordinate of the center of the postcode where the school is located. Our first choice is the closest weather station to the school that the student comes from. Where we do not have information for the nearest weather station, we move on to the second nearest weather station, and so on. Note that we construct the weather variables only over school days, thus excluding school holidays and public holidays, which may vary by states and territories.

2.2 NAPLAN

Our test score data is taken from the National Assessment Program – Literacy and Numeracy (NAPLAN), which is a large-scale standardised test, administered by the Australian Curriculum, Assessment and Reporting Authority (ACARA). The main aim of NAPLAN is to provide standardised and hence comparable measures of student achievement in English literacy (with four main tests: reading, writing, spelling, grammar /punctuation) and in numeracy (with one test covering algebra, geometry, measurement and problem solving) in all public and private schools across the country (ACARA, 2011). The test is undertaken at a national level annually in the second week of the month of May by students in grades 3, 5, 7, and 9, but participation in the assessment program is not mandatory (NAPLAN, 2022).[1]

The advantage of using administrative data, a distinct type of big data, is that unlike survey data, it covers nearly the entire population of interest, providing high quality information that does not suffer from non-response rates and under reporting, thus adding to greater statistical power for robust policy analysis (Connelly et al., 2016; Penner and Dodge, 2019). Administrative data is also considered to be superior because the data record for an individual (i.e. student) can be corrected and updated constantly. In our case, the dataset includes students from all over Australia making ours a unique study from a data perspective.

To score NAPLAN tests in each domain, ACARA developed the National Assessment Scale which has a midpoint of 500, split into 10 bands to cover the range of student achievement on the tests. This system is used to score student performance on every NAPLAN test; however, scores associated with bands differ by domain. For example, a score of 550 on the writing test would not be equal to a score of 550 on the reading test. In this paper, we employ the test scores in all five domains of reading, writing, spelling, grammar, and numeracy. The NAPLAN uses a national reporting format which allows scores to be compared across schools and over time (Daraganova et al., 2013).

We use data for the period 2014-2019 in this study. Traditionally, NAPLAN has been a paper-based assessment. However, since 2018, schools have started to gradually make a transition towards computer-based assessments. In 2018, online multistage adaptive 'tailored' tests were administered for the first time on a trial basis, with 15% of students attempting the test online. In 2019, 50% of students attempted the test online. Rigorous test calibrations were then conducted in order to equate the online tests to the NAPLAN

[1]Precisely, the assessment is conducted yearly on the second Tuesday of the month of May and lasts three days, with writing, spelling, grammar /punctuation on day 1, reading on day 2 and numeracy on day 3.

historic reporting scales (ACARA, 2018). With the online tests, schools are given a 9-day test window in early May to accommodate for students who are absent when their class participates in the tests. For consistency, we only consider paper-based test scores in our main analysis and use the online test scores for robustness checks.

Due to concerns of students being identified in areas that have a very small number of schools, data was not available for postcodes with less than five schools. This has resulted in a drop of around 23% observations in the sample. Our main estimation sample of students who attempted paper-based assessments includes nearly 3.4 million observations. Figure A1 (Appendix) shows the distribution of the scores in the five tests.[2] Specifically, our sample consists of 902,423 observations for grade 3, 866,746 observations for grade 5, 857,199 observations for grade 7 and 809,241 observations for grade 9. The dataset also contains information on students' date of birth, gender, indigenous status, language background, the school sector (private vs public) and their parents' education. Schools have been de-identified but we have postcodes where the schools are located. Likewise, students have also been de-identified and cannot be linked over years to construct a panel.

The socioeconomic status of the school neighbourhood, termed as the 'school composition effect' in the literature (e.g., Opdenakker and Damme, 2001) can be a significant determinant of student performance. Other than parents' socioeconomic status, we also control for postcode-level socioeconomic status given that the school's composition is likely to influence its quality. Precisely, we use the Index of Economic Resources (IER) developed by the Australian Bureau of Statistics (ABS, 2016). In our analysis, we take the average of IER in 2011 and 2016, and assume that the index is constant within a postcode over the period of our analysis. Table A1 (Appendix) presents summary statistics of all the variables used in the analysis. Table A2 (Appendix) provides some preliminary insights on the relationship between temperature and test scores. Looking at the first 5 columns, we observe a negative

[2]The NAPLAN scales are constructed so that any given score represents the same level of achievement over time. For example, a score of 700 in reading will have the same meaning in 2019 as in 2014. For this reason a few outlier scores in the dataset are negative. However their exclusion does not alter our results, see results in Table A3 and A4 in Appendix.

correlation between hot days (temperature of 25°C and above) and the five test scores. The last three columns depict the relationship with heatwaves. With all three measures of heatwaves, we observe a negative relationship with the five test scores.

3 Methods

The impact of temperature on test scores is estimated using the following linear regression model:

$$Y_{isjgt} = \sum_{k=1}^{4} \beta T_{kjgt} + \gamma X_{isjgt} + \theta_g + \theta_t + \epsilon_{isjgt} \quad (3)$$

where Y_{isjgt} represents standardized test scores of student i, attending a school s, in postcode j located in state/territory g, in year t. As discussed above, we look at scores in different subjects including reading, writing, spelling, grammar, and numeracy. For ease of interpretation, all scores are standardised and multiplied by 100.

As described in Section 2, we construct five temperature bins for the maximum temperature. We set the most thermally comfortable temperature bin of 20–25°C as the reference group such that T_{kjgt} represents each of the other four bins. This approach allows us to use the daily variation in temperatures versus an average temperature. In addition, the temperature bins allow for nonlinearities in the temperature-academic performance relationship. Specifically, T_{kjgt} represents the number of school day counts in the 13 months prior to the assessment taken by the student i from school s located in postcode j of state/territory g in year t, when the maximum temperature was in the temperature bin k. The coefficient on the temperature variable, say for the 25–30°C bin, is thus interpreted as the effect of an additional day with a maximum temperature of 25–30°, relative to the reference group of 20–25°C. From Table A1 (Appendix) we can see that in the 13-month period prior to the tests, on average, 126 school days had an ambient temperature of 20–25°C, 68 days had temperatures less than 20°C, and 50, 24 and 7 days had temperatures in the respective range of 25–30°C, 30–35°C and >35°C. We notice a fair amount of variability within most temperature bins.

In order to purge the causal effect of temperature on test scores, we enter a range of controls in equation (3). We include a vector of student and school characteristics X_{isjgt}. They are the child's age, gender, indigenous status, language background, parents' education and the school sector (public vs private). We also control for an indicator of postcode-level socio-economic status using the IER. We use state fixed effects to control for any state-specific factors that may be correlated with climate or local economic patterns, and year fixed effects to control for any policy or trend change over time.

We cluster our errors at the postcode level to allow for potential serial correlation over time within a postcode (Cameron and Miller, 2015). Our identifying assumption is that, conditional on the inclusion of location and year fixed effects, any remaining variation in temperature is essentially random. This allows for a causal interpretation of our coefficient of interest, β, which is expected to be negative.

We also test the robustness of our results by using alternative weather conditions such as night time temperature and precipitation, controlling school fixed effects and using data on online assessments. To confirm that our results are not just a statistical artifact driven by spurious correlations between temperature and test scores, we also conduct a placebo test in which we estimate the effect of temperature by randomising them across postcodes. Next, we estimate the effects of heatwaves on test scores focusing on heat spells longer than 3 days, 6 days and 9 days. This allows us to measure the impact of prolonged days of heat on student performance. Finally, in view of the variety of climates across Australia, we examine spatial heterogeneity in the effects of temperature on student performance. Specifically, we examine if the effects of temperature on test scores vary across the various climate zones in Australia.

4 Results

4.1 Main findings

Our main results are reported in Table 1. We estimate the effect of temperature on test scores in the five areas separately, namely reading, writing, spelling, grammar and numeracy. The reported coefficients represent the estimated respective effects of an additional day in the k^{th} temperature bin on test scores, relative to a day when the temperature is within an ambient 20–25°C range (the reference category). Relative to days with a 20–25°C temperature range, all temperatures appear to negatively affect test scores and are statistically significant. For example, one additional school day in the 13 months prior to the exam with temperature < 20°C, between 25-30°C, between 30-35°C and >35°C, reduces reading test scores by 0.112%, 0.126%, 0.091% and, 0.390% of a standard deviation, respectively. The magnitude of the effects are generally consistent across all five test scores within a temperature band. Clearly, relative to an ambient temperature, low and high temperatures negatively impact on students' performance with hotter days impacting quite severely on test scores. Specifically, one additional school day in the 13 months prior to the exam with a maximum daily temperature of >35°C reduces the five test scores between 0.350-0.448% of a standard deviation. The full set of results are reported in Table A3 in the Appendix.

