Estimating a social cost of carbon for global energy consumption

https://heep.hks.harvard.edu/files/heep/files/carleton_bhy_virtual_sem.pdf
(retrieved 16 March 2021)

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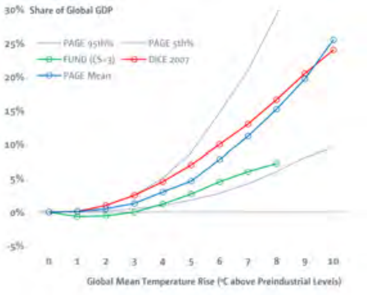
Climate Impact Lab

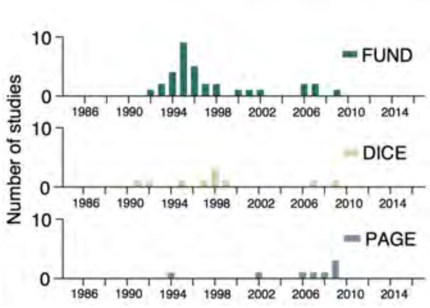
(UC Berkeley, U Chicago, Rutgers, Rhodium Group)

Berkeley-Harvard-Yale Virtual Seminar
Economics of Climate Change and the Energy Transition
May 6^{th}, 2020

Climate damage & the Social Cost of Carbon



Source: Interagency Working Group on Social Cost of Carbon, 2010



Literature informing damage functions (our calculation)

> **"The curvature of the demand for cooling energy is the most important parameter...that determine(s) the social cost of carbon"**
>
> – Anthoff & Tol (2013)

Energy consumption, temperature, & income

Delhi, India (2016)

Dubai, UAE (2016)

Three principles for estimating climate damages

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Damage functions should be based on the best available evidence.

1. **Plausibly Causal:** should be grounded in empirical estimates using exogenous variation & purge unobserved heterogeneity.
2. **Reflect Damage from Around the World:** should use data representing the global population (not just rich countries).
3. **Reflect Adaptation and its Costs:** should reflect that agents adapt given income & climate, include these costs.

Previous literature

- Most empirical work has focused on estimating the impact of local temperature on local energy consumption in **developed country settings** *(Deschênes and Greenstone, 2011 (US); Wenz et al., 2017 (Europe); Auffhammer et al., 2017 (USA); Auffhammer, 2018 (California))*
- Empirical studies **rarely capture adaptation or the role of income growth** in transforming energy demand *(Auffhammer, 2018 (California); Davis and Gertler, 2015 (Mexico))*

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- Empirical studies **rarely capture adaptation or the role of income growth** in transforming energy demand *(Auffhammer, 2018 (California); Davis and Gertler, 2015 (Mexico))*
- Energy modeling studies *(Clarke et al., 2018; Isaac and van Vuuren, 2009)* can be global in scope and account for energy system transformations, but **require credible empirical calibration of parameters** that govern structural relationships

A global empirical SCC for energy consumption

Contribution of this paper

- We provide the first estimate of the global impact of climate change on total energy consumption using globally comprehensive data, accounting for economic development and adaptive behavior
- We use these results to compute the net cost of global energy consumption associated with an additional ton of CO2 emissions – i.e. a "partial" social cost of carbon (SCC) for energy consumption

Partial SCC estimates across sub-sectors of the global economy can be used to compute a total SCC – this is at the core of ongoing CIL work (e.g. Carleton et al., (2019) for mortality).

Outline

Step 1: Estimate **causal relationship** between climate and energy consumption

Step 2: Model energy responses to temperature that reflect **income and climate adaptation**

Step 3: **Predict response functions** spatially and temporally and project impacts into the **future** using high resolution climate projections

Step 4: Estimate empirical damage function accounting for uncertainty, then calculate a **partial energy consumption-only Social Cost of Carbon**

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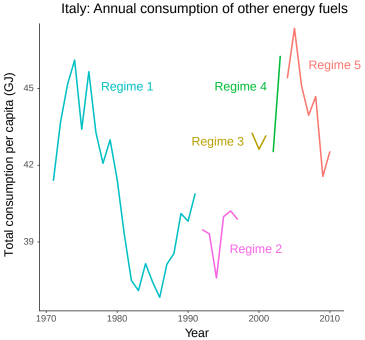
Comprehensive energy consumption data

International Energy Agency (IEA) provides data from 146 Countries (1971-2012).

Residential, Commercial, and Industrial Consumption of Electricity and Other Fuels.

Observational unit is Country $\times$ Year $\times$ Energy source

IEA data: Globally comprehensive, well documented



Solutions:

→ Account for changes in reporting practices using ∼300 "reporting regime"-fixed-effects and dropping 1,529 obs.

→ Down-weight low credibility regimes based on $\frac{1}{var(\hat{\epsilon})}$ (i.e. FGLS).

→ Estimate model in first-differences to limit the influence of discontinuities since energy consumption contains a unit-root. ▸ Unit Root Test

High-resolution climate data

Exploit local daily variation to identify pixel-by-day nonlinear responses using country-by-year outcome data (e.g. Hsiang, 2016)

- Daily temperature and rainfall at $0.25^\circ \times 0.25^\circ$ (Global Meteorological Forcing Dataset, V1)

Aggregating high-resolution climate data to country j × year t

- Let T_{zd} denote the temperature at pixel z on day d.
- We construct a country-year temperature vector composed of nonlinear functions of daily pixel-level average temperature:

$$\boldsymbol{T}_{jt} \equiv \left[\sum_{z \in j} \omega_{zj} \sum_{d \in t} h_1(T_{zd}), \ldots, \sum_{z \in j} \omega_{zj} \sum_{d \in t} h_K(T_{zd}) \right]$$

where ω_{zj} are population weights

Estimating the energy-temperature relationship

Let E denote energy consumption in GJ per capita.

$$E_{jtc} = f_c(\boldsymbol{T}_{jt}) + g_c(\boldsymbol{P}_{jt}) + \alpha_{jic} + \delta_{rtc} + \varepsilon_{jtc}$$

$j =$ country, $i =$ "regime", $r =$ region, $t =$ year

$c =$ fuel category (electricity, other fuels)

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First differencing leads to:

$$\Delta E_{jtc} = \Delta f_c(\boldsymbol{T}_{jt}) + \Delta g_c(\boldsymbol{P}_{jt}) + \Delta\delta_{rtc} + \Delta\varepsilon_{jtc}$$

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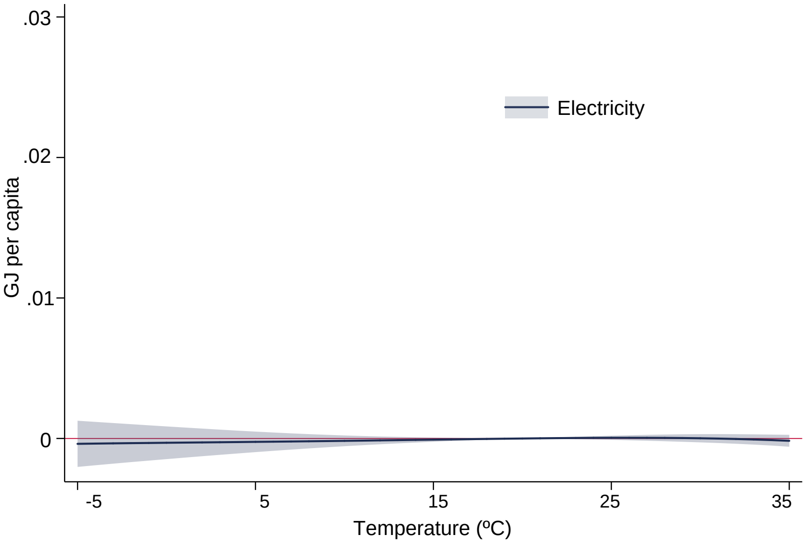
First differencing and **FGLS weighting** leads to:

$$w_i \Big[\Delta E_{jtc} \Big] = w_i \Big[\Delta f_c(\boldsymbol{T}_{jt}) + \Delta g_c(\boldsymbol{P}_{jt}) + \Delta\delta_{rtc} + \Delta\varepsilon_{jtc} \Big]$$

where $w_i = \frac{1}{var(\Delta\varepsilon_{jtc \in i})}$ reflecting variability in "reporting regime" i

