Heat, Human Capital, and Adaptation to Climate Change

Jisung Park, PhD

Sungkyunkwan University Seminar

March 29, 2019
Personal Context

Who I am:

- Assistant Prof. at UCLA (Public Policy)
- Environment and Labor economist by training
- Kansas, Korea, New England, California

Work motivated by:

- Environmental change
- Economic opportunity

This Talk:

- Two related studies on human impacts of CC, its distributional equity implications, and role of public policy.
Motivation and Background Science
The Climate has Already Changed

When you were born, the Los Angeles area could expect about **57 days** per year to reach at least 90 degrees.

Avg. number of days at or above 90°F
The Climate has Already Changed

Today, the Los Angeles area can expect 67 days at or above 90 degrees per year, on average.

Avg. number of days at or above 90°F
The Climate has Already Changed

By the time you're 80, models show there could be 87 of these very hot days. The likely range is between 79 and 97 days.
The Climate has Already Changed

Today, the Daejeon area can expect 20 days at or above 90 degrees per year, on average.
By the time you’re 80, models show there could be **10** of these very hot days. The likely range is between **28 and 52** days.
The Climate has Already Changed

When you were born, the New Delhi area could expect about **179 days** per year to reach at least 90 degrees.
The Climate has Already Changed

Today, the New Delhi area can expect 205 days at or above 90 degrees per year, on average.
The Climate has Already Changed

By the time you’re 80, models show there could be 228 of these very hot days. The likely range is between 218 and 234 days.
Historical Emphasis: “Climate Impacts”
Labor and Human Capital Impacts of Climate Change
Declining Economic Mobility

Whether and how climate change affects these trends is unresolved.

Figure: BLS; Azar et al. (2018)
Climate and educational achievement in cross-section

Students in hotter places exhibit lower educational achievement for any given age or grade: across countries (PISA), and within countries (SEDA)
Temperature and cognition in short run

Hot temperature reduces cognitive performance

Graff-Zivin, Neidell, Hsiang (2017)

But short-run cognition ≠ human capital accumulation

Park (2017)
Outline

1. Motivation and Background Science

2. Heat and Learning
   - Data, Setting, and Empirical Strategy
   - (1) Main effect: cumulative heat and learning
   - (2) Plausible mechanisms, defensive investments
   - (3) Achievement gaps

3. Heat and Labor
   - Data, Setting, and Empirical Strategy
   - Preliminary Findings

4. Summary and Discussion
Whether such lab-based findings extend to actual learning environments remains unclear
Challenges/Gaps in policy application

Only recently have direct heat mechanisms been considered as inputs to climate policy. Important gaps remain.

**Mitigation:**

- SCC estimates do not include labor or human capital impacts (Tol, 2009; Heal and Park, 2016)
- Distribution of damages assumed but unsubstantiated (Anthoff and Emmerling, 2019)

**Adaptation:**

- Unclear whether, how, and at what cost economic agents will adapt over time
- Role of government policy in adaptation unclear
Heat and Learning
Title: Heat and Learning

Authors: Jisung Park, Joshua Goodman, Mike Hurwitz, Jonathan Smith
Anecdotal Evidence

Public school buildings are falling apart, and students are suffering for it

Union talks heat up over widespread air conditioning problems in Hillsborough schools

New York’s Public School Students Sweat Out the End of the Semester
Environmental determinants of achievement gaps?

U.S. Minority-White achievement gaps $\approx 3$ years of formal schooling

Existing research on “environmental factors” typically pertain to social environment
Data and setting

22 million student-level PSAT records, 1997-2012

Survey of school air conditioning, 12,000 schools
Synopsis

Research objectives:

- Can cumulative heat exposure affect the rate of learning?
- What are some plausible mechanisms? How effective are defensive investments?
- What role does physical learning environment play in achievement gaps?
Synopsis

Research objectives:

- Can cumulative heat exposure affect the rate of learning?
- What are some plausible mechanisms? How effective are defensive investments?
- What role does physical learning environment play in achievement gaps?

