Appendix B: Supplemental Information for Analyses in the Extreme Heat Chapter

This appendix describes methods, data sources, and assumptions for the extreme heat analyses presented in Chapter 3 of the main report. First is the information for the detailed analysis of how heat experienced during the school year affects learning among children. Second is information required for the discussion of emergency department visits to children's hospital associated with high heat days.

Detailed Analysis of Heat and Learning Losses

This section describes the detailed analysis of learning losses associated with heat presented in Chapter 3 of the main report.

SUMMARY OF STUDIES USED IN THIS ANALYSIS

PARK ET AL. (2020)[1]

Park et al. investigated how heat inhibits learning among students in the U.S. and how air conditioning (A/C) mitigates those effects. Learning was measured using test results among a nationwide sample of 10 million PSAT takers, generally 10th and 11th grade students, which the authors believe is a true indicator of cognitive performance as opposed to generalized intelligence. Heat exposure was modeled using the heat experienced throughout the school year preceding the test date, as measured by the National Oceanic and Atmospheric Administration's Daily Global Historical Climatology Network. With these data, the authors developed a regression model to estimate a causal impact of cumulative heat exposure on test scores by studying the variation among individual students who take the PSAT at least twice. By employing "student fixed effects," the authors controlled for many unobservable characteristics of individual students that may influence test scores and therefore more readily isolate the effect of heat. The authors offered several important findings. The detailed analysis presented in this report leverages results demonstrating that school A/C reduces some of the effects of heat on learning losses. Using student and guidance counselor responses to a survey about the availability of A/C in schools, the authors develop and utilize these data to show that learning losses are significantly reduced in schools with A/C. When considering the additional relief of having A/C at home, learning losses are mitigated almost entirely on hot days. Table 1 describes the specific coefficients leveraged from the paper for this detailed analysis (as well as the standard errors reported with the results).

CHETTY ET AL. (2011)[2]

Chetty et al. estimated the value of learning loss per standard deviation by studying a cohort of 11,571 students and their teachers from 1985 to 1989, as part of the Student/Teacher Achievement Ratio (STAR) Project. The STAR Project empowered 79 schools in Tennessee to randomly assign kindergarten students to different classrooms within their schools, some large in class size, some small, where students remained until the 4th grade. The STAR Project oversampled lower-income schools in Tennessee; thus, the socioeconomic characteristics of the STAR sample can be considered as poorer (lower income) than U.S. averages. Chetty et al. were able to track data from tax returns of 95% of STAR Project participants 25-27 years old to observe socioeconomic outcomes in adulthood. Chetty et al. found that randomly assigning students to a classroom that is one standard deviation better than average in kindergarten generates an increase in earnings at ages 25-27 of $1,520 (+9.6%) per year for each student. This translates into lifetime earnings gains of approximately $39,200 (2009 dollars).

LEROY ET AL. (2021)[3]

LeRoy et al. estimated the cost of installing A/C in all public schools in the contiguous U.S. The authors used a phone call campaign and news article research for a sample of schools/districts to identify geographic regions with facilities already equipped with HVAC. Observing average temperature data in those HVAC-equipped regions from 1955-1984 (baseline period), they calculated the number of school-year days (32) above 80°F during the baseline period were needed to justify current existence of HVAC in a school/district. The researchers assumed that all public schools in the contiguous 48 states with 32 school-year days above 80°F during the baseline period should already have HVAC, and thus would not be included in the "installations" cost estimate; meanwhile, schools with fewer than 32 days above 80°F during the base period, but with at least 32 days during the study period – a 30-year average centered on 2025 – would be in the "installations" cost estimate pool. Using RSMeans to find cost estimates for Department of Energy Standards-compliant HVAC systems, the authors found the total cost of furnishing all contiguous U.S. public schools with A/C to be about $42.4 billion, composed of $40.5 billion in new installations, $414.8 million in upgrades of existing HVAC technology, and $1.5 billion in annual operating and maintenance costs.

ANALYSIS STEPS

The detailed analysis of the effects of heat on learning relies on the quantitative estimates presented by Park et al., the most recent and nationally representative analysis of this relationship. The results of the analysis describe learning losses experienced by a cohort of students graduating from high school each year (age 17). The learning losses observed in late high school are interpreted as the result of cumulative heat exposure across all preceding school years. Because Park et al. show the importance of A/C in mitigating the impacts of heat, this analysis incorporates "baseline" A/C investments consistent with the data used in Park et al. to present how heat will affect learning if A/C access *does not improve* throughout the 21st century. In other words, the results are consistent with a "no additional adaptation" approach.

Learning losses are valued in terms of lost future income using estimates from Chetty et al., as they appear in Park et al. Applying the income losses from Chetty et al. allows us to consider total lost income per child as well as the annual income losses across all graduating children in a given year.

Lost income associated with learning losses is then compared to the cost of installing A/C in schools estimated by LeRoy et al.

Table 1 that follows details the analytic steps, data sources, and assumptions used to forecast and value learning losses among children resulting from climate change. This analysis considers impacts across all census tracts in the continental U.S. (over 72,000 tracts).

