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Keywords: climate change , temperature, academic performance, NAPLAN, heatwave

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Weather effects on academic performance: An analysis using administrative data

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Abstract

This paper contributes to the growing body of research examining the impact of temperature on educational outcomes. Utilising national-level administrative data on nearly one million Australian students, it investigates whether temperature fluctuations, and prolonged heatwaves influence test performance. The analysis reveals that both heat and cold affect student test scores, with some evidence of the effects intensifying during heatwaves. Australia's vast geographical diversity and climate variability provides a unique opportunity to explore spatial heterogeneity in these effects. Findings suggest that in regions with hot weather conditions, the most thermally comfortable temperature is likely to be higher, whereas students in the coldest parts of the country appear to be less sensitive to cold weather conditions, consistent with the adaptation hypothesis. In contrast, in regions with moderate and temperate weather conditions, student scores are affected by both hot and cold weather.

JEL classification: C3, I2, Q5

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

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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). This constitutes an important concern within the overarching issue of climate change. As global warming progresses, it is anticipated to trigger a wide array of consequences that will impact various facets of our lives. The escalation of weather-related risks underscores the urgency to take policy actions to mitigate its extensive and far-reaching consequences.

A growing number of studies have examined the impact of temperature and weather extremes on a range of economic outcomes such as health and well-being (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 (Prentice et al., 2024). 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 et al., 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 absences or low concentration due to sleep deprivation (e.g., Conte Keivabu, 2024; 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 (see Prentice et al. (2024) for an extensive discussion on potential mechanisms). 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 (Park, 2017; Cho, 2017; Cook and Heyes, 2020; Garg et al., 2020; Zivin et al., 2020; Park et al., 2021; Park, 2022; Roach and Whitney, 2022) have lent further support to existing lab-based findings by showing a causal effect of temperature on academic achievement.

Our contribution to the evolving national and international literature in this area is multifold. Firstly, we use country-wide administrative data on Australian primary and secondary school students. 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, our data covers

a large segment of the student population in Australia and allows us to consider different climatic conditions across the country. Our dataset comprises nearly one 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 7,000 schools across the entire country.

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. Our second contribution lies in examining heatwaves of various durations on student performance. This allows us to assess their impact on student learning separately from the effect of sporadic hot days. 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 third and unique contribution to the existing literature.

Overall, our analysis shows a negative impact of heat and cold on students' test scores. Relative to days with a thermally comfortable temperature of 20–25°C, an additional colder school day in the last academic year can reduce numeracy test scores by approximately 0.071% and an additional hot day exceeding 35°C, by 0.098% of a standard deviation. We also examine the effects of heatwave which has been on an increasing trend in Australia

more recently. We find an additional school day with heatwave longer than 9 days decreases numeracy test scores by 2.021% of a standard deviation, at the 5% level. 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 some scores.

Our findings from the spatial heterogeneity analysis are consistent with adaptation hypothesis, reported in previous studies (Christidis et al., 2010; Korhonen et al., 2018; Folkerts et al., 2020; Johnston et al., 2021). Our results suggest that in regions with hot weather conditions, the most thermally comfortable temperature is very likely to be higher, whereas students in the colder part of the country appear less sensitive to cold weather conditions. In contrast, in regions with moderate and temperate weather conditions, student scores are affected by both hot and cold weather.

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 precipitation bins[1], 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: $\leq$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 1st April of the last year and the 30th April of the current year. This allows us to fully capture the four school terms before the NAPLAN test in May of each year. In a similar way, we construct six temperature bins for minimum daily temperatures as follows: $\leq$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,

[1]Environmental factors, such as air pollution, may have negative impacts on educational outcomes. However, due to data unavailability, we are unable to account for these factors in this study.

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 or equal to 3, 6, and 9. Essentially, we count the number of days when a heatwave has lasted for, at least,

3 days, 6 days, and 9 days is experienced.

In a similar way of generating the temperature bin variables, we constructed five precipitation bin variables for daily precipitation as follows: =0mm (no rain), (0mm, 10mm] (light rain), (10mm, 35.5mm] (moderate rain), (35.5mm, 124.4mm] (heavy rain), and >124.4mm (very heavy rain).

Finally, we link the weather variables to our test score data as follows. A limitation of our data is that we do not have the specific addresses of schools to precisely calculate their distance from the nearest weather station. As an alternative, we estimate the distance between a school and a weather station using the coordinates of the weather station and the center of the postcode where the school is located. Our first choice is the closest weather station to the center of the postcode of the school that the student attends. Where we do not have information for the nearest weather station, we move on to the second nearest weather station, and so on[2]. Note that we construct the weather variables only over school days, thus excluding school holidays and public holidays, which may vary by state and territory.

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 nationally 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). Before it transitioned to an online format, the test was administered during the second week of May to students in grades 3, 5, 7, and 9.[3] While participation in the

[2]The average distance between the weather station and the school postcode area is 12.99 km.

[3]Until 2018, the assessment was conducted yearly on the second Tuesday of May and lasted three days, with writing, spelling, grammar/punctuation on day 1, reading on day 2 and numeracy on day 3.

assessment program is not mandatory, it has remained relatively high and steady throughout the study period, with an average of 95% in grades 3 and 5, and 93% and 89% in grades 7 and 9, respectively, in 2019. Although NAPLAN may not necessarily be considered a high-stake exam from students' perspective, it holds significant importance for schools as the test results influence their reputation. Schools may face scrutiny based on their NAPLAN performance, since the results are published on the 'My School' website (MYSCHOOL, 2024). For more information about NAPLAN test, refer to NAPLAN (2022).

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.

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. For consistency, we therefore consider only paper-based test scores in our analysis. 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. The average number of schools in a postcode area is about 9.5. Figure A.1 (Appendix) shows the distribution of the number of schools over all postcodes (excluding those with less than 5 schools) in our data. Our main estimation sample of students who attempted paper-based assessments includes nearly 3.4 million observations. Figure A.2 (Appendix) shows the distribution of the scores in the five tests.[4] 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. School names have been de-identified but we have school IDs, and 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 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 length of heatwaves, we observe a negative relationship with the five test scores.

[4]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.

3 Methods

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

$$Y_{igsjt} = \sum_{k=1}^{4} \beta_k T_{kjt} + \gamma X_{igsjt} + \theta_{sg} + \theta_t + \epsilon_{igsjt} \tag{3}$$

where Y_{igsjt} represents standardized test scores of student i in grade g, attending school s, in postcode j, 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_{kjt} 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_{kjt} represents the number of school day counts in the 13 months prior to the assessment taken by student i from school s located in postcode j, 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 a thermally comfortable 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 help identify the causal effect of temperature on test scores, we enter a range of controls in equation 3. We include a vector of other weather variables, as well as student and school characteristics X_{igsjt}. Other weather variables include temperature

on the examination day and precipitation bin variables. Student and school characteristics include 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. Potentially confounding factors, such as school facilities and infrastructures, teacher quality, curriculum standards, funding and resources that determine school quality are controlled for with the inclusion of school-grade fixed effects, θ_{sg}. Finally, we use year fixed effects, θ_t, 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 state, climate zones and year fixed effects, any remaining variation in temperature is essentially random. This allows for a causal interpretation of our coefficient of interest, β_k, which is expected to be negative.

We also test the robustness of our results by using alternative weather conditions such as nighttime temperature, holiday temperature, and controlling for only test day temperature. To confirm that our results are not just a statistical artifact driven by spurious correlations between temperature and test scores, we 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 not shorter than 3 days, 6 days, and 9 days. This allows us to measure the additional 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 kth temperature bin on test scores, relative to a day when the temperature is within a thermally comfortable range of 20–25°C (the reference category). Relative to days with a 20–25°C temperature range, in general, cumulative year-long school day temperature appear to negatively affect test scores, with most of the effects being 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 numeracy test scores by 0.071%, 0.054%, 0.042% and 0.098% of a standard deviation, respectively. The positive and statistically significant effect of the >35°C temperature bin on writing score is pervert and unexpected, and appears in many of the results we present below. However, we also find from Table A1 that the >35°C temperature bin has relatively small variation with a mean of 6.66 days. It is also likely that most of our observations in this bin originate from the hotter regions of Australia which typically have a smaller student population. As such, we are uncertain if the accuracy of our estimates results have been compromised in this temperature bin. Overall, our results indicate that relative to a thermally comfortable temperature, low and high temperatures negatively impact on student performance. The full set of results are reported in Table A3 in the Appendix.

Albeit smaller in magnitude, 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, math 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, Math 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, 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 generally consistent with the baseline findings. We also find that the magnitude of the effects are broadly similar across all grades except for a more accentuated impact of cold weather on grader niners.

Gender, socioeconomic status and school type: Previous studies have found a gender differential effect of temperature on cognitive performance (Chang and Kajackaite, 2019; Cook and Heyes, 2020; Johnston et al., 2021) . In accordance with several of those studies, across all test scores, we find that boys are more vulnerable to hot and cold temperatures than girls (Table 3, panel A), with many of the differences being statistically significant at the 10% level.[5] As an example, hot days (>35°C) reduce numeracy test scores by 0.136% and 0.062%, and cold days (≤20°C) by 0.079% and 0.065% of a standard deviation in boys and girls, respectively. We also investigate for any heterogeneous effect of temperature on test scores by parental education (Table 3, panel B).[6] Our results indicate that the effects are quite similar across both groups. Next, we test the heterogeneous effect of school type

[5]We use a t-test to test the equality of coefficients.

[6]We define children with highly-educated parents as those whose mother or father have attained higher than Year 12 education.

(Table 3, panel C). We find that the effects of temperature are mostly larger in students from public schools indicating higher educational penalties due to weather conditions for public school students. This disparity may stem from various factors, including differences in school infrastructure, resource availability, and the capacity to mitigate heat-related disruptions, which are challenges more pronounced in public schools, as well as the socioeconomic backgrounds of students (see for example, Tomaszewski et al. (2024)). A t-test indicates that many of the differences are statistically significant, particularly for colder weather conditions.

