Non-market valuation: Health and Direct Damage Impacts – Climate Change

Reed Walker
UC Berkeley

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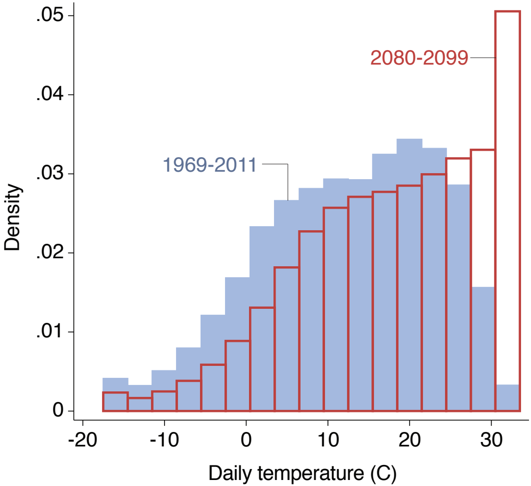
Climate Change is Predicted to Increase the Number of Days at Top of Temperature Distribution



Climate Change Damages

How to estimate?

- Ultimately long run phenomenon that will play out over the next century+
- How do we make inferences about costs of future climate change?

Answer: "It's hard" but maybe we can use past experiences to benchmark

Some relevant questions

- How sensitive is society to variation in temperature?
- What evidence exists about the ability for society to adapt?

Stern Review Report on the Economics of Climate Change

The modern empirical literature on climate damages sprang from the empirically disappointing Stern Report

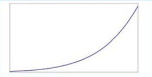
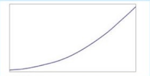
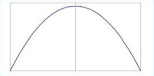
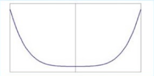
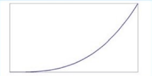
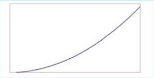
- 700-page report released for the Government of the United Kingdom on 30 October 2006 by economist Nicholas Stern
- Sectoral damage functions parameterized without strong empirical basis (i.e. by assumption)

Assumptions versus Evidence: New Climate Empirics:

- Empirical evidence as to shape of sectoral damages very limited at the time
- Spurred a new wave of researchers to try to put empirical estimates on various sources of climate damages

Box 3.1 The types of relationship between rising damages and sectoral impacts

Basic physical and biological principles indicate that impacts in many sectors will become disproportionately more severe with rising temperatures. Some of these effects are summarised below, but are covered in detail in the relevant section of the chapter. Empirical support for these relationships is lacking. Hitz and Smith (2004) reviewed studies that examined the nature of the relationship between the impacts of climate change and increasing global temperatures. They found increasingly adverse impacts for several climate-sensitive sectors but were not able to determine if the increase was linear or exponential (more details in Box 3.1). For other sectors like water and energy where there was a mix of costs and benefits they found no consistent relationship with temperature.

Type of effect	Sector [location of source]	Proposed Functional Form		Basis
Climate system	Water [Chapter 1]	Exponential $y = e^x$		The Clausius-Clapeyron equation shows that the water holding capacity of air increases exponentially with temperature. This means that the water cycle will intensify, leading to more severe floods and droughts. There will also be more energy to drive storms and hurricanes.
	Extreme temperatures (threshold effects) [Chapter 1]	Convex curve (i.e. gradient increases with temperature)		Because of the shape of the normal distribution, a small increase in the mean dramatically increases the frequency of an extreme event.
Physical impacts	Agricultural production [Section 3.3]	Inverse parabolic ("hill function") $y = - x^2$		In cooler regions, low levels of warming may improve conditions for crop growth (extended growing season and new areas opened up for production), but further warming will have increasingly negative impacts as critical temperature thresholds are crossed more often. Tropical regions may already be past the peak. The shape and location of the curve depend on crop.
	Heat-related human mortality [Section 3.4]	U-shaped		Sharp increase in mortality once human temperature tolerances are exceeded (heatwaves and cold-snaps). Initially mortality will be reduced by warming in cold regions.
	Storm damage [Section 3.6]	Cubic $y = x^3$		Infrastructure damage increases as a cube of wind-speed
Human response	Costs of coastal protection [Section 3.5]	Parabolic $y = x^2$		Costs of sea-wall construction increase as a square of defence height

A brief history of climate damage function estimation

Research Advances

v1.0 Functional form assumptions about GDP-temperature response function

- Causal [No] Adaptation [No]

v2.0 Greenhouse experiments of the response of crop yields to temperature

- Causal [Yes] Adaptation [No]

v3.0 Cross-sectional hedonics (e.g., Mendelsohn, Nordhaus, Shaw 1994)

- Causal [No] Adaptation [Yes]

v4.0 Exploit inter-annual weather variation (e.g., Deschenes and Greenstone 2007)

- Causal [Yes] Adaptation [No]

v5.0 Exploit inter-annual variation and directly model adaptation as function of observables (e.g., Barreca et al. 2016)

- Causal [Yes] Adaptation [Yes]

New Empirical Measurement Approaches

Important empirical takeaways from this literature:

- Non-linearities in human-climate relationships matter
- Careful subtleties associated with data aggregation

Ways to model effects on economics outcomes:

1. Bottom up approaches:
   - Micro-level studies that we can aggregate
   - Lot's! Schlenker and Roberts (2009), Deschenes and Greenstone (2007), Deschenes and Greenstone (2011), ...
2. Top Down Approaches:
   - Cross-country growth regressions (Sometimes with fixed effects!)
   - Dell, Jones, Olken (2012, 2014); Burke, Hsiang, Miguel (2015)

Benefits and costs to both approaches

New Empirical Measurement Approaches

Top-down approach

Benefits

- Comprehensive
- Captures adaptation adjustments
- Easier

Challenges

- Missing nonmarket impacts
- Distant from welfare
- Growth effects not in IAMs

Bottom-up approach

Benefits

- Mechanisms clearer
- Captures distributional effects
- May allow for more credible welfare calculations

?

Challenges

- Requires prices including nonmarket valuations (VSL)
- Missing sectors and missing samples are a major challenge
- Distant from welfare
- Modeling adaptation explicitly sometimes required

Bottom Up Approach: Empirics and Examples

Explosion of recent research exploring how climate/weather affects outcome Y

Modern empirical work originated with focus on agriculture

- Methods started to spillover into other outcomes (mortality, morbidity, labor productivity, etc...)

What are the most compelling methods? [Personal opinion]

- Must account for possible non-linear relationship between X and Y
- Parametric versus non-parametric models: bias/variance tradeoff
- In rough order of preference: semi-parametric bins, splines, parametric functional forms (i.e. quadratic)

Can do more sophisticated model selection (see e.g., Schlenker and Roberts (2009)). Out of sample prediction and RMSE

Aggregation Matters

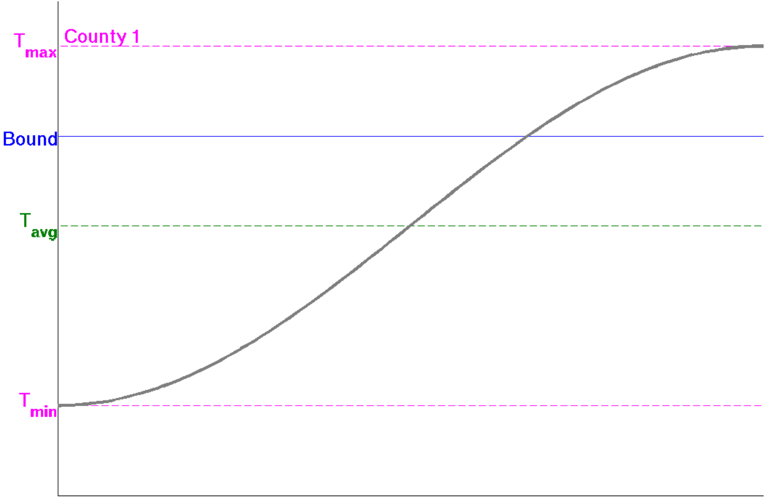
Weather data usually detailed temporal/spatial resolution

- Outcome variables often much more aggregated (e.g. annual)
- Possible to recover non-linear relationships at the spatial and temporal scale at which climate data recorded using time-averaged outcomes

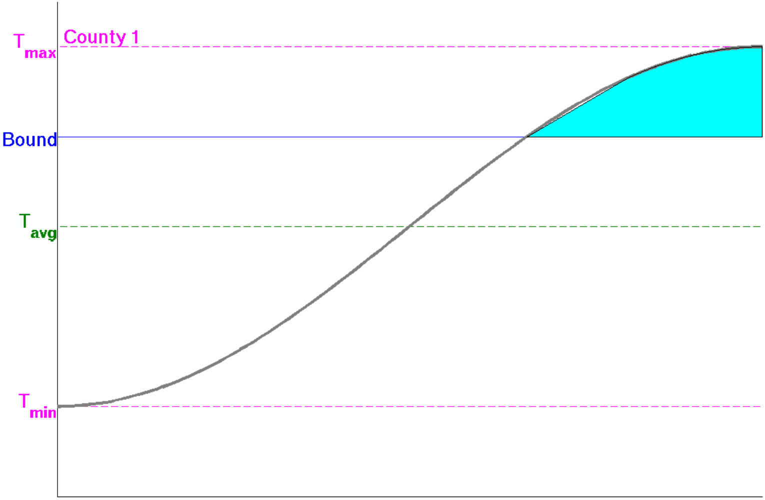
To preserve non-linear mapping, need to take the weighted average of the non-linear function (i.e. NOT the non-linear function of the average)

- This distinction comes up a lot and matters (Dell, Jones, Olken (2012) vs. Burke, Hsiang, and Miguel (2015); Mendelsohn vs. Schlenker)
- See Hsiang (2016) for useful/formal discussion

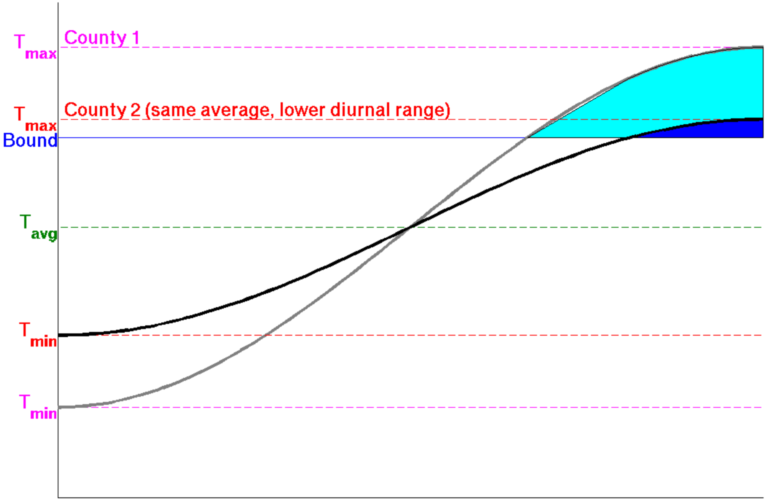
Aggregation Matters



Aggregation Matters

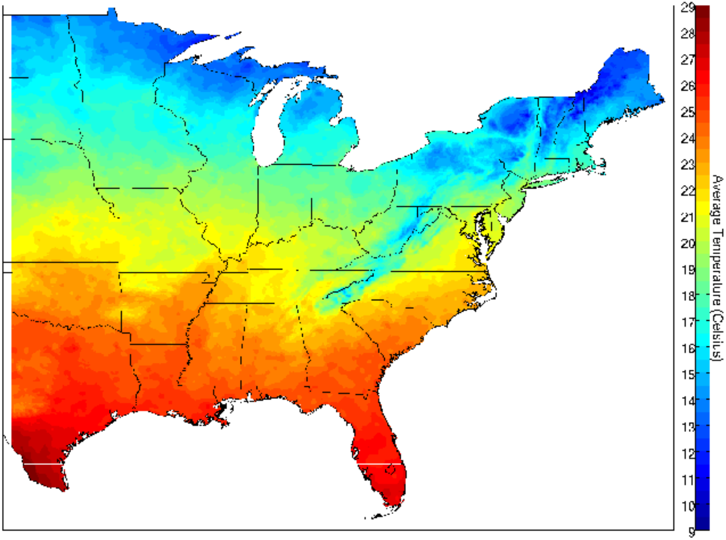


Aggregation Matters



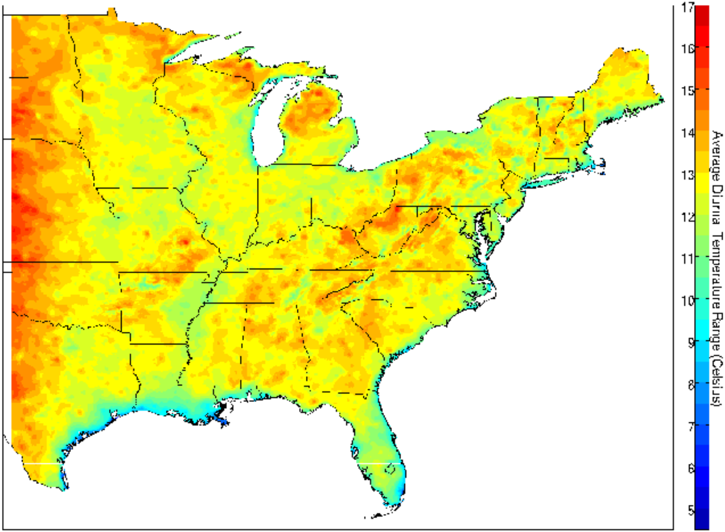
Aggregation Matters

Average Temperature in July-August (Celsius)