Table 1: Analytic Steps in Climate Change Impacts on Heat and Learning Among Students

Step		Data	Methods, Assumptions, and Notes
Baseline Risks	1a. Determine baseline school A/C and home A/C levels	**School A/C:** extracted from Figure 5, Panel A of the paper at the county level (student reports of hot classrooms) **Home A/C:** provided by authors of Park et al. at the county/year level for the years 1997-2011	**School A/C:** Given the proprietary nature of this data, the authors of Park et al. were unable to share. Instead, the information from a county-level map displayed in the paper (Figure 5, panel A, Park et al.) was extracted, which presents the fraction of hot days when classrooms get too hot, as reported by students. The inverse of this value (1-fraction of days when classrooms are too hot) is used as the percent of schools with A/C access. Because the data is displayed as a range in the figure, the midpoint of each range (e.g., 0-10 percent range=5 percent) is assumed. For counties with missing data, state-level averages are applied. **Home A/C:** Data are averaged across years. For counties with missing data, state-level averages are applied. Both school and home A/C are converted to values between 0 and 1, interpreted as the portion of schools and homes with A/C.
	1b. Identify baseline "learning gains" each academic year	Presented in Park et al.	Park et al. report the average gain in PSAT score performance between the 10^{th} and 11^{th} grades is about 0.3 standard deviations. This forms the basis of comparison for future learning losses predicted in Step 3.
Future Climate Stressor	2. Calculate future average daily maximum temperatures during school years	LOCA future climate data at the census tract level Start- and end-dates in school year (provided by study authors at state level)	Consistent with Park et al., future mean daily maximum temperature from all days within the school year among the 365 days preceding the PSAT date (assumed October 15 for all locations) are calculated. For example, for year 2021, and assuming a school year that starts September 1 and ends May 31, the analysis takes the average daily max temperature between October 15, 2020, and October 14, 2021, for all days not in June, July, August. To remove the influence of time not spent in school, the school year start- and end-dates provided by the study authors are used to align the date range with locally appropriate school calendars; see Figure A1 of the Supplemental Materials to Park et al. for details. This approach assumes that the school calendar will not change in response to future warming.

	Step	Data	Methods, Assumptions, and Notes
Future Effects on Children	3a. Estimate future learning losses per student at the census tract level under baseline A/C conditions	Learning impact function from Park et al. (Table 5, specification 2 of the study)	The following relationship is used to forecast learning losses under future heat and baseline A/C levels*: *(-0.569*temp) + (0.235*temp*schoolAC) + (0.324*temp*homeAC)* Because A/C investments are held constant, only the temperature variable changes in the future (see Step 2). Consistent with Park et al., the results are interpreted as hundredths of a standard deviation in learning loss. In other words, the resulting value is divided by 100 to calculate a measure of standard deviations. Future learning losses experience at each degree of global warming are compared with both losses experienced in the baseline time-period as well as relative to average learning "gains" each school year associated with learning progress in general (see Step 1b).
	3b. Value learning losses per student in terms of lost future income	Valuation from Chetty et al., as reported in Park et al. See Chapter 2 of the main report and Appendix A for details on population methods and data sources used throughout the analysis.	As described in Park et al, Chetty et al. finds that having a teacher who raises test scores by 0.1 standard deviations results in net present value of $7,000 (2009 dollars) in future increased earnings for current 12-year-olds. Park et al. apply a 5 percent discount rate to generate a net present value estimate of $8,500 (2009) for the typical 16-year-old. This analysis uses Park et al.'s $8,500 values but adjusts to 2021 dollars using the GDP deflator to arrive at $11,000 in lost future income per student per 0.1 standard deviations in learning losses observed in high school.
	3c. Aggregate lost future income across all graduating students in a given year	See Chapter 2 of the main report and Appendix A for details on population methods and data sources used throughout the analysis.	Total learning losses among a cohort of graduating students are aggregated using the total number of graduating students in a given census tract. The total number of children in the 14-17 age cohort are divided by 4 to approximate the number of students graduating in each future year. (Note: In 2010, there were approximately 4.3 million children aged 17 in CONUS. By 2099, there are expected to be 6.7 million children in the same age cohort, representing a 56 percent increase in population.)
Note: The coefficients leveraged for this analysis are all statistically significant at conventional levels. The standard errors are 0.104, 0.070, and 0.110 for the coefficients on *temp, temp*schoolAC,* and *temp*homeAC,* respectively.			

FUTURE HEAT AND BASELINE A/C

Table 2 presents baseline and future temperatures during school years by degree of global warming. The spatial distribution of these temperature increases at 2°C and 4°C of global warming relative to baseline levels of heat is showcased in Figure 1. Finally, Figure 2 describes the spatial distribution of baseline school and home A/C coverage used in the analysis.

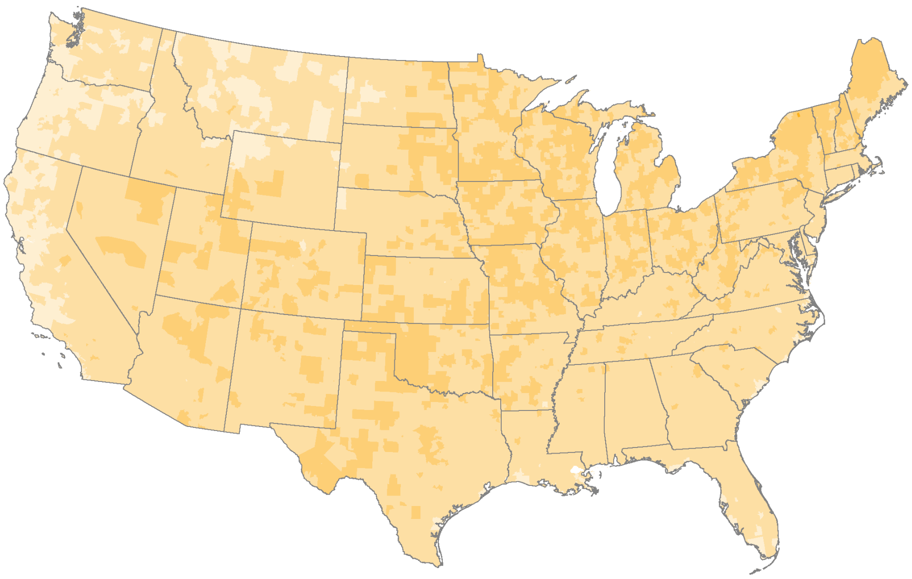
Table 2: Future National Average Maximum Daily Temperature During School Years (°F)

