

Climate Change: Damages and Adaptation

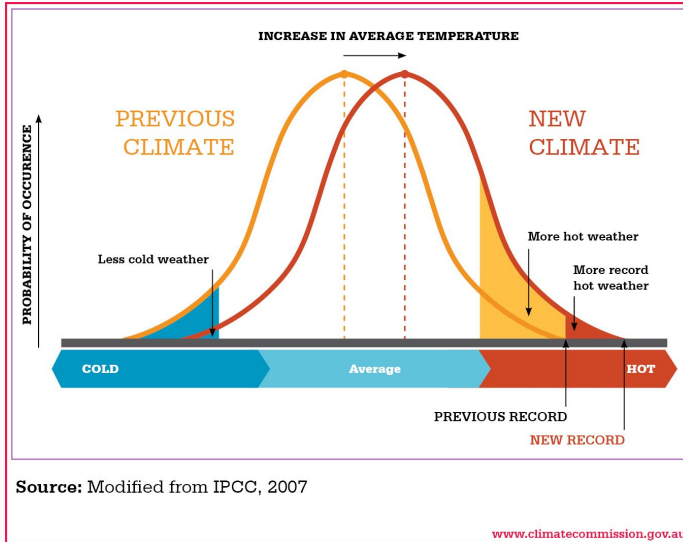
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Motivation

From Shocks to Shifts



Outline for Today

- Background on Integrated Assessment Models and the Social Cost of Carbon
- Focus on the Damage Function and Adaptation
 - Temperature, Mortality, Crop Yields
- Trade, Migration, and Adaptation Frictions
 - The Food Problem
 - Conflict

A Nobel for Climate Economics

William D. Nordhaus won the 2018 Nobel 'for integrating climate change into long-run macroeconomic analysis'



Climate change: The Ultimate Challenge for Economics*

Prize Lecture, December 8, 2018 by
William D. Nordhaus
Yale University, USA.

A Nobel for 26 lines of code

The Entire DICE Model:

```
$ontext
This is the beta version of DICE-2016R2.
$offtext
...
** Equations of the model
**Emissions and Damages
eqeq(t)..      E(t)      =E= EIND(t) + etree(t);
eindeq(t)..    EIND(t)   =E= sigma(t) * YGROSS(t) * (1-(MIU(t)));
ccacca(t+1)..  CCA(t+1)  =E= CCA(t) + EIND(t)*5/3.666;
ccatoteq(t)..  CCATOT(t) =E= CCA(t)+cumetree(t);
force(t)..     FORC(t)   =E= fco22x*((log((MAT(t)/588.000))/log(2)))+forcoth(t);
damfraceq(t).. DAMFRAC(t) =E= (a1*TATM(t))+(a2*TATM(t)*TATM(t));
dameq(t)..     DAMAGES(t) =E= YGROSS(t) * DAMFRAC(t);
abateeq(t)..   ABATECOST(t) =E= YGROSS(t) * cost1(t) * (MIU(t)**expcost2);
mcbateeq(t)..  MCABATE(t) =E= pbacktime(t) * MIU(t)**(expcost2-1);
carbprceeq(t).. CPRICE(t) =E= pbacktime(t) * (MIU(t))**(expcost2-1);

**Climate and carbon cycle
mmat(t+1)..    MAT(t+1)   =E= MAT(t)*b11 + MU(t)*b21 + (E(t)*(5/3.666));
mml(t+1)..     ML(t+1)    =E= ML(t)*b33 + MU(t)*b23;
mmu(t+1)..     MU(t+1)    =E= MAT(t)*b12 + MU(t)*b22 + ML(t)*b32;
tatmeq(t+1)..  TATM(t+1) =E= TATM(t) + c1 * ((FORC(t+1)-(fco22x/t2xco2)*TATM(t))-(c3*(TATM(t)-TOCEAN(t))));
toceaneq(t+1).. TOCEAN(t+1) =E= TOCEAN(t) + c4*(TATM(t)-TOCEAN(t));

**Economic variables
ygrosseq(t)..  YGROSS(t)  =E= (al(t)*(L(t)/1000)**(1-GAMA))*(K(t)**GAMA);
yneteq(t)..    YNET(t)    =E= YGROSS(t)*(1-damfrac(t));
yy(t)..        Y(t)       =E= YNET(t) - ABATECOST(t);
cc(t)..        C(t)       =E= Y(t) - I(t);
cpce(t)..      CPC(t)     =E= 1000 * C(t) / L(t);
seq(t)..       I(t)       =E= S(t) * Y(t);
kk(t+1)..      K(t+1)     =E= (1-dk)**tstep * K(t) + tstep * I(t);
rieq(t+1)..    RI(t)      =E= (1+prstp) * (CPC(t+1)/CPC(t))**(elasmu/tstep) - 1;

**Utility
cemutotperek(t).. CEMUTOTPER(t) =E= PERIODU(t) * L(t) * rr(t);
periodueq(t)..  PERIODU(t) =E= ((C(T)*1000/L(T))**(1-elasmu)-1)/(1-elasmu)-1;
util..         UTILITY    =E= tstep * scale1 * sum(t, CEMUTOTPER(t)) + scale2;
```