4.2 Robustness of our findings

To appreciate the robustness of our findings, we test the sensitivity of our results to the minimum temperature of the day, test day temperature, school holidays, and a placebo test.

Night temperature: Night time temperature fluctuations are also likely to 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 4 show that night temperatures are mostly statistically insignificant at the lower end of the spectrum, with a negative effect only for the 15-20°C temperature bin. In contrast to our expectations, warm night temperatures do not disrupt student performance. Instead we estimate positive and significant effects on performance of higher night temperatures in most test domains. Our results for day-time temperature continue to indicate a negative effect on student scores, consistent with our main results.

Exam day temperature: Our basic specification controls for exam day temperature. Next, we drop the temperature bins for year-long school day temperatures and estimate the model with only exam day temperature. Our results in Table 5 show sporadic significant effects which suggest that exam day temperatures deviating from the thermally comfortable temperature range of 20–25°C only partly influence student performance.

School holidays: We also test whether student scores are sensitive to temperatures during school holidays (including public holidays and weekends). We therefore augment the

model with a set of separate temperature bins for the school holiday periods. Our results in Table 6 indicate that the effects of school day temperatures remain consistent with our main results. We also observe some effects of holiday period heat on student scores, but not as consistently as we observe for school day temperatures, suggesting that heat during school terms is more responsible for the drop in test scores. One challenge in interpreting the coefficients is that temperature variation in holiday period is likely to be highly collinear with temperature variation in school days, especially with summer holidays and school term 1 spanning over the hottest months of the year.

Placebo test: One may argue that the effect of temperature is an artifact 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 is repeated with 1,000 randomisations and the resulting coefficient and t-statistic on the temperature variable are 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 only a negligible number of the placebo runs generate values close to those derived under true assignment, denoted by the dashed vertical lines.

4.3 Cumulative effects of temperature

Following Park et al. (2020), we explore the cumulative effects of temperature to test whether the effects have a lasting effect on student performance or whether they are transient. Specifically, we estimate our model with lagged measures of temperature. This allows us to examine the duration for which the effects of heat and cold persist. In Table 7, 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 further include two-period lagged temperatures. We add the effects of current and lagged periods to calculate the cumulative effects over a two-year (three-year) period prior to the test day in each panel. Looking at the cumulative impact of temperature over the two years (panel A), we find that they are in general higher than our main results. For example, the impact of temperature $\leq$20°C on writing scores over a two-year period prior to the test day increases to 0.132%, from a year-long impact of 0.088% (see Table 1), while the effect of temperature between 30-35°C increases to 0.15%, from 0.035%. This suggests that a prolonged exposure to both heat and cold can exacerbate the effect 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). However, we do not see much higher cumulative effects over a three-year period compared to a two-year period on test scores (panel B).

5 Heatwave

Heatwaves are one of the most important climate change phenomena. According to the Intergovernmental Panel on Climate Change (IPCC), they are growing in frequency, duration and intensity across the globe (Intergovernmental Panel on Climate Change, 2021). Trancoso et al. (2020) find that heatwaves in Australia may be 85% more frequent if global warming increases from 1.5°C to 2.0°C and may last up to a month if global warming increases to 3°C. Within the US, from the 1960s to the 2010s, the frequency of heatwaves has increased

from 2 to over 6 per year and the average length of days for a heatwave has increased from 2.99 to 3.96 days (EPA, 2023).

To assess the impact of heatwaves on test scores, we estimate the model by including alternately heatwaves longer than or equal to 3, 6 and 9 days, respectively, in order to capture the effect of varying intensities of prolonged heat which could have worse effects on students' sleep and level of concentration. The results are presented in Panel A-C of Table 8, respectively. We find that as the spells of heatwaves get longer the estimated effects get larger, although not all of the effects are statistically significant. In particular, one additional day with a heatwave longer than 3 days is found to decrease writing scores by 0.282% of a standard deviation, while one additional day with a heatwave longer than 9 days decreases reading and numeracy scores by 1.890% and 2.021% of a standard deviation, respectively. The effects are significant at the 10% level. Overall our results indicate that heatwaves can further exacerbate the effects of temperature on students' scores relative to sporadic hot days in the year.

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 acclimatise to the local climate, and/or a set of actions are taken in order to reduce the impacts of exposure to extreme weather conditions (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 (see Figure A.3) 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] Figure A.4 shows the temperature (days) distributions for the whole sample and across the seven zones.

Table 9 reports the results across the seven climatic zones. To bring our results into perspective, we refer to the distribution of temperature across the zones in Figure A.4. Zones 1 and 3 are regions with humid and warm to hot summers. They have the highest number of days with temperature above 30°C and almost negligible days with temperature below 20°C. In panels A and C of Table 9, relative to the reference bin of 20-25°C, we find positive effects of temperature on some scores. It is likely that in these regions, with hot weather conditions throughout the year, the thermally comfortable temperature is higher, consistent with the adaptation hypothesis. In zone 2, we find that temperature vary mostly between 20-35°C and there are almost negligible days with temperature below 20°C or above 35°C (Figure A.4). In panel B of Table 9, we find evidence that temperature in the range of 30-35°C has a negative impact on scores. Zone 4 is a region with hot, dry summer and cool winter. From Figure A.4, we see that temperatures are less disparate varying between

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

20-30°C most days of the year. In panel D (Table 9) we find no evidence of any effect of temperature on scores in zone 4. It is likely that in this part of the country, students are thermally comfortable with this temperature range.

Zones 5-7 are regions with temperate weather conditions. Precisely, zone 5 has a warm temperate weather. In panel E of Table 9 we find that student scores decline with both cold and hot days. We find statistically significant effects of temperature $\leq$20°C and 30-35°C, with larger impacts than in the baseline model. Zone 6 has a cool temperate weather with very few days above 35°C. In panel F (Table 9) we find that scores are affected by cold weather. We also find negative effect of heat on some of the domains, in particular reading, grammar and numeracy. Lastly, zone 7 has a cool temperate weather (the coldest region in the country) with a fairly large number of days <20°C and very few days above >25°C (see Figure A.4). The corresponding results in panel G (Table 9) indicate no significant effect of temperature on student scores. We note here that cold weather appear to have no impact on scores in this region.

Overall, our findings are consistent with the adaptation hypothesis. Our results indicate that in hotter regions (zones 1 and 3), the most thermally comfortable temperature is more likely higher than 20-25°. We also find that in zone 7, with mostly cooler conditions throughout the year, students are not sensitive to cold weather. In contrast, in regions with temperate weather conditions, student scores are affected by both hot and cold weather.

7 Conclusion

With the looming threat of global warming, a growing number of studies have examined the impact of weather 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 one million students over a six-year period. Our findings resonate with previous studies which have found a negative effect of temperature on student academic

performance. Extending the analysis over a longer horizon indicates that the effect of temperature is not transient such that hot and cold school days up to two years prior to the assessment date can adversely affect students' test scores.

Our analysis reveals that boys are generally more vulnerable to hot and cold temperatures than girls. However, we observe no significant differences in the impact of temperature on student performance across socioeconomic classes. We also find that the effects of temperature are generally more pronounced among students attending public schools, suggesting greater educational penalties from adverse weather conditions for this group.

We make an important contribution to this literature by estimating the effect of heatwaves, which are becoming longer and more frequent in the advent of climate change. We find some evidence that student learning are exacerbated with long heatwaves relative to sporadic hot days. In particular, one additional day with a heatwave longer than 9 days is found to decrease reading and numeracy scores by 1.890% and 2.021% of a standard deviation, respectively.

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. We find that in regions with moderate and temperate weather, student scores are affected by both heat and cold. Our results also indicate that in regions with hot weather conditions, the most thermally comfortable temperature is likely to be higher relative to other regions while in the coldest part of the country, student performance does not appear to be impacted by cold weather conditions. Overall, our findings are consistent with the adaptation hypothesis which suggests that individuals can potentially adapt through physiological alterations and/or environmental adjustments to improve their well-being and effectively respond to changing circumstances. Unfortunately, our study cannot distinguish between the two underlying mechanisms.

We acknowledge several limitations in our study. First, due to the lack of precise school addresses, we link schools with weather data based on their postcode. Specifically, we determine the distance between each weather station and the geographic centre of a school's postcode area and use weather data from the nearest station to this centre. Second, for confidentiality reasons, data was not available for postcodes with fewer than five schools, resulting in an approximate 23% reduction in the school sample. Finally, environmental factors, such as air pollution, may also adversely affect educational outcomes. Due to data unavailability, we were unable to account for such factors in our analysis. Our work can be expanded in interesting ways with future research and data availability.

References

ABS (2016). *Socio-economic indexes for areas (SEIFA)*. Australian Bureau of Statistics, Canberra.

ACARA (2011). *National protocols for test administration*. Australian Curriculum Assessment and Reporting Authority, Victoria.

Acevedo, S., M. Mrkaic, N. Novta, E. Pugacheva, and P. Topalova (2020). The effects of weather shocks on economic activity: what are the channels of impact? *Journal of Macroeconomics 65*, 103207.

ACSIS (2021). *The Benefits Of Air Conditioning In Classrooms*. `https://www.acsisair.com.au/benefits-air-conditioning-classrooms`. Accessed on 10 March 2022.

Akil, L., H. A. Ahmad, and R. S. Reddy (2014). Effects of climate change on salmonella infections. *Foodborne Pathogens and Disease 11*(12), 974–980.

Andamon, M., Woo, J. and Rajagopalan, P. (2021). *Australian children are learning in classrooms with very poor air quality*. `https://theconversation.com/australian-children-are-learning-in-classrooms-with-very-poor-air-quality-154950`. Accessed on 17 September 2022.

Auffhammer, M. and E. T. Mansur (2014). Measuring climatic impacts on energy consumption: A review of the empirical literature. *Energy Economics 46*, 522–530.

Behrer, A., R. Park, G. Wagner, C. Golja, and D. Keith (2021). Heat has larger impacts on labor in poorer areas. *Environmental Research Communications 3*(9), 095001.