Degree of Global Warming (°C)	Projected Temperature (°F)	Increase in Projected Temperature Relative to Baseline Temperature (°F)
Baseline	63.9	-
1°C	66.8	2.9
2°C	69.7	5.8
3°C	72.1	8.2
4°C	73.9	10.0
5°C	76.3	12.4

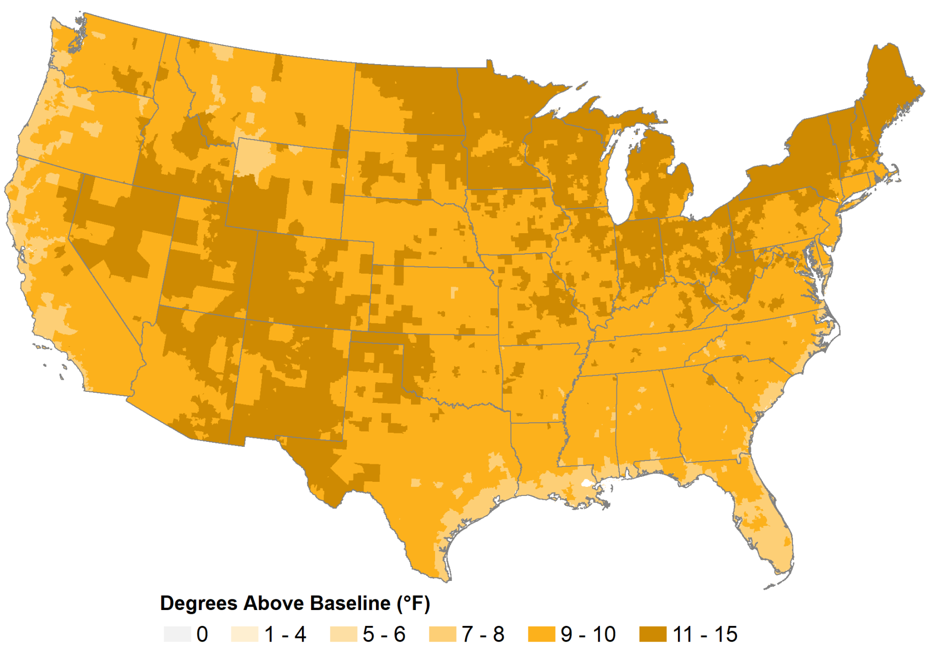
Notes: National averages incorporate state-specific school years and are weighted based on populations. The baseline aligns with averages from 1986-2005.

Figure 1: Future Average Maximum Daily Temperature During School Years (°F) at 2°C and 4°C of Global Warming Relative to Baseline