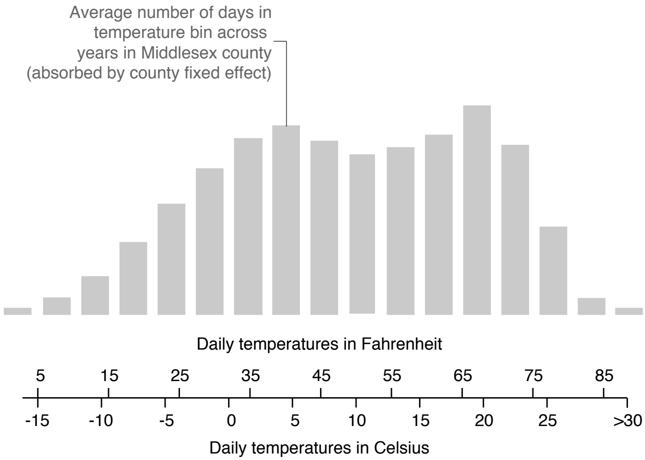
Aggregation Matters

Average Diurnal Range (Max-Min) im July-August (Celsius)

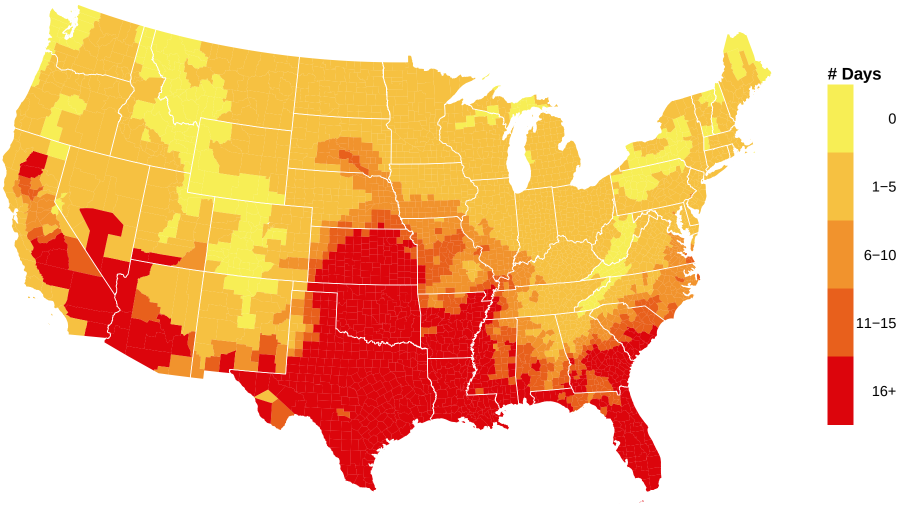


Identification Using Binned Temperature Variation

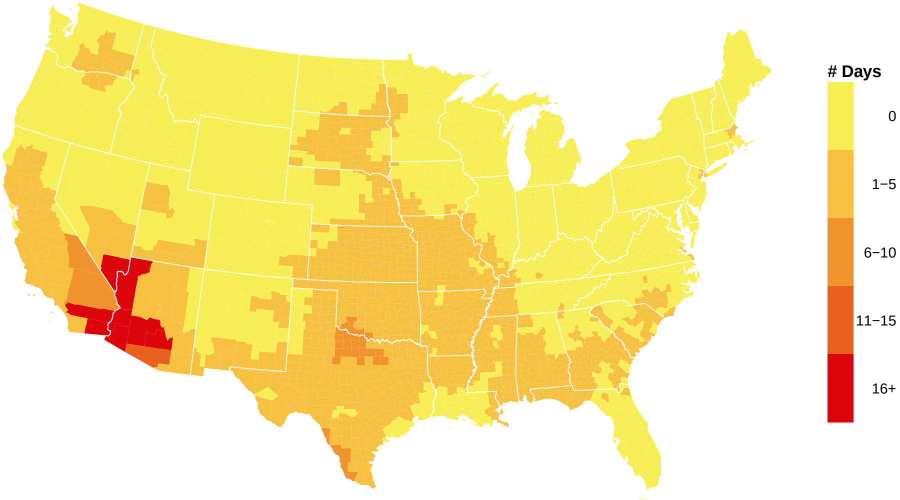
1) Count # of days during gestation in each temperature bin
2) Let response of temperature be different for each temperature bin



Average # of Days with Daily Mean Temperatures between 28-32C

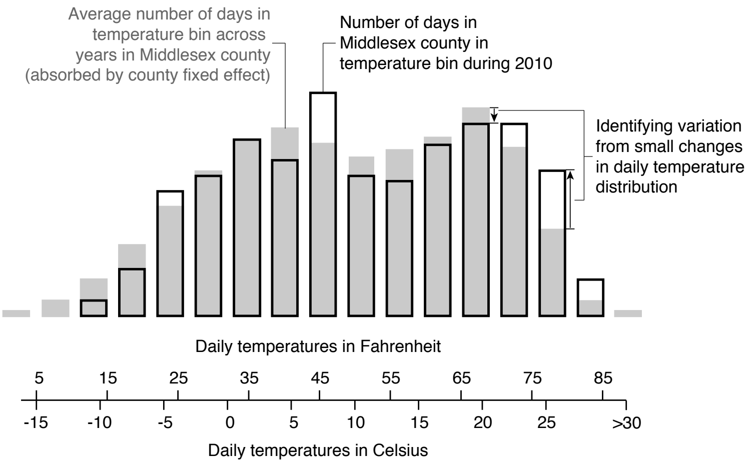


Average # of Days with Daily Mean Temperatures between 32+C

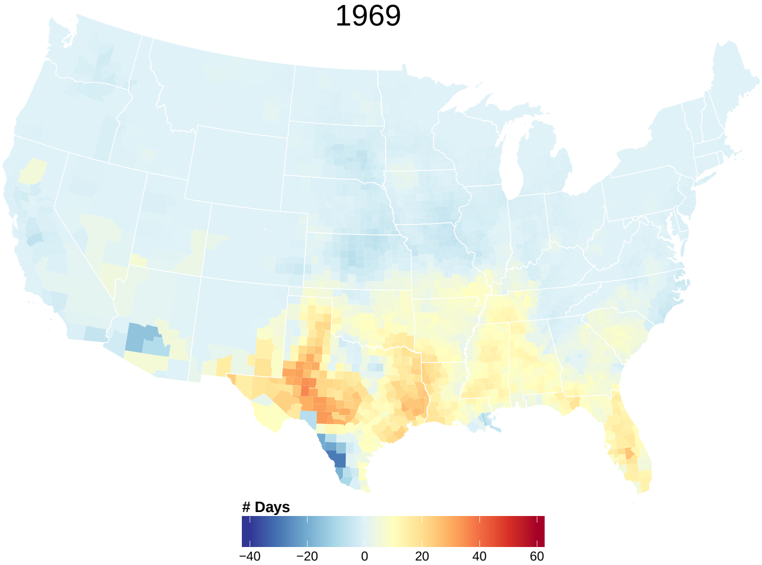


Identification Using Binned Temperature Variation

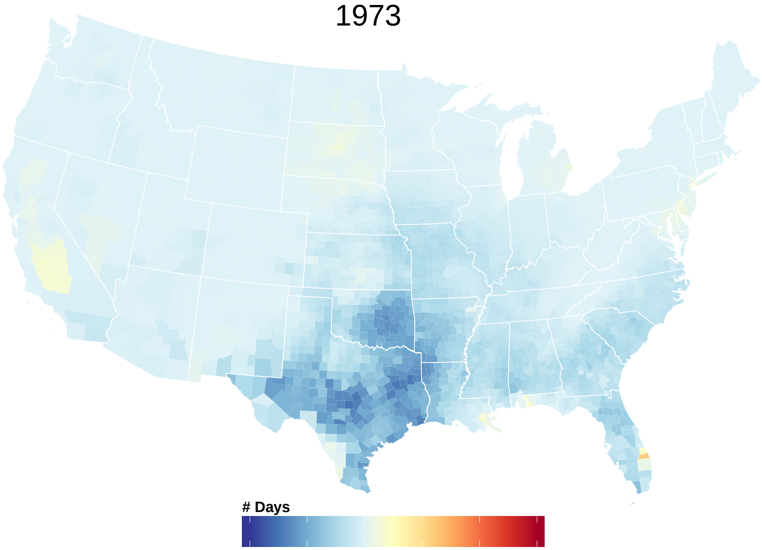
1) Compare each county to itself across years
2) Measure effect of small changes in the annual distribution of daily temp.