Our results are consistent with prior studies that have generally found a significant effect of heat stress on student exam performance (Cho, 2017; Park, 2017; Park et al., 2020). Specifically, Cho (2017) finds an additional day with temperature >34°C reduces reading, maths and English test scores by 0.28%, 0.42%, 0.64% of a standard deviation, respectively. Broadly, our results are also consistent with those estimated by Johnston et al. (2021) who focus on New South Wales, a state with a mostly temperate and humid climate and maximum temperatures ranging from 26°C in summer and 16°C in winter. The authors find that additional cold day with temperature <60°F (around 15°C) reduces reading, maths and English test scores by 0.12-0.16% of a standard deviation. However they do not find any significant effect of hot days on test scores. The authors relate their findings to weather adaptation where individuals living in warmer regions adapt to weather conditions by becoming less susceptible to heat but more susceptible to cold, and vice versa for individuals living in colder regions.

To provide further insights on our results, we next report some heterogeneous effects of temperature by grade levels, year of assessment, paper-based versus online assessment types, and demographic characteristics of both students and parents.

Grade level: In Table 2, we estimate the relationship separately for students in respective grades in order to provide insights on grade related heterogeneous effects. Our results are consistent with the baseline findings across all grades. In general, we find that the magnitude of the effects are higher for Grades 7 and 9 students relative to the younger cohorts, with the effects being even more pronounced for grade niners. For instance, the effects of hot days (>35°C) on test scores of Grade 9 students range between 0.363-0.593. This cohort's age group coincides with the pubertal age of students when the body's sweat glands become much more active, contributing to a higher level of discomfort. Broadly these results indicate that secondary school students are more sensitive to weather conditions than those in primary schools.

To appreciate the extent of the impact on academic performance, we compare the temperature shock effect with the effect of varying a class size on test scores. For example, Fredriksson et al. (2013) find that reducing class size by one pupil at the end of secondary school when student are 16 years old (albeit slightly older than a grade 9 student in Australia who is on average in the age group 14-15) increases academic achievement by 0.023 standard deviation. In direct analogy, a 0.593 hundredths of a standard deviation reduction, in response to an additional day with a maximum daily temperature over 35°C , in the writing score of a grade 9 student is equivalent to the effect of increasing class size by over 0.26 student. Ten such hot days will be equivalent to a 2-3 students' increase in class size.

Year of assessment: We also estimate the regression by looking at the combined grades in each year (Table 3). We find that in 2016 and 2019, the effect of cold days on tests scores are small and statistically insignificant while in all other years we see significant associations between tests scores and temperature as in our baseline results. Interestingly, the magnitude of the effects of cold days was more pronounced in 2017, and the effects of hot days generally higher in all five tests in 2019.

Gender, socioeconomic status and school type: Previous studies have found a gender-based heterogeneity in the effect of temperature on morbidity and mortality. Heat related illness and mortality have been found to be larger for males (Deschenes and Moretti, 2009; Liu et al., 2021). In accordance with the health effects, across all test scores and temperature bins, we find that boys are more vulnerable to temperature than girls (Table 4, panel A).[3] As an example, hot days (>35°C) reduce reading test scores by 0.430% and 0.349% and cold days (<20°C) by 0.128% and 0.095% of a standard deviation in boys and girls, respectively. We also find a heterogeneous effect of temperature on test scores by parental education (Table 4, panel B).[4] Specifically, our results indicate a higher effect of (both low and high) temperature in general on children coming from more educated parents, consistent with the findings reported by Randell and Gray (2019). The authors find that children from more educated households experience higher educational penalties when exposed to hotter early-life conditions.[5] Similar findings are obtained when we test the heterogeneous effect of school type (Table 4, panel C). While we would expect students from non-government schools to be buffered from any adverse weather effects through more extensive use of heating and cooling devices, we find a stronger effect of hot days in general on student performance.[6] Overall, these results indicate a lack of resilience in children from more privileged backgrounds.

[3] A t-test indicates that the differences are statistically significant.

[4] We define children with high-educated parents as those who have mother or father finishing Year 12 or higher.

[5] A t-test indicates that the differences are statistically significant.

[6] Note we observe the opposite for the effect of cold days although a t-test indicates that the differences are generally statistically insignificant. However, differences across hot weather effects are statistically significant.

4.2 Robustness of our findings

To appreciate the robustness of our findings, we test the sensitivity of our results to weather controls other than day maximum temperature, school-specific characteristics, computer-based tests, and a placebo test.

Night temperature: It is quite likely that night time extreme temperatures will affect students' quality of sleep and impact on their performance. We test their effects by augmenting the model with the set of minimum temperature controls. Our results in Table 5 show that only cooler night temperatures have a significant effect on test scores. In contrast to our expectations, warm night temperatures do not significantly affect students' performance, with a positive effect on performance of night temperatures between 20-25°C. Our main results continue to indicate a negative effect of maximum temperature on student's scores although some of the coefficients are now statistically insignificant.

Precipitation: Other than temperature, student performance can also be hampered by precipitation. Previous studies argue that precipitation and temperature are historically correlated (Dell et al., 2012; Auffhammer et al., 2020). We next test the effect of precipitation on student scores, using average precipitation during school days in the past 13 months. Table 6 shows that our effects of temperature remain robust to rainy conditions.

School fixed effects: Next, we test the robustness of our results to school-specific time-invariant characteristics. Specifically, we estimate our model with school-grade fixed effects (Table 7). Once again we find negative effects of temperature on all five scores but the effects are now much smaller and some of the coefficients are statistically insignificant (Table 7). As explained by Johnston et al. (2021), with such fixed effects controls, the temperature coefficients are identified among a sub-set of observations. We believe that this can also potentially weaken the identification of the temperature effects.

Online assessment: As discussed earlier, in recent years, there has been a gradual transition from paper-based to computer-based assessments. Students who completed the tests online comprise 15% of the 2018 cohort and 50% of the 2019 cohort, adding up to just under half a million students. In order to test the sensitivity of our results to paper versus computer tests, we next estimate our model using a sample of students whose tests are computer-based (see Table 8). Broadly our findings are similar albeit smaller in magnitude, given the temperature effects are estimated from cross sectional differences rather than variations across time.

Placebo test: One may argue that the effect of temperature is an artefact of spurious correlation between our temperature series and test scores. If we estimate the chosen specification by replacing the true value of the regressor of interest with an alternative data series that we know should be irrelevant, then we expect the effect of the regressor to be statistically insignificant. However, if this process delivers statistically significant results, then this is consistent with a spurious association, generated by a flaw in the study design. Here, we conduct a 'meta' placebo exercise based on repeated within-sample randomisation. The steps involved: 1) replacing the true temperature value corresponding to a student with temperature from another, randomly-chosen postcode in sample without replacement; 2) estimating the model with the resulting placebo temperature series. We test this on the reading tests scores. This process was repeated with 1,000 randomisations the resulting coefficient and t-statistic on the temperature variable was collected in each regression. The bar charts in Figure 1 summarises the coefficients and t-statistics harvested. As expected, the mean value of the coefficient is close to zero and none of the placebo runs generates values anywhere close to those derived under true assignment, denoted by the dashed vertical lines.

4.3 Immediate and cumulative effects of temperature

In order to examine both immediate and lasting effects of temperature, we next control for temperature on the test day. We find significant effects of test-day temperature only on numeracy, with remarkably reduced scores at both extreme ends of the temperature spectrum (Table 9, panel A). Interestingly we find some significant positive effects of temperature between 25-30°C on reading and writing scores. Nonetheless, the effects of cumulative school days temperature remain broadly consistent with the main results. To provide more insight on the immediate effect of temperature, we next estimate the model with only test day temperature. We find that both cold and hot weather conditions affect student scores quite significantly (Table 9, panel B). For example, relative to a day-time maximum temperature between 20-25°C, a test day with temperature <20°C and >30°C reduce numeracy test scores by 2.527% and 9.739% of a standard deviation, respectively.

Following Park et al. (2020), we further explore the cumulative effects of temperature to test whether the effects have a lasting effect on students' performance or whether they are transitory. Specifically, we estimate our model with lagged measures of temperature. This allows us to examine whether the effects of heat and cold persist over two to three years. In Table 10, panel A we present results where we include one-period lagged temperature (i.e. temperature between 13 months to 25 months prior to the test day) and in panel B we include one- and two-period lagged temperatures. In general, we find statistically significant and sizeable effects of temperature on all test scores with the one-period lagged temperatures. On the other hand, except for temperatures below 20°C, we do not find any significant effect of two-period lagged temperatures on test scores. Focusing on panel A, we next add the effects of current and lagged periods to calculate the cumulative effects over a two-year period prior to the test day. Looking at the cumulative impact of increased exposure to cold over the two years, we find that temperature <20°C decreases reading, writing, spelling, grammar and numeracy scores by 0.144%, 0.197%, 0.176%, 0.140% and 0.163% of a standard deviation respectively, indicating an approximate 30% higher effect of cold days than the impact over a one-year period. Similarly, the two-year cumulative impacts of temperatures >35°C are associated with 0.430%, 0.500%, 0.425%, 0.432% and 0.395% of a standard deviation lower test scores respectively, reflecting approximately 10% higher effect than a one-year period impact on test scores. These findings are consistent with persistent effects of temperature on student performance reported in previous studies (Johnston et al., 2021; Park et al., 2020).