2°C of Global Warming

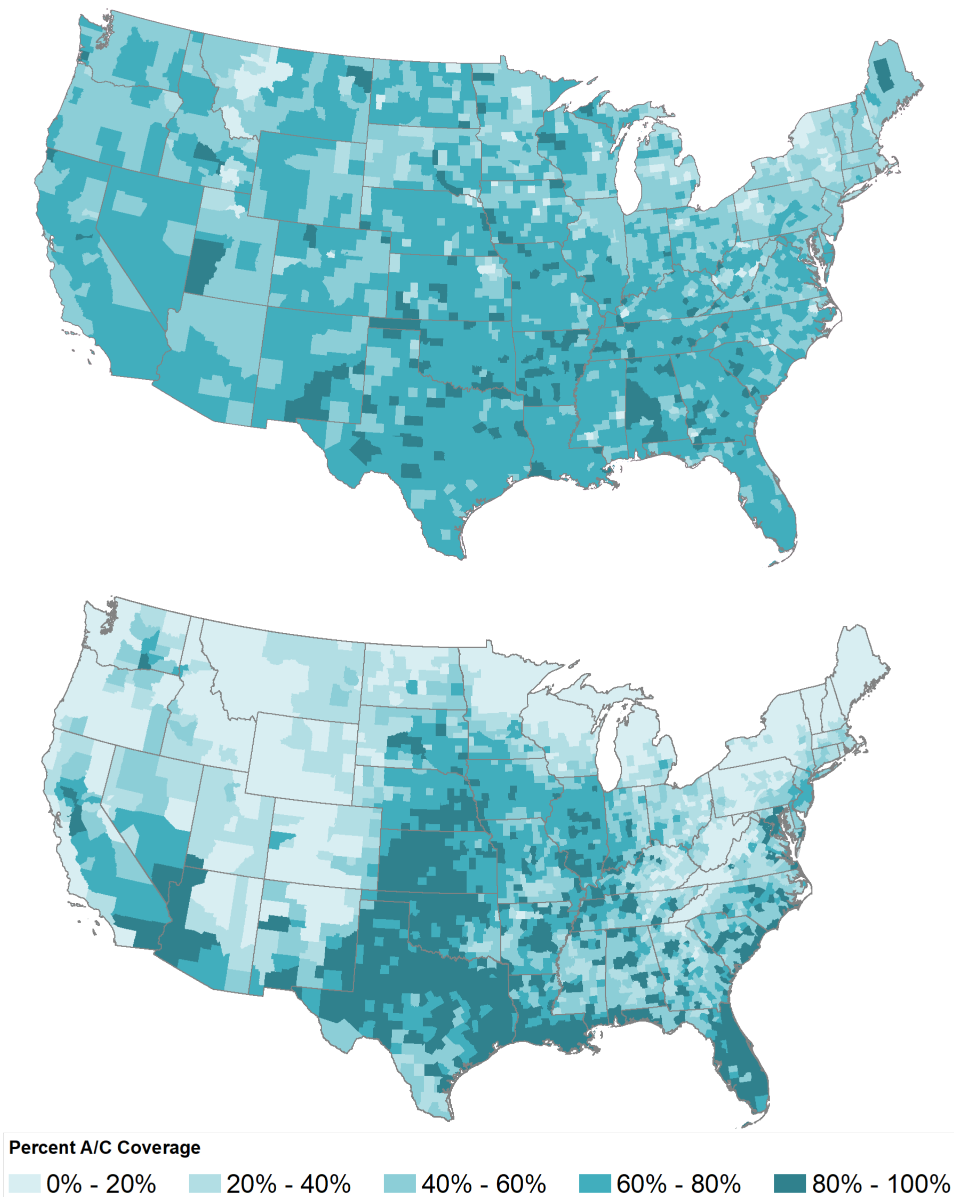


4°C of Global Warming



Note: These maps describe the number of degrees (in Fahrenheit) above baseline levels during state-specific school years projected for each degree of global warming listed. Darker shading describes larger increases, lighter shading describes smaller increases. See Step 2 of Table 1 for additional details.

Figure 2: Baseline School A/C (top) and Home A/C (bottom) Market Penetration (%)



Note: These maps describe A/C market penetration identified in Park et al. and used in the detail analyses presented in this report. See Step 1a of Table 1 for additional details.

EFFECTS ON CHILDREN RESULTS

Table 4 presents the national average learning losses per child in terms of standard deviations, percent reduction relative to average gain in test scores per year, and how these results translate into lost future income. Table 5 aggregates across graduating high school students to express lost annual income at each degree of global warming under different population assumptions.

Table 4: Projected National Average Learning Losses Per Child

Degree of Global Warming (°C)	(1) National Average Learning Losses Per Child (Standard Deviations)	(2) National Average Learning Losses Per Child (%)	(3) National Average Lost Future Income Per Child Per Year (2021 Dollars)
1°C	0.0062 *(-0.0020 to 0.0156)*	2.1% *(-0.7% to 5.2%)*	$677 *(-$222 to $1710)*
2°C	0.0119 *(0.0034 to 0.0217)*	4.0% *(1.1% to 7.2%)*	$1,310 *($378 to $2,390)*
3°C	0.0173 *(0.0090 to 0.0269)*	5.8% *(3.0% to 9.0%)*	$1,900 *($988 to $2,960)*
4°C	0.0213 *(0.0140 to 0.0290)*	7.1% *(4.7% to 9.7%)*	$2,340 *($1,550 to $3,190)*
5°C	0.0265	8.8%	$2,920

Note: All estimates presented in columns (1) and (3) are incremental relative to baseline learning losses associated with heat exposure. Averages per student are population weighted and assume population growth. The learning losses in column (2) are presented in terms of a "percent" relative to 0.3 standard deviations (average gain in PSAT score performance between 10th and 11th grades, see Table 1). The table displays the average and range across climate models; a range for 5°C is not feasible because only one climate model reaches this temperature threshold before 2100.

Table 5: Projected Total Lost Annual Income Related to Learning Losses Across Graduating High School Students (Billion 2021 Dollars)

Degree of Global Warming (°C)	With Population Growth	Constant 2010 Population
1°C	$3.2 *(-$1.0 to $8.2)*	$3.0 *(-$0.9 to $7.4)*
2°C	$6.9 *($1.9 to $12.7)*	$5.8 *($1.7 to $10.6)*
3°C	$10.6 *($5.6 to $16.6)*	$8.5 *($4.5 to $13.2)*
4°C	$13.4 *($8.9 to $18.3)*	$10.5 *($7.0 to $14.2)*
5°C	$17.1	$13.0

Note: All estimates presented are incremental relative to baseline learning losses associated with heat exposure. See Table 1 for additional details. The table displays the average and range across climate models; a range for 5°C is not feasible because only one climate model reaches this temperature threshold before 2100.

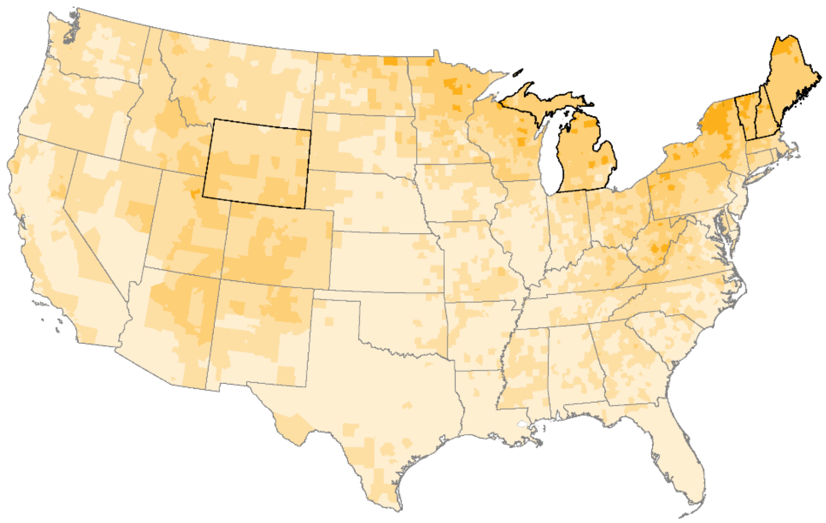
Figure 3 presents the spatial distribution of learning losses per child at 2°C and 4°C of global warming. The five states with largest impacts per child are outlined in black and listed below each map.

