Some Growth Effects of Climate Change

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How do we know we are changing the climate?

Gradually increasing confidence of the scientific community can be understood by noting the envelope of model results published in association with the 2007 IPCC report (displayed ending in simulation year 2000) were less cleanly separated than those published in association with the 2013 IPCC report (displayed ending in 2010), although the separation visible through 2000 was already reflected in the IPCC's 2007 statement that temperatures were "very likely due to anthropogenic greenhouse gas concentrations" (Table 2).

It is now virtually certain (at least 99 percent probability) that the observed modern warming trend exceeds the bounds of natural variability (Bindoff et al. 2013). Furthermore, humans are likely (with at least 66 percent probability) responsible for 0.6°C–0.8°C of the observed 0.6°C of warming over 1951–2010. Values greater than 0.6°C are possible for the anthropogenic contribution because of the possibility that natural forcing and variability could otherwise impose a slightly negative baseline trend (for example, as a result of volcanic eruptions), a pattern which is visible in the control runs of Figure 2.

![Graph showing change in global mean surface temperature over time.](image)

- Models including greenhouse gas emissions from humans (90% range)
- Observations
- Control runs with only natural emissions
- Change in global mean surface temp. (°C)

Climate change in context

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Figure 2
Average Annual Global Mean Surface Temperature, Compared to Distributions of Climate Model Simulations

Sources: Data comes from Jones, Stott, and Christidis (2013), Morice, Kennedy, Rayner, and Jones (2012), and Taylor, Stouffer, and Meehl (2012).

Note: This graph is best viewed in color; the electronic version of this article available at the JEP website is in color. The heavy black line shows observed average annual global mean surface temperature. The red [or light grey] distributions are exogenously "treated" with anthropogenic greenhouse gas emissions, while the blue [or light grey] distributions (shown only in the left panel) are "control" runs that only contain natural forcings. In the left panel, climate model distributions are from the Third Coupled Model Intercomparison Project (CMIP3) published in 2007 and displayed until 2000, and CMIP5 published in 2013 and displayed until 2010. In the right panel, all climate model projections come from CMIP5 in the moderate emissions scenario (RCP 4.5). Temperatures shown are relative to the 1880–1900 average.

Moderate emissions: +1°C over next 30 years

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Climate change in context

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Moderate emissions: +1°C over next 30 years

= +0.033 °C / yr = + \frac{1}{10,000} °C / day

Hsiang & Kopp (JEP, 2018)
Climate change in context

2080–2099 high emission (RCP 8.5) scenario

1981–2010 (Historical)

Annual average temperature

Hsiang & Kopp (JEP, 2018)
Climate change as an economic problem

Atmospheric carbon-dioxide (parts per million)

- “Business as usual” (RCP8.5)
- Medium emission reduction (RCP6.0)
- Strong emission reduction (RCP4.5)
- Very strong reduction (RCP2.6)

The resources used to mitigate climate change should reflect the benefit of these investments to society.
Core scientific problem

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Ultimately, this requires that we distinguish between

Hypothesis 1: The climate has small impact on modern human society.

Hypothesis 2: The climate has a large impact.

(Thinkers have debated this issue for centuries.)
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This is a hard problem because

→ climate is high-dimensional
→ human society is high-dimensional
→ many confounding factors
Tackling the problem through research design

**The Ideal Experiment**

1. Take two identical planets.
2. Change the climate of one (treatment).
3. Compare to control planet.

**The Quasi-Experiment** (that we can actually do)

Step one:
Reconstruct a history of each population's physical exposure to climatic conditions.

Step two:
Estimate the effect of changes over time for each population:
- High climate exposure - “treatment”
- Low climate exposure - “control”
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High climate exposure - “treatment”
Low climate exposure - “control”
Climate variable

Time

Social outcome variable

climate 1
climate 2
outcomes

dist. 1
outcomes
dist. 2

climates (prob. distributions)
weather (time series)

Probability

Prob.
dose-response
functions

a
b
c
d
f

f1(X)
f2(X)

Social outcome variable

dose-response
functions

Carleton & Hsiang (Science 2016)

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Typhoon Haiyan – how do you rebuild after such destruction?
The devastation caused in the Philippines will take years to repair. Previous efforts in Haiti, Japan and elsewhere point the way, but how can we build back better?