Bentham, G. and I. H. Langford (2001). Environmental temperatures and the incidence of food poisoning in england and wales. *International Journal of Biometeorology 45*(1), 22–26.

Brothers, R. M., J. E. Wingo, K. A. Hubing, and C. G. Crandall (2009). The effects of reduced end-tidal carbon dioxide tension on cerebral blood flow during heat stress. *The Journal of Physiology 587*(15), 3921–3927.

Bureau of Meteorology (2022). *Average annual & monthly maximum, minimum, & mean temperature*. `http://www.bom.gov.au/jsp/ncc/climate_averages/temperature/index.jsp`. Accessed on 4 November 2022.

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

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Chang, T. Y. and A. Kajackaite (2019). Battle for the thermostat: Gender and the effect of temperature on cognitive performance. *PloS one 14*(5), e0216362.

Chen, S., X. Chen, and J. Xu (2016). Impacts of climate change on agriculture: Evidence from china. *Journal of Environmental Economics and Management 76*, 105–124.

Cho, H. (2017). The effects of summer heat on academic achievement: a cohort analysis. *Journal of Environmental Economics and Management 83*, 185–196.

Christidis, N., G. C. Donaldson, and P. A. Stott (2010). Causes for the recent changes in cold-and heat-related mortality in england and wales. *Climatic Change 102*(3), 539–553.

Cian, C., P. Barraud, B. Melin, and C. Raphel (2001). Effects of fluid ingestion on cognitive function after heat stress or exercise-induced dehydration. *International Journal of Psychophysiology 42*(3), 243–251.

Ciuha, U., T. Pogačar, L. K. Bogataj, M. Gliha, L. Nybo, A. D. Flouris, and I. B. Mekjavic (2019). Interaction between indoor occupational heat stress and environmental

temperature elevations during heat waves. *Weather, Climate, and Society 11*(4), 755–762.

Connelly, R., C. J. Playford, V. Gayle, and C. Dibben (2016). The role of administrative data in the big data revolution in social science research. *Social Science Research 59*, 1–12.

Conte Keivabu, R. (2024). Temperature and school absences: evidence from england. *Population and Environment 46*(1), 6.

Cook, N. and A. Heyes (2020). Brain freeze: outdoor cold and indoor cognitive performance. *Journal of Environmental Economics and Management 101*, 102318.

Crandall, C. and J. Gonzalez-Alonso (2010). Cardiovascular function in the heat-stressed human. *Acta physiologica 199*(4), 407–423.

Crandall, C. G. and T. E. Wilson (2015). Human cardiovascular responses to passive heat stress. *Comprehensive Physiology 5*(1), 17.

Daraganova, G., B. Edwards, and M. Sipthorp (2013). *Using National Assessment Program Literacy and Numeracy (NAPLAN) Data in the Longitudinal Study of Australian Children (LSAC)*. Department of Families, Housing, Community Services and Indigenous Affairs.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Deryugina, T. and S. M. Hsiang (2014). Does the environment still matter? daily temperature and income in the united states. Technical report, National Bureau of Economic Research.

Deschenes, O. (2014). Temperature, human health, and adaptation: A review of the empirical literature. *Energy Economics 46*, 606–619.

Deschênes, O. and M. Greenstone (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics 3*(4), 152–85.

Diffenbaugh, N. S. and M. Burke (2019). Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences 116*(20), 9808–9813.

EPA (2023). *Climate Change Indicators Heat Waves*. https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves, accessed on 24 April 2023.

Folkerts, M. A., P. Bröde, W. Botzen, M. L. Martinius, N. Gerrett, C. N. Harmsen, and H. A. Daanen (2020). Long term adaptation to heat stress: Shifts in the minimum mortality temperature in the netherlands. *Frontiers in Physiology*, 225.

Garg, T., M. Jagnani, and V. Taraz (2020). Temperature and human capital in india. *Journal of the Association of Environmental and Resource Economists 7*(6), 1113–1150.

Graff Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*(1), 1–26.

Heyes, A. and S. Saberian (2019). Temperature and decisions: evidence from 207,000 court cases. *American Economic Journal: Applied Economics 11*(2), 238–65.

Hsiang, S. M., M. Burke, and E. Miguel (2013). Quantifying the influence of climate on human conflict. *Science 341*(6151), 1235367.

Intergovernmental Panel on Climate Change (2021). Climate Change Widespread, Rapid, and Intensifying – IPCC. `https://www.ipcc.ch/2021/08/09/ar6-wg1-20210809-pr/`. Accessed: 2024-12-06.

Johnston, D. W., R. Knott, S. Mendolia, and P. Siminski (2021). Upside-down down-under: Cold temperatures reduce learning in australia. *Economics of Education Review 85*, 102172.

Kenny, G. P., T. E. Wilson, A. D. Flouris, and N. Fujii (2018). Heat exhaustion. *Handbook of Clinical Neurology 157*, 505–529.

Korhonen, M., S. Kangasraasio, and R. Svento (2018). Do people adapt to climate change? evidence from the industrialized countries. *International Journal of Climate Change Strategies and Management*.

Masson-Delmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. Gomis, et al. (2021). "Summary for Policymakers". Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change. Cambridge University Press Cambridge, UK.

McMorris, T., J. Swain, M. Smith, J. Corbett, S. Delves, C. Sale, R. C. Harris, and J. Potter (2006). Heat stress, plasma concentrations of adrenaline, noradrenaline, 5-hydroxytryptamine and cortisol, mood state and cognitive performance. *International Journal of Psychophysiology 61*(2), 204–215.

Mendell, M. J. and G. A. Heath (2005). Do indoor pollutants and thermal conditions in schools influence student performance? a critical review of the literature. *Indoor air 15*(1), 27–52.

Miller, S., K. Chua, J. Coggins, and H. Mohtadi (2021). Heat waves, climate change, and economic output. *Journal of the European Economic Association 19*(5), 2658–2694.

MYSCHOOL (2024). *MY School*. https://www.myschool.edu.au/, accessed on 26 November 2024.

NAPLAN (2022). *National Assessment Program*. https://www.nap.edu.au/, accessed on 10 March 2022.

National Construction Code (2022). *Climate Zone Map Australia*. https://abcb.gov.au/, accessed on 31 October 2022.

Ogoh, S., K. Sato, K. Okazaki, T. Miyamoto, A. Hirasawa, K. Morimoto, and M. Shibasaki (2013). Blood flow distribution during heat stress: cerebral and systemic blood flow. *Journal of Cerebral Blood Flow & Metabolism 33*(12), 1915–1920.

Okamoto-Mizuno, K. and K. Mizuno (2012). Effects of thermal environment on sleep and circadian rhythm. *Journal of Physiological Anthropology 31*(1), 1–9.

Opdenakker, M.-C. and J. Damme (2001). Relationship between school composition and characteristics of school process and their effect on mathematics achievement. *British Educational Research Journal 27*(4), 407–432.

Park, J. (2017). Heat stress and human capital production. *Unpublished, Harvard University, Cambridge, MA*.

Park, R. J. (2022). Hot temperature and high-stakes performance. *Journal of Human Resources 57*(2), 400–434.

Park, R. J., A. P. Behrer, and J. Goodman (2021). Learning is inhibited by heat exposure, both internationally and within the united states. *Nature human behaviour 5*(1), 19–27.

Park, R. J., J. Goodman, M. Hurwitz, and J. Smith (2020). Heat and learning. *American Economic Journal: Economic Policy 12*(2), 306–39.

Patz, J. A., D. Campbell-Lendrum, T. Holloway, and J. A. Foley (2005). Impact of regional climate change on human health. *Nature 438*(7066), 310–317.

Penner, A. M. and K. A. Dodge (2019). Using administrative data for social science and policy. *RSF: The Russell Sage Foundation Journal of the Social Sciences 5*(2), 1–18.

Pilcher, J. J., E. Nadler, and C. Busch (2002). Effects of hot and cold temperature exposure on performance: a meta-analytic review. *Ergonomics 45*(10), 682–698.

Prentice, C. M., F. Vergunst, K. Minor, and H. L. Berry (2024). Education outcomes in the era of global climate change. *Nature Climate Change 14*(3), 214–224.

Roach, T. and J. Whitney (2022). Heat and learning in elementary and middle school. *Education Economics 30*(1), 29–46.

Robertson, C. V. and F. E. Marino (2017). Cerebral responses to exercise and the influence of heat stress in human fatigue. *Journal of Thermal Biology 63*, 10–15.

Schlader, Z. J., D. Gagnon, A. Adams, E. Rivas, C. M. Cullum, and C. G. Crandall (2015). Cognitive and perceptual responses during passive heat stress in younger and older adults. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology 308*(10), R847–R854.

Schlader, Z. J., T. E. Wilson, and C. G. Crandall (2016). Mechanisms of orthostatic intolerance during heat stress. *Autonomic Neuroscience 196*, 37–46.

Schlenker, W. and M. J. Roberts (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences 106*(37), 15594–15598.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy 129*(6), 1797–1827.

Tomaszewski, W., N. Xiang, and Y. Huang (2024). School climate, student engagement and academic achievement across school sectors in australia. *The Australian Educational Researcher 51*(2), 667–695.

Trancoso, R., J. Syktus, N. Toombs, D. Ahrens, K. K.-H. Wong, and R. Dalla Pozza (2020). Heatwaves intensification in australia: A consistent trajectory across past, present and future. *Science of the Total Environment 742*, 140521.

Wenz, L., A. Levermann, and M. Auffhammer (2017). North–south polarization of european electricity consumption under future warming. *Proceedings of the National Academy of Sciences 114*(38), E7910–E7918.

Wilby, R. L. (2007). A review of climate change impacts on the built environment. *Built Environment 33*(1), 31–45.

Zivin, J. G., Y. Song, Q. Tang, and P. Zhang (2020). Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in china. *Journal of Environmental Economics and Management 104*, 102365.