Energy consumption and temperature



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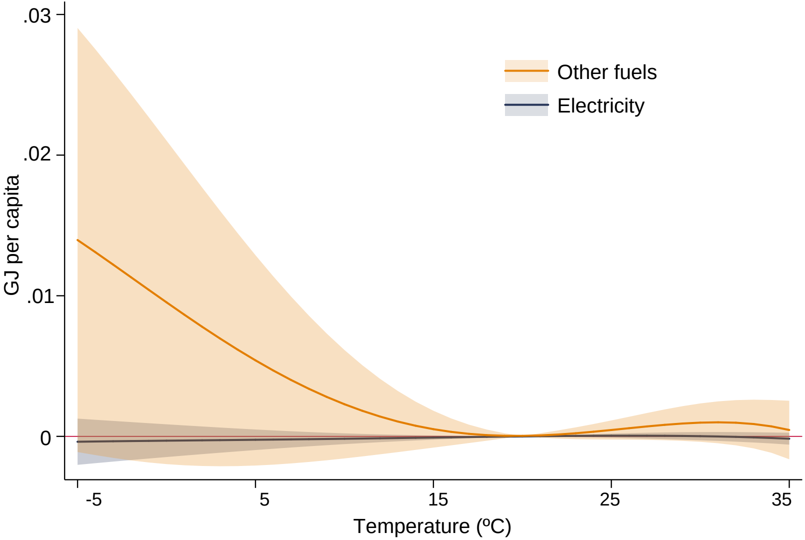
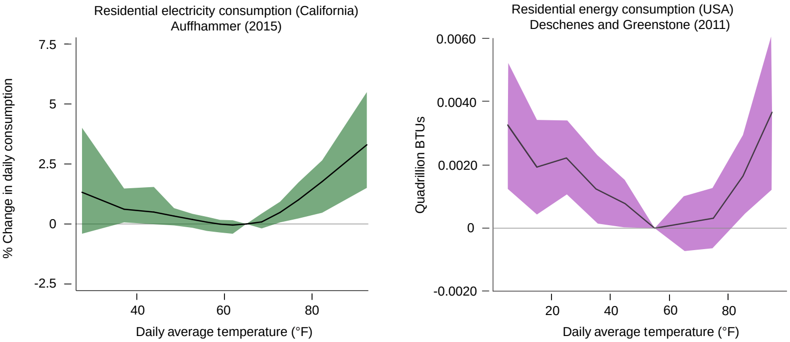


Prior literature



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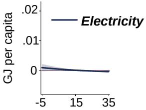
Accounting for economic development is crucial



Temperature (ºC)

Poorest Decile → ***Richest Decile***

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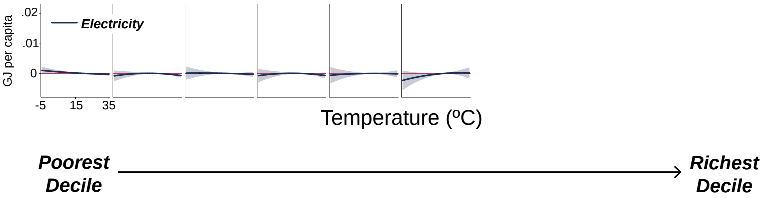

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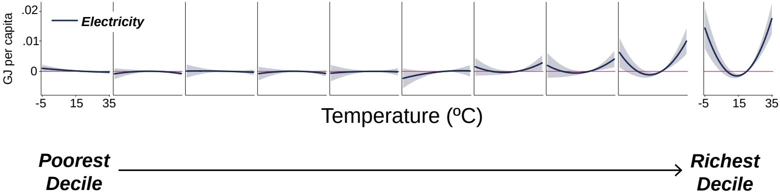

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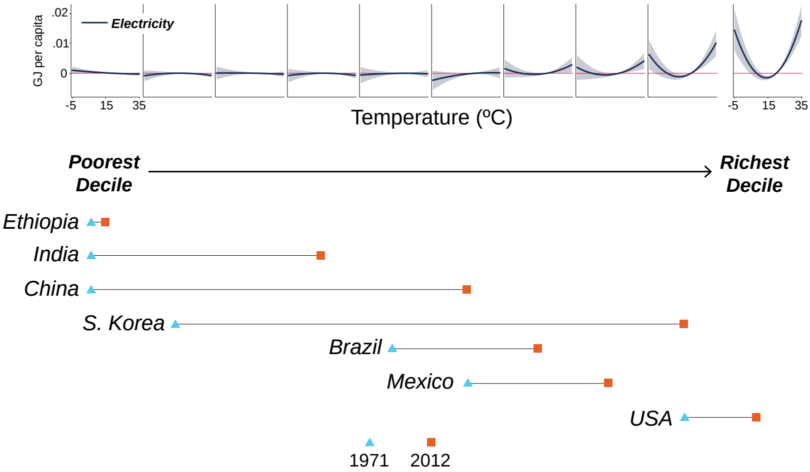

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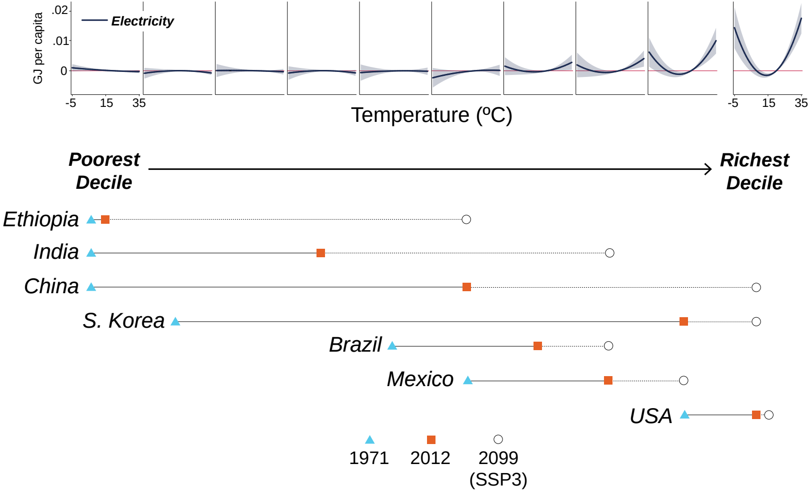

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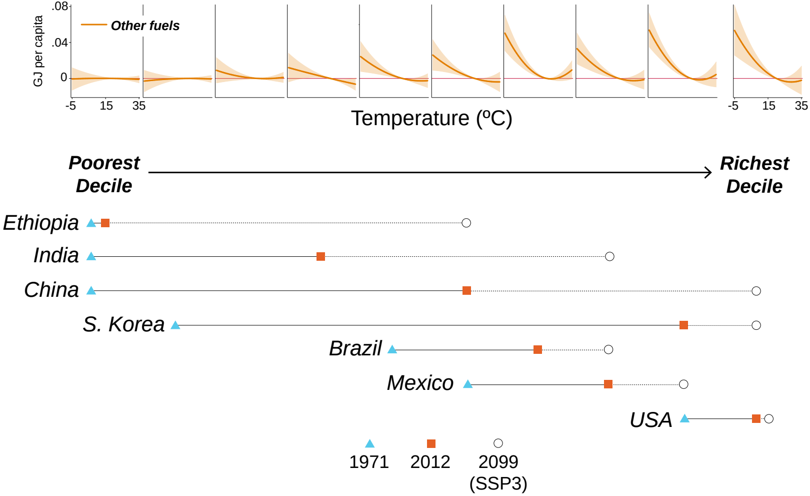
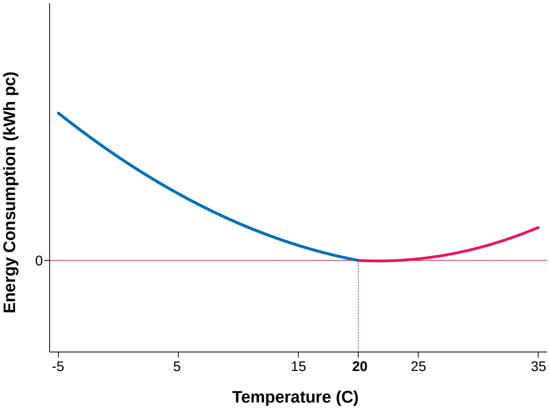