Vittorio Infante
The Guardian, Friday 15 November 2013 19:04 GMT
Jump to comments (25)
Total wind speed at surface

\[ v_x^{\text{max}} = 37.901, \quad V_{x}^{\text{storm}} = 1, \quad V_{y}^{\text{storm}} = 5 \text{ (m/s)} \]

Hsiang (PNAS, 2010)
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 60
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 84
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 96
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 108
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 120
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 132
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 144
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 156
Super Typhoon Joan (Sening)
Max wind (m/s)
October 1970
Hour: 168
Super Typhoon Joan (Sening)

Max wind (m/s)
October 1970
Hour: 180
All storms within a year (LICRICE)

Maximum Wind Speed (m/s) 2008

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Direct damage: Insured loss in % state GDP (USA)

- New Jersey
  - Katrina (2005)
  - Camille (1969)
  - Andrew (1992)
- Louisiana
  - Irene (2011)
  - Floyd (1999)
  - Sandy (2012)

Bolliger, et al (in prep)
Household economics after a typhoon (Philippines)

Probability asset is missing (%)

Wind speed (m/s)

(Anttila-Hughes & Hsiang, 2012)
Household economics after a typhoon (Philippines)

(Anttila-Hughes & Hsiang, 2012)
Macroeconomics: Theories vs. Evidence

(Hsiang & Jina, 2014)
Macroeconomics: Theories vs. Evidence


(Hsiang & Jina, 2014)
Global generalizability

(Hsiang & Jina, 2014)
Repeated shocks slow growth

“Sandcastle depreciation”: \[ \bar{\delta} \approx \frac{1}{s_2 - s_1} \int_{s_1}^{s_2} \delta(t)dt \]

\( growth = investment - \bar{\delta} - pop\_growth - tech\_growth \)

Hsiang & Jina (AER, 2015)
Long run evidence consistent w/ “sandcastle depreciation”

East Asia

Avg. annual growth rate observed 1970-2008 (%)

Hsiang & Jina (AER, 2015)
### Comparing cyclones to other macroeconomic events

<table>
<thead>
<tr>
<th>Event</th>
<th>Growth</th>
<th>Duration</th>
<th>Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature ↑ (+1°C)(^1)</td>
<td>-1.0%</td>
<td>10 yrs</td>
<td>6.4%</td>
</tr>
<tr>
<td>Civil war(^2)</td>
<td>-3.0%</td>
<td>10 yrs</td>
<td>6.3%</td>
</tr>
<tr>
<td>Taxes ↑ (+1% GDP)(^3)</td>
<td>-3.1%</td>
<td>4 yrs</td>
<td>(\dagger)16.8%</td>
</tr>
<tr>
<td>1-σ cyclone</td>
<td>-3.6%</td>
<td>20 yrs</td>
<td>14.4%</td>
</tr>
<tr>
<td>Currency crisis(^2)</td>
<td>-4.0%</td>
<td>10 yrs</td>
<td>34.7%</td>
</tr>
<tr>
<td>Executive constraints ↓(^2)</td>
<td>-4.0%</td>
<td>10 yrs</td>
<td>3.7%</td>
</tr>
<tr>
<td>90-percentile cyclone</td>
<td>-7.4%</td>
<td>20 yrs</td>
<td>5.8%</td>
</tr>
<tr>
<td>Banking crisis(^2)</td>
<td>-7.5%</td>
<td>10 yrs</td>
<td>15.7%</td>
</tr>
<tr>
<td>Financial crisis(^4)</td>
<td>-9.0%</td>
<td>2 yrs</td>
<td>&lt;0.1%</td>
</tr>
<tr>
<td>99-percentile cyclone</td>
<td>-14.9%</td>
<td>20 yrs</td>
<td>0.6%</td>
</tr>
<tr>
<td>Democratization(^5)</td>
<td>+21.2%</td>
<td>30 yrs</td>
<td>1.4%</td>
</tr>
</tbody>
</table>

\(^1\)Poor countries only. \(^2\)USA only. \(^3\)Number of quarters with any tax change.

\(^1\)Dell, Jones & Olken (AEJ: Macro, 2012), \(^2\)Cerra & Saxena (AER, 2008), \(^3\)Romer & Romer (AER, 2010), \(^4\)Reinhart & Rogoff (AER 2009), \(^5\)Acemoglu, Naidu, Restrepo, Robinson (NBER, 2014)

Hsiang & Jina (2014)
Entering a “new normal”? 

Maximum surface wind speed during Hurricane Maria

Hsiang (2017)
Undoing 26 years of Puerto Rican growth in 12 hours

In Just 12 Hours, an Economic Wipeout

Hurricane devastation in Puerto Rico is expected to have much worse economic effects than many other recent crises that unfolded over months or years.