Figures

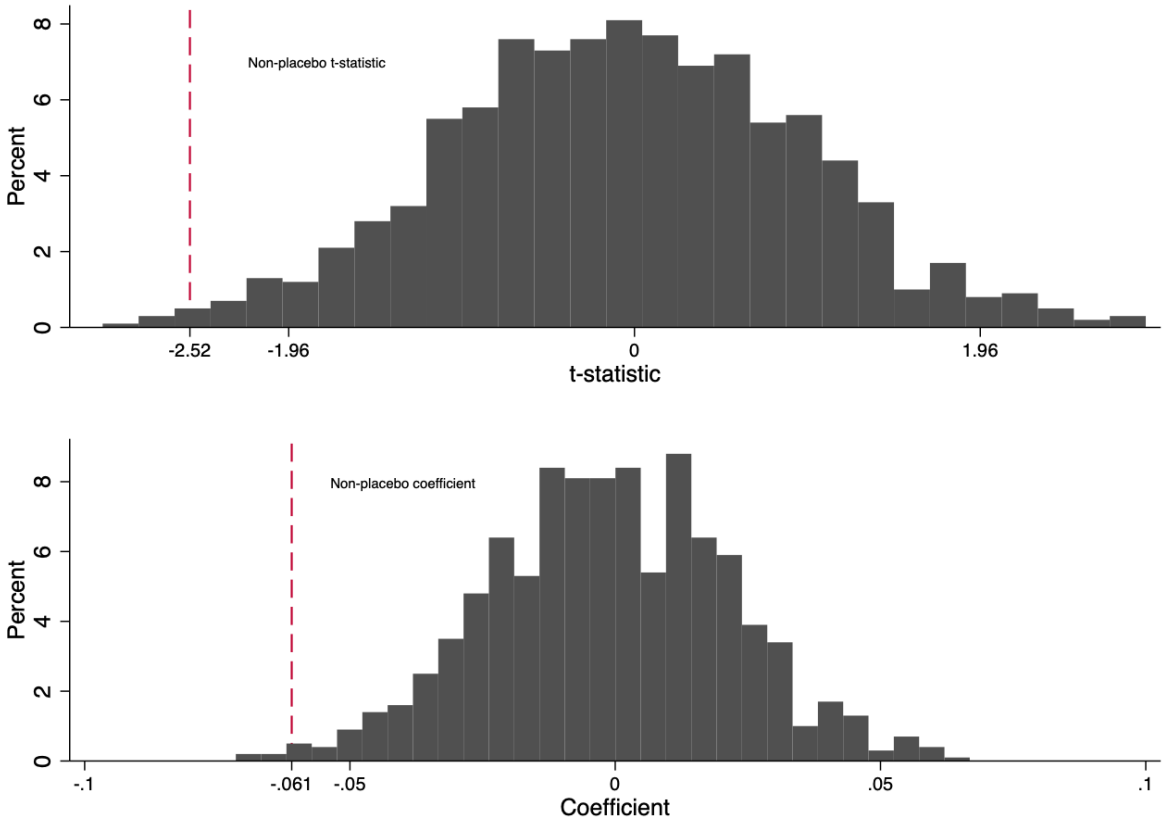

Figure 1: Placebo test – Random postcode ID

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 $\leq$ 20°C	-0.069***	-0.088***	-0.026***	-0.092***	-0.071***
	(0.009)	(0.016)	(0.009)	(0.010)	(0.009)
Days (25°C, 30°C]	-0.069***	-0.009	-0.040***	-0.080***	-0.054***
	(0.011)	(0.017)	(0.010)	(0.012)	(0.010)
Days (30°C, 35°C]	-0.064***	-0.035**	-0.050***	-0.101***	-0.042***
	(0.012)	(0.015)	(0.012)	(0.013)	(0.012)
Days > 35°C	-0.061**	0.094***	-0.007	-0.084***	-0.098***
	(0.024)	(0.033)	(0.024)	(0.027)	(0.024)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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	0.494	0.487	0.515	0.419	0.627

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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	-0.042**	-0.075***	-0.034*	-0.057***	-0.075***
	(0.018)	(0.019)	(0.018)	(0.021)	(0.016)
Days (25°C, 30°C]	-0.081***	-0.041*	-0.062***	-0.028	-0.072***
	(0.024)	(0.021)	(0.021)	(0.027)	(0.019)
Days (30°C, 35°C]	-0.098***	-0.047**	-0.046**	-0.095***	-0.068***
	(0.028)	(0.023)	(0.022)	(0.029)	(0.022)
Days > 35°C	-0.076	0.048	-0.093**	-0.125**	-0.109***
	(0.047)	(0.045)	(0.047)	(0.054)	(0.041)
Observations	901,047	900,185	902,423	900,009	899,592
R-squared	0.219	0.253	0.197	0.213	0.235
Panel B: Grade 5					
Days ≤ 20°C	-0.040**	-0.074***	-0.003	-0.085***	-0.005
	(0.017)	(0.018)	(0.014)	(0.018)	(0.014)
Days (25°C, 30°C]	-0.060***	-0.025	-0.030*	-0.122***	-0.041**
	(0.020)	(0.021)	(0.017)	(0.021)	(0.017)
Days (30°C, 35°C]	-0.065***	-0.024	-0.017	-0.115***	0.006
	(0.023)	(0.019)	(0.018)	(0.022)	(0.017)
Days > 35°C	-0.132***	0.034	-0.036	-0.182***	-0.088**
	(0.040)	(0.045)	(0.038)	(0.046)	(0.036)
Observations	865,899	864,702	866,746	866,336	863,130
R-squared	0.224	0.245	0.192	0.221	0.257
Panel C: Grade 7					
Days ≤ 20°C	-0.044***	-0.098***	-0.005	-0.070***	-0.076***
	(0.014)	(0.023)	(0.015)	(0.017)	(0.016)
Days (25°C, 30°C]	-0.036**	0.010	-0.036**	-0.089***	-0.039**
	(0.017)	(0.026)	(0.017)	(0.019)	(0.016)
Days (30°C, 35°C]	-0.041**	-0.030	-0.062***	-0.113***	-0.067***
	(0.019)	(0.026)	(0.020)	(0.026)	(0.019)
Days > 35°C	-0.021	0.073	0.059	-0.158***	-0.117***
	(0.038)	(0.059)	(0.041)	(0.046)	(0.042)
Observations	854,427	855,402	857,199	857,199	851,259
R-squared	0.257	0.251	0.202	0.247	0.323
Panel D: Grade 9					
Days ≤ 20°C	-0.131***	-0.103***	-0.067***	-0.158***	-0.127***
	(0.014)	(0.028)	(0.016)	(0.019)	(0.017)
Days (25°C, 30°C]	-0.102***	0.028	-0.044**	-0.082***	-0.060***
	(0.020)	(0.032)	(0.019)	(0.022)	(0.020)
Days (30°C, 35°C]	-0.040*	-0.013	-0.068***	-0.056**	-0.025
	(0.021)	(0.034)	(0.021)	(0.024)	(0.021)
Days > 35°C	-0.005	0.205***	0.032	0.108**	-0.077*
	(0.048)	(0.073)	(0.047)	(0.046)	(0.046)
Observations	805,381	807,392	809,241	809,241	801,460
R-squared	0.254	0.248	0.214	0.244	0.346
Other controls	Yes	Yes	Yes	Yes	Yes
School FEs	Yes	Yes	Yes	Yes	Yes
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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father education, school sector (public/private), and Postcode Index of Economic Resources; ***p<0.01, **p<0.05, *p<0.1.

Table 3: 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	-0.080***	-0.099***	-0.039***	-0.100***	-0.079***	-0.058***	-0.078***	-0.015	-0.086***	-0.065***
	(0.011)	(0.019)	(0.012)	(0.012)	(0.011)	(0.011)	(0.017)	(0.011)	(0.013)	(0.011)
Days (25°C, 30°C]	-0.084***	-0.052**	-0.059***	-0.098***	-0.062***	-0.055***	0.035**	-0.021*	-0.064***	-0.048***
	(0.013)	(0.021)	(0.012)	(0.013)	(0.012)	(0.014)	(0.017)	(0.012)	(0.015)	(0.012)
Days (30°C, 35°C]	-0.081***	-0.047**	-0.061***	-0.120***	-0.051***	-0.044***	-0.020	-0.038***	-0.082***	-0.033**
	(0.015)	(0.019)	(0.015)	(0.016)	(0.015)	(0.015)	(0.017)	(0.014)	(0.016)	(0.014)
Days > 35°C	-0.093***	0.091**	-0.053*	-0.114***	-0.136***	-0.029	0.093**	0.037	-0.054	-0.062**
	(0.031)	(0.040)	(0.030)	(0.032)	(0.030)	(0.030)	(0.037)	(0.028)	(0.035)	(0.027)
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
Panel B: Parental education										
			Low education					High education		
Days ≤ 20°C	-0.069***	-0.092***	-0.043***	-0.097***	-0.074***	-0.068***	-0.082***	-0.014	-0.084***	-0.073***
	(0.011)	(0.017)	(0.011)	(0.012)	(0.011)	(0.010)	(0.020)	(0.011)	(0.012)	(0.011)
Days (25°C, 30°C]	-0.066***	-0.028	-0.042***	-0.086***	-0.054***	-0.070***	0.023	-0.043***	-0.068***	-0.058***
	(0.013)	(0.019)	(0.012)	(0.013)	(0.011)	(0.014)	(0.020)	(0.014)	(0.015)	(0.014)
Days (30°C, 35°C]	-0.059***	-0.033*	-0.062***	-0.106***	-0.057***	-0.074***	-0.037**	-0.041***	-0.093***	-0.026
	(0.013)	(0.019)	(0.013)	(0.015)	(0.013)	(0.017)	(0.019)	(0.015)	(0.019)	(0.016)
Days > 35°C	-0.080***	0.091**	-0.024	-0.099***	-0.113***	-0.018	0.082**	0.014	-0.060	-0.086**
	(0.029)	(0.037)	(0.029)	(0.031)	(0.026)	(0.036)	(0.040)	(0.031)	(0.038)	(0.035)
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
Panel C: School type										
			Government					Non-government		
Days ≤ 20°C	-0.088***	-0.111***	-0.045***	-0.120***	-0.087***	-0.042***	-0.065***	-0.003	-0.061***	-0.054***
	(0.011)	(0.019)	(0.012)	(0.013)	(0.011)	(0.013)	(0.022)	(0.013)	(0.016)	(0.014)
Days (25°C, 30°C]	-0.088***	-0.056***	-0.056***	-0.111***	-0.063***	-0.044***	0.060**	-0.015	-0.039**	-0.041**
	(0.014)	(0.019)	(0.013)	(0.015)	(0.011)	(0.016)	(0.025)	(0.016)	(0.019)	(0.016)
Days (30°C, 35°C]	-0.073***	-0.047**	-0.037**	-0.103***	-0.041***	-0.053***	-0.030	-0.067***	-0.102***	-0.040**
	(0.015)	(0.020)	(0.014)	(0.017)	(0.015)	(0.017)	(0.024)	(0.016)	(0.021)	(0.016)
Days > 35°C	-0.139***	0.063	-0.029	-0.164***	-0.124***	0.051	0.117**	0.041	0.024	-0.055*
	(0.032)	(0.044)	(0.031)	(0.034)	(0.032)	(0.032)	(0.046)	(0.035)	(0.040)	(0.033)
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
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, 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 4: Controlling for night temperature