Modeling climate adaptation: Warm temperatures



Long-run average Cooling Degree Days (CDD) modulate the response to $T \geq 20C$

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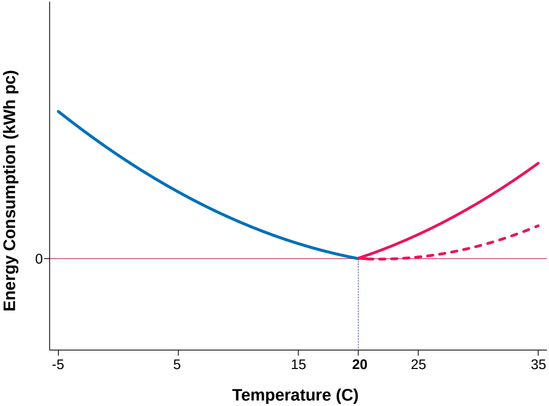

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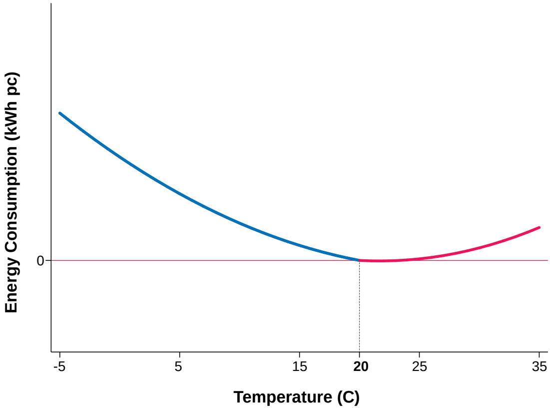
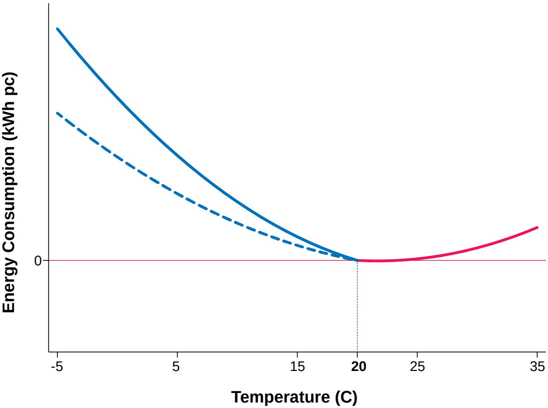


Long-run average Heating Degree Days (HDD) modulate the response to $T < 20C$

Modeling climate adaptation: Cool temperatures



Long-run average Heating Degree Days (HDD) modulate the response to $T < 20\text{C}$

Estimating an energy-temperature relationship reflecting adaptation

Concept

Allow the shape of the function describing the energy-temperature relationship at a location be a function of conditions at that location.

$$E_{jct} = f_c(\boldsymbol{T}_{jt} \mid \overline{\log GDPpc}_{jt}, \overline{CDD}_j, \overline{HDD}_j) + g_c(\boldsymbol{P}_{jt}) + \alpha_{jic} + \delta_{rtc} + \varepsilon_{jtc}$$

j = country, i = "regime", r = region, c = fuel category, t = year

Covariates

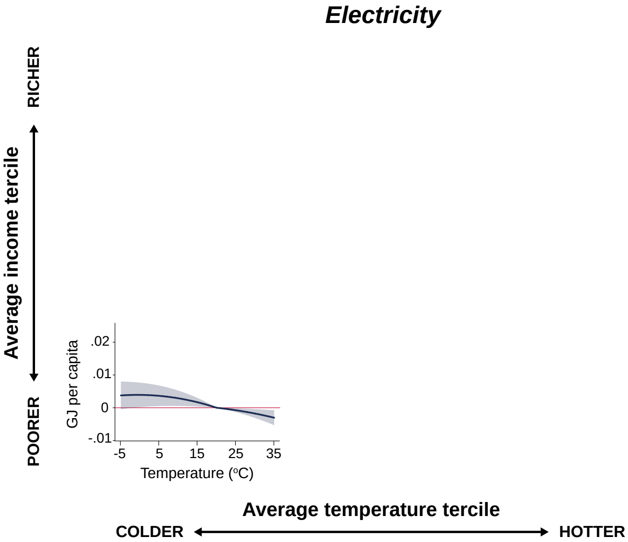
$\rightarrow$ CDD_j = long-run avg. cooling degree days (>20°C)

$\rightarrow$ HDD_j = long-run avg. heating degree days (<20°C)

$\rightarrow$ $\log(GDPpc)_{jt}$ = moving average of log income per capita

▸ Full specification

Electr. cons. = f(weather | climate, income)



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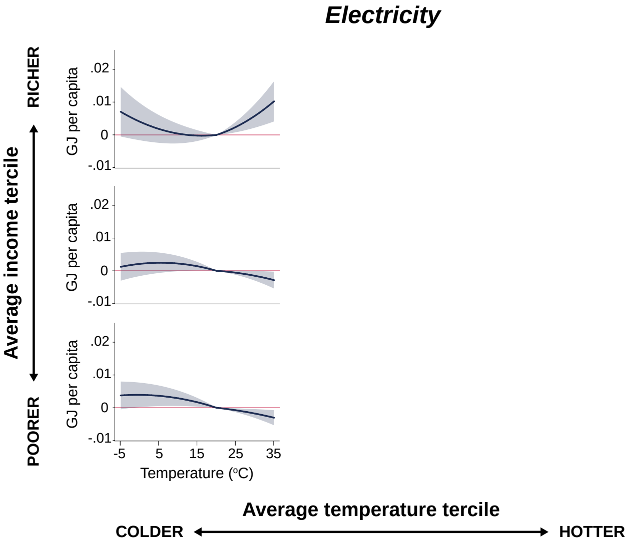

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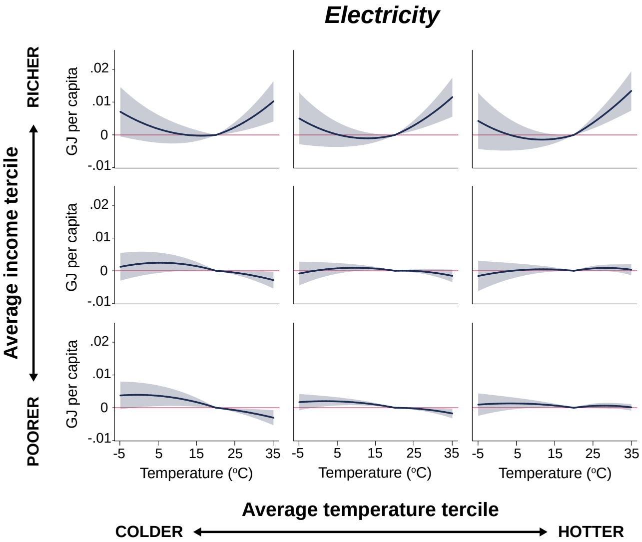
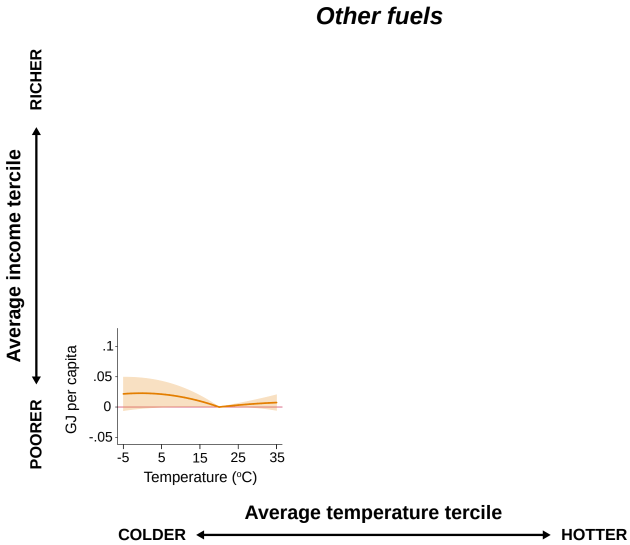