Table 6 and Table 7 then follow with the impacts per child for each state at 2°C and 4°C of global warming to provide perspective on the range of impacts across states, although there can be considerable heterogeneity within states (see Figure 3).

Figure 4 shows the total lost income from learning losses across graduating students in each census tract. Impacts are generally highest in areas with large children's populations. The five states with largest total impacts are outlined in black and listed below each map. The relevant quantities or rates presented in each figure are provided in parentheses after the state name in the lists of top 5 states.

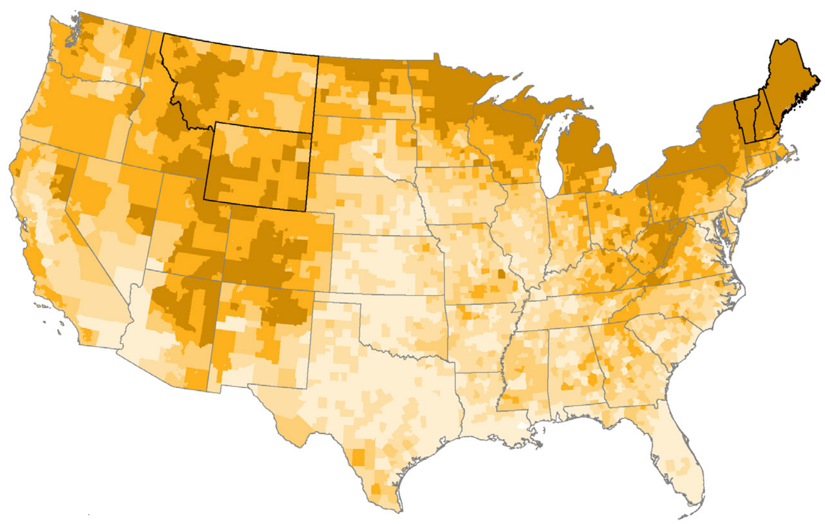
Figure 3: Projected Lost Future Income Per Child Per Year Associated with Learning Losses from Heat Exposure

2°C of Global Warming



Top five states: VT ($3,050), ME ($2,760), NH ($2,630), WY ($2,320), MI ($2,230)

4°C of Global Warming



Top five states: VT ($5,520), ME ($4,980), NH ($4,620), WY ($4,280), MT ($4,060)

Lost Future Income Per Child

$0 | $1 - $1,450 | $1,451 - $2,350 | $2,351 - $3,250 | $3,251 - $4,300 | $4,301 - $7,300

Note: These maps describe projected future lost income per child per year associated with learning losses from heat exposure at 2°C and 4°C of global warming (expressed in 2021 dollars). The five states with the highest average impacts are outlined in black (see Tables 6 and 7 for related details). See Table 1 for analytic details.

Table 6: Projected Lost Future Income Per Child Per Year Associated with Learning Losses by State with 2°C Global Warming (with Population Growth)

State	Lost Future Income Per Child	State	Lost Future Income Per Child
Vermont	$3,050	New Mexico	$1,330
Maine	$2,760	Kentucky	$1,300
New Hampshire	$2,630	Delaware	$1,290
Wyoming	$2,320	California	$1,270
Michigan	$2,230	North Carolina	$1,270
West Virginia	$2,230	Virginia	$1,250
Colorado	$2,150	Iowa	$1,240
Massachusetts	$2,140	Illinois	$1,240
Wisconsin	$2,100	Maryland	$1,160
Rhode Island	$2,090	Mississippi	$1,050
New York	$1,990	Georgia	$1,020
Montana	$1,970	Missouri	$1,010
Idaho	$1,960	South Carolina	$984
Pennsylvania	$1,890	Tennessee	$959
Utah	$1,860	Arkansas	$929
Ohio	$1,820	Nevada	$891
Washington	$1,800	Kansas	$885
Minnesota	$1,760	Arizona	$858
Connecticut	$1,740	Alabama	$856
North Dakota	$1,620	Oklahoma	$747
Oregon	$1,560	Nebraska	$733
Washington, DC	$1,550	Texas	$651
South Dakota	$1,500	Louisiana	$625
Indiana	$1,410	Florida	$538
New Jersey	$1,330		

Notes: This table describes average future lost income per child per year at 2°C of global warming using the methods described in Table 1 averaged to the state level (2021 dollars). States are listed from largest to smallest impacts.