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.064***	-0.083***	-0.022**	-0.087***	-0.071***
	(0.010)	(0.016)	(0.010)	(0.011)	(0.010)
Days (25°C, 30°C]	-0.064***	0.003	-0.034***	-0.082***	-0.045***
	(0.012)	(0.018)	(0.011)	(0.013)	(0.011)
Days (30°C, 35°C]	-0.063***	-0.035**	-0.052***	-0.103***	-0.036***
	(0.013)	(0.017)	(0.013)	(0.015)	(0.012)
Days > 35°C	-0.079***	0.069*	-0.039	-0.106***	-0.107***
	(0.026)	(0.036)	(0.026)	(0.031)	(0.025)
Minimum temperature reference: Days (5°C, 10°C]					
Days ≤ 5°C	0.005	0.024	0.013	-0.002	0.002
	(0.014)	(0.021)	(0.013)	(0.015)	(0.013)
Days (10°C, 15°C]	0.022**	0.014	0.016	0.035***	-0.004
	(0.011)	(0.014)	(0.010)	(0.012)	(0.010)
Days (15°C, 20°C]	-0.040***	-0.028	-0.037***	-0.017	-0.029***
	(0.012)	(0.018)	(0.012)	(0.013)	(0.011)
Days (20°C, 25°C]	0.032**	0.041**	0.046***	0.034**	0.020
	(0.016)	(0.020)	(0.015)	(0.017)	(0.013)
Days > 25°C	0.111***	0.028	0.110***	0.099**	0.074***
	(0.034)	(0.049)	(0.030)	(0.040)	(0.028)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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	0.494	0.487	0.515	0.419	0.627

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father education, school sector (public/private), and Postcode Index of Economic Resources; ***p<0.01, **p<0.05, *p<0.1.

Table 5: Controlling for exam day temperature

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Temperature $\leq$ 20°C	0.012	0.556*	0.009	0.278	-0.291
	(0.211)	(0.322)	(0.266)	(0.288)	(0.211)
Temperature (25°C, 30°C]	0.399	1.253***	-1.096***	-0.395	-0.604***
	(0.263)	(0.355)	(0.242)	(0.281)	(0.189)
Temperature $\geq$ 30°C	-0.817	-0.542	-0.905	1.370*	-1.209***
	(0.542)	(0.974)	(0.597)	(0.701)	(0.461)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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	0.493	0.487	0.515	0.419	0.627

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father education, school sector (public/private), and Postcode Index of Economic Resources; ***p<0.01, **p<0.05, *p<0.1.

Table 6: Controlling for temperature during holidays

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.063***	-0.040**	-0.031**	-0.069***	-0.066***
	(0.013)	(0.018)	(0.013)	(0.014)	(0.012)
Days (25°C, 30°C]	-0.066***	0.004	-0.026**	-0.071***	-0.044***
	(0.011)	(0.017)	(0.011)	(0.012)	(0.010)
Days (30°C, 35°C]	-0.061***	-0.019	-0.046***	-0.092***	-0.031**
	(0.013)	(0.017)	(0.013)	(0.014)	(0.012)
Days > 35°C	-0.058**	0.043	-0.000	-0.081***	-0.111***
	(0.025)	(0.035)	(0.024)	(0.028)	(0.025)
Temperature during holiday - Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.018	-0.105***	-0.015	-0.062***	-0.028
	(0.019)	(0.023)	(0.017)	(0.020)	(0.018)
Days (25°C, 30°C]	-0.007	-0.018	-0.069***	-0.019	-0.034**
	(0.015)	(0.021)	(0.016)	(0.018)	(0.014)
Days (30°C, 35°C]	-0.014	-0.034	-0.059***	-0.047**	-0.053***
	(0.018)	(0.027)	(0.018)	(0.021)	(0.016)
Days > 35°C	-0.026	0.155***	-0.058**	-0.063**	0.006
	(0.025)	(0.036)	(0.025)	(0.029)	(0.022)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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	0.494	0.487	0.515	0.419	0.627

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father education, school sector (public/private), and Postcode Index of Economic Resources; ***p<0.01, **p<0.05, *p<0.1.

Table 7: 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	-0.052***	-0.108***	-0.014	-0.071***	-0.074***
	(0.010)	(0.017)	(0.010)	(0.012)	(0.011)
Days (25°C, 30°C]	-0.070***	-0.019	-0.047***	-0.075***	-0.063***
	(0.011)	(0.017)	(0.011)	(0.012)	(0.010)
Days (30°C, 35°C]	-0.060***	-0.054***	-0.053***	-0.091***	-0.053***
	(0.012)	(0.016)	(0.012)	(0.014)	(0.012)
Days > 35°C	-0.068***	0.079**	-0.019	-0.090***	-0.105***
	(0.024)	(0.034)	(0.023)	(0.028)	(0.024)
Temperature lag 1 (Reference: Days (20°C , 25°C])					
Days ≤ 20°C	0.041***	-0.025*	0.038***	0.055***	-0.002
	(0.011)	(0.014)	(0.009)	(0.011)	(0.010)
Days (25°C, 30°C]	-0.003	-0.051***	-0.033***	0.006	-0.048***
	(0.012)	(0.015)	(0.011)	(0.012)	(0.011)
Days (30°C, 35°C]	0.038***	-0.096***	0.030**	0.051***	-0.025*
	(0.015)	(0.017)	(0.013)	(0.016)	(0.013)
Days > 35°C	0.012	0.020	-0.098***	0.023	-0.074***
	(0.032)	(0.034)	(0.027)	(0.030)	(0.023)
Cumulative effects					
Days ≤ 20°C	-0.011	-0.132***	0.024	-0.016	-0.077***
	(0.018)	(0.026)	(0.015)	(0.019)	(0.018)
Days (25°C, 30°C]	-0.073***	-0.070***	-0.079***	-0.069***	-0.111***
	(0.018)	(0.024)	(0.017)	(0.019)	(0.017)
Days (30°C, 35°C]	-0.021	-0.150***	-0.023	-0.040*	-0.077***
	(0.021)	(0.025)	(0.020)	(0.023)	(0.020)
Days > 35°C	-0.056	0.099**	-0.117***	-0.067	-0.180***
	(0.043)	(0.049)	(0.040)	(0.046)	(0.036)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year 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	0.486	0.515	0.419	0.627

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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	-0.049***	-0.086***	-0.008	-0.062***	-0.071***
	(0.012)	(0.018)	(0.012)	(0.014)	(0.012)
Days (25°C, 30°C]	-0.063***	-0.026	-0.040***	-0.075***	-0.066***
	(0.013)	(0.017)	(0.012)	(0.014)	(0.012)
Days (30°C, 35°C]	-0.065***	-0.044***	-0.051***	-0.087***	-0.054***
	(0.013)	(0.016)	(0.012)	(0.014)	(0.013)
Days > 35°C	-0.082***	0.106***	-0.019	-0.079***	-0.107***
	(0.025)	(0.036)	(0.023)	(0.029)	(0.024)
Temperature lag 1 (Reference: Days (20°C, 25°C])					
Days ≤ 20°C	0.049***	-0.019	0.046***	0.060***	-0.003
	(0.012)	(0.015)	(0.011)	(0.014)	(0.012)
Days (25°C, 30°C]	0.012	-0.056***	-0.025**	0.008	-0.047***
	(0.013)	(0.016)	(0.012)	(0.015)	(0.012)
Days (30°C, 35°C]	0.046***	-0.094***	0.036**	0.054***	-0.022
	(0.016)	(0.018)	(0.014)	(0.018)	(0.014)
Days > 35°C	0.008	0.031	-0.111***	0.035	-0.075***
	(0.033)	(0.036)	(0.028)	(0.032)	(0.024)
Temperature lag 2 (Reference: Days (20°C, 25°C])					
Days ≤ 20°C	-0.002	0.039**	0.002	0.020	0.004
	(0.011)	(0.016)	(0.012)	(0.014)	(0.011)
Days (25°C, 30°C]	0.027**	-0.038**	0.002	-0.001	-0.007
	(0.013)	(0.017)	(0.014)	(0.016)	(0.012)
Days (30°C, 35°C]	0.040***	-0.014	0.045***	-0.004	-0.003
	(0.014)	(0.019)	(0.015)	(0.017)	(0.012)
Days > 35°C	0.085***	0.042	0.057**	0.008	0.046**
	(0.022)	(0.032)	(0.023)	(0.027)	(0.021)
Cumulative effects					
Days ≤ 20°C	-0.002	-0.066*	0.040	0.019	-0.069**
	(0.029)	(0.039)	(0.029)	(0.034)	(0.029)
Days (25°C, 30°C]	-0.024	-0.120***	-0.064**	-0.068*	-0.120***
	(0.030)	(0.036)	(0.031)	(0.036)	(0.029)
Days (30°C, 35°C]	0.021	-0.153***	0.029	-0.037	-0.078***
	(0.031)	(0.036)	(0.029)	(0.036)	(0.028)
Days > 35°C	0.011	0.180***	-0.073	-0.037	-0.136***
	(0.052)	(0.062)	(0.051)	(0.058)	(0.044)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year 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	0.486	0.515	0.419	0.627

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father education, school sector (public/private), and Postcode Index of Economic Resources; ***p<0.01, **p<0.05, *p<0.1.