<table>
<thead>
<tr>
<th>Economic Disaster</th>
<th>Years</th>
<th>Drop in Per Capita G.D.P.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asian financial crisis: Thailand</td>
<td>1997-99</td>
<td>-25%</td>
</tr>
<tr>
<td>Great Recession's effect on Nevada</td>
<td>2007-09</td>
<td>-22%</td>
</tr>
<tr>
<td>Hurricane Maria in Puerto Rico</td>
<td>2017</td>
<td><strong>-21%</strong></td>
</tr>
<tr>
<td>Asian financial crisis: Indonesia</td>
<td>1997-99</td>
<td>-21%</td>
</tr>
<tr>
<td>Great Recession's effect on Arizona</td>
<td>2007-09</td>
<td>-18%</td>
</tr>
<tr>
<td>Great Recession's effect on Michigan</td>
<td>2007-09</td>
<td>-13%</td>
</tr>
<tr>
<td>Average international financial crisis</td>
<td></td>
<td>-9%</td>
</tr>
<tr>
<td>Great Recession: U.S. overall</td>
<td>2007-09</td>
<td>-9%</td>
</tr>
<tr>
<td>U.S. recessions</td>
<td>1980-1982</td>
<td>-8%</td>
</tr>
<tr>
<td>Mexico peso crisis</td>
<td>1994-95</td>
<td>-8%</td>
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</tbody>
</table>

Nevada, Arizona and Michigan were among the hardest-hit states in the Great Recession of 2007-09.

Climate Change $\rightarrow$ $\Delta$ Hurricanes $\rightarrow$ $\Delta$ Growth

NPV roughly $9.7$ trillion (3% discount rate)
Climate Change $\rightarrow$ $\Delta$ Hurricanes $\rightarrow$ $\Delta$ Growth

NPV roughly $9.7$ trillion (3% discount rate)

Climate Change $\rightarrow$ $\Delta$ Temperature $\rightarrow$ $\Delta$ Growth?
Why might temperature matter?

British Naval Experiments
C. Mackworth (1947)
British Journal of Psychology

Fig. 1. Pull test apparatus.

Fig. 3. The same proportional deterioration for high as for low incentive conditions when atmospheric temperature is raised.

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Temperature affects productivity of labor & capital

Annual corn yields

% change

Temperature (°C)

Schlenker & Roberts (2009)

Daily labor supply

minutes

Temperature (°C)

Graff Zivin & Neidell (2014)

Carleton & Hsiang (Science 2016)
Building a macro-economy from temperature-sensitive units

$T_d$ - temperature on day $d$ of year $t$

$K_j$ - capital in sector $j$ with productivity $A_j^K$

$L_j$ - labor is sector $j$ with productivity $A_j^L$

Each day, based on temperature, capital and labor may be optimally reallocated between sectors:

$$q_j(T_d) = (A_j^K(T_d)K_j(T_d))^{\alpha}(A_j^L(T_d)L_j(T_d))^{1-\alpha}$$

Optimal supply ($q^*$) and temperature-sensitive demand affects prices ($p$).

Repeated daily:

$$annual\_revenue_t = \sum_{d=1}^{365} \sum_j \underbrace{p_j(T_d) \cdot q_j^*(T_d)}_{\text{daily income sector } j}$$

Deryugina & Hsiang (2014)
How should micro productivity map to macro?

Annual temperature slope = $b_1$

slope = $b_2$

probability mass = $m_1$

probability mass = $m_2$

slope = $m_1b_1 + m_2b_2$

years have different daily temperature distributions

Burke, Hsiang, Miguel (Nature, 2015)
Global non-linear response of growth to temperature

Burke, Hsiang, Miguel (Nature, 2015)
Historical marginal effect of +1°C temperature on growth

Burke, Hsiang, Miguel (2015)
Using within-country variation to estimate a global function

Burke, Hsiang, Miguel (Nature, 2015)
Rich vs Poor? Early vs late?

B

Rich vs. poor countries

C

Early vs. late period

Burke, Hsiang, Miguel (2015)
Really in rich countries? Check in USA

Income per person

Globally (countries)

United States (counties)

Burke, Hsiang & Miguel (2015)

Deryugina & Hsiang (2017)

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Effect in USA is stable over time

Deryugina & Hsiang (2017)
Replication with alternative data sets & samples

India

![Graph showing the relationship between annual average temperature and GDP growth rates for India.](image)

The figure displays the nonlinear relationship between annual average temperature and GDP growth rates for the fiscal years 1982-83 to 2014-15. The black line represents the impact of temperature on growth, relative to the optimum. The shaded blue area denotes the 95% confidence interval. The regression model controls for one-year lagged growth rates, state fixed effects, year fixed effects, and precipitation. The histogram shows the distribution of annual temperature.