Deviation from Mean # Days Between 28-32 in a Year



Deviation from Mean # Days Between 28-32 in a Year



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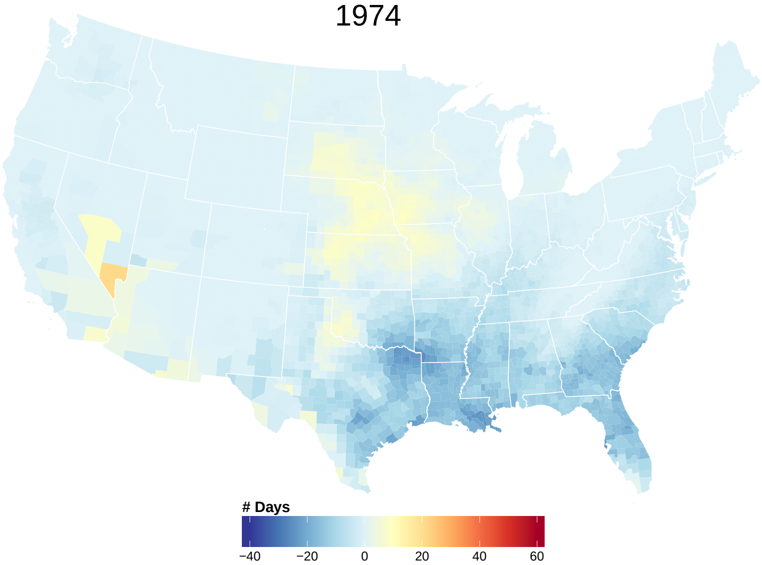
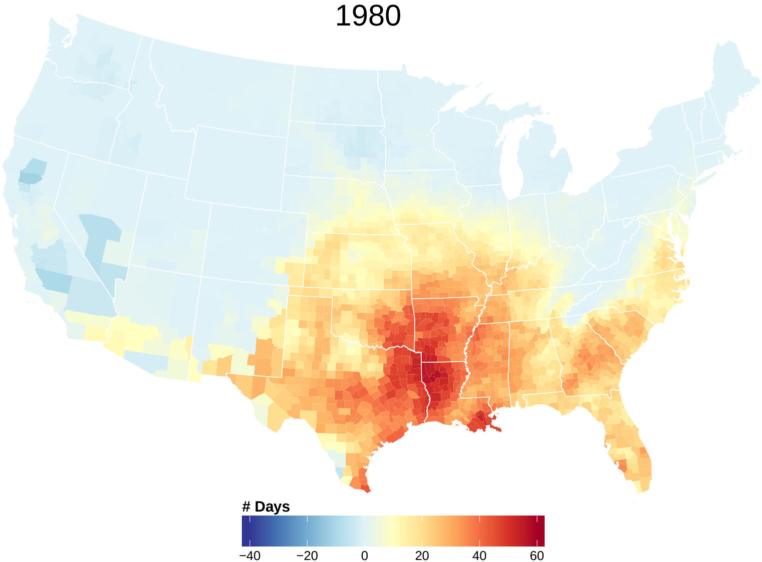


Deviation from Mean # Days Between 28-32 in a Year



Additional Empirical Issues

1. Displacement / Harvesting and other time transitional dynamics
    - Often solved by direct investigation (distributed lags)
2. Adaptation vs. treatment effect heterogeneity
    - Hard to distinguish effect heterogeneity (e.g. by income) from adaptation
    - Correlated unobservables
    - Few examples of exogenous variation in adaptability
      (e.g. Barreca et al. 2016 and introduction of AC, albeit non-experimental)
3. Statistical Inference and Spatial Correlations
    - Conley or aggregated cluster robust s.e.

Barreca et al. (2017)

What is the question and why is it interesting?

- Climate change impacts are important + so is understanding adaptation

Why is the existing literature crappy, non-existent, and/or unresolved?

- "While much attention has been devoted to reducing GHG emissions, comparatively little has been devoted to understanding how societies will adapt to climate change"

What is this paper going to do to solve it?

- "Paper provides the first large-scale empirical evidence on long-run adaptation opportunities through changes in the use of currently existing technologies."
- State-month data + State FE + time controls + binned temp. models
- State-year variation in AC penetration
- Interactions to see differential marginal effects

Barreca et al. (2017)

Empirical Specification

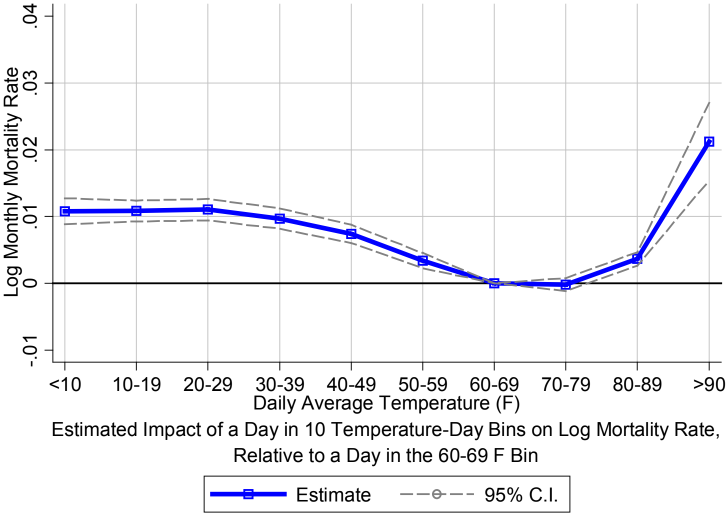
$$(1)\ \log(Y_{sym}) = \sum_j \theta_j TMEAN_{symj} + \pi_L LOWP_{sym} + \pi_H HIGHP_{sym} + X_{sym}\beta + \alpha_{sm} + \rho_{ym} + \varepsilon_{sym}$$

- Mortality rate (log of rate?)
- TMEAN$_j$ = temperature bin j in state, year, month
    - # of days in a state-month where daily mean temp is in jth of 10 bins
- Low/High = precip indicators
- State-month FE, Year-month FE
- X's (control for residual variation in mortality)

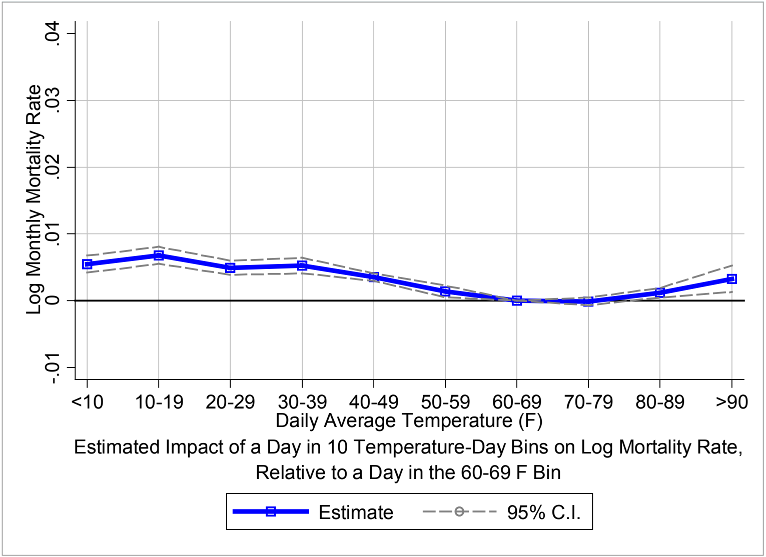
Temperature bins span entire distribution and are jointly collinear

- Forced to drop a reference bin (Here, 60-69F)
- What other restrictions does this model impose?

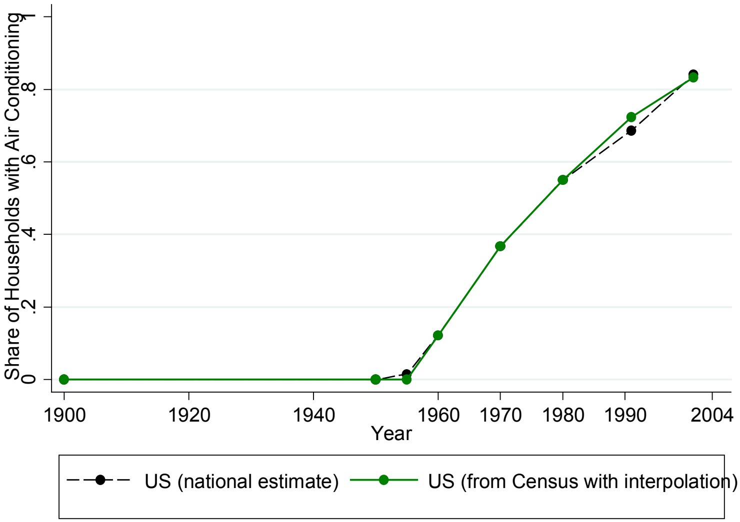
Temperature and Mortality: Response Function 1931-1959



Temperature and Mortality: Response Function 1960-2004

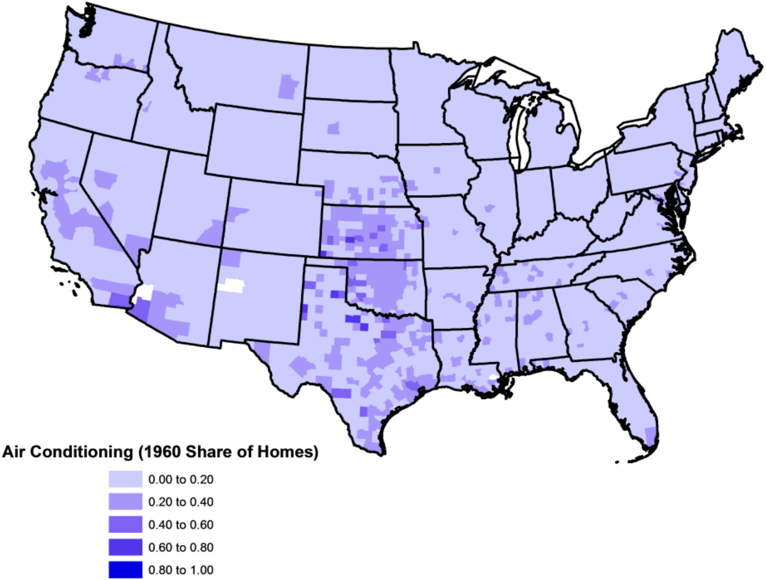


Household Air Conditioning Penetration Over Time

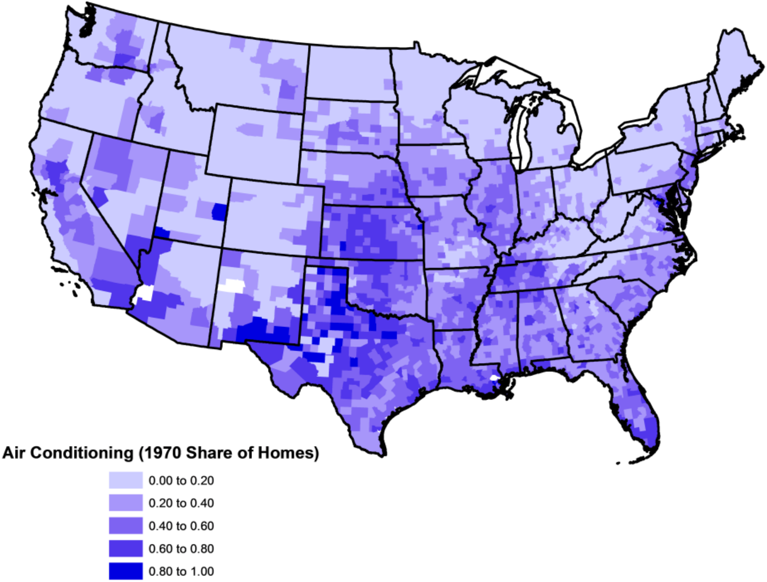


Source: Barecca, Clay, Deschenes, Greenstone, and Shapiro (2015)

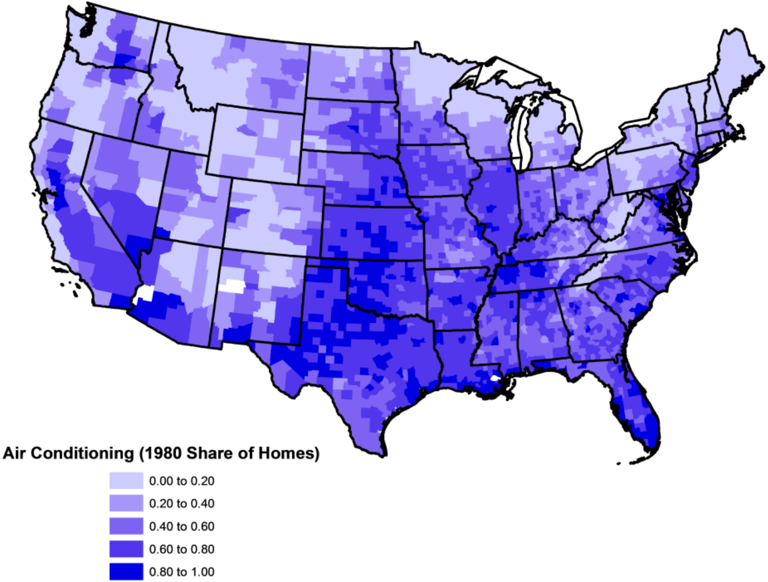
Share of Households With Air Conditioning: 1960