5 Heatwave

With climate change, we do not only observe a rise in temperature globally but also prolonged extreme events like heatwaves. Heatwaves result in more significant damage to human health, agriculture, energy production, and the economy than sporadic hot days (Christidis et al., 2010; Korhonen et al., 2018; Folkerts et al., 2020). In Australia, a larger number of heatwave days are being recorded each year. A study by Trancoso et al. (2020) has revealed that heatwaves have increased in intensity, frequency and duration across Australia over the past 67 years and such intensification has been on a rise in recent decades. In this study, we construct heatwave variables to count school days in the 13 months prior to assessment experiencing heatwaves longer than 3, 6 and 9 days. As expected, our results in Table 11 indicate large and statistically significant effects of heatwaves on all test scores. As the spells of heatwaves get longer the estimated effects get larger. The largest effect is observed for numeracy test scores; an additional heatwave lasting longer than 9 days is found to decrease test scores by 8.328% of a standard deviation. Once again, using the estimated decrease of 0.023 standard deviation estimated by Fredriksson et al. (2013) for a one-pupil increase in class size as a comparison, this is equivalent to increasing class size by about 3-4 students.

6 Climate heterogeneity and adaptability

A few studies have found that individuals become resilient to the weather conditions in the region they live in because the human body can physiologically adapt to the local climate (Folkerts et al., 2020; Korhonen et al., 2018; Christidis et al., 2010). As discussed earlier, Johnston et al. (2021) find that cold days significantly reduce test performance while high temperatures do not have any statistically significant effect on children's scores, which the authors relate to adaptability. Their study focuses on children in New South Wales with mostly temperate weather conditions such that for 90% of student observations in their dataset, the mean temperature was between 21-26°C. If adaption reduces temperature effect, students who live in hotter Australian states and territories will be less affected by high temperatures and vice versa. It is also likely that the temperature effects are subdued because schools in warm regions are more likely to equip their classes with air conditioning and those in cold regions are likely to invest in better insulation and heating systems with an aim to provide better thermal comfort to students.

Since our dataset comprises national data on Australian children, this allows us to test the adaptation hypothesis. Australia is exposed to a variety of climates due to its large geographical size and meridional location. To assist with energy efficiency in different locations around the country that have different heating and cooling requirements, eight climate zones have been created by the National Construction Code using climatic data from the Bureau of Meteorology (National Construction Code, 2022). In each state and territory the climatic zones are available at the local government area (LGA). We map our data to the climatic zones by first matching postcodes at the LGA level.[7] We then estimate our model separately in each climatic zone.

Table 12 reports the results across the seven climatic zones. Zone 1 is a region with hot humid summer, warm winter and highly humid. Our estimates show cold days have a large, statistically significant negative effect on all five scores (panel A). The effects of all other temperature bins are statistically insignificant. Zone 2 is a region with warm humid summer and mild winter. Results in panel B show that mostly very hot days affect scores, with larger effects than in the baseline model. Zone 3 is a region with hot dry summer, warm winter but low humidity. Interestingly, the corresponding results in panel C indicate positive significant effects of 25-30°C on all five scores, while effects of >35°C are significantly positive for four scores except for numeracy. The remaining temperature effects are statistically insignificant. Zone 4 is a region with hot dry summer, cool winter and low humidity. In panel D, we find mostly no significant effect of temperature on scores. Zone 5 has a warm temperate weather.

[7] LGAs in Zone 8 (alpine) are included in the climate zones which mostly surround the area. In most cases these are Zone 6 and 7 (mild/cool temperate).

In panel E we find that student scores decline with both cold and hot days. Specifically, we find statistically significant effects of temperature <20°C and in the range of 30-35°C. Zone 6 has a cool temperate weather. In panel F we find that both extreme temperatures have significant effects but the intermediate ones are statistically insignificant. The size of both the effects are larger than in the baseline model. Zone 7 has a cool temperate weather. The corresponding results in panel G indicate that cold weather has significant negative but smaller effects than in the main results. High temperature effects are significant for grammar and numeracy scores.

Overall our results are consistent with adaptation hypothesis. We do not find evidence that students who live in regions with hot dry or high humid summer (zones 1,3 and 4) are negatively impacted by hot temperatures. Likewise, we do not find that students facing cool winter or cool temperate weather (zones 4 and 7) are greatly affected by cold temperatures. Of all climatic zones, the lowest number of cold days have been reported in zone 1. Given the rarity of cold temperatures in the region, students' scores appear to be significantly influenced by cold temperature shocks. We also find evidence that students in colder regions (zones 6 and 7) are sensitive to hot weather. Finally, we find that students who live in regions with warm to mild temperate weather conditions, are affected by both hot and cold temperatures.

7 Conclusion

With the looming threat of global warming, a growing number of studies have examined the impact of temperature and weather extremes on a range of economic outcomes. In this study we examine the link between temperature and academic performance using national level administrative data comprising of nearly 1 million students over a period of six years. Our findings resonate with previous studies which have found a negative effect of heat on student's academic performance, with the effects exacerbating with heatwaves. Our study also finds evidence that cold weather affects students' performance but to a lesser degree. Extending the analysis over a longer horizon indicates that the effect of temperature is not transient such that hot and cold school days one to two years prior to the assessment day worsen students' scores.

Due to its large geographical size and location with respect to the equator, Australia is one of the very few countries in the world to span several climate zones, ranging from tropical zone in the north to temperate zones in the south. We exploit the variability in temperatures to examine spatial heterogeneity in the effects of temperature on student performance, making a unique contribution to the existing literature. Overall, we find that students who live in regions with hot dry or high humid summer are not impacted by hot temperatures but they are sensitive to cold weather. Likewise, students facing cool winter or cool temperate weather conditions are not greatly affected by cold temperatures but their academic performance is affected by hot weather. Our findings are consistent with the adaptation hypothesis which asserts that individuals become tolerant to the temperature in the region they live in because the human body can physiologically adapt to the local climate.

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Figures

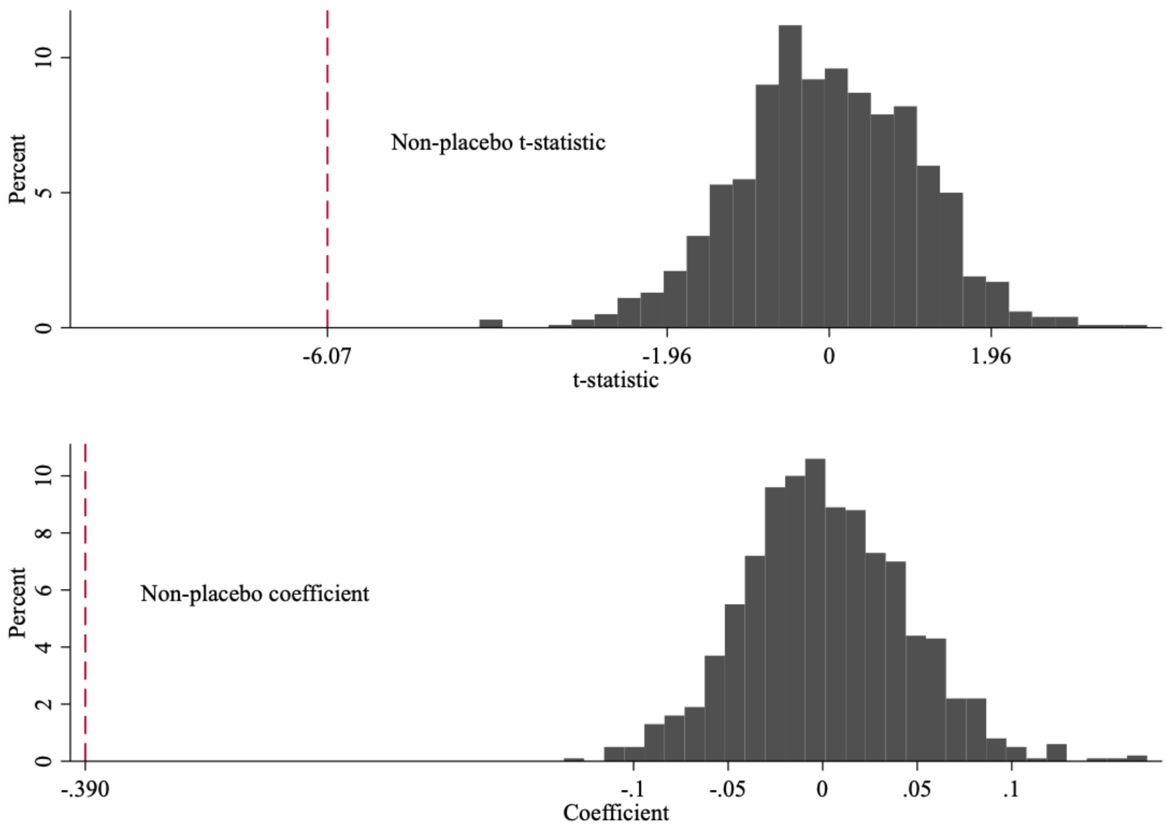

Figure 1: Placebo test – Random postcode ID

Notes: Outcome is reading score. Results of placebo postcode series (1,000 randomizations).