Other fuels cons. = f(weather | climate, income)



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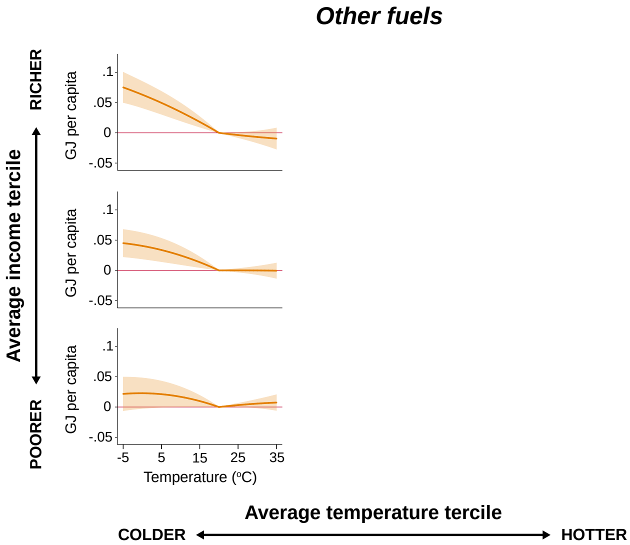

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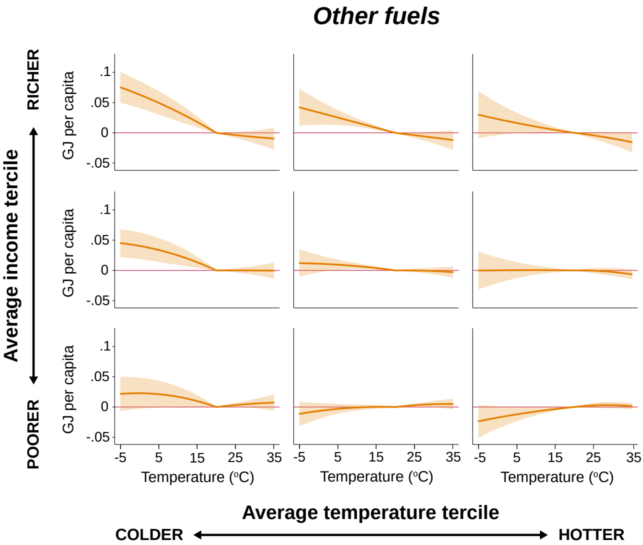

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A high resolution impact space

- We create a set of **"impact regions"** to be standardized units of analysis in projections.

- Impact regions are engineered to

  $\rightarrow$ represent or amalgamate **existing political units** (county-like),
  $\rightarrow$ be **comparable in population size** across regions,
  $\rightarrow$ have **internally homogenous climate** within each region.

- We then **interpolate energy-temperature response functions** for each impact region using **high-resolution covariate data**.

Spatial resolution of early IAMs

DICE (1992)

1 region

Spatial resolution of early IAMs

DICE (1992)

1 region

FUND (1996)

16 regions

Re-imagining possibilities w/ distributed computing

Climate Impact Lab (2020)

25,000 regions

How to fairly represent the global population?

We use our estimated response surface to predict response functions for all "impact regions" globally.

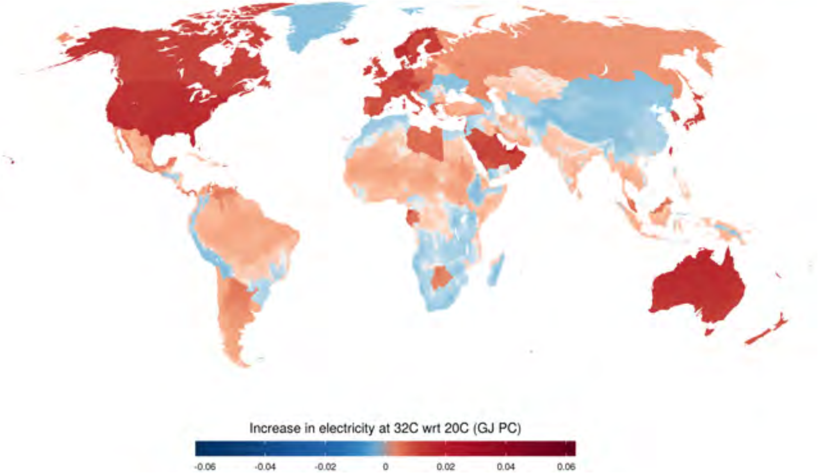
$$energy\_temp\_response_{rt} = \hat{f}_c(\boldsymbol{T}_{rt} \mid \overline{CDD}_{rt}, \overline{HDD}_{rt}, \overline{\log GDPpc}_{rt})$$

Requires we assemble data for present (and future) in each region

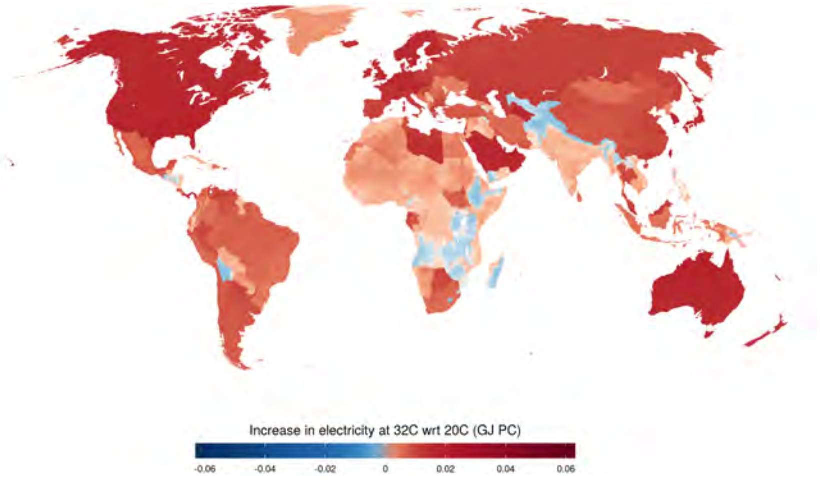
- **Income & populaton:**
  - OECD $\times$ nightlights $\rightarrow$ downscale income to subnational level
  - IIASA Shared Socioeconomic Pathways (SSP) incomes to 2100
- **Weather & climate:**
  - 33 GCMs downscaled to impact region level
  - Average climate calculated as 15 year average of temperature

▸ Sample overlap

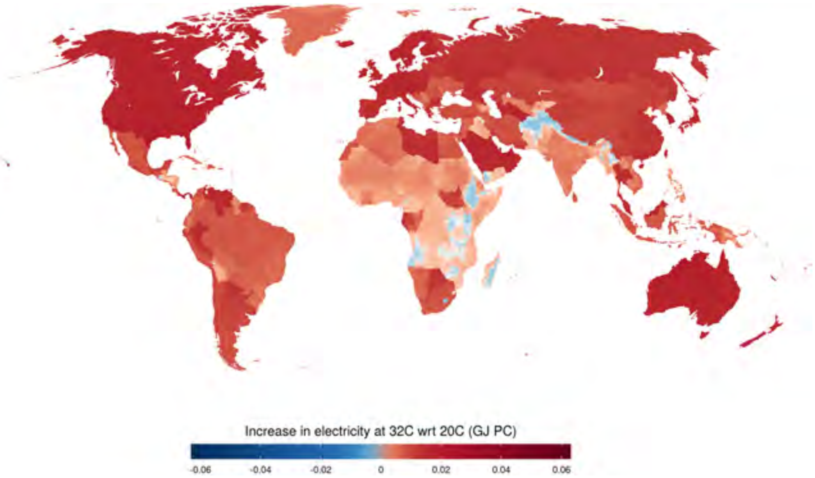
Additional electricity demand at 32°C in 2015