Share of Households With Air Conditioning: 1970



Share of Households With Air Conditioning: 1980



Barreca et al. (2017): Interacting Air Conditioning

Empirical Specification

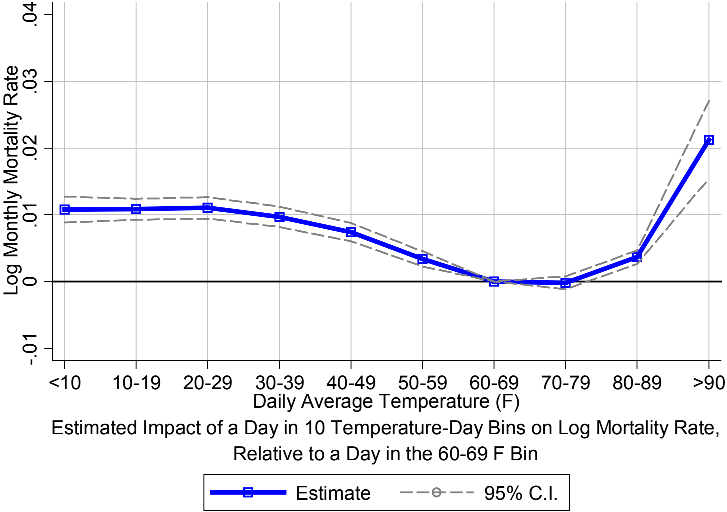
$$(2)\ \log(Y_{sym}) = \sum_j \theta_j TMEAN_{symj} + \sum_j \delta_j TMEAN_{symj} \times MOD_{sy} + MOD_{sy}\phi + \pi_L LOWP_{sym} + \pi_H HIGHP_{sym} + X_{sym}\beta + \alpha_{sm} + \rho_{ym} + \varepsilon_{sym}$$

Where MOD is "modifier" (i.e. AC adoption rate) $\in [0, 1]$

- Notice baseline term
- Interpretation of θ_j? δ_j?

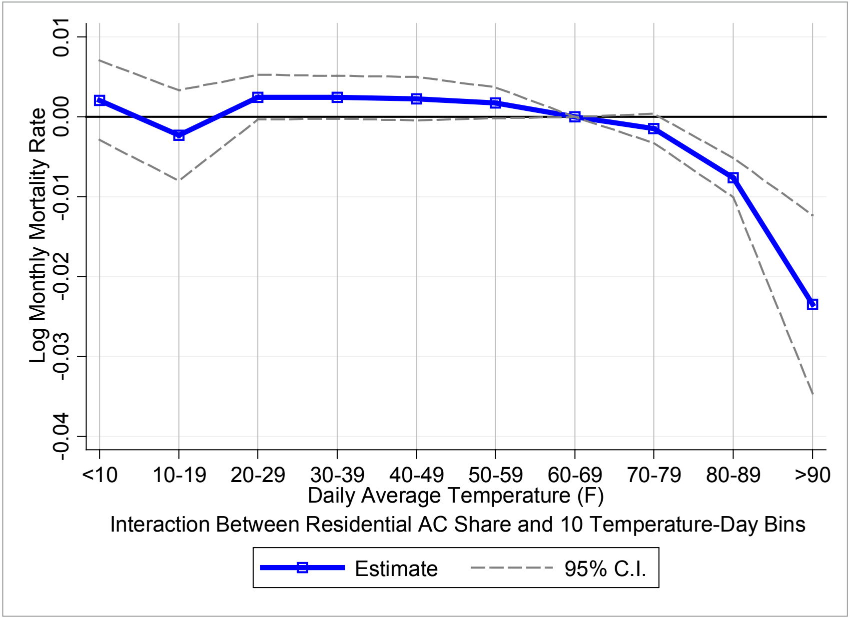
Conditional on controls, is AC adoption random?

Temperature and Mortality: Response Function 1931-1959



Estimated Impact of a Day in 10 Temperature-Day Bins on Log Mortality Rate, Relative to a Day in the 60-69 F Bin

Temperature and Mortality: AC Interaction



Surplus from Air Conditioning Adoption

Monetizing the benefits of air conditioning: could sum across wide variety of benefits (mortality reductions, etc...) or estimate consumer surplus directly.

Estimate electricity demand for AC users using Dubin-McFadden's (1984) discrete-continuous model

- Discrete: AC Adoption
- Continuous: AC (vis a vis electricity) usage

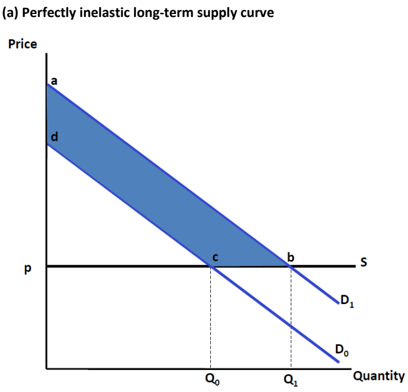
Conditional Electricity Demand Function:

$$q_{is} = \beta_0 + \beta_1 AC_{is} + \beta_2 p_{is} + X_{is}\gamma + \epsilon_{is}$$

Identification challenges: AC_{is} and p_{is} are endogenous

Solution: Selection correction for selection into AC; argue p_{is} isn't endogenous (regional price variation related to fuel shares and not consumer demand) and and/or instrument using regional dummy variables

Surplus from Air Conditioning Adoption



Amount of surplus depends not only on demand but on assumptions about supply

- CS gain: $5-$10 billion (2012$) annually at 1980 AC penetration rate

Barreca et al. (2017): Wrapping Up

Additional Empirical Issues: Did they effectively address?

- Displacement / Harvesting and other time transitional dynamics?
- Statistical inference?
- Marginal damages / SCC?

Burgess, Deschenes, Donaldson, Greenstone (2017)

"Weather, Climate Change and Death in India"

- Similar setup to BCDGS, although start with finding that urban/rural differences in Indian heat mortality are stark
- What causes differences? And what can mitigate differences?

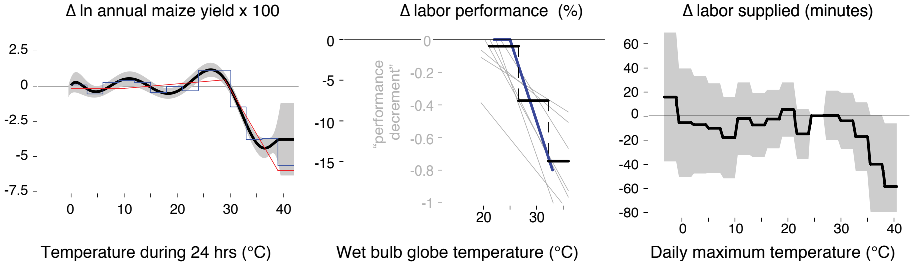
Agricultural yields / wages fall – inability to smooth consumption

- Mitigating technology: formal banking
- Quasi-random roll out of banking system (Burgess and Pande 2005) mitigates observed temperature impacts

Conclusion: Temperature and Climate

Temperature has a direct & non-linear effect on the elementary building blocks of the economy.

- Lot's of examples (e.g., agriculture, labor productivity, conflict)



From: Schlenker & Roberts (2009, PNAS) From: Hsiang (2010, PNAS) From: Graff Zivin & Neidell (2013, JLE)

How do all these effects add up?

Top Down Approaches

"Top down" approach: examines how macro-economy as a whole responds to climatic conditions.

- i.e., rather than examining individual/sectoral responses to climate
- Total income or GDP per capita often the outcome of interest
- Avoids assumptions about what mechanisms to include and how they operate, interact, or aggregate (i.e. by examining aggregate outcomes directly)

Representative Papers: Temperature, Cyclones, Rainfall, etc...

- Temperature: Burke, Hsiang, Miguel (2015), Dell, Jones, and Olken (2012)
- Cyclones: Hsiang and Jina (2015)

Combine dose-response estimates with climate projections to forecast future damages (ceteris paribus)

Dell, Jones, and Olken (2012)

What is the question and why is it interesting?

- Debate 100's of years long as to whether temperature is, or is not, central to understanding economic development.

Why is the existing literature crappy, non-existent, and/or unresolved?

- Cross-sectional papers (Sachs and Warner 1997; Gallup, Sachs, and Mellinger 1999; Nordhaus 2006)
- Micro-evidence + IAMS (many candidate mechanisms, complex, difficult aggregation problems)

What is this paper going to do to solve it?

- Takes an alternative approach – country-level regressions (1950-2003)
- Historical relationship between temperature and output

Dell, Jones, and Olken (2012)

Empirical Specification

To estimate these effects, we run panel regressions of the form

$$g_{it} = \theta_i + \theta_{rt} + \sum_{j=0}^{L} \rho_j T_{it-j} + \varepsilon_{it}, \tag{4}$$

where θ_i are country fixed effects, θ_{rt} are time fixed effects (interacted separately with region dummies and a poor country dummy in our main specifications), ε_{it} is an

- Output growth per capita
- Country FE, Continent-year FE, temperature (contemporaneous and lags)

Dell, Jones, and Olken (2012)

TABLE 2—MAIN PANEL RESULTS

Dependent variable is the annual growth rate	(1)	(2)	(3)	(4)	(5)
Temperature	−0.325	0.261	0.262	0.172	0.561*
	(0.285)	(0.312)	(0.311)	(0.294)	(0.319)
Temperature interacted with…					
Poor country dummy		−1.655***	−1.610***	−1.645***	−1.806***
		(0.485)	(0.485)	(0.483)	(0.456)
Hot country dummy				0.237	
				(0.568)	
Agricultural country dummy					−0.371
					(0.409)
Precipitation			−0.083*	−0.228***	−0.105**
			(0.050)	(0.074)	(0.053)
Precipitation interacted with…					
Poor country dummy			0.153*	0.160**	0.145*
			(0.078)	(0.075)	(0.087)
Hot country dummy				0.185**	
				(0.078)	
Agricultural country dummy					0.010
					(0.085)
Observations	4,924	4,924	4,924	4,924	4,577
Within R^2	0.00	0.00	0.00	0.01	0.01
R^2	0.22	0.22	0.22	0.22	0.24

Dell, Jones, and Olken (2012)

Takeaways:

- Mean temperature matters for poor countries
- Limited effect of temperature on rich countries
- Evidence of Adaptation?

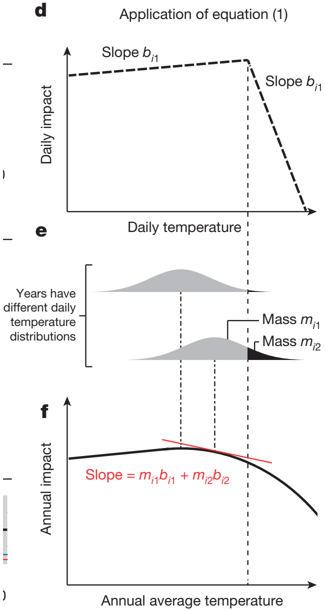
Lots of other results:

- mechanisms: sub-sector value added
- non-linearities: misspecified

Epilogue: Example of a paper that was so far from existing (macro) priors that it met a lot of resistance...