Integrated Assessment Models and the SCC

Key Components:

- Environment affects humans
- Humans affect the environment
- Humans optimize (respond to incentives) and are forward looking
- Environment evolves over time

Why?

- A 'social cost of carbon'
 - What is the NPV of the damages associated with emitting 1 ton of GhG
- An optimal carbon tax: the SCC on the optimal emissions trajectory
- Why might they differ?

Nordhaus' Critics:

- Ehrlich - Limits to Growth
 - Neo-Malthusians - infinite growth in a world of finite resources will lead to population collapse
- Stern - Discounting
 - Nordhaus used a 7% discount rate based on market interest rates - leads to small effects of climate change in the future
 - Stern took an 'ethical' perspective arguing for discount rates closer to 2%
- Weitzman - Uncertainty/Tipping Points
 - The Dismal Theorem: If uncertainty from climate damages is fat-tailed, SCC is infinite.

It is threatening for us economists to admit that constructive “can do” climate change BCA may be up against some basic limitations on the ability of quantitative analysis to yield robust policy advice. But if this is the way things are with the economics of climate change, then this is the way things are. Nonrobustness to subjective assumptions about catastrophic outcomes is an inconvenient truth to be lived with rather than a fact to be denied or evaded just because it looks less scientifically objective in BCA.

What we can do constructively as economists is to better explain both the magnitudes of the unprecedented structural uncertainties involved and why this feature limits what we can say... At the end of the day, policy makers must decide what to do on the basis of an admittedly sketchy economic analysis of a gray area that just cannot be forced to render clear robust answers... Economists should not pursue a narrow, superficially crisp, analysis by blowing away the low-probability, high impact catastrophic scenarios... marginalizing the very possibilities that make climate change so grave in the first place.

State of the art models feature:

- Tipping Points and Natural Disasters - Cai and Lontzek (2019 JPE), Nordhaus (2019 PNAS),
- Inequality, heterogeneity, other market failures - Dennig et al (2015 PNAS), Fried (2022 Restud)
- Political Economy - Harstad (2016 JPE), Nordhaus (2015 AER)
- Spatial Heterogeneity with migration, trade, and technological change - Cruz and Rossi-Hansberg (2024 Restud)

Lots of computational power

Recent Progress in IAMs and the SCC

- 1992: Nordhaus DICE model shows optimal carbon tax of \$5
- 2009-2013: Obama Interagency Working Group (\$45 in 2020)
- 2020: Trump Administration lowers to \$1
 - Exclude damages outside the US
 - 7% discount rate
- 2024: Biden Administration Update (\$190 in 2020)
- 2025: ???