Table 8: Effects of heat waves on NAPLAN test scores

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Panel A: heatwave longer than 3 days					
Heatwave	-0.046	-0.282***	0.053	-0.109	-0.062
	(0.067)	(0.086)	(0.061)	(0.078)	(0.064)
Temperature (Reference: Days (20°C, 25°C])					
Days ≤ 20°C	-0.069***	-0.087***	-0.026***	-0.092***	-0.071***
	(0.009)	(0.016)	(0.009)	(0.010)	(0.009)
Days (25°C, 30°C]	-0.070***	-0.011	-0.039***	-0.081***	-0.055***
	(0.011)	(0.017)	(0.010)	(0.012)	(0.010)
Days (30°C, 35°C]	-0.062***	-0.022	-0.052***	-0.096***	-0.039***
	(0.012)	(0.016)	(0.012)	(0.014)	(0.012)
Days > 35°C	-0.055**	0.127***	-0.013	-0.071***	-0.090***
	(0.025)	(0.033)	(0.024)	(0.027)	(0.025)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.494	0.487	0.515	0.419	0.627
Panel B: heatwave longer than 6 days					
Heatwave	-0.289	0.238	0.117	0.005	-0.255
	(0.208)	(0.289)	(0.189)	(0.219)	(0.180)
Temperature (Reference: Days (20°C, 25°C])					
Days ≤ 20°C	-0.070***	-0.087***	-0.025***	-0.092***	-0.073***
	(0.009)	(0.016)	(0.009)	(0.010)	(0.009)
Days (25°C, 30°C]	-0.070***	-0.008	-0.039***	-0.080***	-0.055***
	(0.011)	(0.017)	(0.010)	(0.012)	(0.010)
Days (30°C, 35°C]	-0.064***	-0.034**	-0.050***	-0.101***	-0.043***
	(0.012)	(0.015)	(0.012)	(0.013)	(0.012)
Days > 35°C	-0.058**	0.092***	-0.008	-0.084***	-0.096***
	(0.024)	(0.034)	(0.024)	(0.027)	(0.024)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.494	0.487	0.515	0.419	0.627
Panel C: heatwave longer than 9 days					
Heatwave	-1.890*	-0.339	-1.796	-1.371	-2.021*
	(1.130)	(1.675)	(1.484)	(1.253)	(1.064)
Temperature (Reference: Days (20°C, 25°C])					
Days ≤ 20°C	-0.069***	-0.088***	-0.026***	-0.092***	-0.071***
	(0.009)	(0.016)	(0.009)	(0.010)	(0.009)
Days (25°C, 30°C]	-0.069***	-0.009	-0.040***	-0.080***	-0.054***
	(0.011)	(0.017)	(0.010)	(0.012)	(0.010)
Days (30°C, 35°C]	-0.064***	-0.035**	-0.050***	-0.102***	-0.042***
	(0.012)	(0.015)	(0.012)	(0.013)	(0.012)
Days > 35°C	-0.059**	0.094***	-0.005	-0.083***	-0.096***
	(0.024)	(0.033)	(0.024)	(0.027)	(0.024)
Observations	3,426,754	3,427,681	3,435,609	3,432,785	3,415,441
R-squared	0.494	0.487	0.515	0.419	0.627
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father education, school sector (public/private), and Postcode Index of Economic Resources; ***p<0.01, **p<0.05, *p<0.1.

Table 9: Estimated effects of temperature on NAPLAN test scores by climatic zone

Panel A: Climatic zone 1 - Hot humid summer, warm winter

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.436*	-1.116**	-0.172	-0.041	-0.407
	(0.238)	(0.420)	(0.288)	(0.432)	(0.407)
Days (25°C, 30°C]	-0.119**	0.128	0.026	-0.168**	-0.189***
	(0.058)	(0.115)	(0.054)	(0.074)	(0.058)
Days (30°C, 35°C]	-0.032	0.107	0.100*	0.005	-0.047
	(0.055)	(0.099)	(0.050)	(0.079)	(0.049)
Days > 35°C	-0.079	0.454***	0.173**	0.185	-0.076
	(0.086)	(0.152)	(0.076)	(0.128)	(0.095)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	114,626	114,940	115,291	114,840	113,952
R-squared	0.536	0.489	0.546	0.459	0.659

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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 - Warm humid summer, mild winter

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.082	-0.125	-0.034	0.022	-0.061
	(0.057)	(0.095)	(0.063)	(0.062)	(0.048)
Days (25°C, 30°C]	-0.041*	-0.011	-0.024	-0.048*	-0.072***
	(0.023)	(0.029)	(0.021)	(0.026)	(0.018)
Days (30°C, 35°C]	-0.079***	-0.043	-0.052**	-0.087***	-0.048**
	(0.019)	(0.033)	(0.020)	(0.026)	(0.019)
Days > 35°C	0.012	0.059	0.117*	-0.054	-0.061
	(0.064)	(0.077)	(0.067)	(0.090)	(0.062)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	634,069	634,254	636,223	635,821	631,808
R-squared	0.472	0.451	0.512	0.398	0.616

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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 - Hot dry summer, warm winter

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	0.359	0.118	0.358	0.241	0.383
	(0.260)	(0.132)	(0.266)	(0.339)	(0.244)
Days (25°C, 30°C]	0.210***	0.142	0.179**	0.188***	0.158
	(0.067)	(0.082)	(0.071)	(0.063)	(0.099)
Days (30°C, 35°C]	0.288***	0.101	0.152*	0.265***	0.200*
	(0.087)	(0.100)	(0.084)	(0.077)	(0.098)
Days > 35°C	0.059	0.104	0.231*	0.298**	0.077
	(0.122)	(0.142)	(0.124)	(0.113)	(0.104)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	32,489	32,659	32,763	32,611	32,339
R-squared	0.502	0.460	0.533	0.430	0.637

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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 - Hot dry summer, cool winter

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.053	0.020	-0.085**	-0.063	-0.018
	(0.044)	(0.068)	(0.041)	(0.043)	(0.042)
Days (25°C, 30°C]	0.011	-0.030	-0.124**	-0.069	0.015
	(0.063)	(0.076)	(0.061)	(0.056)	(0.073)
Days (30°C, 35°C]	0.053	0.098	-0.071	-0.022	0.035
	(0.058)	(0.070)	(0.074)	(0.075)	(0.056)
Days > 35°C	-0.027	0.146	-0.177**	-0.259**	0.015
	(0.085)	(0.116)	(0.087)	(0.106)	(0.093)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	141,418	141,415	141,807	141,628	140,684
R-squared	0.487	0.436	0.496	0.414	0.618

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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 - Warm temperate

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.068***	-0.081***	-0.017	-0.073***	-0.052***
	(0.012)	(0.019)	(0.016)	(0.014)	(0.013)
Days (25°C, 30°C]	0.006	0.005	-0.008	-0.002	0.010
	(0.022)	(0.028)	(0.028)	(0.026)	(0.024)
Days (30°C, 35°C]	-0.128***	0.049	-0.132***	-0.115***	-0.062**
	(0.026)	(0.039)	(0.026)	(0.031)	(0.026)
Days > 35°C	-0.015	-0.107*	0.006	-0.108*	-0.158***
	(0.052)	(0.060)	(0.044)	(0.055)	(0.054)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	928,440	928,844	930,358	929,775	925,406
R-squared	0.509	0.512	0.531	0.430	0.644

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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 - Mild temperate

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.090***	-0.136***	-0.072***	-0.110***	-0.122***
	(0.021)	(0.032)	(0.023)	(0.023)	(0.020)
Days (25°C, 30°C]	-0.094***	0.035	-0.045*	-0.096***	-0.048*
	(0.028)	(0.040)	(0.026)	(0.029)	(0.024)
Days (30°C, 35°C]	-0.075**	0.029	-0.029	-0.109**	-0.069*
	(0.034)	(0.054)	(0.038)	(0.047)	(0.037)
Days > 35°C	0.002	0.182**	0.105*	0.002	-0.050
	(0.068)	(0.084)	(0.060)	(0.066)	(0.064)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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	0.485	0.481	0.495	0.407	0.614

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father 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 - Cool temperate

Variables	Reading	Writing	Spelling	Grammar	Numeracy
	(1)	(2)	(3)	(4)	(5)
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	0.021	0.085	-0.058	-0.094	-0.047
	(0.053)	(0.065)	(0.045)	(0.065)	(0.049)
Days (25°C, 30°C]	0.028	0.168*	-0.058	-0.025	-0.048
	(0.057)	(0.092)	(0.041)	(0.066)	(0.045)
Days (30°C, 35°C]	0.122	0.062	0.043	-0.009	0.032
	(0.097)	(0.075)	(0.078)	(0.129)	(0.082)
Days > 35°C	0.055	0.313	0.182	-0.099	0.010
	(0.147)	(0.223)	(0.127)	(0.161)	(0.135)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	258,764	259,001	259,771	259,537	257,832
R-squared	0.466	0.452	0.487	0.408	0.599

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 precipitation bins (no rain – reference, light rain, moderate rain, heavy rain, very heavy rain), temperature on the day of the exam, age, gender, indigenous status, language background, mother education, father education, school sector (public/private), and Postcode Index of Economic Resources; ***p<0.01, **p<0.05, *p<0.1.