- Written by "outsiders"
- Some difficulty publishing

Burke, Hsiang, and Miguel (2015)



Written as an attempt to reconcile disparate findings in literature

- Why is the existing literature crappy, non-existent, and/or unresolved?
- Temperatures have no effect on economic output in some countries but larger effects in others

Hypothesis: Manifestation of non-linearities + aggregation

Test: Data on 160 countries from 1960-2010

- Fixed effects growth model with non-linear temperature response

Burke, Hsiang, and Miguel (2015)

Basic Model:

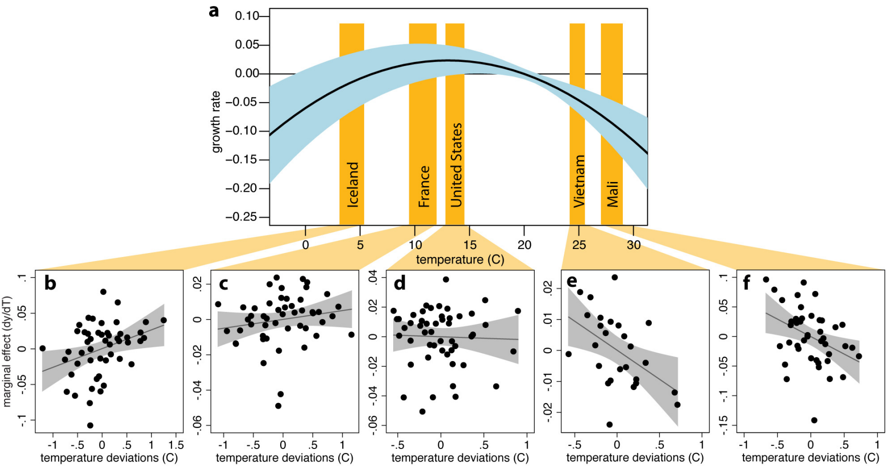
Using a 51-year longitudinal sample of countries around the world, we take first differences of the natural log of annual real (inflation-adjusted) gross domestic product per capita Y. These first differences (ΔY) can be interpreted as per-period growth rates in income. We deconvolve the factors that might affect these changes in income with a simple and general model:

$$\Delta Y_{it} = h(T_{it}) + \lambda_1 P_{it} + \lambda_2 P_{it}^2 + \mu_i + \nu_t + \theta_i t + \theta_{i2} t^2 + \varepsilon_{it} \tag{15}$$

- **Functional form for temperature**: Quadratic
- Country FE, year FE, country specific trends (quadratic), and precipitation (quadratic)

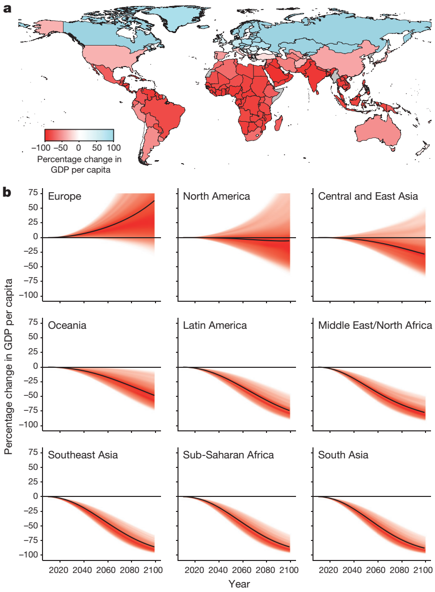
Paper explores other functional forms for temperature and sensitivity to other controls

Burke, Hsiang, and Miguel (2015): Headline



Questions: Single dose-response function (BHM) or separate dose response functions (DJO)? Empirically difficult to separate.

Burke, Hsiang, and Miguel (2015)



Project forward future climate impacts using "business as usual" RCP8.5 prediction of future warming

- "climate change reduces projected global output by 23% in 2100 relative to a world without climate change"
- Potential issues?

Top Down Approaches: Conclusion

Simple to implement but a bit of a black box:

- Hard to understand ability for society to adapt
- Through reallocation / migration
- Price effects / induced innovation / etc...

What leads to heterogeneous effects?

- Is it adaptive responses?
- Differences in health stock?
- Non-linearities in dose-response?

Very difficult to empirically identify causal source of treatment effect heterogeneity (see e.g. Hsiang, Oliva, and Walker 2017)

Conclusion: Climate Damage - Bottom-Up / Top-Down

Frontier: Underlying Drivers of Adaptation and/or "Adaptation Gap"

- Not well understood why some populations "adapt" in some dimensions while entirely failing to adapt in other contexts.

- High costs of adaptation, other incentives (or lack thereof), credit constraints, behavioral biases, incorrect or limited information, weak institutions / political economy concerns, collective action problems, and/or access to adaptive technologies

- Existing evidence is primarily suggestive / cross-sectional.

Two strains of research that may lend insight: (i.e. arbitrage opportunities)

- Huge health/development lit trying to understand why people do not invest in seemingly positive NPV investments (see e.g. Kremer and Glennerster 2011)
- Large literature on "energy-efficiency gap"

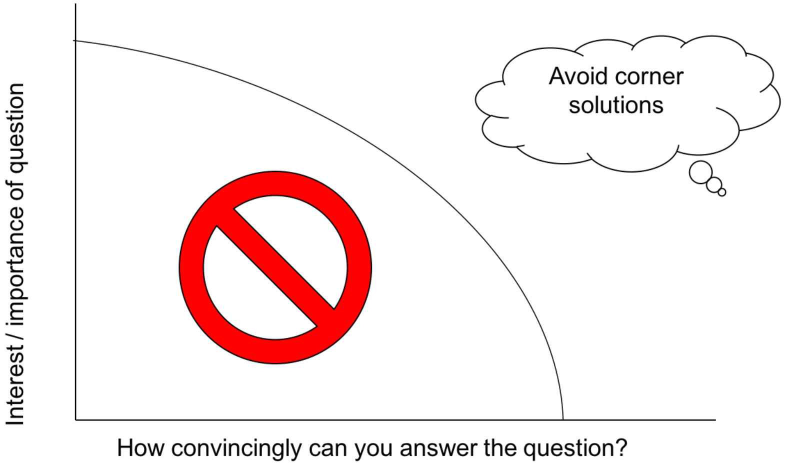
Future and ongoing work

How do we build this into a workable damage function?

Next Steps:

- Integrated Assessment Models (IAMs)
- Combining Empirical Results (within and across sectors): Models and Meta-Analysis

Estimating the Social Cost of Carbon



Social Cost of Carbon

What is the Social Cost of Carbon (SCC)?

Social Cost of Carbon

"The **social cost of carbon** is an economic metric intended to provide a comprehensive estimate of the net damage – that is, the monetized value of the net impacts, both negative and positive – from the global climate change that results from a small (1-metric ton) increase in carbon-dioxide (CO_2) emissions."
(NAS 2017)

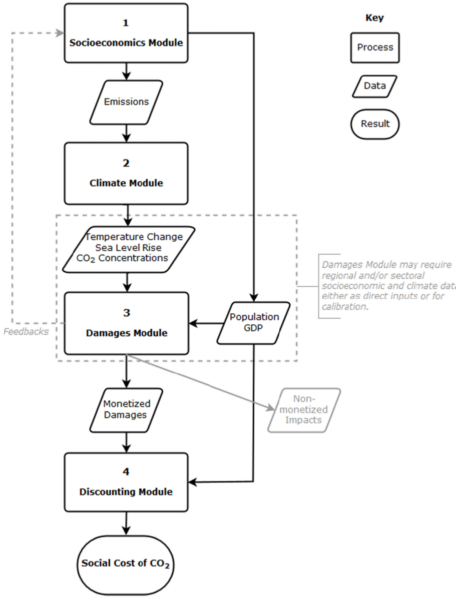
Intended to be a comprehensive measure of climate change damages, including (but not limited to):

- changes in net agricultural productivity
- net energy demand
- human health
- property damages from increased flood risk
- value of ecosystem services

Integrated Assessment Models

Integrated Assessment Models

- e.g. Nordhaus 1994
- provided a big step forward in understanding complex relationships between CO_2 emissions and human well being



Social Cost of Carbon

Estimating the SC-CO2 via IAMs involves four steps:

1. Projecting future global and regional population, output, and emissions;
2. Calculating the effect of emissions on temperature, sea level, and other climate variables;
3. Estimating (explicitly or implicitly) the physical impacts of climate and, to the extent possible, monetizing those impacts on human welfare (i.e., estimating net climate damages); and
4. Discounting monetary damages to the year of emission.

Studies supporting SC-CO2 estimation have used integrated assessment models (IAMs) that incorporate some or all of the four components in a single model

Integrated Assessment Models: Damages

IAM Damage Function: include, but are not limited to...

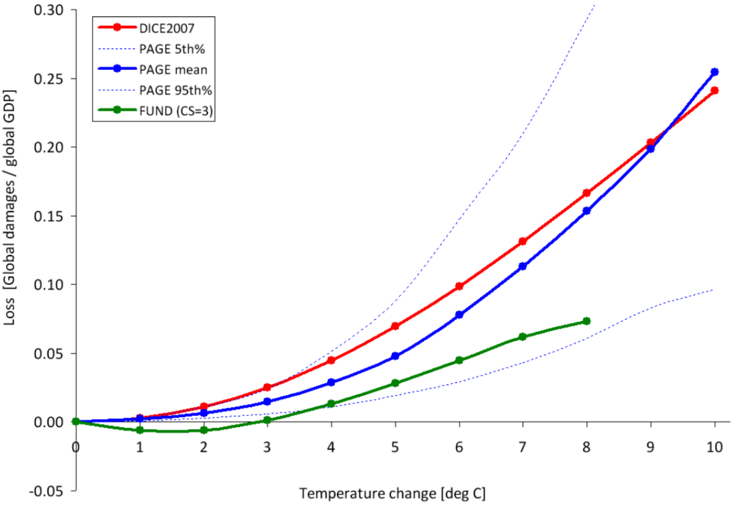
- market damages (e.g. changes in ag productivity, energy use, and property damage from increased flood risk...)
- Nonmarket damages (e.g. human health and to ecosystem services)

Time Horizon: Because most of the warming caused by an emission of CO2 into the atmosphere persists for well over a millennium, changes in CO2 emissions today may affect economic outcomes for centuries to come.

- Streams of monetized damages over time are converted into present value terms by discounting. The present value of damages reflects society's willingness to trade value in the future for value today.
- As one can imagine, **the discount rate matters**

Integrated Assessment Models

Annual consumption loss as fraction of global GDP in 2100 due to an increase in annual global temperatures in 3 different IAMs



Putting it all together

Interagency Working Group on the Social Cost of Greenhouse Gases

Pooled estimates from multiple models

- (3 models) x (5 socioeconomic scenarios) x (1 climate sensitivity distribution) x (3 discount rates)
- 45 separate SCC distributions for a given year
- three separate probability distributions for SCC in a given emissions year, one for each of the three discount rates (equal weight to each model)

From the 3 distributions, the interagency group selected 4 values:

- The average SCC at each discount rate: 2.5%, 3%, and 5%
- The 95th percentile at a 3% discount rate, representing higher than expected economic impacts further out in the tails of the distribution.

USG SCC Estimates (Feb 2010)

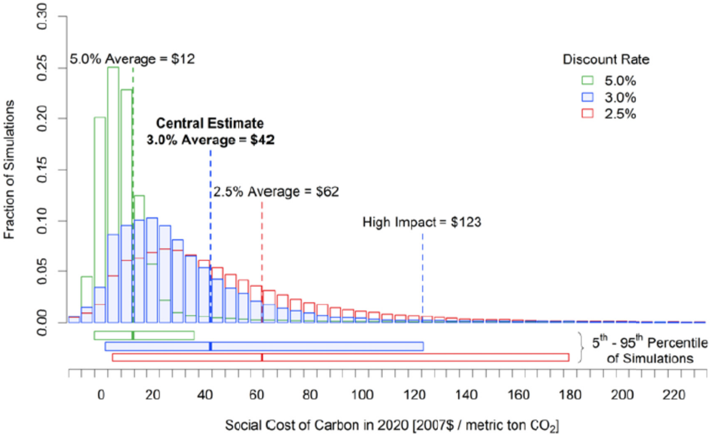


FIGURE 1-1 Frequency distributions of SC-CO_2 estimates for 2020 (in 2007 dollars per metric ton of CO_2).

Where do we go from here?

What might we not like so much about damage estimates?