Tables

Table 1: Estimated effects of temperature on NAPLAN test scores – Main results

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.112***	-0.147***	-0.130***	-0.117***	-0.121***
	(0.024)	(0.029)	(0.026)	(0.027)	(0.026)
Days (25°C, 30°C]	-0.126***	-0.136***	-0.112***	-0.124***	-0.097**
	(0.038)	(0.041)	(0.034)	(0.040)	(0.038)
Days (30°C, 35°C]	-0.091***	-0.095**	-0.074**	-0.090***	-0.104***
	(0.035)	(0.038)	(0.032)	(0.035)	(0.033)
Days > 35°C	-0.390***	-0.448***	-0.364***	-0.396***	-0.350***
	(0.064)	(0.074)	(0.065)	(0.063)	(0.051)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.44	0.429	0.455	0.358	0.553

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector (public/private), and Postcode Index of Economic Resources. Full results are presented in Table A3 (Appendix). ***p<0.01, **p<0.05, *p<0.1.

Table 2: Effects by grade

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Panel A: Grade 3					
Days ≤ 20 °C	-0.117***	-0.126***	-0.147***	-0.106***	-0.108***
	(0.028)	(0.030)	(0.030)	(0.031)	(0.025)
Days (25°C, 30°C]	-0.126***	-0.075*	-0.118***	-0.061	-0.068*
	(0.042)	(0.040)	(0.039)	(0.043)	(0.038)
Days (30°C, 35°C]	-0.078**	-0.027	-0.048	-0.074**	-0.068**
	(0.036)	(0.034)	(0.032)	(0.035)	(0.031)
Days > 35°C	-0.369***	-0.340***	-0.362***	-0.311***	-0.282***
	(0.052)	(0.056)	(0.054)	(0.050)	(0.039)
Observations	901,047	900,185	902,423	900,009	899,592
Panel B: Grade 5					
Days ≤ 20°C	-0.089***	-0.125***	-0.106***	-0.111***	-0.086***
	(0.025)	(0.026)	(0.024)	(0.027)	(0.023)
Days (25°C, 30°C]	-0.106***	-0.105***	-0.104***	-0.152***	-0.073**
	(0.041)	(0.038)	(0.033)	(0.042)	(0.036)
Days (30°C, 35°C]	-0.083**	-0.059*	-0.053*	-0.077**	-0.068**
	(0.034)	(0.034)	(0.028)	(0.034)	(0.028)
Days > 35°C	-0.354***	-0.363***	-0.330***	-0.383***	-0.298***
	(0.070)	(0.074)	(0.061)	(0.069)	(0.045)
Observations	865,899	864,702	866,746	866,336	863,130
Panel C: Grade 7					
Days ≤ 20°C	-0.085***	-0.137***	-0.098***	-0.089***	-0.104***
	(0.026)	(0.030)	(0.026)	(0.029)	(0.033)
Days (25°C, 30°C]	-0.103**	-0.124***	-0.086**	-0.108**	-0.078
	(0.040)	(0.045)	(0.038)	(0.044)	(0.048)
Days (30°C, 35°C]	-0.084**	-0.101**	-0.072*	-0.080*	-0.121***
	(0.041)	(0.047)	(0.039)	(0.043)	(0.046)
Days > 35°C	-0.392***	-0.510***	-0.357***	-0.458***	-0.376***
	(0.079)	(0.100)	(0.078)	(0.087)	(0.071)
Observations	854,427	855,402	857,199	857,199	851,259
Panel D: Grade 9					
Days ≤ 20°C	-0.123***	-0.156***	-0.122***	-0.129***	-0.137***
	(0.027)	(0.037)	(0.028)	(0.030)	(0.033)
Days (25°C, 30°C]	-0.160***	-0.200***	-0.120***	-0.161***	-0.149***
	(0.044)	(0.058)	(0.042)	(0.048)	(0.050)
Days (30°C, 35°C]	-0.101**	-0.170***	-0.110***	-0.106**	-0.136***
	(0.042)	(0.055)	(0.041)	(0.044)	(0.045)
Days > 35°C	-0.423***	-0.593***	-0.363***	-0.422***	-0.425***
	(0.071)	(0.095)	(0.075)	(0.076)	(0.068)
Observations	805,381	807,392	809,241	809,241	801,460
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. Reference group of temperature is Days (20°C, 25°C]. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector (public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 3: Effects by year

Variables	Reading	Writing	Spelling	Grammar	Numeracy	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Year 2014					*Panel B: Year 2015*				
Days ≤ 20°C	-0.182***	-0.233***	-0.191***	-0.193***	-0.202***	-0.133***	-0.198***	-0.173***	-0.141***	-0.176***
	(0.040)	(0.045)	(0.036)	(0.043)	(0.049)	(0.041)	(0.046)	(0.040)	(0.045)	(0.046)
Days (25°C, 30°C]	-0.205***	-0.204***	-0.152***	-0.201***	-0.203***	-0.165***	-0.195***	-0.192***	-0.170**	-0.189***
	(0.058)	(0.061)	(0.049)	(0.059)	(0.064)	(0.059)	(0.074)	(0.061)	(0.069)	(0.066)
Days (30°C, 35°C]	-0.181***	-0.199***	-0.153***	-0.168***	-0.158***	-0.115***	-0.155***	-0.119***	-0.111***	-0.134***
	(0.045)	(0.046)	(0.036)	(0.042)	(0.047)	(0.040)	(0.043)	(0.039)	(0.040)	(0.040)
Days > 35°C	-0.423***	-0.515***	-0.398***	-0.439***	-0.466***	-0.357***	-0.455***	-0.381***	-0.393***	-0.356***
	(0.072)	(0.084)	(0.067)	(0.073)	(0.077)	(0.058)	(0.071)	(0.071)	(0.065)	(0.058)
Observations	588,513	588,321	589,770	589,369	586,712	628,887	629,308	630,908	630,908	627,177
	Panel C: Year 2016					*Panel D: Year 2017*				
Days ≤ 20°C	-0.024	-0.02	-0.041	0.009	-0.02	-0.219***	-0.285***	-0.263***	-0.257***	-0.246***
	(0.041)	(0.041)	(0.042)	(0.044)	(0.047)	(0.033)	(0.037)	(0.033)	(0.037)	(0.038)
Days (25°C, 30°C]	0.009	0.008	0.014	0.033	0.053	-0.313***	-0.355***	-0.326***	-0.366***	-0.305***
	(0.060)	(0.056)	(0.054)	(0.061)	(0.065)	(0.061)	(0.065)	(0.057)	(0.068)	(0.072)
Days (30°C, 35°C]	-0.075**	-0.049	-0.062*	-0.056	-0.090**	-0.096***	-0.147***	-0.096***	-0.114***	-0.129***
	(0.037)	(0.035)	(0.033)	(0.036)	(0.037)	(0.037)	(0.046)	(0.037)	(0.041)	(0.036)
Days > 35°C	-0.336***	-0.346***	-0.297***	-0.292***	-0.277***	-0.502***	-0.558***	-0.455***	-0.490***	-0.435***
	(0.070)	(0.075)	(0.067)	(0.066)	(0.060)	(0.072)	(0.078)	(0.062)	(0.073)	(0.067)
Observations	641,556	641,390	642,691	642,203	639,450	661,787	661,885	663,249	662,558	659,673
	Panel E: Year 2018					*Panel F: Year 2019*				
Days ≤ 20°C	-0.057	-0.142***	-0.141***	-0.055	-0.085**	-0.06	-0.087	-0.09	-0.052	-0.072
	(0.035)	(0.050)	(0.040)	(0.040)	(0.040)	(0.057)	(0.063)	(0.060)	(0.064)	(0.060)
Days (25°C, 30°C]	-0.038	-0.149**	-0.136**	-0.039	-0.026	-0.104	-0.141*	-0.053	-0.045	-0.035
	(0.056)	(0.073)	(0.055)	(0.064)	(0.060)	(0.082)	(0.080)	(0.072)	(0.086)	(0.086)
Days (30°C, 35°C]	-0.102**	-0.052	-0.038	-0.088**	-0.122***	0.013	0.038	0.004	-0.008	-0.066
	(0.040)	(0.057)	(0.042)	(0.045)	(0.043)	(0.065)	(0.063)	(0.058)	(0.065)	(0.059)
Days > 35°C	-0.378***	-0.641***	-0.453***	-0.424***	-0.353***	-0.563***	-0.681***	-0.458***	-0.541***	-0.403***
	(0.099)	(0.138)	(0.103)	(0.112)	(0.084)	(0.143)	(0.168)	(0.139)	(0.133)	(0.096)
Observations	579,133	579,850	581,062	580,216	576,845	326,878	326,927	327,929	327,531	325,584
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. Reference group of temperature is Days (20°C, 25°C]. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector (public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 4: Heterogeneity analysis - By gender, parental education and school type