OMB Circular A-4: how to count costs and benefits

Key Updates to BCA

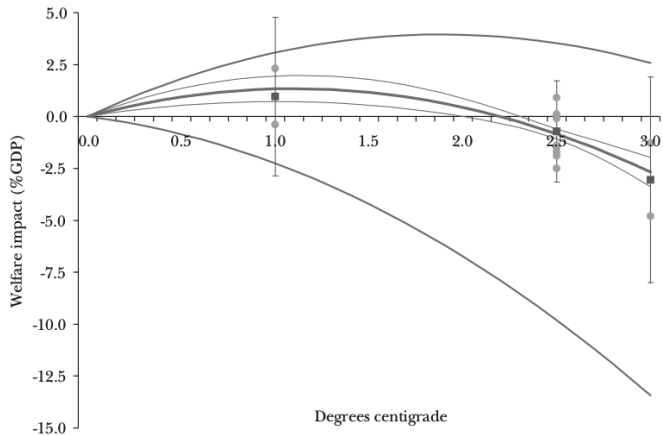
- Discounting
- Distributional Analysis
- Benefits outside of US
- Non-market valuation



The Nordhaus-Tol Damage Function

Figure 1

Fourteen Estimates of the Global Economic Impact of Climate Change



The New SCC

The New SCC:

- Moving away from IAMs to separate modules
- Bottom up damage functions (based on what we'll cover today)
- Move towards cost effectiveness rather than optimal carbon price

Key Uncertainties:

- Discount rate (still)
- How to value mortality across countries
- How to value natural capital

Table 2.3.1: Current Coverage of Climate Damages in DSCIM

Sector	Damage Categories Represented	Empirical Basis for Damage Function Estimation	Accounting for Adaptation	Documentation
Health	Heat- and cold-related mortality	Subnational annual mortality statistics for 40 countries covering 38% of global population; 1990-2010 or longer for most countries	Accounts for adaptive effects of income growth and estimates the costs of adaptive investments using a revealed preference approach	Carleton et al. (2022)
Energy	Expenditures for electricity and other direct fuel consumption	Annual country-level energy consumption data (residential, commercial, and industrial) by energy source for 146 countries, 1971-2010	Accounts for both climate- and socioeconomics-driven adaptive responses	Rode et al. (2021)
Labor Productivity	Labor disutility costs from labor supply responses to increased temperature	Daily worker-level labor supply data (minutes worked) from 7 countries representing nearly 30% of global population	Accounts for shifts in workforce composition to less weather-exposed industries	Rode et al. (2022)
Agriculture	Production impacts for six crops: maize, rice, wheat, soybeans, sorghum, and cassava	Subnational crop production data for over 12,658 sub-national administrative units from 55 countries	Accounts for CO ₂ fertilization effects, varietal switching, changes in production methods (e.g., irrigation, fertilization, planting dates), crop switching, and trade effects	Hultgren et al. (2022)
Coastal regions	Impacts of SLR as realized through inundation, migration, protection, dry and wetland loss, and mortality and physical capital loss from SLR	Numerous empirical findings are used to parameterize the CIAM process model for 9,000 coastal segments. (Low levels of SLR in the historical record prohibit the use of a fully empirical model)	Reflects retreat or protective infrastructure and costs under an optimal adaptation scenario with perfect foresight of SLR	Kopp et al. (2016) and Garner et al. (2021) for SLR; Diaz (2016) and Depsky et al. (2022) for damages

Damages - Adaptation

How to estimate the effects of climate change?