Appendix

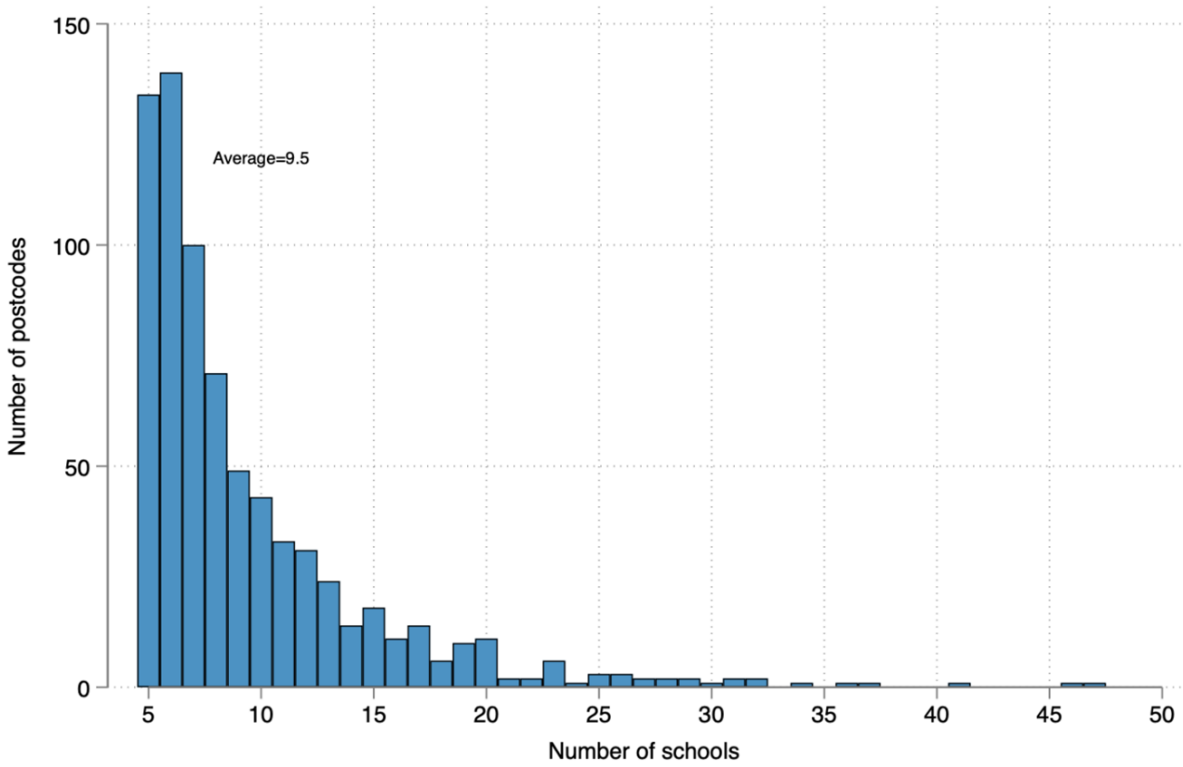

Figure A.1: Distribution of schools by postcode

Notes: Postcodes with less than 5 schools are excluded in the analysis.