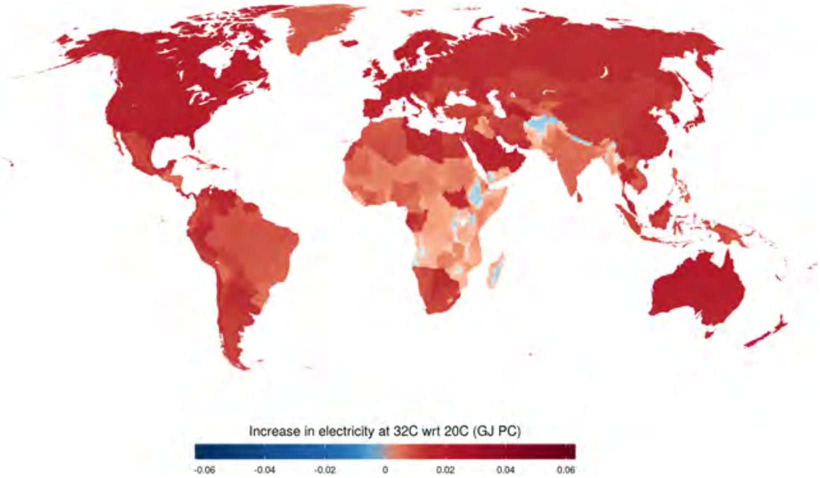
Additional electricity demand at 32°C in 2050



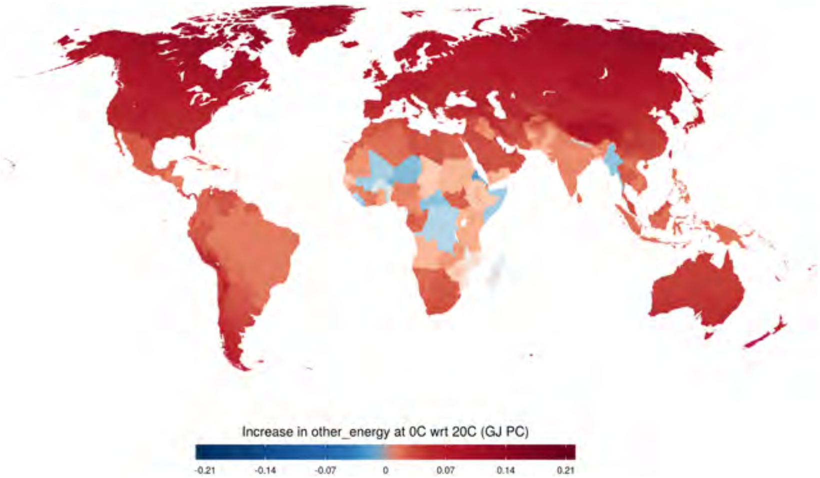
Additional electricity demand at 32°C in 2075



Additional electricity demand at 32°C in 2099



Additional other fuels demand at 0°C in 2099



Projecting the energy impacts of climate change

Goal: compute the additional impact of climate change net of other factors (e.g. income) that will change in the future.

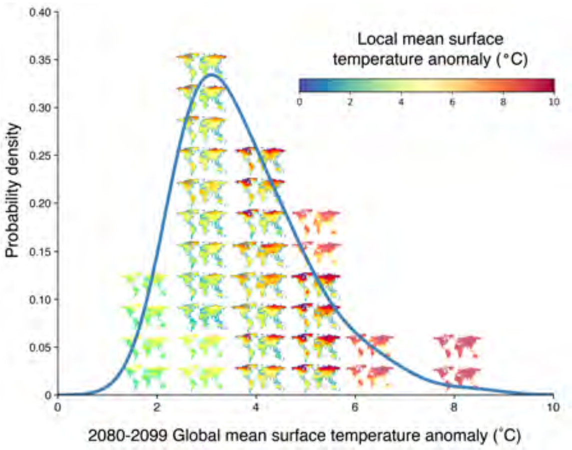
Let predicted energy consumption be $E = \beta T$, with climate change causing $T_1 \rightarrow T_2$

- $\beta(Income_2, Climate_2)$ = sensitivity with income and climate adaptation
- $\beta(Income_2, Climate_1)$ = sensitivity with income adaptation

Impact of climate change, with income and climate adaptation:

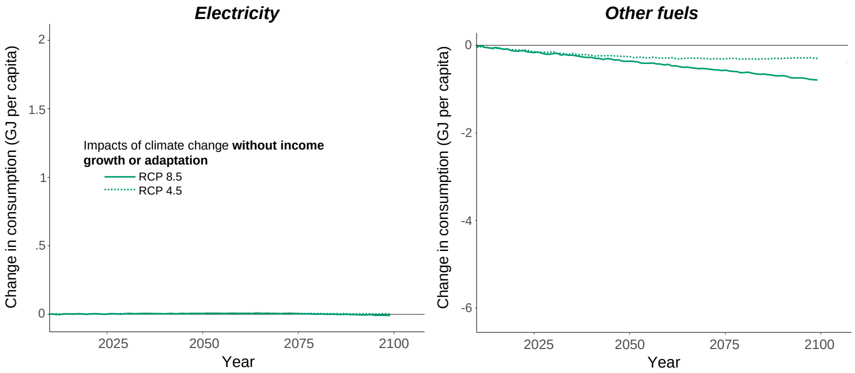
$$\hat{E}^{CC} - \hat{E}^{NoCC} = \underbrace{\hat{\beta}(Income_2, Climate_2)T_2}_{\text{richer, w/ }\Delta Temp} - \underbrace{\hat{\beta}(Income_2, Climate_1)T_1}_{\text{richer, no }\Delta Temp}$$

Probabilisitic climate change impacts



We combine this climate uncertainty with statistical uncertainty from the estimation of energy-temperature response functions to compute **probabilistic impact estimates** for all regions

ΔGlobal energy consumption due to climate change



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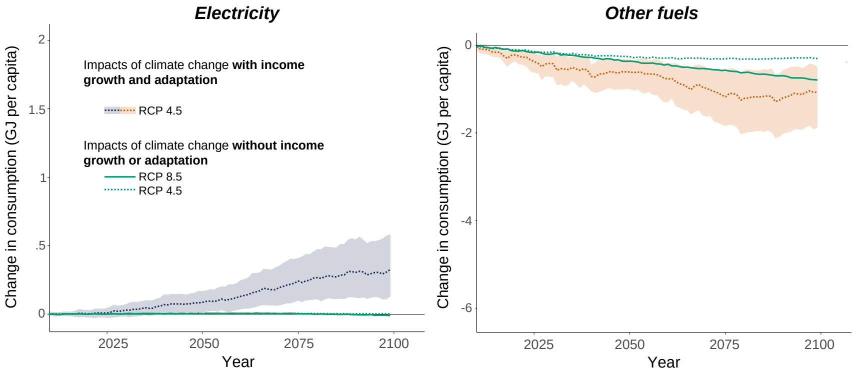
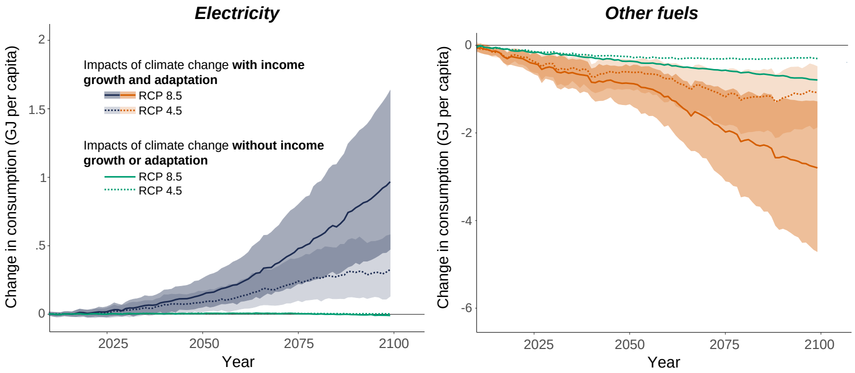
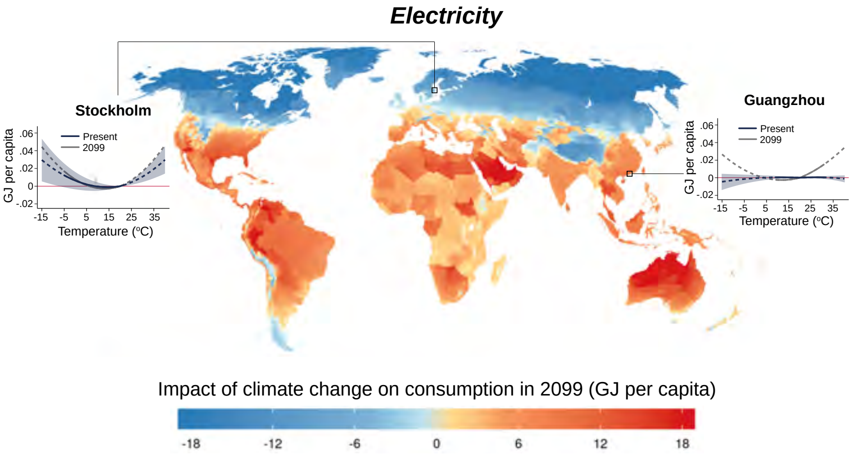