VARIABLES	(1) Reading	(2) Writing	(3) Spelling	(4) Grammar	(5) Numeracy	(6) Reading	(7) Writing	(8) Spelling	(9) Grammar	(10) Numeracy
Panel A: Gender										
			Male					Female		
Days ≤ 20°C	-0.128***	-0.172***	-0.157***	-0.138***	-0.139***	-0.095***	-0.122***	-0.103***	-0.095***	-0.102***
	(0.026)	(0.031)	(0.028)	(0.028)	(0.029)	(0.024)	(0.027)	(0.024)	(0.026)	(0.025)
Days (25°C, 30°C]	-0.137***	-0.166***	-0.132***	-0.140***	-0.111***	-0.115***	-0.103***	-0.090***	-0.107***	-0.084**
	(0.039)	(0.043)	(0.036)	(0.040)	(0.041)	(0.037)	(0.039)	(0.033)	(0.041)	(0.037)
Days (30°C, 35°C]	-0.114***	-0.122***	-0.109***	-0.114***	-0.130***	-0.067**	-0.067*	-0.038	-0.066*	-0.077**
	(0.037)	(0.040)	(0.034)	(0.036)	(0.037)	(0.033)	(0.036)	(0.031)	(0.034)	(0.031)
Days > 35°C	-0.430***	-0.493***	-0.409***	-0.433***	-0.397***	-0.349***	-0.401***	-0.317***	-0.357***	-0.302***
	(0.066)	(0.073)	(0.067)	(0.065)	(0.056)	(0.064)	(0.076)	(0.065)	(0.063)	(0.049)
Observations	1,742,260	1,741,499	1,746,929	1,745,003	1,738,277	1,684,494	1,686,182	1,688,680	1,687,782	1,677,164
R-squared	0.431	0.378	0.433	0.346	0.535	0.446	0.461	0.475	0.359	0.574
Panel B: Parental education										
			Low education					High education		
Days ≤ 20°C	-0.075***	-0.109***	-0.107***	-0.079***	-0.075***	-0.159***	-0.195***	-0.169***	-0.172***	-0.190***
	(0.025)	(0.031)	(0.027)	(0.028)	(0.025)	(0.028)	(0.030)	(0.029)	(0.031)	(0.035)
Days (25°C, 30°C]	-0.082**	-0.104**	-0.089**	-0.078*	-0.048	-0.178***	-0.169***	-0.148***	-0.186***	-0.158***
	(0.039)	(0.046)	(0.040)	(0.043)	(0.039)	(0.039)	(0.038)	(0.034)	(0.040)	(0.045)
Days (30°C, 35°C]	-0.067*	-0.066	-0.061*	-0.066*	-0.075**	-0.129***	-0.150***	-0.106***	-0.128***	-0.146***
	(0.034)	(0.041)	(0.035)	(0.035)	(0.031)	(0.041)	(0.038)	(0.034)	(0.041)	(0.046)
Days > 35°C	-0.332***	-0.421***	-0.361***	-0.343***	-0.285***	-0.481***	-0.416***	-0.331***	-0.477***	-0.493***
	(0.065)	(0.078)	(0.067)	(0.063)	(0.045)	(0.066)	(0.055)	(0.055)	(0.064)	(0.070)
Observations	1,908,887	1,910,351	1,915,593	1,913,285	1,900,391	1,517,867	1,517,330	1,520,016	1,519,500	1,515,050
R-squared	0.430	0.380	0.434	0.339	0.551	0.377	0.447	0.443	0.291	0.512
Panel C: School type										
			Government					Non-government		
Days ≤ 20°C	-0.123***	-0.139***	-0.132***	-0.128***	-0.133***	-0.092***	-0.147***	-0.122***	-0.097***	-0.106***
	(0.029)	(0.033)	(0.031)	(0.033)	(0.032)	(0.024)	(0.030)	(0.026)	(0.027)	(0.028)
Days (25°C, 30°C]	-0.135***	-0.129***	-0.103**	-0.121**	-0.089*	-0.107***	-0.132***	-0.116***	-0.119***	-0.114***
	(0.044)	(0.049)	(0.043)	(0.049)	(0.046)	(0.035)	(0.041)	(0.034)	(0.038)	(0.039)
Days (30°C, 35°C]	-0.084**	-0.055	-0.051	-0.077*	-0.105***	-0.113***	-0.160***	-0.126***	-0.125***	-0.110***
	(0.038)	(0.044)	(0.037)	(0.041)	(0.039)	(0.035)	(0.039)	(0.032)	(0.034)	(0.036)
Days > 35°C	-0.371***	-0.413***	-0.355***	-0.375***	-0.307***	-0.397***	-0.475***	-0.334***	-0.401***	-0.422***
	(0.068)	(0.077)	(0.064)	(0.066)	(0.054)	(0.065)	(0.083)	(0.079)	(0.069)	(0.066)
Observations	2,012,076	2,012,505	2,017,850	2,015,537	2,004,169	1,414,678	1,415,176	1,417,759	1,417,248	1,411,272
R-squared	0.423	0.387	0.441	0.347	0.539	0.436	0.456	0.458	0.349	0.555
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. Reference group of temperature is Days (20°C, 25°C]. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender (not in Panel A), indigenous status, language background, mother's and father's education (not in Panel B), school sector (not in Panel C), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Controlling for minimum temperature

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°C	-0.032	-0.039	-0.041*	-0.030	-0.033
	(0.025)	(0.029)	(0.024)	(0.027)	(0.026)
Days (25°C, 30°C]	-0.127***	-0.117***	-0.098***	-0.124***	-0.106***
	(0.034)	(0.036)	(0.030)	(0.035)	(0.036)
Days (30°C, 35°C]	-0.055*	-0.047	-0.032	-0.050	-0.063**
	(0.031)	(0.035)	(0.029)	(0.031)	(0.032)
Days > 35°C	-0.320***	-0.360***	-0.288***	-0.323***	-0.279***
	(0.059)	(0.070)	(0.062)	(0.059)	(0.046)
Minimum temperature reference: Days (5°C, 10°C]					
Days $\leq$ 5C	-0.057*	-0.133***	-0.163***	-0.108***	-0.088**
	(0.031)	(0.034)	(0.029)	(0.033)	(0.035)
Days (10°C, 15°C]	0.122***	0.063*	0.012	0.066*	0.071*
	(0.034)	(0.037)	(0.031)	(0.036)	(0.040)
Days (15°C, 20°C]	0.046	0.038	-0.007	0.030	0.057
	(0.039)	(0.043)	(0.034)	(0.041)	(0.044)
Days (20°C, 25°C]	0.137***	0.088**	0.057	0.111***	0.131***
	(0.040)	(0.041)	(0.037)	(0.042)	(0.046)
Days > 25°C	-0.039	-0.049	-0.096	-0.098	-0.108*
	(0.072)	(0.083)	(0.078)	(0.077)	(0.060)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	3,387,806	3,388,718	3,396,546	3,393,747	3,376,658
R-squared	0.441	0.430	0.456	0.359	0.554

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 6: Controlling for precipitation

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°C	-0.105***	-0.134***	-0.127***	-0.112***	-0.121***
	(0.026)	(0.031)	(0.026)	(0.029)	(0.030)
Days (25°C, 30°C]	-0.122***	-0.114***	-0.115***	-0.128***	-0.112**
	(0.040)	(0.042)	(0.036)	(0.044)	(0.043)
Days (30°C, 35°C]	-0.090**	-0.106***	-0.074**	-0.087**	-0.104***
	(0.036)	(0.041)	(0.032)	(0.037)	(0.035)
Days > 35°C	-0.313***	-0.373***	-0.294***	-0.316***	-0.289***
	(0.062)	(0.071)	(0.064)	(0.060)	(0.050)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	2,906,605	2,907,222	2,914,072	2,911,681	2,897,075
R-squared	0.440	0.430	0.455	0.359	0.554

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 7: Controlling for school-grade fixed effects