Two basic approaches:

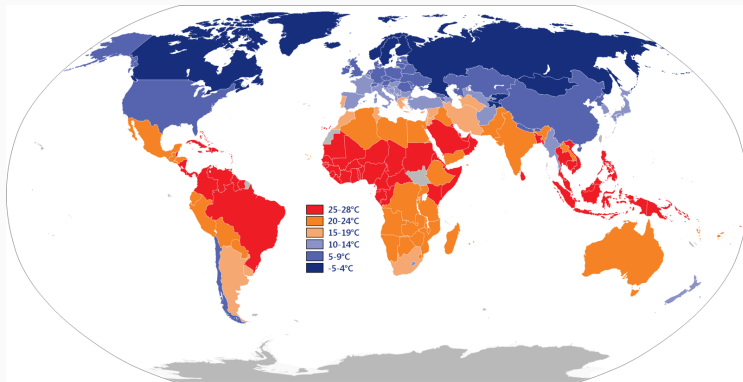
$$Y_i = f(\bar{T}_i) + e_i \quad (1)$$

vs:

$$Y_{it} = f(T_{it}) + \mu_i + e_{it} \quad (2)$$

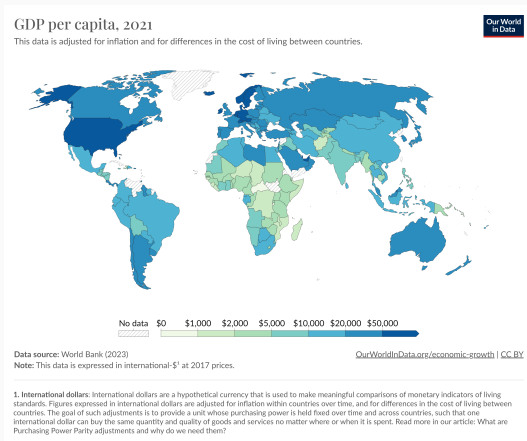
Effects of Average Temperature

$$Y_i = f(\bar{T}_i) + e_i \quad (3)$$



Effects of Average Temperature

$$Y_i = f(\bar{T}_i) + e_i \quad (3)$$



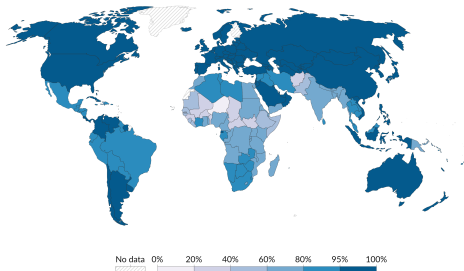
Effects of Average Temperature

$$Y_i = f(\bar{T}_i) + e_i \quad (3)$$

Literacy rate, 2017

The share of adults aged 15 and older who can both read and write.

Our World
in Data



Data source: WDI, CIA World Factbook, & other sources

OurWorldInData.org/literacy | CC BY

Note: Specific definitions and measurement methodologies vary across countries and time. See the 'Sources'-tab for more details.

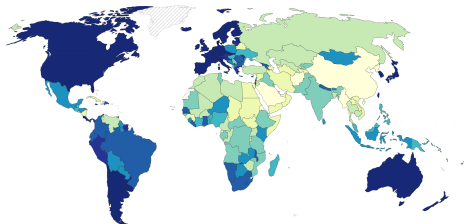
Effects of Average Temperature

$$Y_i = f(\bar{T}_i) + e_i \quad (3)$$

Electoral democracy index, 2022

Based on the expert assessments and index by V-Dem¹. It captures to which extent political leaders are elected under comprehensive voting rights in free and fair elections, and freedoms of association and expression are guaranteed. It ranges from 0 to 1 (most democratic).

Our World
in Data



Data source: V-Dem (2023)

OurWorldInData.org/democracy | CC BY

1. V-Dem: The Varieties of Democracy (V-Dem) project publishes data and research on democracy and human rights. It relies on evaluations by around 3,500 country experts and supplementary work by its own researchers to assess political institutions and the protection of rights. The project is managed by the V-Dem Institute, based at the University of Gothenburg in Sweden. Learn more: Democracy data: how do researchers measure democracy? The 'Varieties of Democracy' data: how do researchers measure democracy? The 'Varieties of Democracy' data: how do researchers measure human rights?