ΔGlobal energy consumption due to climate change

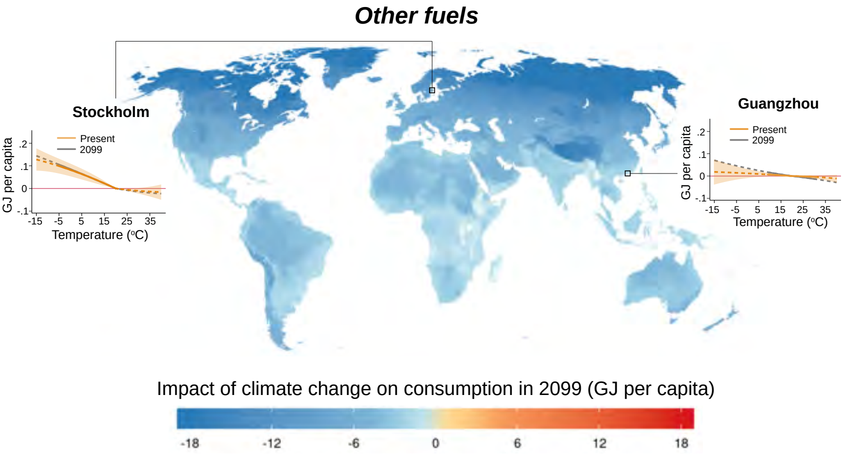


ΔElectricity consumption due to climate change: 2099



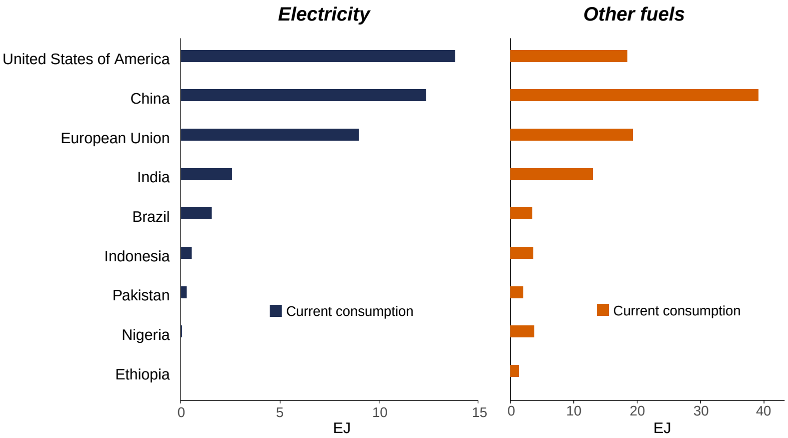
Scenario: RCP 8.5

ΔOther fuels consumption due to climate change: 2099



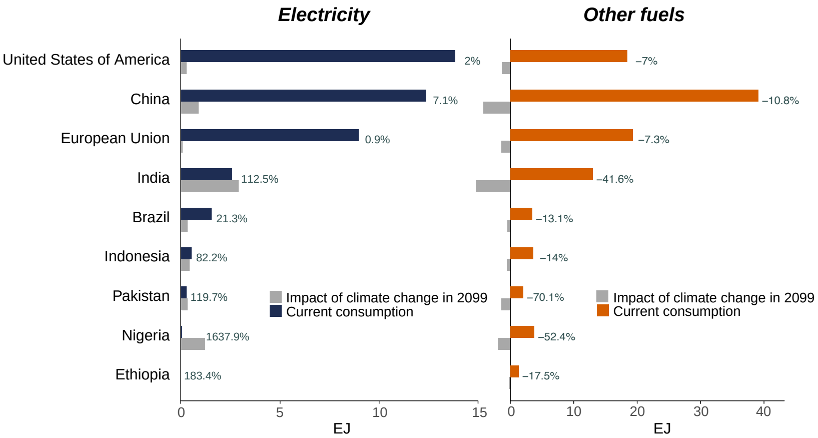
Scenario: RCP 8.5

Impacts at 2099 vs current energy consumption



RCP 8.5, selected countries

Impacts at 2099 vs current energy consumption



RCP 8.5, selected countries

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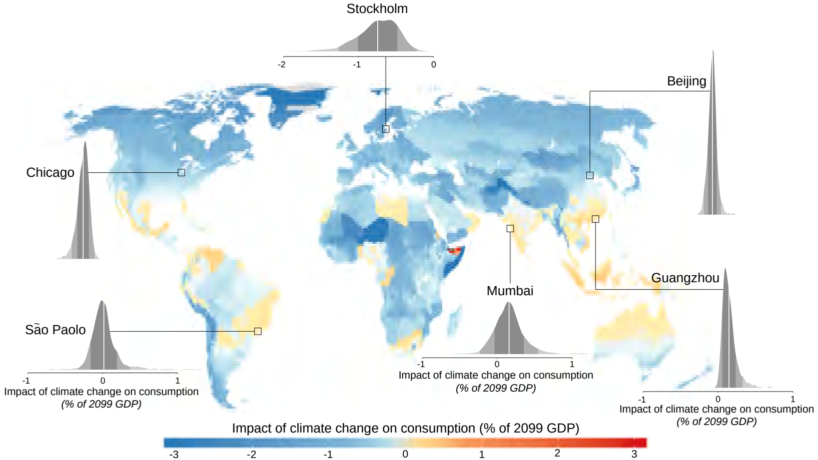
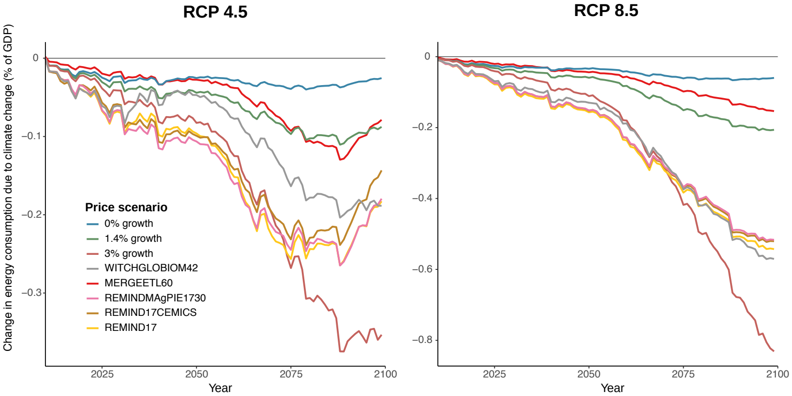
Constructing an energy-specific damage function

1. Compute changes in electricity and other fuels attributable to climate change in every region and year
2. Assemble global data on electricity generation costs and other fuel prices; monetize impacts, allowing prices to grow under different scenarios
3. Index these monetized damages in each of *33 climate models* against the change in *Global Mean Surface Temperature* (GMST)
4. Compute probability distribution of damages in each year, conditional on GMST
5. This is a damage function, in the sense of Nordhaus (1992)