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°C	-0.112***	0.073***	-0.049***	-0.062***	-0.043***
	(0.009)	(0.017)	(0.009)	(0.010)	(0.011)
Days (25°C, 30°C]	-0.106***	0.016	-0.043***	-0.034***	-0.036***
	(0.011)	(0.021)	(0.010)	(0.010)	(0.010)
Days (30°C, 35°C]	-0.074***	-0.035	-0.058***	-0.076***	0.004
	(0.012)	(0.023)	(0.012)	(0.013)	(0.015)
Days > 35°C	-0.114***	0.194***	-0.014	-0.048**	0.091***
	(0.022)	(0.034)	(0.021)	(0.022)	(0.023)
Other controls	Yes	Yes	Yes	Yes	Yes
School-grade FEs	Yes	Yes	Yes	Yes	Yes
Observations	3,426,454	3,427,384	3,435,313	3,432,484	3,415,138
R-squared	0.493	0.485	0.515	0.419	0.627

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 8: Estimated effects of temperature on NAPLAN test scores – Online tests only

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.031	-0.161***	-0.119***	-0.069*	-0.016
	(0.032)	(0.044)	(0.035)	(0.036)	(0.036)
Days (25°C, 30°C]	-0.030	-0.189***	-0.088	-0.053	0.024
	(0.059)	(0.072)	(0.056)	(0.067)	(0.067)
Days (30°C, 35°C]	-0.125***	-0.138***	-0.097**	-0.121***	-0.109**
	(0.040)	(0.049)	(0.038)	(0.043)	(0.043)
Days > 35°C	-0.229***	-0.407***	-0.280***	-0.272***	-0.229***
	(0.044)	(0.063)	(0.047)	(0.047)	(0.049)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	470,455	343,647	467,399	467,399	465,336
R-squared	0.446	0.307	0.467	0.382	0.565

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 9: Controlling for temperature on test day

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Panel A: Controlling for temperature on the test day					
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.112***	-0.141***	-0.115***	-0.115***	-0.112***
	(0.025)	(0.028)	(0.024)	(0.026)	(0.026)
Days (25°C, 30°C]	-0.127***	-0.139***	-0.112***	-0.125***	-0.095**
	(0.039)	(0.040)	(0.034)	(0.039)	(0.038)
Days (30°C, 35°C]	-0.092***	-0.107***	-0.074**	-0.104***	-0.090***
	(0.034)	(0.039)	(0.034)	(0.036)	(0.033)
Days > 35°C	-0.387***	-0.449***	-0.363***	-0.401***	-0.342***
	(0.064)	(0.073)	(0.064)	(0.060)	(0.056)
Temperature on test day; Reference: Days (20°C, 25°C]					
Days ≤ 20°C	0.071	-0.959	-2.265***	-0.292	-1.994***
	(0.488)	(0.689)	(0.658)	(0.800)	(0.550)
Days (25°C, 30°C]]	0.958*	2.255***	0.327	0.983	-0.899
	(0.547)	(0.737)	(0.555)	(0.658)	(0.551)
Days > 30°C	-1.676	1.218	0.386	3.238	-6.581***
	(1.982)	(2.222)	(2.067)	(2.116)	(1.484)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.440	0.429	0.455	0.358	0.553
Panel B: Controlling ONLY for temperature on test day					
Temperature on test day; Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.714	-1.930**	-3.090***	-0.924	-2.527***
	(0.538)	(0.922)	(0.829)	(1.000)	(0.665)
Days (25°C, 30°C]	-0.590	0.641	-0.818	-0.620	-1.062*
	(0.659)	(0.822)	(0.636)	(0.749)	(0.600)
Days > 30°C	-5.897***	-6.803***	-5.488***	-4.473**	-9.739***
	(2.070)	(2.210)	(1.732)	(2.240)	(1.450)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.439	0.428	0.454	0.357	0.553
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 10: Effects of lagged periods

Panel A: Controlling for one-period lagged temperature

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.093***	-0.108***	-0.094***	-0.111***	-0.089***
	(0.018)	(0.022)	(0.018)	(0.020)	(0.019)
Days (25°C, 30°C]	-0.096***	-0.080**	-0.081***	-0.102***	-0.054*
	(0.028)	(0.031)	(0.026)	(0.030)	(0.030)
Days (30°C, 35°C]	-0.082***	-0.017	-0.077***	-0.099***	-0.057**
	(0.021)	(0.024)	(0.021)	(0.023)	(0.023)
Days > 35°C	-0.270***	-0.248***	-0.148***	-0.286***	-0.201***
	(0.043)	(0.051)	(0.045)	(0.044)	(0.039)
Temperature lag 1 (Reference: Days (20°C , 25°C])					
Days ≤ 20°C	-0.051**	-0.089***	-0.082***	-0.029	-0.075***
	(0.020)	(0.022)	(0.020)	(0.022)	(0.023)
Days (25°C, 30°C]	-0.077**	-0.120***	-0.093***	-0.060*	-0.098***
	(0.032)	(0.034)	(0.029)	(0.033)	(0.033)
Days (30°C, 35°C]	-0.019	-0.104***	-0.009	0.006	-0.067***
	(0.023)	(0.027)	(0.020)	(0.022)	(0.022)
Days > 35°C	-0.159***	-0.253***	-0.276***	-0.146***	-0.194***
	(0.046)	(0.052)	(0.046)	(0.045)	(0.039)
Cumulative effects					
Days ≤ 20°C	-0.144***	-0.197***	-0.176***	-0.140***	-0.163***
	(0.034)	(0.039)	(0.035)	(0.037)	(0.037)
Days (25°C, 30°C]	-0.172***	-0.200***	-0.174***	-0.161***	-0.153***
	(0.054)	(0.059)	(0.050)	(0.056)	(0.055)
Days (30°C, 35°C]	-0.101**	-0.121***	-0.085**	-0.094**	-0.124***
	(0.040)	(0.044)	(0.037)	(0.039)	(0.039)
Days > 35°C	-0.430***	-0.500***	-0.425***	-0.432***	-0.395***
	(0.075)	(0.085)	(0.077)	(0.074)	(0.061)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.439	0.429	0.454	0.357	0.553

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Panel B: Controlling for two-period lagged temperature

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.078***	-0.103***	-0.072***	-0.096***	-0.071***
	(0.014)	(0.019)	(0.015)	(0.016)	(0.016)
Days (25°C, 30°C]	-0.103***	-0.063**	-0.080***	-0.096***	-0.060**
	(0.024)	(0.026)	(0.023)	(0.026)	(0.027)
Days (30°C, 35°C]	-0.102***	-0.021	-0.095***	-0.098***	-0.070***
	(0.020)	(0.025)	(0.020)	(0.023)	(0.023)
Days > 35°C	-0.296***	-0.209***	-0.152***	-0.271***	-0.233***
	(0.041)	(0.052)	(0.042)	(0.045)	(0.043)
Temperature lag 1 (Reference: Days (20°C, 25°C])					
Days ≤ 20°C	-0.021	-0.086***	-0.045***	-0.008	-0.046**
	(0.018)	(0.020)	(0.017)	(0.019)	(0.019)
Days (25°C, 30°C]	-0.073***	-0.114***	-0.086***	-0.053*	-0.091***
	(0.026)	(0.028)	(0.024)	(0.028)	(0.027)
Days (30°C, 35°C]	-0.029	-0.130***	-0.026	0.002	-0.069***
	(0.018)	(0.021)	(0.016)	(0.019)	(0.019)
Days > 35°C	-0.182***	-0.231***	-0.282***	-0.132***	-0.223***
	(0.039)	(0.042)	(0.037)	(0.038)	(0.036)
Temperature lag 2 (Reference: Days (200C, 250C])					
Days ≤ 20°C	-0.060***	-0.021	-0.082***	-0.052***	-0.063***
	(0.018)	(0.021)	(0.017)	(0.019)	(0.020)
Days (25°C, 30°C]	-0.012	-0.046	-0.037	-0.034	-0.019
	(0.027)	(0.033)	(0.024)	(0.028)	(0.028)
Days (30°C, 35°C]	0.028	0.03	0.031	-0.002	0.011
	(0.027)	(0.030)	(0.024)	(0.025)	(0.026)
Days > 35°C	0.04	-0.08	-0.011	-0.046	0.055
	(0.048)	(0.062)	(0.053)	(0.051)	(0.043)
Cumulative effects					
Days ≤ 20°C	-0.159***	-0.210***	-0.199***	-0.156***	-0.179***
	(0.041)	(0.046)	(0.040)	(0.044)	(0.044)
Days (25°C, 30°C]	-0.188***	-0.223***	-0.202***	-0.182***	-0.171***
	(0.065)	(0.072)	(0.060)	(0.068)	(0.066)
Days (30°C, 35°C]	-0.103**	-0.121***	-0.090**	-0.098**	-0.127***
	(0.041)	(0.046)	(0.038)	(0.041)	(0.041)
Days > 35°C	-0.438***	-0.520***	-0.445***	-0.449***	-0.401***
	(0.080)	(0.092)	(0.083)	(0.080)	(0.066)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.439	0.429	0.454	0.357	0.553