Effects of Temperature Shocks

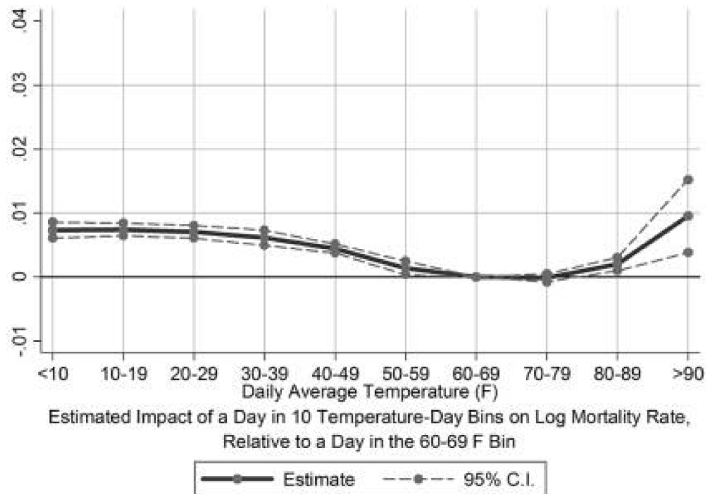
Barreca et al (2016) JPE basically estimate a version of (2) above with a few modifications:

$$\log(Y_{sym}) = \sum_j \theta_j T_{symj} + X_{sym}\beta + \alpha_{sm} + \rho_{ym} + e_{ysm} \quad (4)$$

- Semi-parametric approach to temperature - number of days in a month in a certain degree range
- Time varying controls for precipitation and population age structure
- State seasonal fixed effects and national month fixed effects

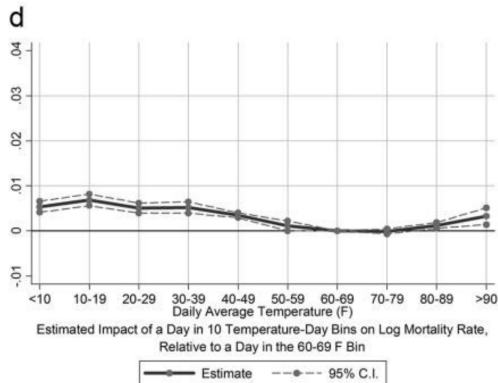
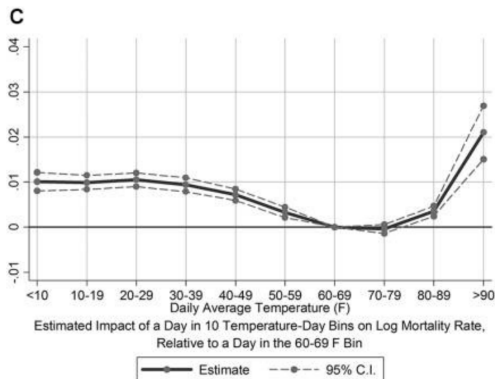
Barecca et al Results