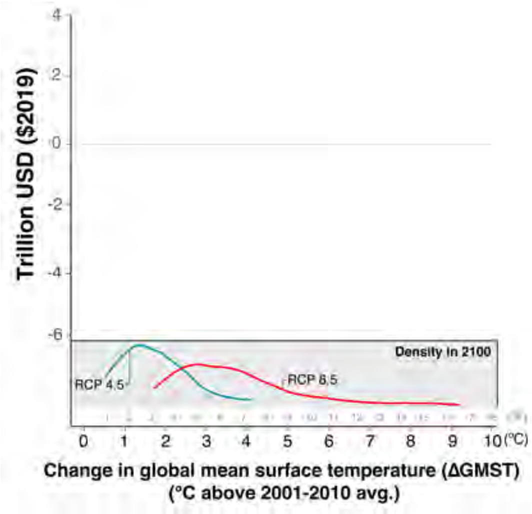
Monetized impacts: 1.4% annual price growth



Monetized impacts: Sensitivity to price growth scenario



Empirical energy damage function



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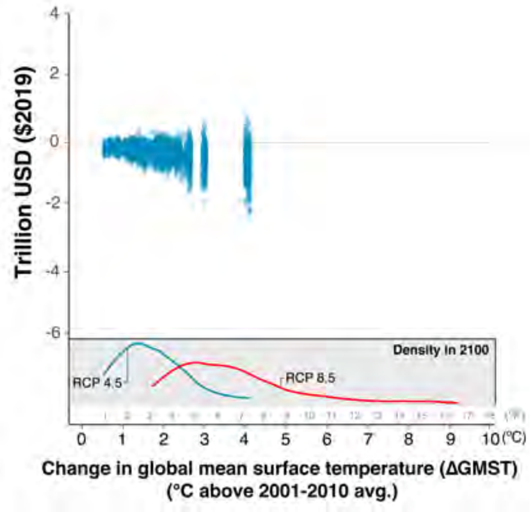

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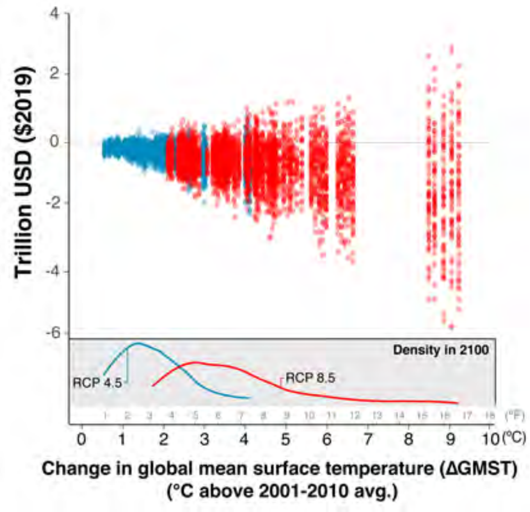

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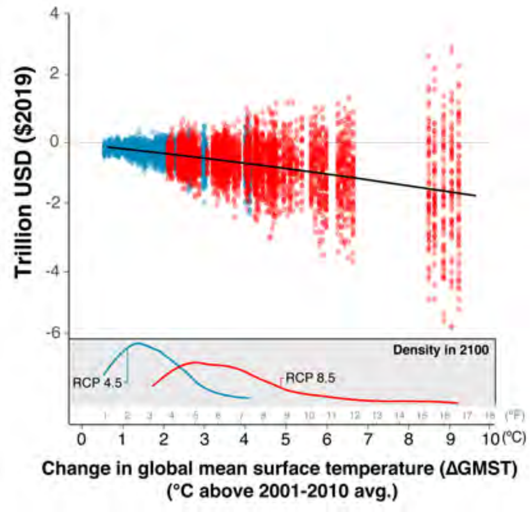


For each 1°C, electricity cons. rises $\sim$6% of current global consumption, other fuels cons. falls $\sim$6%

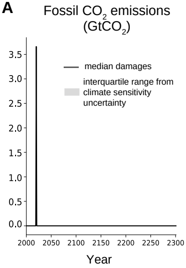
Calculating a "Partial SCC" for energy consumption

Issue: The 33 high-resolution global climate models and economic scenarios we have used in projections (1) end in 2100 and (2) do not represent every climate sensitivity.

Solution: Use a "simple climate model" (FAIR) to sample all sensitivities and project global temperatures to 2300.

1. Compute damages in standard scenario (e.g. RCP 8.5)
2. Perturb temperature trajectory with a pulse of CO_2 emissions today
3. Value discounted stream of additional damages from this pulse
4. This is the NPV of marginal damages from a marginal emission: a *"partial SCC" for energy* (total SCC includes other sectors).

Damages from a single ton of CO_2



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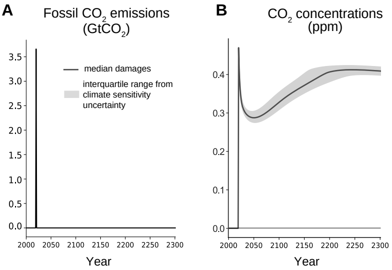
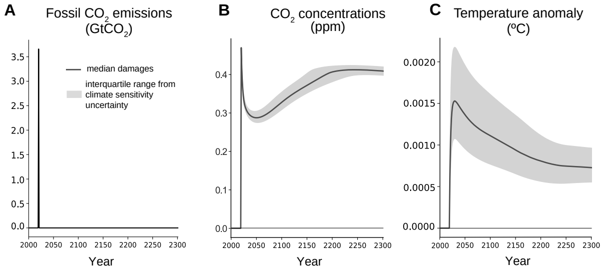
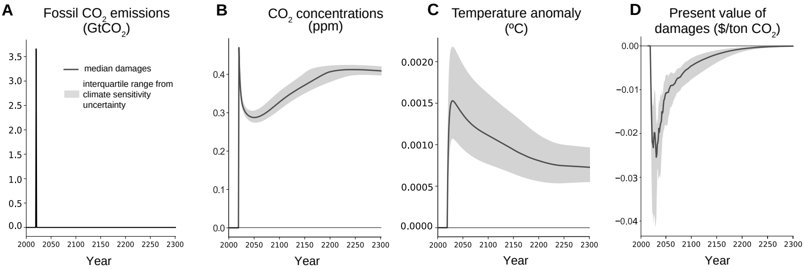


Damages from a single ton of CO_2



Damages from a single ton of CO_2



Partial SCC for energy consumption

Discount rate:	$\delta = 2.5\%$	$\delta = 3\%$	$\delta = 5\%$
		I: 1.4% price growth	
RCP 8.5	-1.51	-1.16	-0.60
	[-6.59,0.06]	[-4.76,-0.14]	[-2.24,-0.19]

[Brackets] indicate 5-95% uncertainty ranges.

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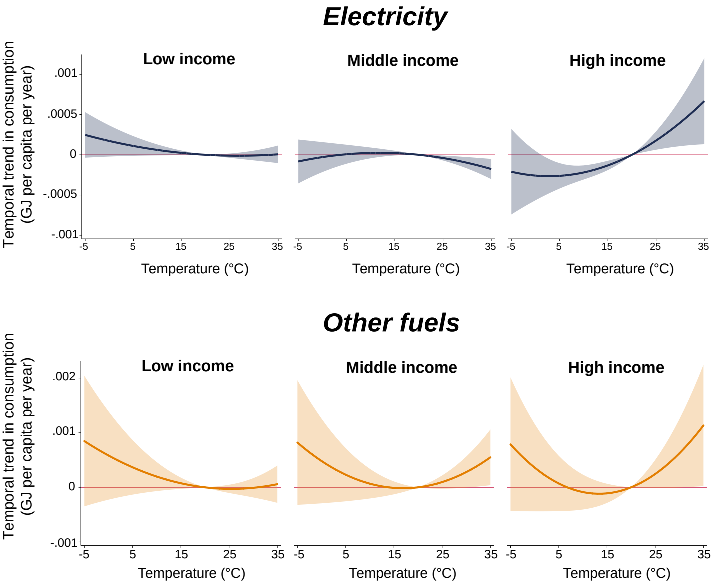
	[-6.00,-0.20]	[-4.29,-0.26]	[-1.98,-0.19]
		II: 0% price growth	
RCP 8.5	-0.72	-0.61	-0.39
	[-2.63,-0.15]	[-2.19,-0.17]	[-1.39,-0.13]
		III: MERGE-ETL 6.0 prices	
RCP 8.5	-1.12	-0.82	-0.39
	[-3.88,-0.31]	[-2.80,-0.24]	[-1.38,-0.12]

[Brackets] indicate 5-95% uncertainty ranges.