China

![Graph showing the relationship between daily temperature and manufacturing output, TFP, labor, and capital inputs.](image)

Panel A in Fig. 2 depicts the temperature-output relationship and shows an inverted U-shaped relationship. The negative effects of extremely high temperatures (above 90°F) are both economically and statistically significant. The point estimate suggests that an extra day with temperature larger than 90°F decreases output by 0.45%, relative to an extra day with temperature between 50–60°F. To put this in value terms, the average output of a sample firm was $1.82 million in 2007 dollars. Thus, the effect of an extra day with temperature above 90°F lowers output by $8,160 for the average firm. At the aggregate level, the average total output of manufacturing firms in our sample during 1998-2007 was $334 billion in 2007 dollars. If all firms in our sample were to jointly experience an extra day with temperatures above 90°F instead of a day between 50–60°F, total output would decrease by $1.50 billion.

To provide a point of comparison with prior other studies, if there were a 1°F shift to the entire annual distribution of daily temperature and the manufacturing output share of Chinese GDP were to remain 32%, our results imply a 0.92% reduction in Chinese GDP from temperature impacts in the manufacturing sector alone. This is consistent with Hsiang (2010) and Dell et al. (2012)'s evidence from other parts of the world.

We next turn to exploring which component of output drives the temperature-output relationship shown in panel A. Panels B, C, and D of Fig. 2 plot the response function between daily temperature and TFP, labor, and capital inputs, respectively. The temperature-TFP relationship closely mirrors the shape of the temperature-output relationship. The magnitudes of each set of point estimates are also mostly similar. The extreme high temperature effect depicted in panel B is slightly larger than in panel A, though the two point estimates do not appear to be statistically different.

Fig. 2. Estimated Effects of Daily Temperature on Manufacturing Output, TFP, Labor Input, and Capital Input

Notes: Panels show the estimated temperature-log output relationship (panel A), temperature-log TFP relationship (panel B), temperature-log labor relationship (panel C), and temperature-log capital relationship (panel D). Figures show point estimates in blue and the associated 95% confidence intervals in gray. Each panel is a separately estimated regression using Eq. (3) and includes firm fixed effects, year-by-region fixed effects, and year-by-sector fixed effects. 50–60°F is the omitted temperature category. Standard errors are clustered at firm and county-year levels. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Centigrade bin boundaries are converted from Fahrenheit and rounded to the nearest integer to conserve space.

Also: Brazil, Indonesia, Europe, etc.
Relative to global distribution

- 1st (poor)
- 2nd
- 3rd
- 4th
- 5th (rich)

Burke & Hsiang (in prep)
Is it really a growth effect? (Global)

Burke, Hsiang, Miguel (2015)
Is it really a growth effect? (USA)

Deryugina & Hsiang (2017)
How to account for adaptation?

1. Adaptations to climate may alter (attenuate) climate impacts.

2. But the costs of these adaptations must be accounted for as a burden.

3. Full accounting is fundamentally difficult because adaptation involves many unobserved adjustments.
How to account for adaptation?

1. Adaptations to climate may alter (attenuate) climate impacts.
2. But the costs of these adaptations must be accounted for as a burden.
3. Full accounting is fundamentally difficult because adaptation involves many unobserved adjustments.

One solution: Take a “top down” view of the macroeconomy and estimate the “marginal product of climate.” (Deryugina & Hsiang, 2017)

Why this works: All adaptations are reallocations of resources, with costs equal to opportunity costs.

→ The net benefit of all adaptations will be captured in total revenue of the economy.
Markets endogenously maximize total revenue in general equilibrium (Koopmans, 1957):

\[ b^*(C) = \arg \max_b Y(C, b(C)) \mid p(C), U(C, b) \]
The “Marginal Product of Climate”

Income per person

Globally (countries)  United States (counties)

Annual temperature (°C)  Daily temperature (°C)


S. Hsiang | Global Policy Laboratory
Valuation of historical temperatures (1968-1990) in current annual income

Deryugina & Hsiang (2017)
Projecting forward: avg loss = 23% World GDP

Burke, Hsiang & Miguel (Nature 2015)
A poorer, more uncertain, more unequal world

Income per person (% change)

World income

Burke, Hsiang & Miguel (Nature 2015)

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Thank you

www.globalpolicy.science
One single nonlinear damage function

Model 1

Model 2
Model 1

One single nonlinear damage function

Temp 1 2 Temp

Model 2

High vulnerability damage function

Low vulnerability damage function

Temp 1 2 Temp

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Differences over space or time?

**B**
Rich vs. poor countries

**C**
Early vs. late period

**D**
Agricultural GDP

**E**
Non-agricultural GDP

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Change in global GDP/cap (%)

BHM 1-yr lag model

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Change in global GDP/cap (%)

DJO 1-yr lag model

BHM 1-yr lag model

DJO 5-yr lag model

BHM 5-yr lag model

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