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 11: Estimated effects of heatwaves on NAPLAN test scores

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Panel A: heatwave longer than 3 days					
Heatwave	-0.557***	-0.570***	-0.501***	-0.545***	-0.638***
	(0.173)	(0.190)	(0.163)	(0.193)	(0.183)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.439	0.428	0.454	0.357	0.553
Panel B: heatwave longer than 6 days					
Heatwave	-1.974***	-2.052***	-2.143***	-1.767***	-2.204***
	(0.449)	(0.479)	(0.423)	(0.484)	(0.445)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.439	0.428	0.454	0.357	0.553
Panel C: heatwave longer than 9 days					
Heatwave	-7.628***	-7.773**	-7.271***	-7.535***	-8.328***
	(2.336)	(3.024)	(2.070)	(2.842)	(2.209)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.439	0.428	0.454	0.357	0.553
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Table 12: Estimated effects of temperature on NAPLAN test scores by climatic zone

Panel A: Climatic zone 1

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-1.765**	-4.058***	-2.305**	-1.895*	-1.510*
	(0.829)	(1.233)	(1.033)	(1.072)	(0.870)
Days (25°C, 30°C]	0.139	0.149	0.119	0.155	0.105
	(0.241)	(0.377)	(0.245)	(0.307)	(0.283)
Days (30°C, 35°C]	0.066	0.101	0.096	0.05	-0.019
	(0.205)	(0.324)	(0.226)	(0.278)	(0.252)
Days > 35°C	-0.138	-0.19	-0.129	-0.136	-0.141
	(0.227)	(0.345)	(0.254)	(0.298)	(0.267)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	114,626	114,940	115,291	114,840	113,952
R-squared	0.485	0.423	0.486	0.404	0.603

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Panel B: Climate zone 2

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.024	-0.194**	-0.101	-0.070	-0.054
	(0.080)	(0.076)	(0.061)	(0.086)	(0.066)
Days (25°C, 30°C]	0.081	0.104	0.084	0.144**	0.099**
	(0.057)	(0.073)	(0.065)	(0.062)	(0.048)
Days (30°C, 35°C]	0.077	0.013	0.021	0.116*	0.095*
	(0.061)	(0.074)	(0.060)	(0.065)	(0.056)
Days > 35°C	-0.498***	-0.611***	-0.452***	-0.597***	-0.650***
	(0.130)	(0.138)	(0.110)	(0.141)	(0.146)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	634,069	634,254	636,223	635,821	631,808
R-squared	0.430	0.407	0.467	0.352	0.564

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Panel C: Climate zone 3

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	0.268	0.039	0.221	0.075	0.066
	(0.202)	(0.222)	(0.191)	(0.205)	(0.140)
Days (25°C, 30°C]	0.269**	0.277**	0.248***	0.236**	0.150**
	(0.116)	(0.119)	(0.080)	(0.105)	(0.067)
Days (30°C, 35°C]	0.011	-0.016	-0.049	0.002	0.031
	(0.139)	(0.148)	(0.109)	(0.115)	(0.078)
Days > 35°C	0.175**	0.164**	0.221***	0.134*	0.007
	(0.064)	(0.072)	(0.061)	(0.064)	(0.044)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	32,489	32,659	32,763	32,611	32,339
R-squared	0.454	0.409	0.480	0.382	0.588

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Panel D: Climate zone 4

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.014	0.085	-0.009	0.001	-0.011
	(0.063)	(0.073)	(0.067)	(0.068)	(0.057)
Days (25°C, 30°C]	-0.035	-0.038	-0.182*	-0.116	-0.016
	(0.075)	(0.108)	(0.094)	(0.080)	(0.081)
Days (30°C, 35°C]	0.012	0.129	0.014	0.016	0.017
	(0.093)	(0.091)	(0.098)	(0.098)	(0.087)
Days > 35°C	0.007	0.126	0.115	-0.053	0.023
	(0.139)	(0.117)	(0.138)	(0.146)	(0.123)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	141,418	141,415	141,807	141,628	140,684
R-squared	0.449	0.395	0.448	0.372	0.574

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Panel E: Climate zone 5

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°CC	-0.103**	-0.116***	-0.067*	-0.098**	-0.069
	(0.042)	(0.042)	(0.038)	(0.043)	(0.048)
Days (25°C, 30°C]	-0.108	-0.112	-0.013	-0.067	0.003
	(0.086)	(0.089)	(0.077)	(0.089)	(0.103)
Days (30°C, 35°C]	-0.415***	-0.342**	-0.300**	-0.354***	-0.391**
	(0.129)	(0.141)	(0.117)	(0.135)	(0.156)
Days > 35°C	-0.030	-0.095	0.050	-0.066	-0.036
	(0.135)	(0.145)	(0.128)	(0.141)	(0.163)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	928,440	928,844	930,358	929,775	925,406
R-squared	0.450	0.451	0.468	0.364	0.564

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Panel F: Climate zone 6

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°C	-0.210***	-0.300***	-0.262***	-0.271***	-0.279***
	(0.074)	(0.073)	(0.063)	(0.078)	(0.081)
Days (25°C, 30°C]	-0.169	-0.111	-0.065	-0.118	-0.116
	(0.105)	(0.110)	(0.095)	(0.120)	(0.124)
Days (30°C, 35°C]	-0.085	-0.186	-0.186	-0.140	-0.130
	(0.116)	(0.137)	(0.117)	(0.136)	(0.135)
Days > 35°C	-0.731***	-0.778***	-0.677***	-0.909***	-0.947***
	(0.206)	(0.198)	(0.181)	(0.236)	(0.250)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	1,316,948	1,316,568	1,319,396	1,318,573	1,313,420
R-squared	0.428	0.422	0.431	0.341	0.532

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Panel G: Climate zone 7

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°C	-0.092*	-0.083	-0.105**	-0.125**	-0.103*
	(0.050)	(0.060)	(0.043)	(0.057)	(0.061)
Days (25°C, 30°C]	-0.159*	-0.034	-0.162*	-0.179*	-0.185*
	(0.090)	(0.104)	(0.089)	(0.107)	(0.098)
Days (30°C, 35°C]	0.095	-0.113	0.041	0.048	0.017
	(0.117)	(0.125)	(0.096)	(0.135)	(0.134)
Days > 35°C	-0.408	-0.107	-0.106	-0.587*	-0.659**
	(0.280)	(0.368)	(0.214)	(0.317)	(0.289)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	258,764	259,001	259,771	259,537	257,832
R-squared	0.424	0.408	0.441	0.359	0.548

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector(public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.