Data:

- Outcome variable: PSAT (multiple) performance for (10m) multiple takers, 28K schools, 1997-2012

Empirical strategy:

- Assume gains in PSAT performance reflect gains in learning/human capital accumulation
- Leverage quasi-experimental within-school variation in year-to-year heat exposure
Data and setting

PSAT data (College Board):
- student-level exam records: universe of PSAT takers 1997-2012; 10m students; 28K schools
- nationwide survey of school AC; responses from 11,800 schools; 87% of students in sample represented

Weather data (NCDC, EPA, GSOD):
- station-level weather data: daily max temp; precip; snow; EPA criteria air pollutants
- construct contemporaneous (exam-day) and cumulative (e.g. school year) measures of temp, precip, pollution; state-specific academic calendars (map)

Geographic covariates (CBP, RECS, Census):
- county-level exposed sector payroll; residential AC (1980-2014)
Institutional setting: PSAT

PSAT \approx \text{“SAT but slightly easier, earlier, only once per year”}

Advantages:
- Rigid and centralized administration: once/year, fixed timing, at home school
- Cumulative assessment: designed to capture secondary school achievement (algebra, trig, reading, science, 3 hrs total)

Disadvantages:
- Out-of-sample validity (within US): more educated parents, higher income, slightly more coastal representation
- Out-of-sample validity (general): high income, non-agrarian setting

More on PSAT here
Summary Statistics

Geographic distribution of PSAT takers (1997-2012)
Average number of hot (90F+) days during school year
Geographic variation in PSAT performance (math + verbal z-scores, 1997-2012)
Empirical framework

Panel data model with student, cohort by date by take number fixed effects

\[ \text{Score}_{iscyn} = \beta \text{Heat}_{sy} + \eta_i + \gamma_{cyn} + \epsilon_{isycn} \]  

with

- \( \text{Score}_{iscyn} \) = z-score for student \( i \), school \( s \), cohort \( c \), year \( y \), on \( n \)th take
- \( \text{Heat}_{sy} \) = avg max temp (or vector of degree day counts) in year prior in school \( s \), on year \( y \)
- \( \eta_i \) = student fixed effect
- \( \gamma_{cyn} \) = high school class by test date by take number fixed effect

Identification:

\[ E(\epsilon_{isycn}|\text{Heat}_{sy}, \eta_i, \gamma_{cyn}) = 0 \]  

e.g. variation in temperature is exogenous conditional on fixed effects
Identifying Variation

(A) Mean temperature

(B) Days above 90 °F
Identifying Variation

(A) Mean temperature (°F)

SD = 1.05

(B) Days above 90 °F

SD = 3.17
(1) Main effect: cumulative heat and learning
Main effect

+1°F $\Rightarrow -0.2\%$ (se=0.03) of sd learning $\approx -1\%$ of avg annual learning gains

Magnitude:

+5 hot (90°F+) school days $\approx -5\%$ sd teacher VA

2-3 times larger for low-income (bottom decile) and minority (B/H) students

Robust to:

- controls for test day temperature
- precip & snow: test day and cumulative
- state-specific linear and non-linear trends
- subset of schools $\leq 5$ mi from weather sensor
- subject-specific impacts: both math and verbal affected
- placebo using lead temperature: future shocks have no impact
Robust to potential endogenous selection

Endogenous selection into retake?

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior year temperature (°F)</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0003</td>
<td>-0.0001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>Following year temperature (°F)</td>
<td>0.0003</td>
<td>0.0003</td>
<td>0.0003</td>
<td>-0.0004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>27,021,551</td>
<td>27,021,551</td>
<td>27,021,551</td>
<td>27,021,551</td>
<td>27,021,551</td>
</tr>
</tbody>
</table>

Test day temperature  | No   | No   | No   | Yes  | Yes  |
State-specific time trends | No   | No   | No   | No   | Yes  |

**Figure:** Dependent variable is probability of retake, conditional on taking once

No evidence of within-student selection due to temperature (acute or cumulative)

School FE regressions may result in spurious correlation due to trends in B/H takers + regional warming [here](#)
(2) Plausible mechanisms

What might be driving these cumulative learning impacts?

Effects persist when controlling for correlated, time-varying economic/pollution shocks:

- local economic shocks (exposed sector payroll)
- local air pollution: o3, pm10, co, no2, so2
(2) Plausible mechanisms

What might be driving these cumulative learning impacts? Effects persist when controlling for correlated, time-varying economic/pollution shocks:

- local economic shocks (exposed sector payroll)
- local air pollution: o3, pm10, co, no2, so2

Timing of heat events:

- **school days** vs summer days:
- **weekdays** vs weekends and national holidays
Mechanisms

School year vs Summer (state-specific calendars); Weekdays vs Weekends & Holidays