Journal of Economic Literature 2013, 51(3), 860–872
http://dx.doi.org/10.1257/jel.51.3.860

Climate Change Policy: What Do the Models Tell Us?†

Robert S. Pindyck*

Very little. A plethora of integrated assessment models (IAMs) have been constructed and used to estimate the social cost of carbon (SCC) and evaluate alternative abatement policies. These models have crucial flaws that make them close to useless as tools for policy analysis: certain inputs (e.g., the discount rate) are arbitrary, but have huge effects on the SCC estimates the models produce; the models' descriptions of the impact of climate change are completely ad hoc, with no theoretical or empirical foundation; and the models can tell us nothing about the most important driver of the SCC, the possibility of a catastrophic climate outcome. IAM-based analyses of climate policy create a perception of knowledge and precision, but that perception is illusory and misleading. (*JEL* C51, Q54, Q58)

Where do we go from here?

To make matters worse, we don't even know the correct functional forms for some of the key relationships. This is particularly a problem when it comes to the damage function. The damage function used in the Nordhaus DICE model, for example, is a simple inverse-quadratic relationship:

$$L(T) = 1/(1 + \pi_1 T + \pi_2 T^2) \quad (1)$$

Here T is the anthropomorphic increase in temperature, and $L(T)$ gives the reduction in GDP and consumption for any value of T. (Thus GDP = $L(T)$GDP', where GDP' is what GDP would be if there were no warming.) But remember that this damage function is made up out of thin air. It isn't based on any economic (or other) theory, or any data. Furthermore, even if this inverse-quadratic function were somehow the true damage function, there is no theory or data that can tell us the values for the parameters π_1 or π_2, or the correct probability distributions for those parameters, or even the correct means and variances.

Pindyck (2015)

Reasonable criteria for damage function inputs

Underlying estimates that factor into a damage function should satisfy two key criteria:

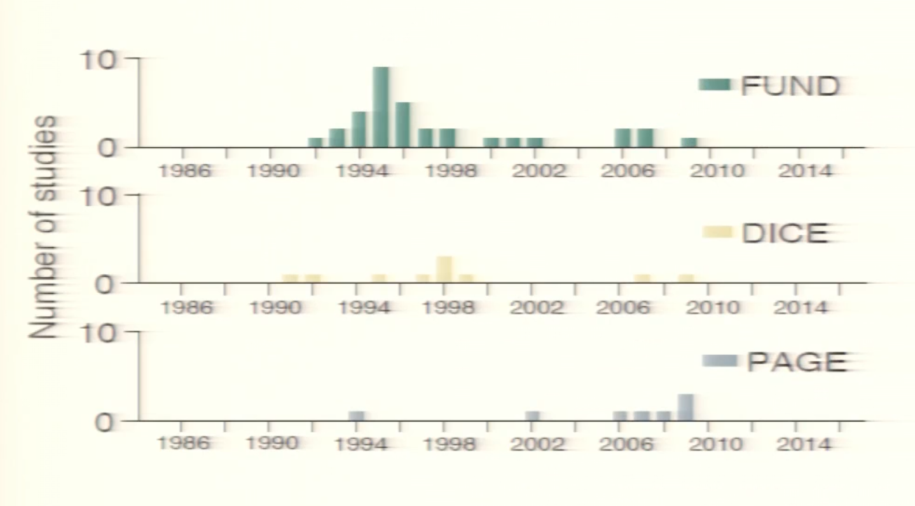
1. **Plausibly causal**: Damage functions should be derived from empirical estimates that are purged of underlying sources of unobserved heterogeneity and are plausibly causal
2. **Reflect adaptation and it's costs**: Damage functions should reflect that agents choose optimal adaptation opportunities and incur costs of compensatory investments

Additional Criteria for Developing Damage Functions

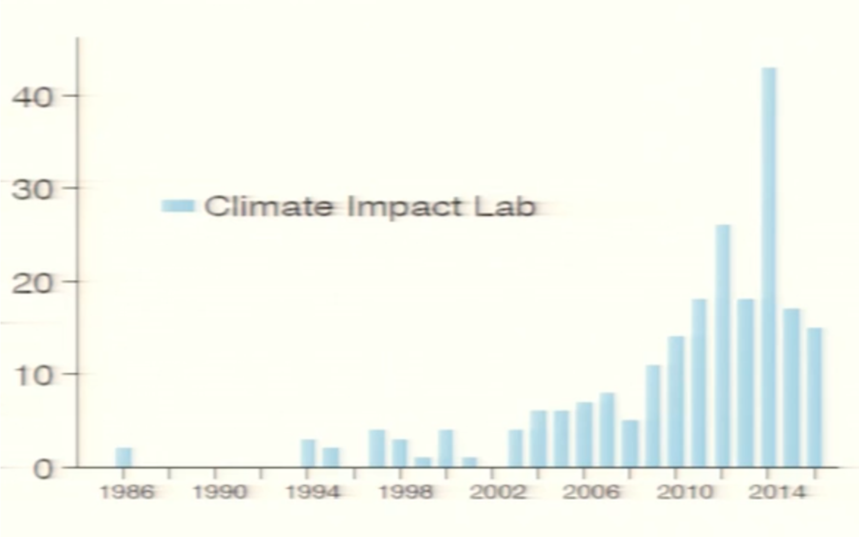
Seemingly other useful criteria for judging whether damage function is reliable:

- **Representative**: Estimate should be representative of the population that it is applied to
- **Flexible**: Allow for non-linearity using semi-parametric approaches
- **Non-market valuations**: Allow for valuations of market and non-market impacts
- **Updatable and transparent**: SCC estimating framework should be easily updatable to incorporate latest research, be replicable and transparent
- **Risk and inequality**: Capture distributional effects of climate impacts

IAM Literature Input



Modern Empirical Research That Satisfies Above Mentioned Criteria

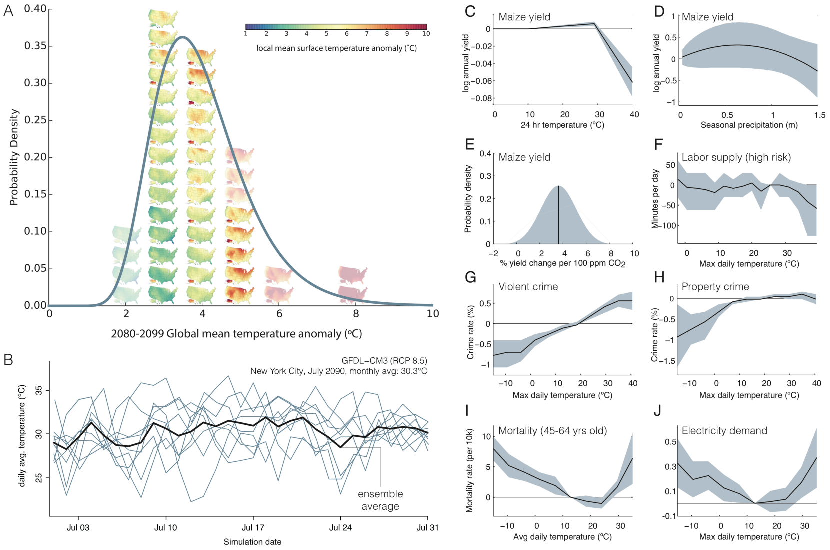


Aggregation and Projection

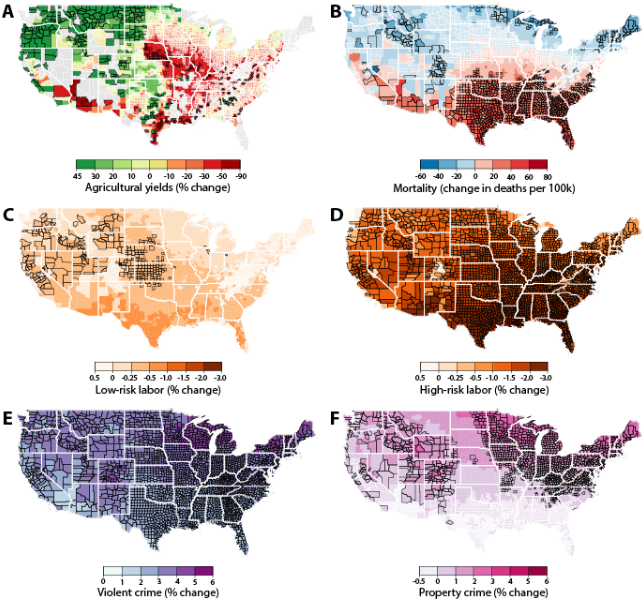
Ongoing work (Hsiang + others)

1. Take and/or develop plausibly causal estimates of relationship between measures of climate and human welfare in multiple sectors using continuously updating estimates: `http://dmas.berkeley.edu/`
   - Ability to incorporate future research findings
2. Build a model of direct responses based on historical adaptation and interpolate around the world where studies may not exist [in progress]
   - Marginal effect of temperature as a function of income
   - Out of sample prediction where outcome data (e.g. mortality) is not available
3. Project responses into the future using high resolution climate projections
4. Obtain empirical damage function that accounts for multiple sources of uncertainty to calculate an SCC that meets all criteria above

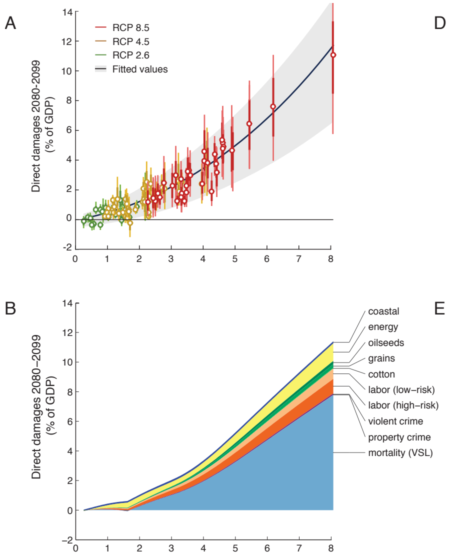
Proof of Concept: American Climate Prospectus (Houser et al. 2015)



Spatial distribution of projected impacts



Estimates of total US damage from climate



Taking a Step Back: What to do with all the evidence

What is the "correct" temperature-mortality dose-response function?

- To what extent do differences reflect sampling variability?
- Versus fundamental treatment effect heterogeneity?

How can we use all available information to forecast future damages (while also building in inherent uncertainties)

One possible answer: **meta-analysis**

Why go Meta?

Meta-analysis, i.e. quantifying replicability and generalizability across a body of literature, is an important step in the Scientific Method that is not yet standard practice in applied economics.

It should be.

1) It helps us distill larger quantities of information (many studies and their associated details) into generalized (stylized) results.

2) It helps us (and disciplines us to) quantify the extent to which findings agree/disagree.

3) It is how findings eventually become facts,

Economics produces mountains of stand-alone empirical results that are too often "put on the shelf" and not integrated into larger frameworks of generalizable quantitative understanding.

When can we compare or consolidate results?

- Must have (reasonably) comparable units.
- Units of measure must be comparable (e.g. standardized to %).
- Models must be structurally similar enough for comparison (e.g. local linearization).
- Methods should not have systematic bias relative to one another. Must have limited publication bias.

Bayesian Hierarchical Model: Meta-Analysis Application

Hsiang, Burke, Miguel (2013): "Quantifying the Influence of Climate on Human Conflict"

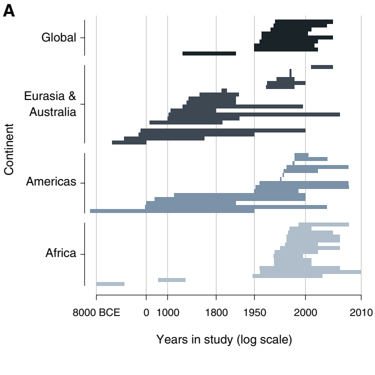


Fig. 1. Samples and spatiotemporal resolutions of 60 studies examining intertemporal associations between climatic variables and human conflict. (**A**) The location of each study region (*y* axis) plotted against the period of time included in the study (*x* axis). The *x* axis is scaled according to log years before the present but is labeled according to the year of the common era. (**B**) The level of aggregation in social outcomes (*y* axis) plotted against the time scale of climatic events (*x* axis). The envelope of spatial and temporal scales where associations are documented is shaded, with studies at extreme vertices labeled for reference. Marker size indicates the number of studies at each location, with the smallest bubbles marking individual studies and the largest bubble denoting 10 studies.