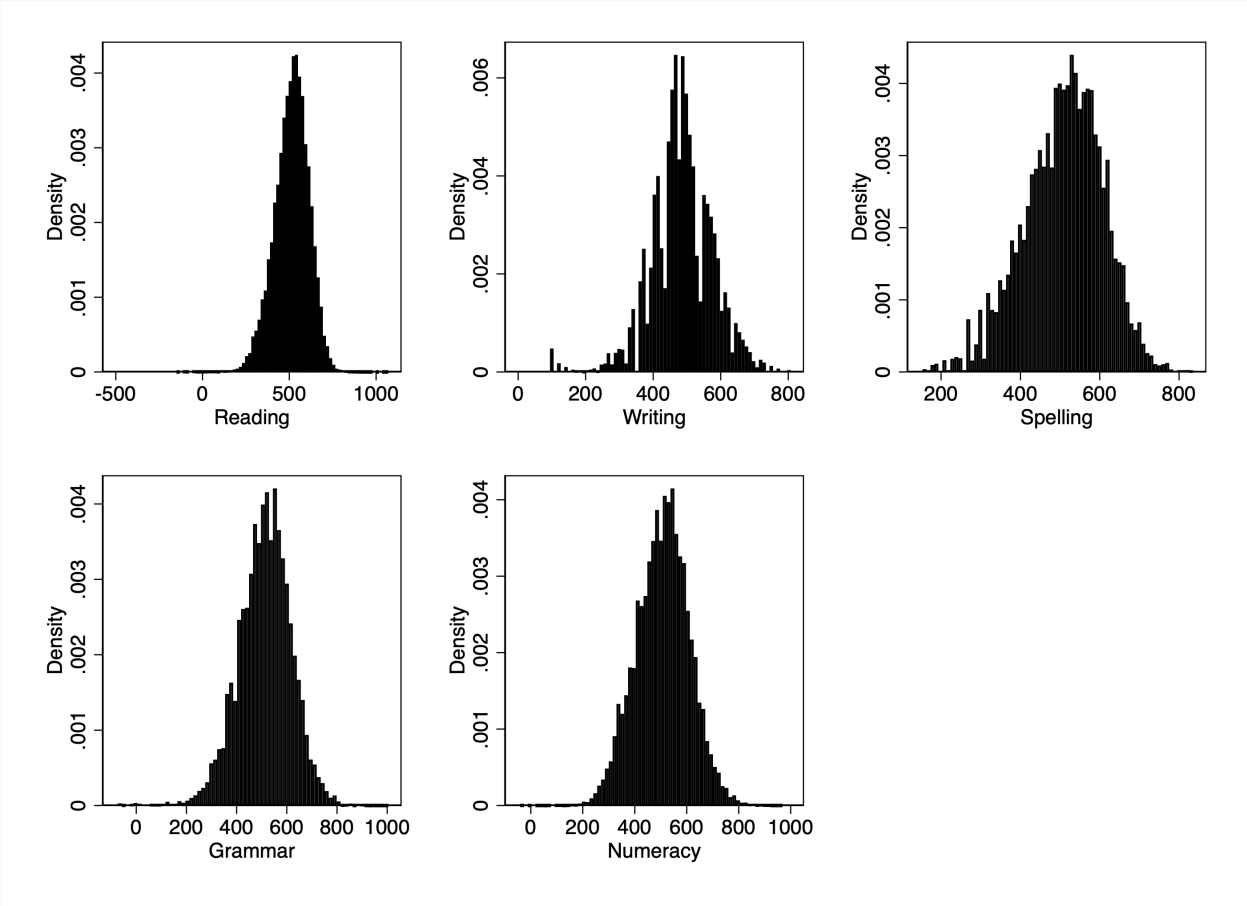

Figure A.2: Distribution of test scores

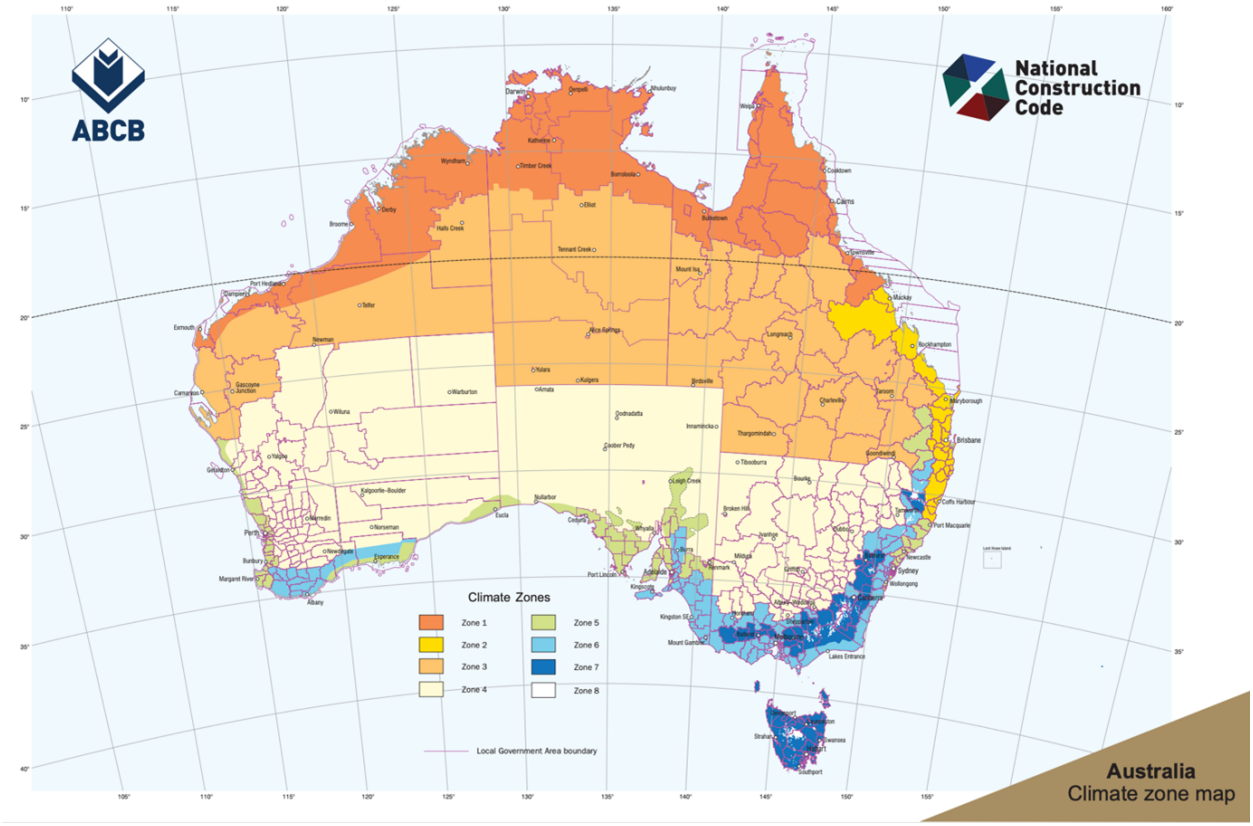

Figure A.3: Australia climate zone

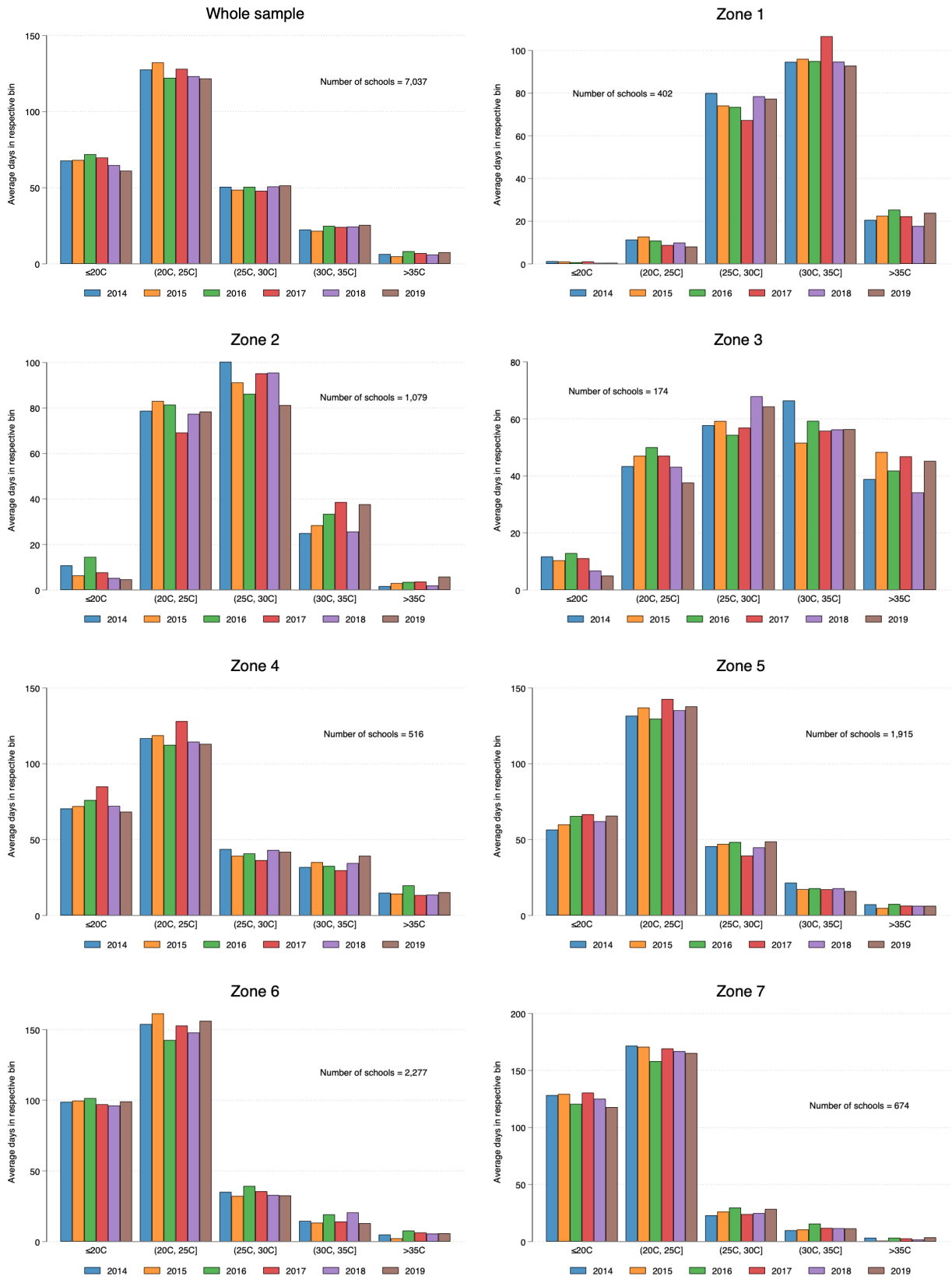

Figure A.4: Distribution of temperature (days)

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 (20°C, 25°C]	126.27	43.03	0.00	212.00
Days (25°C, 30°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
Temperature on test day				
Day 1	21.40	4.21	0.30	37.00
Day 2	20.75	4.53	-0.60	37.20
Day 3	21.16	4.64	-0.50	37.10
Precipitation				
Days no rain	109.54	50.08	0.00	198.00
Days light rain	52.58	27.95	0.00	145.00
Days moderate rain	8.59	5.61	0.00	39.00
Days heavy rain	1.33	2.03	0.00	15.00
Days very heavy rain	0.10	0.35	0.00	6.00
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
Temperature during school holiday				
Days $\leq$ 20°C	50.68	33.85	0.00	187.00
Days (20°C, 25°C]	102.98	38.18	0.00	192.00
Days (25°C, 30°C]	48.43	24.93	0.00	131.00
Days (30°C, 35°C]	25.70	21.94	0.00	180.00
Days > 35°C	9.28	11.23	0.00	146.00
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				
Private 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
Reference: Days (20°C, 25°C]					
Days ≤ 20°C	-0.069***	-0.088***	-0.026***	-0.092***	-0.071***
	(0.009)	(0.016)	(0.009)	(0.010)	(0.009)
Days (25°C, 30°C]	-0.069***	-0.009	-0.040***	-0.080***	-0.054***
	(0.011)	(0.017)	(0.010)	(0.012)	(0.010)
Days (30°C, 35°C]	-0.064***	-0.035**	-0.050***	-0.101***	-0.042***
	(0.012)	(0.015)	(0.012)	(0.013)	(0.012)
Days > 35°C	-0.061**	0.094***	-0.007	-0.084***	-0.098***
	(0.024)	(0.033)	(0.024)	(0.027)	(0.024)
Temperature on Test Day (Reference: Days (20°C, 25°C])					
Days ≤ 20°C	0.251	0.132	-0.032	0.009	-0.490**
	(0.210)	(0.316)	(0.269)	(0.285)	(0.211)
Days (25°C, 30°C]	0.213	1.621***	-1.156***	-0.390	-0.978***
	(0.245)	(0.368)	(0.252)	(0.290)	(0.199)
Days > 30°C	-0.763	-0.223	-1.021	0.926	-1.434***
	(0.509)	(1.016)	(0.657)	(0.770)	(0.485)
Precipitation Bin (Reference: No Rain)					
Light Rain	-0.015*	0.019*	-0.008	-0.008	-0.017**
	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)
Moderate Rain	0.068***	-0.045*	0.026	0.042*	0.034
	(0.022)	(0.027)	(0.020)	(0.023)	(0.020)
Heavy Rain	-0.055	-0.347***	0.040	0.001	-0.029
	(0.046)	(0.070)	(0.048)	(0.053)	(0.050)
Very Heavy Rain	0.112	-0.421	0.172	-0.077	0.104
	(0.194)	(0.305)	(0.201)	(0.205)	(0.206)
Mother Education (Reference: Less than Year 12)					
Year 12	12.958***	12.180***	11.715***	13.463***	11.253***
	(0.267)	(0.260)	(0.274)	(0.260)	(0.229)
Certificate I to IV	9.924***	8.599***	8.133***	9.904***	7.645***
	(0.214)	(0.236)	(0.253)	(0.229)	(0.198)
Advanced Diploma/Diploma	16.121***	13.924***	12.090***	15.566***	12.985***
	(0.263)	(0.265)	(0.289)	(0.260)	(0.236)
Bachelor Degree or Above	34.111***	25.751***	24.635***	33.817***	29.121***
	(0.284)	(0.281)	(0.334)	(0.292)	(0.257)
Father Education (Reference: Less than Year 12)					
Year 12	15.044***	13.554***	14.165***	15.585***	12.666***
	(0.307)	(0.274)	(0.286)	(0.311)	(0.258)
Certificate I to IV	10.438***	9.844***	8.960***	10.629***	8.760***
	(0.234)	(0.249)	(0.253)	(0.251)	(0.225)
Advanced Diploma/Diploma	19.835***	17.028***	16.858***	19.957***	16.036***
	(0.298)	(0.294)	(0.302)	(0.313)	(0.284)
Bachelor Degree or Above	35.211***	27.641***	29.318***	36.323***	31.007***
	(0.332)	(0.300)	(0.319)	(0.334)	(0.298)
Other Control Variables					
Age	4.858***	2.233***	-2.849***	0.998***	1.946***
	(0.267)	(0.267)	(0.297)	(0.277)	(0.229)
Gender (Female=1)	12.738***	31.133***	14.654***	19.420***	-9.181***
	(0.146)	(0.251)	(0.202)	(0.151)	(0.184)
Indigenous (Yes=1)	-24.674***	-25.994***	-18.710***	-26.615***	-21.941***
	(0.639)	(0.683)	(0.535)	(0.638)	(0.566)
Other Language at Home (Yes=1)	-8.947***	2.012***	12.866***	-1.820***	2.656***
	(0.316)	(0.270)	(0.388)	(0.382)	(0.501)
School Sector (Private=1)	-49.189***	155.493***	-26.777***	0.529**	-16.490***
	(0.261)	(0.300)	(0.275)	(0.248)	(0.258)
IER	-0.002	-0.018	-0.003	0.021	-0.002
	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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	0.494	0.487	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. ***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 ≤ 20°C	-0.068***	-0.088***	-0.026***	-0.088***	-0.071***
	(0.009)	(0.016)	(0.009)	(0.010)	(0.009)
Days (25°C, 30°C]	-0.069***	-0.009	-0.040***	-0.077***	-0.054***
	(0.011)	(0.017)	(0.010)	(0.011)	(0.010)
Days (30°C, 35°C]	-0.064***	-0.035**	-0.050***	-0.101***	-0.042***
	(0.012)	(0.015)	(0.012)	(0.013)	(0.012)
Days > 35°C	-0.053**	0.094***	-0.007	-0.078***	-0.099***
	(0.025)	(0.033)	(0.024)	(0.029)	(0.024)
Other controls	Yes	Yes	Yes	Yes	Yes
School-Grade FEs	Yes	Yes	Yes	Yes	Yes
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	0.493	0.487	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 precipitation bins, temperature on the day of the exam, 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.