<table>
<thead>
<tr>
<th>(B) Days above 90 °F</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>School days, 1 year prior</td>
<td>-0.056***</td>
<td>-0.061***</td>
<td>-0.073***</td>
<td>-0.078***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.016)</td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>Summer days, 1 year prior</td>
<td>0.016</td>
<td></td>
<td></td>
<td></td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
<td></td>
<td></td>
<td>(0.011)</td>
</tr>
<tr>
<td>Weekend days, 1 year prior</td>
<td></td>
<td></td>
<td>0.043</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.028)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School days, post-summer</td>
<td></td>
<td></td>
<td></td>
<td>-0.074***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.019)</td>
<td></td>
</tr>
<tr>
<td>School days, pre-summer</td>
<td></td>
<td></td>
<td></td>
<td>-0.074***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>School days, 2 years prior</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.051***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.013)</td>
</tr>
<tr>
<td>School days, 3 years prior</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.048***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>N</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
</tr>
</tbody>
</table>
Mechanisms

School year vs Summer (state-specific calendars); Weekdays vs Weekends & Holidays

<table>
<thead>
<tr>
<th>(B) Days above 90 °F</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>School days, 1 year prior</td>
<td>-0.056***</td>
<td>-0.061***</td>
<td>-0.073***</td>
<td>-0.078***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.016)</td>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>Summer days, 1 year prior</td>
<td>0.016</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekend days, 1 year prior</td>
<td></td>
<td></td>
<td>0.043</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.028)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School days, post-summer</td>
<td></td>
<td></td>
<td></td>
<td>-0.074***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.019)</td>
<td></td>
</tr>
<tr>
<td>School days, pre-summer</td>
<td></td>
<td></td>
<td></td>
<td>-0.074***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>School days, 2 years prior</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.051***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.013)</td>
</tr>
<tr>
<td>School days, 3 years prior</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.048***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>N</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
</tr>
</tbody>
</table>
Plausible mechanisms, defensive investments

Driven by hot school days (weekdays during state-specific school year).

Consistent with:
- School closures: reduced learning time + disrupted pedagogy
- Reduced productivity of class time

“"I have more kids who will put their heads down, they’ll be grouchier, less compliant, they don’t want to do anything,” one Baltimore teacher said last year."
School AC survey responses

CB survey: responses from students in 12,000 schools; counselors in 2,000 schools. 87% of student obs represented.

Estimated % of classrooms without functioning AC in 2016:
(2) Defensive investments: school air conditioning

Presence of school AC associated with reduced learning impacts: $\beta$ reduced by $\approx -75\%$

AC penetration not experimental, but triple-difference estimates are suggestive

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean temp.</td>
<td>-0.322***</td>
<td>-0.565***</td>
<td>-0.229***</td>
<td>-0.457***</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.103)</td>
<td>(0.060)</td>
<td>(0.168)</td>
</tr>
<tr>
<td>Mean temp. * School AC penetration</td>
<td>0.253**</td>
<td>0.227***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.071)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean temp. School AC penetration change * HS class</td>
<td></td>
<td>0.117***</td>
<td>0.116***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td>(0.038)</td>
<td></td>
</tr>
<tr>
<td>Mean temp. * HS class</td>
<td></td>
<td>-0.011</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.015)</td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>Mean temp. * School AC penetration change</td>
<td></td>
<td>-0.218</td>
<td>-0.272*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.168)</td>
<td>(0.153)</td>
<td></td>
</tr>
<tr>
<td>Mean temp. * Home AC penetration</td>
<td></td>
<td>0.323***</td>
<td>0.213</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.110)</td>
<td>(0.185)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>18,665,967</td>
<td>18,665,967</td>
<td>2,935,907</td>
<td>2,935,907</td>
</tr>
<tr>
<td>Interactions with area income, racial composition, temperature</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
</tbody>
</table>
Low-income, minority students less likely to have school AC

Residualized variation controlling for average climate and zip code income.
(3) Racial achievement gaps

Back-of-the-envelope calculation:

Persistent heat exposure + lower levels of school AC may contribute 4% to 7% of minority-white achievement gaps

Leveling temperature component of environmental playing field could narrow achievement gaps by \( \approx 20\% \) of realized gain over past 4 decades
Recap of findings

Extreme heat appears to disrupt learning and human capital formation. Defensive investments appear to be effective when present, but realized disruptions are persistent, cumulative.
Recap of findings

Extreme heat appears to disrupt learning and human capital formation. Defensive investments appear to be effective when present, but realized disruptions are persistent, cumulative.