Appendix

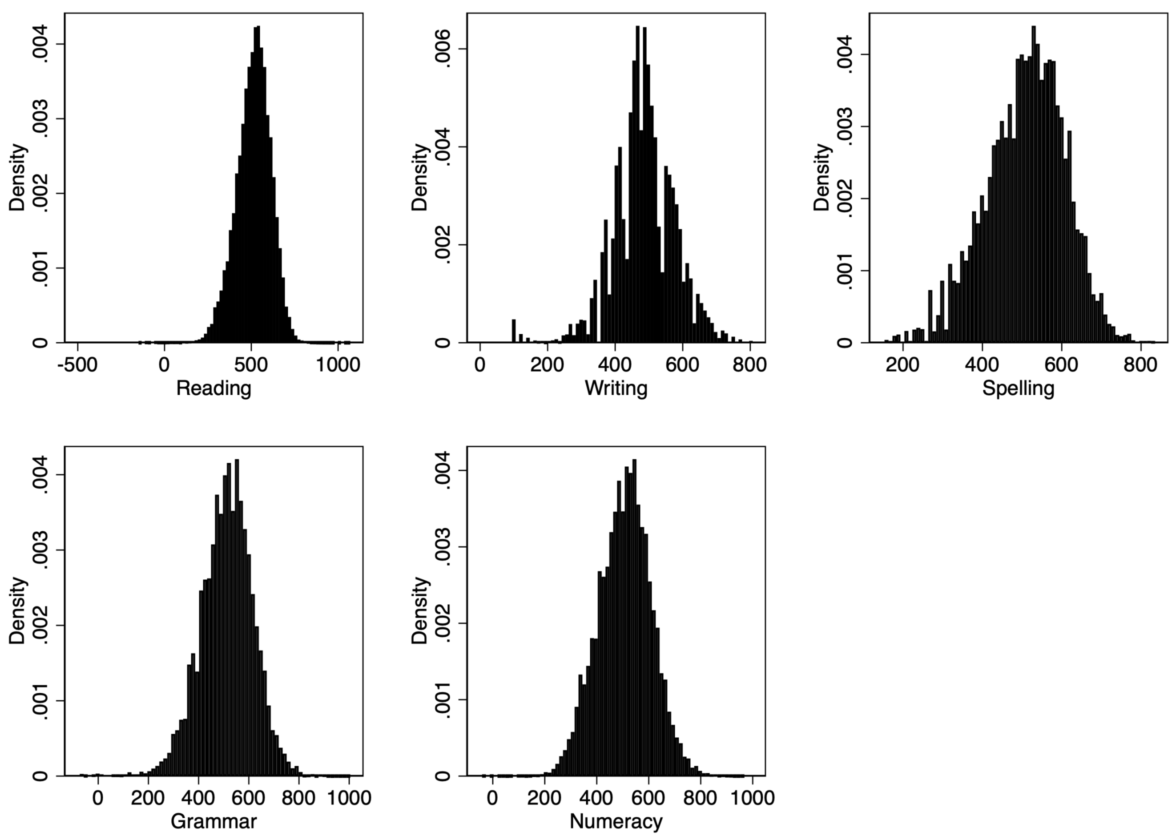

Figure A.1: Distribution of test scores

Table A.1: Summary statistics

Variable	Mean	Std. dev.	Min	Max
Test scores				
Reading	513.08	99.30	9.90	1036.00
Writing	484.47	92.33	94.50	807.20
Spelling	508.84	100.56	153.20	835.30
Grammar	512.68	104.26	1.50	1004.50
Numeracy	507.83	102.80	29.20	968.10
Maximum temperature				
Days $\leq$ 20°C	67.90	45.38	0.00	205.00
Days (25°C, 30°C]	126.27	43.03	0.00	212.00
Days (30°C, 35°C]	49.85	27.26	0.00	147.00
Days (30°C, 35°C]	23.73	21.77	0.00	189.00
Days $>$ 35°C	6.66	10.76	0.00	140.00
Minimum temperature				
Days $\leq$ 5°C	21.16	22.70	0.00	175.00
Days (5°C, 10°C]	52.65	25.07	0.00	126.00
Days (10°C, 15°C]	63.98	17.94	0.00	119.00
Days (15°C, 20°C]	48.09	23.18	0.00	137.00
Days (20°C, 25°C]	18.93	24.98	0.00	164.00
Days $>$ 25°C	1.76	7.83	0.00	154.00
Precipitation				
Average precipitation	2.32	1.12	0.00	10.82
Control variables				
Age	11.48	2.27	7.00	17.50
Female	0.49	0.50	0.00	1.00
Indigenous	0.06	0.23	0.00	1.00
Other language background	0.24	0.43	0.00	1.00
Mother's education				
Less than Year 12	0.17	0.37	0.00	1.00
Year 12	0.12	0.32	0.00	1.00
Certificate I to IV	0.25	0.43	0.00	1.00
Advanced diploma/Diploma	0.15	0.36	0.00	1.00
Bachelor degree or above	0.31	0.46	0.00	1.00
Father's education				
Less than Year 12	0.15	0.36	0.00	1.00
Year 12	0.10	0.30	0.00	1.00
Certificate I to IV	0.33	0.47	0.00	1.00
Advanced diploma/Diploma	0.13	0.33	0.00	1.00
Bachelor degree or above	0.29	0.46	0.00	1.00
School sector				
Public school	0.35	0.48	0.00	1.00
Postcode socioeconomic status				
IER	1,001.17	65.42	584	1,167.00

Table A.2: NAPLAN test score and temperature – Correlation matrix

	Days $\leq$ 20°C	Days (20°C, 25°C]	Days (25°C, 30°C]	Days (30°C, 35°C]	Days $>$ 35°C	Heatwave $>$ 3 days	Heatwave $>$ 6 days	Heatwave $>$ 9 days
Reading	0.055	0.088	-0.026	-0.085	-0.104	-0.034	-0.021	-0.014
Writing	0.086	0.121	-0.056	-0.106	-0.108	-0.037	-0.026	-0.013
Spelling	0.034	0.074	-0.019	-0.076	-0.085	-0.026	-0.025	-0.013
Grammar	0.035	0.074	-0.008	-0.081	-0.104	-0.033	-0.023	-0.013
Numeracy	0.049	0.084	-0.027	-0.082	-0.091	-0.033	-0.024	-0.014

Table A.3: Estimated effects of temperature on NAPLAN test scores – Full results

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°C	-0.112***	-0.147***	-0.130***	-0.117***	-0.121***
	(0.024)	(0.029)	(0.026)	(0.027)	(0.026)
Days (25°C, 30°C]	-0.126***	-0.136***	-0.112***	-0.124***	-0.097**
	(0.038)	(0.041)	(0.034)	(0.040)	(0.038)
Days (30°C, 35°C]	-0.091***	-0.095**	-0.074**	-0.090***	-0.104***
	(0.035)	(0.038)	(0.032)	(0.035)	(0.033)
Days > 35°C	-0.390***	-0.448***	-0.364***	-0.396***	-0.350***
	(0.064)	(0.074)	(0.065)	(0.063)	(0.051)
Mother's education (Reference: Less than Year 12)					
Year 12	16.983***	16.595***	15.594***	17.723***	15.673***
	(0.399)	(0.408)	(0.412)	(0.416)	(0.420)
Certificate I to IV	12.348***	11.107***	10.338***	12.308***	10.145***
	(0.314)	(0.352)	(0.367)	(0.336)	(0.329)
Advanced diploma/Diploma	21.798***	19.528***	16.835***	21.263***	19.051***
	(0.425)	(0.442)	(0.459)	(0.447)	(0.485)
Bachelor degree or above	44.142***	34.688***	32.472***	43.762***	40.016***
	(0.564)	(0.588)	(0.608)	(0.616)	(0.693)
Father's education (Reference: Less than Year 12)					
Year 12	19.267***	18.281***	18.271***	20.005***	17.063***
	(0.445)	(0.426)	(0.405)	(0.462)	(0.446)
Certificate I to IV	12.979***	12.382***	11.270***	13.238***	11.309***
	(0.312)	(0.351)	(0.340)	(0.336)	(0.325)
Advanced diploma/Diploma	25.775***	23.129***	22.192***	26.146***	22.330***
	(0.420)	(0.449)	(0.430)	(0.454)	(0.486)
Bachelor degree or above	46.758***	38.341***	38.960***	48.199***	43.954***
	(0.692)	(0.707)	(0.674)	(0.754)	(0.872)
Other control variables					
Age	25.344***	24.062***	26.992***	21.767***	30.461***
	(0.121)	(0.148)	(0.124)	(0.133)	(0.165)
Gender (Female=1)	13.884***	32.517***	16.318***	20.792***	-7.650***
	(0.238)	(0.319)	(0.271)	(0.260)	(0.335)
Indigenous (Yes=1)	-32.627***	-36.434***	-26.474***	-35.129***	-28.770***
	(1.124)	(1.607)	(1.223)	(1.182)	(0.941)
Other language at home (Yes=1)	-6.489***	8.781***	21.111***	3.675***	8.271***
	(0.827)	(0.816)	(0.887)	(0.975)	(1.251)
School sector (private=1)	5.409***	12.331***	3.461***	4.659***	3.230***
	(0.668)	(0.701)	(0.706)	(0.801)	(0.892)
SEIFA index	0.071***	0.076***	0.061***	0.072***	0.064***
	(0.011)	(0.012)	(0.010)	(0.012)	(0.014)
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.440	0.429	0.455	0.358	0.553

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. ***p<0.01, **p<0.05, *p<0.1.

Table A.4: Estimated effects of temperature on NAPLAN test scores – Including negative test scores

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days $\leq$ 20°C	-0.113***	-0.147***	-0.130***	-0.120***	-0.121***
	(0.024)	(0.029)	(0.026)	(0.027)	(0.026)
Days (25°C, 30°C]	-0.127***	-0.136***	-0.112***	-0.127***	-0.097**
	(0.038)	(0.041)	(0.034)	(0.040)	(0.038)
Days (30°C, 35°C]	-0.086**	-0.095**	-0.074**	-0.077**	-0.104***
	(0.035)	(0.038)	(0.032)	(0.037)	(0.033)
Days $>$ 35°C	-0.405***	-0.448***	-0.364***	-0.433***	-0.351***
	(0.069)	(0.074)	(0.065)	(0.076)	(0.052)
Other controls	Yes	Yes	Yes	Yes	Yes
State and Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	3,427,459	3,427,681	3,435,609	3,435,609	3,415,522
R-squared	0.438	0.429	0.455	0.357	0.553

Notes: Robust standard errors in parentheses. Standard errors are clustered at postcode level. The dependent variable is the standardized NAPLAN test score multiplied by 100. Control variables include age, gender, indigenous status, language background, mother's education, father's education, school sector (public/private), and Postcode Index of Economic Resources. ***p<0.01, **p<0.05, *p<0.1.