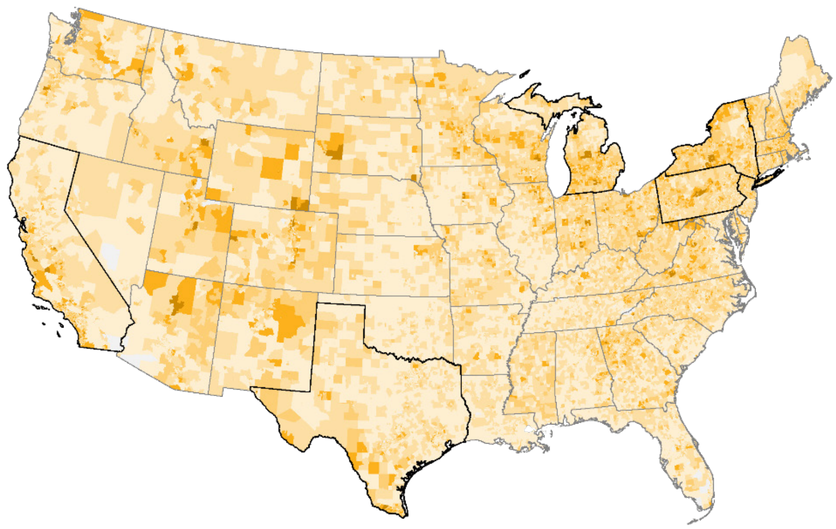
Table 7: Projected Lost Future Income Per Child Per Year Associated with Learning Losses by State with 4°C Global Warming (with Population Growth)

State	Lost Future Income Per Child	State	Lost Future Income Per Child
Vermont	$5,520	New Jersey	$2,460
Maine	$4,980	New Mexico	$2,430
New Hampshire	$4,620	Delaware	$2,310
Wyoming	$4,280	Kentucky	$2,280
Montana	$4,060	Virginia	$2,180
Rhode Island	$4,040	North Carolina	$2,160
Michigan	$3,930	Illinois	$2,150
Colorado	$3,900	Maryland	$2,060
West Virginia	$3,900	Iowa	$2,050
Massachusetts	$3,890	Georgia	$1,750
Idaho	$3,880	Mississippi	$1,750
Washington	$3,790	South Carolina	$1,710
Wisconsin	$3,610	Tennessee	$1,660
New York	$3,560	Missouri	$1,650
Oregon	$3,420	Nevada	$1,600
Pennsylvania	$3,380	Arizona	$1,590
Utah	$3,370	Arkansas	$1,510
North Dakota	$3,250	Alabama	$1,480
Ohio	$3,190	Kansas	$1,400
Connecticut	$3,170	Nebraska	$1,270
Minnesota	$3,120	Oklahoma	$1,200
Washington, DC	$2,760	Texas	$1,070
South Dakota	$2,630	Louisiana	$1,030
California	$2,490	Florida	$924
Indiana	$2,480	--	

Notes: This table describes average future lost income per child per year at 4°C of global warming using the methods described in Table 1 averaged to the state level (2021 dollars). States are listed from largest to smallest impacts.

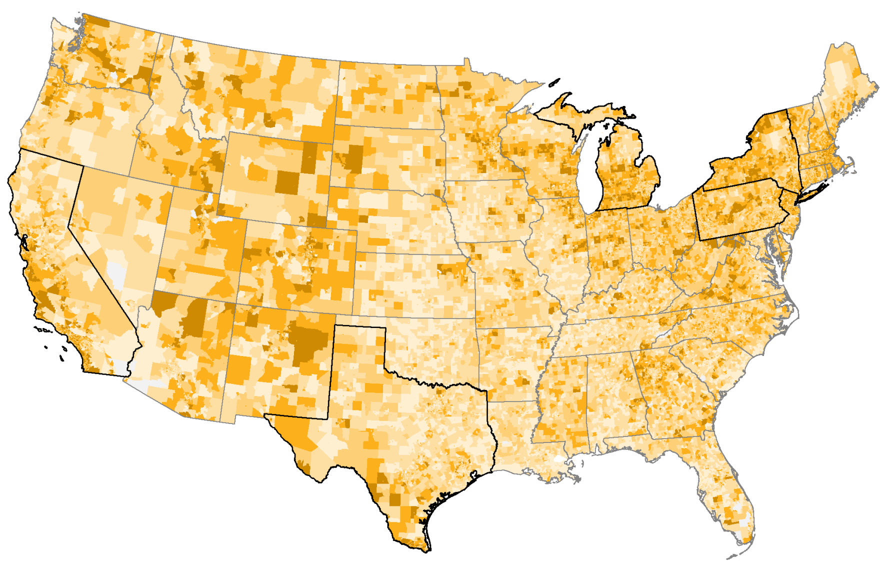
Figure 4: Total Lost Annual Income Across Graduating Students with 2°C and 4°C Global Warming (with Population Growth)

2°C of Global Warming



Top five states: CA ($997 mil), NY ($679 mil), TX ($349 mil), MI ($337 mil), PA ($325 mil)

4°C of Global Warming



Top five states: CA ($2.2 bil), NY ($1.3 bil), TX ($646 mil), MI ($606 mil), PA ($575 mil)

Total Lost Annual Income

$0 | $1 - $64,000 | $64,001 - $140,000 | $140,001 - $250,000 | $250,001 - $500,000 | $500,001 - $7,200,000

Note: These maps describe projected lost annual income across each cohort of graduating high school students associated with learning losses from heat exposure at 2°C and 4°C of global warming (expressed in 2021 dollars). The five states with the highest impacts are outlined in black. See Table 1 for analytic details.

Table 7 demonstrates hypothetical future learning losses under different scenarios featuring increased installation of A/C in schools: a 10% increase in school A/C, 20% increase in school A/C, and complete A/C coverage in schools.