1. Main effect:
   - +1°F hotter school year $\Rightarrow$ -1% avg learning gains
   - +5 school days above 90°F $\Rightarrow$ -5% sd teacher VA

2. Mechanisms and Adaptation:
   - effect driven by hot school days: disrupted learning time
   - implied PV of school AC in Houston = $2,000 per student-year

3. Distributional implications:
   - effects 2-3 times as large for minorities and low-income students
   - climatic factors contribute 4% to 7% of US racial achievement gaps
In progress: external validity

US 3-8th graders (SEDA); International 15-year olds (PISA)
Heat and Labor
Title: Heat, Labor, and Adaptation to Climate Change

Authors: Jisung Park, Patrick Behrer
Motivation

Stylized facts:

- Exposed industries make up approx. 23% of US workforce (NIOSH): construction, agriculture, transportation, manufacturing, mining, utilities
  - Over 180m construction workers worldwide (World Bank, 2017)
- Relatively little causally identified work on effects of temperature on labor
  - Notable exceptions include: Hsiang et al. (2011), Graff Zivin and Neidell (2014), Colmer (2018), Dillender et al. (forthcoming)
Empirical Analyses

Three research objectives

1. What is the causal impact of heat on worker occupational safety?
   - Quasi-experimental variation in temperature by zipcode-month

2. How does this risk vary by income/skill level?
   - Heterogeneity by wage level using WC claims data and occupation codes

3. What - if any - is the role of public policy?
   - Evaluation of CA Outdoor heat-illness prevention standard (2007)
Data and Setting

Employment and earnings data (CBP, QCEW):
- QCEW, CBP: average wages, employment, and payroll data

Occupational injury and fatality data (OSHA, BLS, CA Workers’ comp):
- US OSHA, BLS: occupational injury and fatality by zipcode and month, 1990-2013
- CA Division of Labor: universe of workers’ compensation claims, 2000-2017 (N=17m)

Weather data:
- NCDC: station-level daily weather data (≈3,000 stations)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Identifying Variation

Number of extreme heat days, relative to county average (1986-2011)
Preliminary Findings

Temperature and worker take-home pay (highly exposed industries, 1986-2011)

Residualized variation including county and year fixed effects, state trends, degree day controls.
Preliminary Findings

Temperature and worker take-home pay (Construction, 1986-2011)

Residualized variation including county and year fixed effects, state trends, degree day controls.
Preliminary Findings

Temperature and worker take-home pay (Manufacturing, 1986-2011)

Residualized variation including county and year fixed effects, state trends, degree day controls.
Preliminary Findings

Temperature and workplace injury risk (OSHA 1990-2013)

Residualized variation. Dropping county-years with zero fatalities.
Preliminary Findings

Temperature and workplace fatality risk (OSHA 1990-2013)

Residualized variation. Dropping county-years with zero fatalities.
Next steps

Preliminary estimates of magnitude:

- Earnings: 90°F (32°C) day → -9% of weekly earnings
- Injury risk: 90°F (32°C) day → +2.5% weekly injuries

Next steps:

- Heterogeneity by income and skill-level
- Evaluation of CA workplace heat safety mandate (circa 2007)
Heterogeneity by Income

ONET occupational exposures by mean income (2017):
Heterogeneity by Income

ONET occupational exposures by mean income (2017):
In 2007, California passed first worker heat-illness prevention standard:

The standard provides an important opportunity for applied research.

UCLA-based team currently working with CA agencies to assess implications for climate adaptation, possible insights for other states/countries.
In progress: triple-difference (+ synthetic control) to assess impacts of CA policy

Data comes from BLS SOII 2003-2017
Summary and Discussion
Summary

- Heat-related human impacts of climate change more pervasive than previously appreciated
- Evidence for inequity in the distribution of heat-related impacts, as well as adaptive capacity
- Role of public policy remain as yet unclear
Concluding Observations

Lee Kwan Yiu: “Air conditioning was one of the signal inventions of human history. Without it development would not have been possible in the tropics. The first thing I did upon becoming prime minister was to install air-conditioners in buildings where the civil service worked.”

Matt Kahn: “The rich have more strategies than the poor for coping with climate risk... An important area for research is to investigate how poorer households are likely to cope with the new challenges that will be posed by climate change.”
Summary Statistics

Students, exams, years:
- 10 million multiple taker (22m obs); exams taken 1997-2012 (cohorts 2001 to 2014)

Temperature:
- Avg school year: $65^\circ F$ daily max temp, 12 days above $90^\circ F$
- Avg test day: $72^\circ F$

Racial disparities:
- Achievement gaps: $B-W = -0.99$ sd
- Climate gaps: $B-W = +5.7^\circ F$
Institutional Background: PSAT

Kaplan: “The Preliminary SAT is a preparatory version of the SAT exam. You can only take the PSAT once per year, and most students take the test in both 10th and 11th grade. If you earn a high score on the PSAT your junior year, you could qualify to receive a National Merit Scholarship – $180 million dollars in merit scholarships are awarded to students each year!”