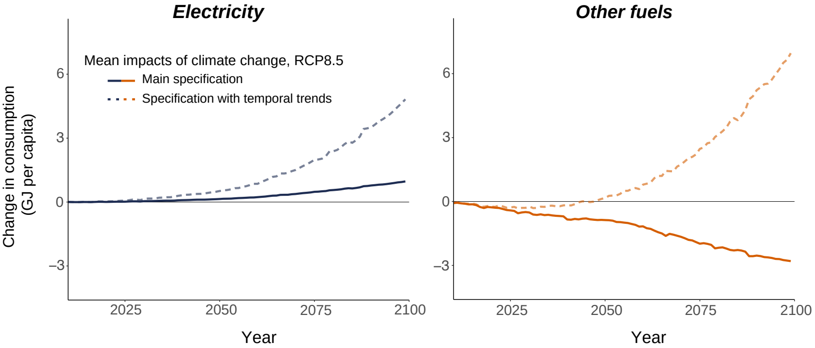
Modeling technological progress

- Our model proxies for diffusion and advancement of technologies in accordance with **climate** and **income**
- **We do not explicitly consider other forms of technological progress** that may affect the temperature sensitivity of energy consumption (e.g. climate change-induced technological change)
- To address this concern, **we introduce a third interacted variable** – time – to capture changes in energy-temperature responses driven by historical technological progress.
- Future dose-response functions are then predicted as a function of **income**, **climate**, and a **linear time trend**.

Responses are getting more extreme over time



ΔGlobal energy consumption due to climate change



Note that the assumptions required to generate this result are difficult to defend:

- Linear extrapolation of historical time trends
- Falling costs of energy services w/o compensatory efficiency gains

Partial SCC for energy consumption with temporal extrapolation

Discount rate:	$\delta = 2.5\%$	$\delta = 3\%$	$\delta = 5\%$
		Main model	
RCP 8.5	-1.51	-1.16	-0.60
RCP 4.5	-1.37	-1.08	-0.58
		Extrapolating trends	
RCP 8.5	9.33	5.67	1.24
RCP 4.5	9.96	5.88	1.20

All other robustness checks recover strikingly similar results to the main analysis – alternative price scenarios; data quality sensitivity checks; slower climate adaptation assumptions

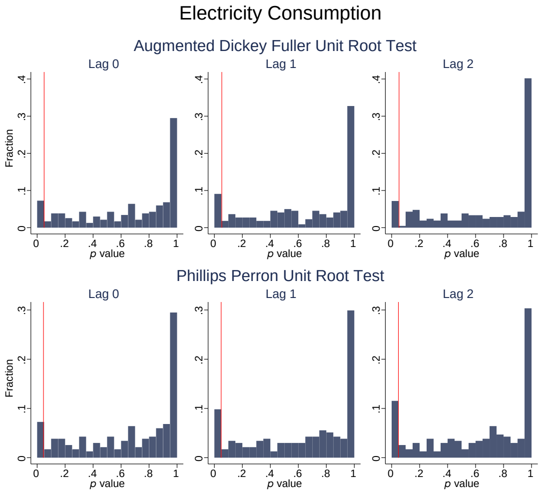
Summary of findings

1. We design a **"bottom-up" approach** to develop partial SCC estimates for an individual sector of the global economy
2. The partial SCC is based upon **econometrically derived, probabilistic, local damage estimates** for thousands of geographic regions
3. We compute **a partial SCC for energy consumption of $\sim$-\$1** ($\delta = 3\%$), accounting for future adaptation and impacts of income growth
4. This result is driven by **sharply nonlinear relationship** between income and temperature-induced energy consumption
   - Many regions remain too poor to increase energy consumption in response to climate change
   - Emerging (hot) economies' increases in electricity are offset by wealthy (cold) economies' savings of other fuels
5. Building an empirically-based SCC has **first order policy implications:**
   - Partial SCC for energy consumption in FUND = \$8 (Diaz, 2014)
   - Partial SCC for mortality in FUND $\leq$ \$1.50 (Diaz, 2014), versus \$23.6 (Carleton et al., 2019)

EXTRA SLIDES

Unit root tests for energy consumption time series

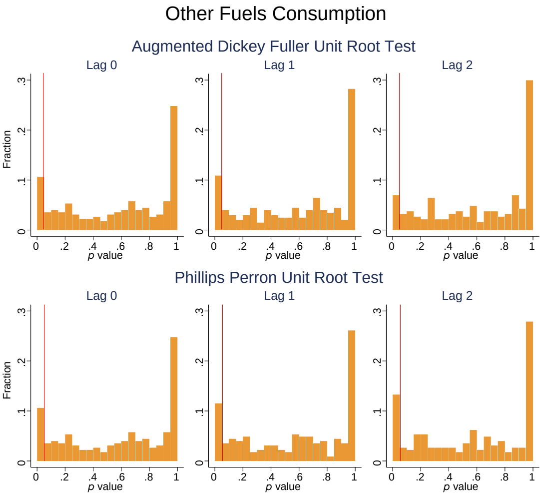
Histograms of *p*-values from unit root tests of "regime" time series



Back

Unit root tests for energy consumption time series

Histograms of *p*-values from unit root tests of "regime" time series



Back

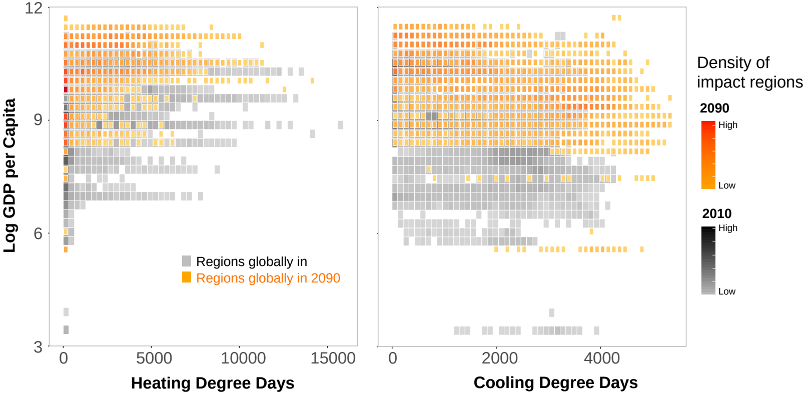
Estimating an energy-temperature relationship reflecting adaptation

$$
\begin{aligned}
E_{jtc} = {} & \boldsymbol{\beta}_c \cdot \boldsymbol{T}_{jt} + [\boldsymbol{\eta}_{1c} \cdot \boldsymbol{T}_{jt}](\bar{I}_c - \overline{LogGDPPC}_{jt}) \mathbf{I}_{\overline{LogGDPPC}_{jt} < \bar{I}_c} \\
& + [\boldsymbol{\eta}_{2c} \cdot \boldsymbol{T}_{jt}](\overline{LogGDPPC}_{jt} - \bar{I}_c) \mathbf{I}_{\overline{LogGDPPC}_{jt} \geq \bar{I}_c} \\
& + \sum_{k=1}^{2} \gamma_{kc} \overline{CDD}_j \sum_{d \in t} (T_{jd}^k - 20^k) \mathbf{I}_{T_{jd} \geq 20} \\
& + \sum_{k=1}^{2} \lambda_{kc} \overline{HDD}_j \sum_{d \in t} (20^k - T_{jd}^k) \mathbf{I}_{T_{jd} < 20} \\
& + \left[\kappa_{1c} \overline{LogGDPPC}_{jt} + \phi_1 \right] \mathbf{I}_{\overline{LogGDPPC}_{jt} < \bar{I}_c} \\
& + \left[\kappa_{2c} \overline{LogGDPPC}_{jt} + \phi_2 \right] \mathbf{I}_{\overline{LogGDPPC}_{jt} \geq \bar{I}_c} \\
& + \boldsymbol{\theta}_c \cdot \boldsymbol{P}_{jt} + \alpha_{jic} + \delta_{rtc} + \varepsilon_{jtc} \qquad (1)
\end{aligned}
$$

Where j = country, i = "regime", r = region, c = fuel category, t = year

Back

Sample overlap between present & future



Most remain within the support of historical observations.

Back