Table 7: National Average Learning Losses Per Child Under Alternate Future School A/C Coverage Relative to Baseline A/C Coverage and Temperatures

Degree of Global Warming (°C)	10% Increase in School A/C		20% Increase in School A/C		Complete A/C Coverage in Schools	
	Overall	Baseline Corrected	Overall	Baseline Corrected	Overall	Baseline Corrected
Baseline	0.147		0.147		0.147	
1°C	0.137	-0.010	0.122	-0.025	0.090	-0.057
2°C	0.142	-0.005	0.126	-0.021	0.093	-0.054
3°C	0.147	0.000	0.130	-0.017	0.096	-0.050
4°C	0.150	0.004	0.133	-0.014	0.099	-0.048
5°C	0.155	0.008	0.137	-0.010	0.102	-0.045

Note: This table provides hypothetical future learning losses under different scenarios featuring increased installation of A/C in schools. The baseline considers both baseline temperature (relative to 1986-2005) as well as baseline school A/C (see Table 1). The cells in gray demonstrate future learning "gains" relative to these baseline levels.

LIMITATIONS

Below are several limitations of the detailed analysis of heat exposure on learning losses.

1. ***PSAT scores may not be representative of learning losses for students who do not plan to attend college.*** Park et al. argue that PSAT scores are a suitable proxy for "learning" because the test is not designed to measure overall intelligence of IQ. However, it may be a subsample of high school students that elect to take the PSAT, especially college-bound students. It is uncertain whether the learning losses measured by PSAT scores are necessarily transferrable to students who do not take the PSAT.
2. ***Valuation of learning losses relies on one study from Tennessee.*** In order to offer a total magnitude of learning losses across students, learning losses are valued using income losses associated with standard deviations in learning losses using the same approach in Park et al., which transfers the value from Chetty et al. The income loss value in Chetty et al., however, is drawn from a relatively small sample of students in Tennessee that over-samples among poorer students. It is uncertain if the income losses observed in Chetty et al. and used by Park et al. are necessarily transferrable to all students across the U.S.
3. ***School and home A/C levels are observed at high level of spatial granularity.*** The school A/C data used in Park et al. are at the school level and reflects considerable variation across

space. The data are considered confidential and are not available for use in this study. Instead, the analysis in this report relies on county-level information as presented in a map in Park et al. which likely masks within-county variation in access to school A/C. Home A/C is modeled in Park et al. and was provided by the authors at the county level. To the extent that access to A/C significantly varies within counties, this analysis will not be able to decipher these differences.

4. *Survey-based responses about school A/C penetration may be imperfect measures.* Park et al. rely on survey-based responses from students and staff at schools to predict A/C coverage. While the authors determined this metric to be a good indicator on how well schools are air conditioned, it relies on subjective information about whether classrooms were too hot and at a single point in time.
5. *Cumulative learning losses may be under-estimated.* Park et al. demonstrate that heat experienced in one year can affect PSAT scores four years later (see Table 4 of Park et al.), although do not offer this relationship controlling for school and home A/C. The study authors conclude that the cumulative effect of heat experienced in these four years is three to five times higher than the impact of the one school year prior. Given Park et al.'s findings, the approach used in this report is likely to under-estimate total learning losses associated with all heat exposure experienced during a child's time in grade school. Similarly, Roach and Whitney provide evidence that learning losses associated with heat can start very early.
6. *Unable to differentiate between public and private schools.* This study considers the impacts on all students, although there may be important differences between students who attend public vs. private schools. Moreover, the LeRoy et al. study that estimates the cost of installing A/C is specifically focused on infrastructure gaps in public schools. Given less than 10% of school-aged students likely attend private school[4] (U.S. Department of Education 2019) and the more considerable difference between the lost income from learning losses and cost of installing A/C, the potential over-inclusion of private school students in our valuation estimate is not concerning.
7. *Average temperatures during the school year may not be the best indicator of heat that reduces learning:* Park et al. find a statistically significant relationship between average maximum temperature across the school year and learning. However, it is possible there is a better indicator of school buildings being too hot for productive learning.

DATA SOURCES

Table 8: Summary of Data Sources Used in Heat and Learning Analysis

Data Type	Description	Data Documentation and Availability
Historical temperature data	Daily temperature data from 3,000 weather stations covered by the National Oceanic and Atmospheric Administration's Daily Global Historical Climatology Network between 1996 and 2014	Global Historical Climatology Network daily (GHCNd)

Data Type	Description	Data Documentation and Availability
Baseline A/C coverage in schools	Generated by Park et al. using data from surveys administered by the College Board to students and guidance counselors at high schools across the U.S. (provided to the study authors via a data use agreement with the College Board, see Park et al. for details)	Data not publicly available
Baseline A/C coverage in homes	Generated by Park et al. using the 1980 decennial Census (county-year level) with data on changes in penetration over time (census-region level) from the Energy Information Agencies Residential Energy Consumption surveys (see Park et al. for details)	1980 Census of Population and Housing Residential Energy Consumption Survey (RECS)
PSAT scores	Park et al. used test scores (math and reading) from the universe of PSAT-takers from high school classes between 2001 and 2014 (provided to the study authors via a data use agreement with the College Board, see Park et al. for details)	Data not publicly available
Income losses	Originally derived from Chetty et al. and adjusted in Park et al. Converted to 2021 dollar-year using the U.S. Bureau of Economic Analysis's "National Income and Product Accounts" product	U.S. Bureau of Economic Analysis's "National Income and Product Accounts" (Table 1.1.9 in the Section 1)
Future heat during school years	*See Appendix A for data sources*	
Future population of children	*See Appendix A for data sources*	
Note: See Park et al. for other data sources used in the underlying study, including demographic and other control variables not leveraged for projection purposes.		