<table>
<thead>
<tr>
<th>PSAT Section</th>
<th>Order on Test</th>
<th>Time Allotted</th>
<th># of Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reading</td>
<td>1</td>
<td>60 mins</td>
<td>47</td>
</tr>
<tr>
<td>Writing and Language</td>
<td>2</td>
<td>35 mins</td>
<td>44</td>
</tr>
<tr>
<td>Math No Calculator</td>
<td>3</td>
<td>25 mins</td>
<td>17</td>
</tr>
<tr>
<td>Math Calculator</td>
<td>4</td>
<td>45 mins</td>
<td>31</td>
</tr>
</tbody>
</table>

Back to psat [here]
School years

(A) School year start date

(B) School year end date

Back to background here
### Table A.5: Future Temperature Shocks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean temp., 1 year prior (°F)</td>
<td>-0.181*** (0.028)</td>
<td>-0.229*** (0.039)</td>
<td>-0.182*** (0.028)</td>
<td>-0.178*** (0.029)</td>
<td>-0.228*** (0.049)</td>
</tr>
<tr>
<td>Mean temp., 1 year after (°F)</td>
<td></td>
<td>-0.090* (0.048)</td>
<td></td>
<td></td>
<td>-0.092 (0.080)</td>
</tr>
<tr>
<td>Mean temp., 2 years after (°F)</td>
<td></td>
<td></td>
<td>0.053 (0.032)</td>
<td></td>
<td>-0.006 (0.073)</td>
</tr>
<tr>
<td>Mean temp., 3 years after (°F)</td>
<td></td>
<td></td>
<td></td>
<td>-0.037 (0.033)</td>
<td>-0.037 (0.051)</td>
</tr>
<tr>
<td>N</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
</tr>
</tbody>
</table>
Subject-specific impacts

Table A.3: Temperature Effects by Test Subject

<table>
<thead>
<tr>
<th></th>
<th>Math (1)</th>
<th>Verbal (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A) Average heat</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean temperature (°F)</td>
<td>-0.159***</td>
<td>-0.177***</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>(B) Hot days</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days above 90 °F</td>
<td>-0.042***</td>
<td>-0.062***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>N</td>
<td>21,046,448</td>
<td>21,046,448</td>
</tr>
</tbody>
</table>

Back to main
Heterogeneity by Take Number

Table A.4: Heterogeneity by Take Number

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean temp. (°F)</td>
<td>-0.152***</td>
<td>-0.200***</td>
<td>-0.269***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.027)</td>
<td>(0.069)</td>
<td></td>
</tr>
<tr>
<td>Mean temp. * 1st take</td>
<td>-0.152***</td>
<td>0.048**</td>
<td>0.116</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.021)</td>
<td>(0.079)</td>
<td></td>
</tr>
<tr>
<td>Mean temp. * 2nd take</td>
<td>-0.200***</td>
<td>-0.048**</td>
<td>0.069</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.021)</td>
<td>(0.065)</td>
<td></td>
</tr>
<tr>
<td>Mean temp. * 3rd take</td>
<td>-0.269***</td>
<td>-0.116</td>
<td>-0.069</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.079)</td>
<td>(0.065)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
<td>21,046,448</td>
</tr>
</tbody>
</table>
### Average humidity data

#### Table A.6: Heterogeneity in Prior Year Temperature Impacts by Humidity

<table>
<thead>
<tr>
<th></th>
<th>Humid areas (1)</th>
<th>Arid areas (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean temperature (°F)</td>
<td>-0.186***</td>
<td>-0.111***</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Days above 90 °F</td>
<td>-0.068***</td>
<td>-0.035**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>N</td>
<td>14,492,113</td>
<td>6,435,636</td>
</tr>
</tbody>
</table>
Defensive investments: school air conditioning

Using Chetty et al. (2011) estimates of later-life earnings impacts of higher teacher VA, estimate benefits of school air conditioning.

- Without AC: implied earnings impacts of -$212 per student per °F warmer school year
- In Texas ($\bar{T} = 80°F$): NPV of school AC $\approx$ $53,000 per classroom per year
- Climate change will increase PDV of school air conditioning by $\approx$ $1 million per school by 2050


Dillender, Marcus et al. (forthcoming), “Climate change and occupational health.” *Journal of Human Resources*.