Meta-Analysis: Evaluating and combining effect sizes

A variety of different approaches: hinges on DGP for treatment effects

- Do we think that true effect is fixed β or random β_i?

Four Main Approaches

1. Approach #1: Median of effects
   - Benefit: Easy/transparent
   - Cost: Ignores other margins of uncertainty / information
2. Approach #2: Weighted mean of standardized effects
   - Using inverse variance weights

Replications with same effect and same error structure

Obs. i in multiple experiments indexed by j, with outcome variable y:

$$y_{ij} \sim N(\beta, \sigma^2)$$

where estimates are

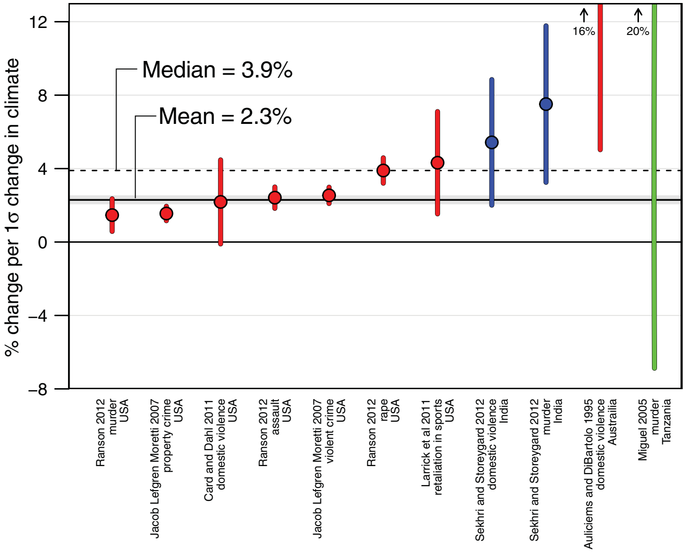
$$\hat{\beta}_j = \frac{1}{n}\sum_i y_{ij}, \qquad \hat{\sigma}_j^2 = \frac{\sigma^2}{n_j}$$

If experiments only differ by sample size n_j (i.e. σ^2 and β are the same for all j), then we should pool observations into one mega-experiment:

$$\tilde{\beta} = \frac{\sum_j \frac{1}{\hat{\sigma}_j^2}\hat{\beta}_j}{\sum_j \frac{1}{\hat{\sigma}_j^2}} = \frac{\sum_j \frac{n_j}{\sigma^2}\hat{\beta}_j}{\sum_j \frac{n_j}{\sigma^2}} = \frac{\sum_j n_j \hat{\beta}_j}{\sum_j n_j}$$

$\frac{1}{\hat{\sigma}_j^2}$ is called **the precision** of $\hat{\beta}_j$.

Inter-personal conflict and climate



Replications with same effect but different error structure

Obs. i in multiple experiments indexed by j, with outcome variable y:

$$y_{ij} \sim N(\beta, \sigma_j^2)$$

We look for a weighted average of prior estimates:

$$\tilde{\beta} = \sum_j \omega_j \hat{\beta}_j$$

where ω_j is the weight for study j.

$$Var(\tilde{\beta}) = \sum_k \sum_j \left[\omega_k \omega_j Cov(\hat{\beta}_k, \hat{\beta}_j) \right]$$

If the studies are independent, then $Cov(\hat{\beta}_k, \hat{\beta}_j) = 0$ for all $k \neq j$ and

$$Var(\tilde{\beta}) = \sum_j \omega_j^2 \hat{\sigma}_j{}^2$$

Meta Analysis: "Precision-Weighting"

To minimize variance of $Var(\tilde{\beta})$ "optimal" weights are

$$\omega_j = \frac{\frac{1}{\hat{\sigma}_j}}{\sum_{j=1}^{M} \frac{1}{\hat{\sigma}_j}}$$

assuming normality in $\hat{\beta}_j$ (i.e. Central Limit Theorem)

- i.e. weight assigned to each estimate is proportional to the inverse of its estimated variance
- Proof: minimize $Var(\tilde{\beta})$ s.t. $\sum \omega_j = 1$

Optimal if effects are the same across studies, regardless of whether or not error structure is the same across studies.

When do error structures change across studies?

- More orthogonal controls reduce residual variance
- Populations are subject to different disturbances
- Observational units are aggregated differently across samples

Meta Analysis: "Precision-Weighting" Distributions

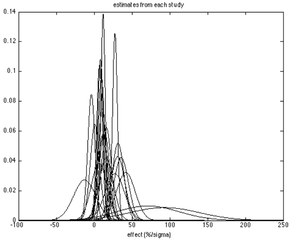
Why stop at the mean? What about full distribution of β? **[Approach #3]**

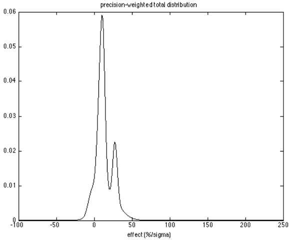
Defining $N_\beta(m, s)$ to be normally distributed PDF over values of β centered on m with s.d. s

Estimate for the pdf $\tilde{B}_\beta$ that describes the probability of obtaining an estimate $\hat{\beta}$ unconditional on the study sample:

$$\tilde{B}_\beta = \sum_{j=1}^{M} \omega_j N_\beta(\hat{\beta}_j, \hat{\sigma}_j)$$

using same weights as before





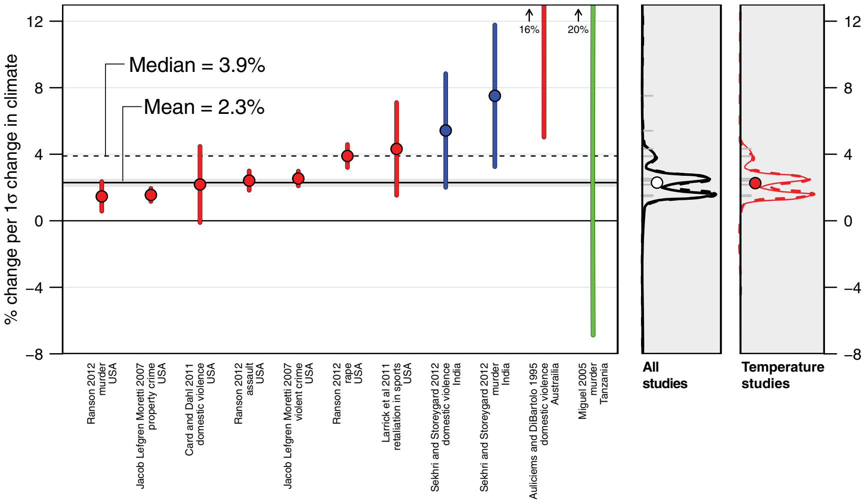
Summarizing results for climate and conflict

Table: **Summary statistics for the distribution of effects across studies**

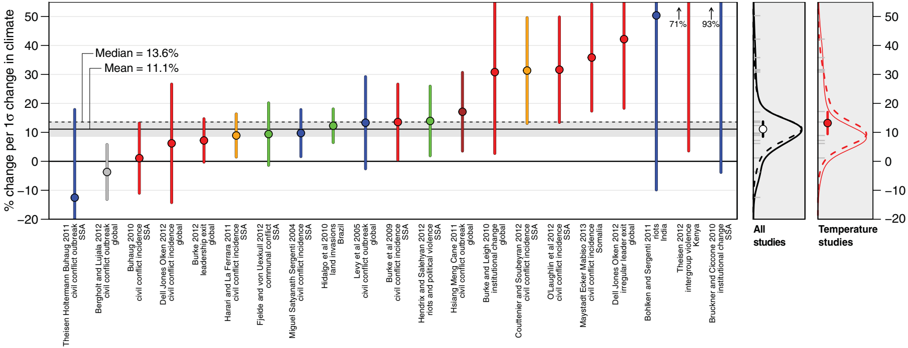
	Median	$\tilde{\beta}$	$\sigma(\tilde{\beta})$	Percentiles of $\tilde{B}_\beta$				
				5%	25%	50%	75%	95%
Intergroup	13.56	11.12	1.34	-4.60	5.80	10.20	14.30	32.00
Interpersonal	3.89	2.29	0.12	1.20	1.50	2.20	2.60	4.00

Hsiang, Burke, Miguel (Science, 2013)

Meta-Analysis Application



Meta-Analysis Application



Bayesian Hierarchical ("Random-Effects") Model

Treatment Effect Heterogeneity: Seems likely that differences among estimated effect sizes are not due to sampling variability alone.

- Some studies may share some similarities
  (different outcomes might be related)
- Some outcomes or samples might exhibit different responses to climate

Bayesian Hierarchical Normal Model: model distribution of effect sizes while simultaneously allowing for similarities and differences across studies.

- See e.g. Gelman, et al. (2014). Bayesian data analysis (Chapter 5) for more formal treatment

Bayesian Hierarchical Meta-Analysis

Consider set of M independent studies, each estimating a treatment effect β_j.

- Individual study's estimate of treatment effect $\hat{\beta}_j$, with standard error $\hat{\sigma}_j$
- Treatment effects β_j are drawn from $N(\mu, \tau)$ where μ and τ are called hyperparameters

Scenarios:

1. Could be the case that β_j is same across studies and observed variation in the $\hat{\beta}_j$ results from sampling error alone (implying $\tau = 0$ and $\beta_j = \mu$ for all j)
2. Could be the case that the "true" effect in each study is different (meaning $\tau > 0$)

Goal: compute distribution of τ's that are consistent with observed $\hat{\beta}_j$'s and $\hat{\sigma}_j$'s

- Then use these estimates to simulate the distribution of each β_j.

Bayesian Solution

The conditional posterior

$$\beta_j | \mu, \tau, y \sim N(\breve{\beta}_j, V_j)$$

where

$$\breve{\beta}_j = \frac{\frac{1}{\hat{\sigma}_j^2}\hat{\beta}_j + \frac{1}{\tau^2}\mu}{\frac{1}{\hat{\sigma}_j^2} + \frac{1}{\tau^2}}, \qquad V_j = \frac{1}{\frac{1}{\hat{\sigma}_j^2} + \frac{1}{\tau^2}}$$

Common component of studies is μ

$$\mu | \tau, y \sim N(\hat{\mu}, V_\mu)$$

where

$$\hat{\mu} = \frac{\sum_j \frac{1}{\hat{\sigma}_j^2 + \tau^2}\hat{\beta}_j}{\sum_j \frac{1}{\hat{\sigma}_j^2 + \tau^2}}, \qquad V_\mu^{-1} = \sum_j \frac{1}{\hat{\sigma}_j^2 + \tau^2}$$

Bayesian Hierarchical Meta-Analysis

Intuition:

- If all estimated treatment effects are similar and have overlapping CI, then most simulated values of τ are likely to be close to zero.
- If large variation in estimates but each effect is estimated precisely, then $\tau > 0$ (i.e. "true" treatment effect heterogeneity likely exists)

Simulation Heuristic:

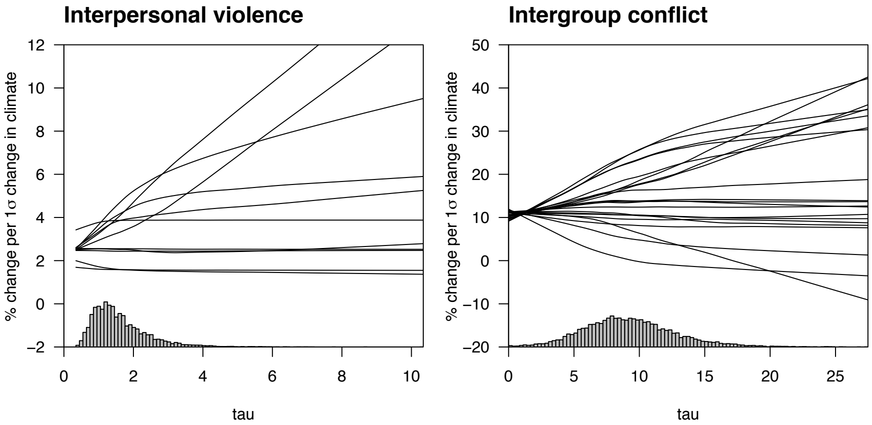
- Assume uniform prior over τ
- Sample τ and update guess using observed $\hat{\beta}$'s and $\hat{\sigma}$'s.
  - If $\hat{\sigma}$'s are very tight but $\hat{\beta}$'s are far apart, posterior τ gets bigger
- Calculate μ as precision weighted combination of $\hat{\beta}$'s, where weights depend on individual $\hat{\sigma}_j$ as well as τ.
- Update estimate for each $\hat{\beta}$: weighted average of your earlier estimate and μ
  - τ informs the weight on μ
  - If τ is small then $\beta \to \mu$ (i.e. observed diff in β's just sampling variation)
- Do this a bunch of times, taking a new guess of τ each time to recover posterior probabilities

Predicting true study-specific effects β_j conditional on hyperparameter τ

Supplementary Table S2: Posterior quantiles of treatment effects for the 10 studies on interpersonal violence, based on 10,000 simulation draws from a Bayesian hierarchical model. The $\hat{\beta}_j$ and $\hat{\sigma}_j$ columns represent our original estimated effect and standard error from each study. The last three rows give the posterior distributions for the population parameters μ and τ, as well as the "predicted effect" $\hat{\beta}_j^*$ (the predicted outcome of a new study).

					Posterior distribution				
#	Study	year	$\hat{\beta}_j$	$\hat{\sigma}_j$	2.5%	25%	median	75%	97.5%
1	Ranson	2012	1.47	0.45	0.77	1.33	1.64	1.93	2.50
2	Jacob Lefgren Moretti	2007	1.55	0.20	1.20	1.46	1.59	1.72	1.98
3	Card and Dahl	2011	2.18	1.17	0.66	1.90	2.52	3.11	4.34
4	Ranson	2012	2.42	0.30	1.87	2.25	2.45	2.64	3.00
5	Jacob Lefgren Moretti	2007	2.54	0.23	2.12	2.40	2.55	2.70	2.99
6	Ranson	2012	3.89	0.35	3.13	3.59	3.82	4.06	4.52
7	Larrick et al	2011	4.32	1.42	1.69	2.93	3.63	4.40	5.99
8	Sekhri and Storeygard	2012	5.43	1.74	1.74	3.09	3.90	4.87	6.93
9	Sekhri and Storeygard	2012	7.51	2.17	1.90	3.36	4.33	5.53	8.19
10	Auliciems and DiBartolo	1995	16.28	5.74	1.01	2.77	3.79	5.16	9.47
11	Miguel	2005	21.45	14.45	0.01	2.20	3.16	4.34	8.23
	Mean, μ				1.94	2.64	3.02	3.49	4.84
	Standard deviation, τ				0.62	1.05	1.43	1.98	3.77
	Predicted effect, $\hat{\beta}_j^*$				1.05	2.08	2.78	3.91	6.84

Predicting true study-specific effects β_j conditional on hyperparameter τ



Hsiang, Burke, Miguel (2013): Takeaways

1. Simulated values of τ are distributed away from zero
    - estimated treatment effects are very unlikely to describe a single underlying value
    - Strong evidence of important differences between studies
2. Component of the effects β that is common across studies (μ) tends to be substantial
3. Simultaneously strong evidence that there is also something in common between these studies.

Some interesting debate/discussion of the Hsiang, Burke, Miguel paper

- Critique (link)
- Response #1 (link)
- Response #2 (link)
- Response #3 (link)

Meta-Analysis: Additional usefulness

1. Formally consider plausibility of point estimates reported by new studies

   When $\hat{\beta}_j$ is far out in the tail of the posterior distribution

   $\rightarrow$ point estimate is unlikely to be accurate

   $\rightarrow$ something unique about the study that sets it apart from the literature

2. Can formally consider "value" of new intervention / experiment by how much it would affect posterior (see e.g. Vivalt 2015)
   - New version of power calculation?

Recent and Ongoing Applications

1. Used to construct composite estimates for use in climate projections discussed above (Houser et al., 2015)
2. Used in upcoming "empirical SCC" estimates from Hsiang, Greenstone, et al.
3. Used in recent JMP to aggregate microcredit literature (Meager 2016)
   - Nice paper at the research "frontier" + textbook treatment of material

Treatment Effect Heterogeneity

Burgeoning Interest in Understanding Treatment Effect Heterogeneity

- Separating out sampling variability from fundamental heterogeneity

See recent work by:
Heckman, Tobias, & Vytlacil 2001, Angrist 2004, Angrist & Fernandez-Val 2010, Bertanha & Imbens 2014, Allcott 2015, Dehejia, Pop-Eleches and Samii 2015, Gechter 2015, Athey & Imbens 2016

For the most part, these econometric problems have not received a lot of attention in the energy/environment space

Circling Back: Empirical SCC - Integrating Empirical Findings into IAMS

Some Recent Examples: Moore, Baldos, Hertel, Diaz (2017)

- Lot's of solid empirical work on agricultural yields
- Try to integrate this work into IAM

Process:

1. IPCC database $\approx$ 1000 results on yield response to temp + extra work to get yield-temp response functions that can be extrapolated to a global grid
2. Productivity shocks $\neq$ welfare, which is what is needed for damages
3. Incorporate predicted productivity shocks into 140-region GTAP CGE model
4. Gives Δwelfare due to ag impacts at different levels of warming
5. Replace agricultural damages from FUND with new estimates to get SCC

Punchline: Improving damage function in Ag alone leads overall SCC to double.

Global Trade Analysis Project (GTAP)

Global Trade Analysis Project (GTAP): static general equilibrium model that tracks bilateral trade flows between countries and models consumption + production.

- Producers are assumed to maximize profits; consumers maximize utility.
- Factor market clearing: supply = demand for ag + non-ag skilled + unskilled labor and capital, natural resources, and ag land
- Market adjustments in response to the climate change shocks determines resulting wage + rental rate impacts

Healthy amount of skepticism amongst modern empirical researchers re: GTAP

- Hundreds of equations / parameters without much in the way of identification

Moore, Baldos, Hertel, Diaz (2017)

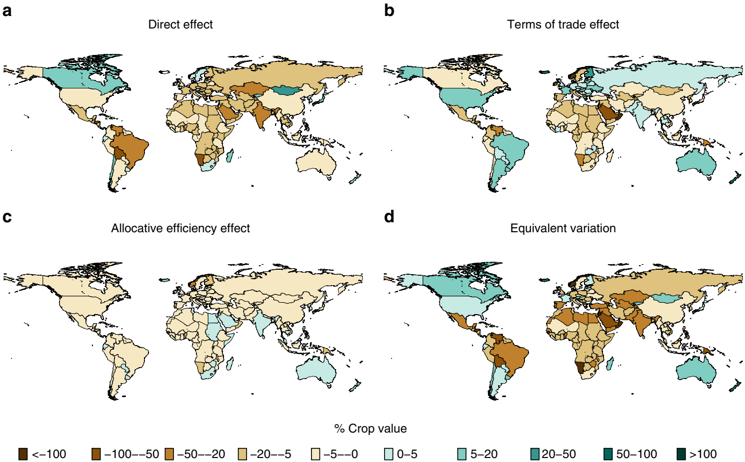


Fig. 2 Welfare changes from 3 °C of global average warming. Changes are relative to a 1995–2005 global average baseline and use yield changes based on the meta-analysis results shown in Fig. 1: **a** the direct technical effect of climate change on agricultural productivity; **b** terms of trade effects; **c** the allocative efficiency effect; and **d** total welfare change reported as equivalent variation. Results are based on yield changes that include adaptation and the CO_2 fertilization effect for C_3 crops but not for maize. Welfare changes are normalized by the value of production of the affected crops (maize, rice, wheat, and soybeans)

Moore, Baldos, Hertel, Diaz (2017)

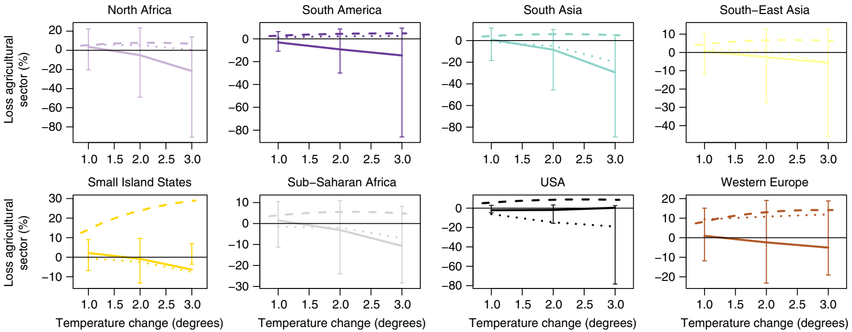


Fig. 3 Three agriculture-sector damage functions for each of the 16 FUND regions. Solid lines are from meta-analysis results, dotted lines are AgMIP results, and dashed lines are the existing FUND damage functions. Error bars show the damage functions based on the 2.5th and 97.5th quantiles of the meta-analysis results. Temperature changes are global averages and are relative to a global average 1995–2005 baseline. A version of the figure excluding error bars, which allows differences in the point-estimates to be more easily distinguished, is given in Supplementary Fig. 12

Moore, Baldos, Hertel, Diaz (2017)

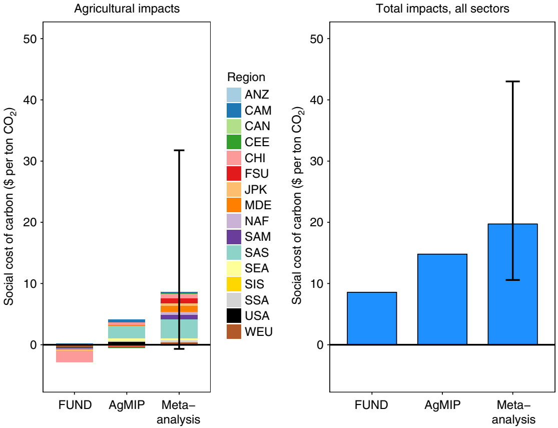


Fig. 4 Changes in the social cost of carbon resulting from new damage functions in the agricultural sector. **a** Agricultural impacts only, decomposed by geographic region (see Supplementary Table 4 for region definitions). **b** The total social cost of carbon (SCC), keeping damages in all non-agricultural sectors fixed. Results are based on a business-as-usual emissions scenario and a 3% discount rate. Uncertainty bars give the SCC resulting from the 95% confidence interval of yield response parameter estimates from the meta-analysis

Reconciling Results

Costinot, Donaldson, and Smith (2016): Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World

- Develop model of ag markets designed to capture where crops are produced, how shocks affect supply/prices, and how changes in productivity and prices map into consumption and welfare changes
- Much more parsimonious than GTAP - the key parameters to estimate:
  1. elasticity of substitution between different varieties of the same crop;
  2. the elasticity of substitution between different crops;
  3. extent of within-field heterogeneity in productivity
- Impact of climate change on agriculture $\approx$ 0.26 percent reduction in global GDP (when trade and production patterns are allowed to adjust).
- Findings in Moore, Baldos, Hertel, Diaz (2017) quite a bit larger

Why is the existing literature crappy, nonexistent, and/or unresolved?