Heat and Emergency Department Visits

Chapter 3 highlights research linking daily maximum temperature and the incidence of ED visits among a sample of children's hospitals across the U.S. from Bernstein et al. (2022).[5] The study authors apply a two-stage analytic approach to estimate the association between day-to-day variation in maximum temperature and the relative risk of emergency department visits for the 47 children's hospitals in their sample, adjusting for temporal trends. Extreme heat was associated with a relative risk (RR) of all-cause ED visits of 1.17 over the next 7 days relative to hospital-specific minimum morbidity temperature (MMT) and the 95th percentile of the temperature distribution. Given the geographic variation of the hospitals in their sample, especially relative to existing literature studying similar relationships, the authors offer their results as generalizable to other geographies and hospitals. The analysis in this report extrapolates the findings from Bernstein et al. to other children's hospitals with emergency departments.

To determine the locations of all children's hospitals in the U.S. with emergency departments, and characteristics similar to those in the study sample, the authors of the study were consulted to help determine which hospitals among all 260 listed in a directory from the Children's Hospital Association met these criteria.[6] The authors identified 38 hospitals that are not pediatric acute care facilities (e.g., burn hospitals, rehab hospitals, mental health facilities) and which do not have an ED. The final list of relevant hospitals includes all other children's hospitals (222 total).

Healthcare Cost and Utilization Project's Kids' Impatient Database (HCUP KID), a database of hospital admissions data for kids, was then leveraged for two recent years (2016 and 2019) to approximate the baseline number of ED visit incidence among children. Following the below-listed steps revealed that children's hospitals see approximately 22,000 children in their EDs each day in summer months:

1. Identify all hospital admissions associated with children's hospital (KID_STRATUM variable)
2. Identify all admissions with evidence of ED services in the discharge record (HCUP_ED variable)
3. Retain admissions for May through September, consistent with the months included in the original study
4. Apply the sample weighting approach described in HCUP (2005)[7] to establish national counts
5. Estimate the number of ED visits indirectly through a ratio of hospital admissions to all ED visits (including those that do not result in hospital admissions) by dividing the total observed hospital admissions in HCUP KID by 3.3% (McDermott et al., Table 1[8])
6. Average the findings from 2016 and 2019 to produce an estimate of total annual number of ED visits at children's hospitals between May and September

Information was not available to identify the MMT and 95th percentile for the locations of the 222 children's hospitals, which limited the application of Bernstein et al.'s findings to climate projections used elsewhere in this chapter. Instead, the analysis assumes that the national average MMT is approximately 62°F (drawn from Figure S1 of Bernstein et al.) and the 95th percentile is approximately 95°F. If the RR between those two temperature levels is 1.17, then that assumes a 0.5% increase in ED visits per degree between those two temperatures. Therefore, if temperatures increase 1°F for each of the 153 days between May and September, this analysis estimates an additional 113 ED visits at children's hospitals per day, or 17,340 total visits throughout the summer months.

DATA SOURCES

Table 9: Summary of Data Sources Used in Heat and Emergency Department Visits Analysis

Data Type	Description	Data Documentation and Availability
Children's hospitals	Population and location of all children's hospitals in the U.S. Discussions with the authors of Bernstein et al. helped to narrow the dataset to only those hospitals that included an ED.	Children's Hospital Association directory

Data Type	Description	Data Documentation and Availability
Baseline number of ED visits at children's hospitals	Identified hospitalizations admitted through the ED. These data were then "inflated" to correct for the number of ED visits that did not result in hospitalization using information presented in McDermott et al.	Healthcare Cost and Utilization Project's Kids' Impatient Database (2016 and 2019)
Note: This table only provides the data sources used in the analysis presented in this report. For the underlying data sources used in Bernstein et al., see the paper.		

References

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

[2] Chetty, R., Friedman, J.N., Hilger, N., Saez, E., Schanzenbach, D.W. and Yagan, D., 2011. How does your kindergarten classroom affect your earnings? Evidence from Project STAR. *The Quarterly Journal of Economics*, *126*(4), pp.1593-1660.

[3] LeRoy, S., Matthews, M., Wiles R., 2021. *Hotter Days, Higher Costs: The Cooling Crisis in America's Classrooms*. The Center for Climate Integrity. https://coolingcrisis.org/uploads/media/HotterDaysHigherCosts-CCI-September2021.pdf

[4] U.S. Department of Education, National Center for Education Statistics. 2019. "Public and private school comparison." Available at: https://nces.ed.gov/fastfacts/display.asp?id=55. Accessed on September 16, 2022.

[5] Bernstein, A.S., Sun, S., Weinberger, K.R., Spangler, K.R., Sheffield, P.E. and Wellenius, G.A., 2022. Warm Season and Emergency Department Visits to US Children's Hospitals. *Environmental Health Perspectives*, *130*(1), p.017001.

[6] Children's Hospital Association Directory. n.d. Available at: https://www.childrenshospitals.org/hospital-directory#sort=%40z95xdisplayname%20ascending

[7] Healthcare Cost and Utilization Project. 2005. "Calculating Kids' Inpatient Database (KID) Variances." Methods Series Report #2005-5. Available at: https://www.hcup-us.ahrq.gov/db/nation/kid/reports/CalculatingKIDVariances.pdf

[8] McDermott, K.W., Stocks, C. and Freeman, W.J., 2020. "Statistical Brief #242: Overview of Pediatric Emergency Department Visits. 2015." Available at: https://www.ncbi.nlm.nih.gov/books/NBK526418/