High and Low Temps Increase Mortality



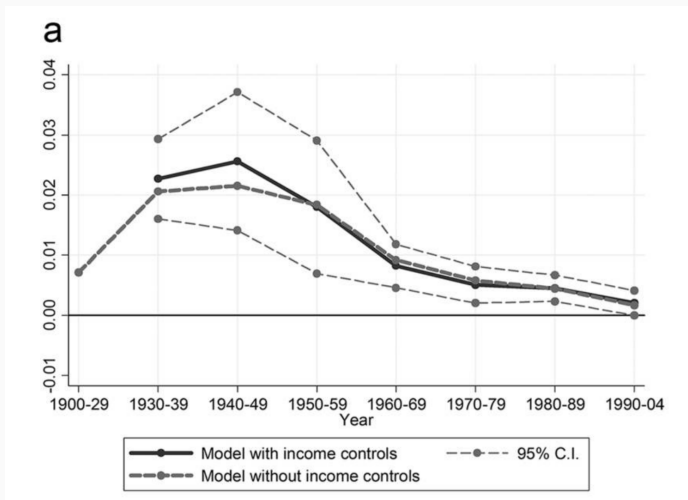
Barecca et al Results

On the left - effects before 1960, on the right - after 1960



Barecca et al Results

The effect of a hot day on mortality over time

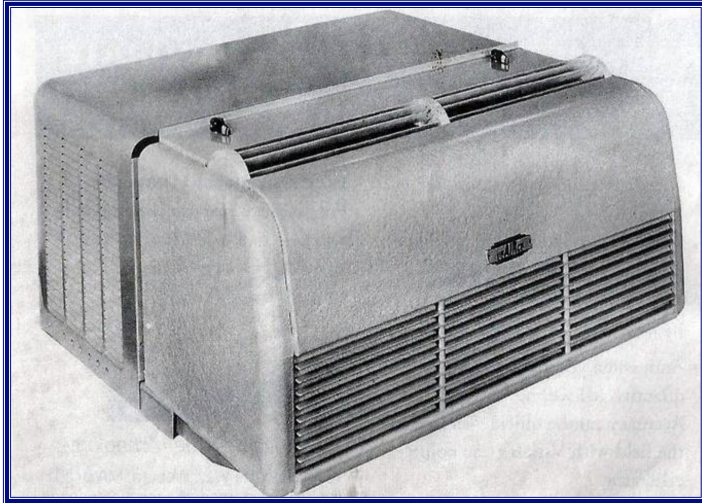


Adaptation and Innovation



De La Vergne room air conditioning unit, mid-1930s

Adaptation and Innovation



Window air conditioning unit by US Air Conditioning Corporation, c.1950

TABLE 8
ROBUSTNESS ANALYSIS OF THE EFFECT OF RESIDENTIAL AIR CONDITIONING
ON THE TEMPERATURE-MORTALITY RELATIONSHIP, 1960–2004

	(1)	(2)	(3)	(4)	(5)
Number of days above 90°F × share with residential AC	−.0212*** (.0054)	−.0212*** (.0055)	−.0343* (.0139)	−.0376*** (.0065)	−.0264** (.0088)
Number of days between 80°F and 89°F × share with residential AC	−.0048*** (.0010)	−.0048*** (.0010)	−.0060** (.0020)	−.0041** (.0013)	−.0013 (.0011)
Number of days below 40°F × share with residential AC	−.0004 (.0009)	−.0003 (.0009)	.0038 (.0024)	.0016 (.0014)	−.0010 (.0012)
Baseline controls	Yes	Yes	Yes	Yes	Yes
State-month cubic time trends	No	Yes	No	No	No
2-year window around census years	No	No	Yes	No	No
Temperature × year trends	No	No	No	Yes	No
Exposure window = 4 months	No	No	No	No	Yes
Observations	26,411	26,411	4,655	26,411	26,313

- This is essentially about the external validity of a reduced form result
- We use relationships estimated from historical data to project the effects of policy into the future
- but if something outside the model changes, then the relationship of interest can change too
- But adaptation not always smooth...

Annan and Schlenker (2015) Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat.

- Crop yields respond to extreme temperatures
- Lots of innovation in drought resistant crops, irrigation technologies, should mitigate this relationship over time...
- ...if there is an incentive for farmers adopt

Annan and Schlenker (2015) Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat.

- Farmers buy crop insurance against weather fluctuations
- If an insurer can see who is adopting better technologies, they can give them cheaper policies
- If not, then we are in a very similar setting as the Wagner flood insurance paper we discussed last time

$$\log Yields_{it} = \beta_1 W_{it} + \beta_2 W_{it} f_{it} + \gamma f_{it} + \alpha_i + \delta_t + g_i(t) + e_{it} \quad (5)$$

- Similar to what we just saw - county and year fixed effects (this time with a time trend)
- Again, W is vector of binned weather degree day variables
- Interacting weather with level of insurance coverage

Annan and Schlenker Results

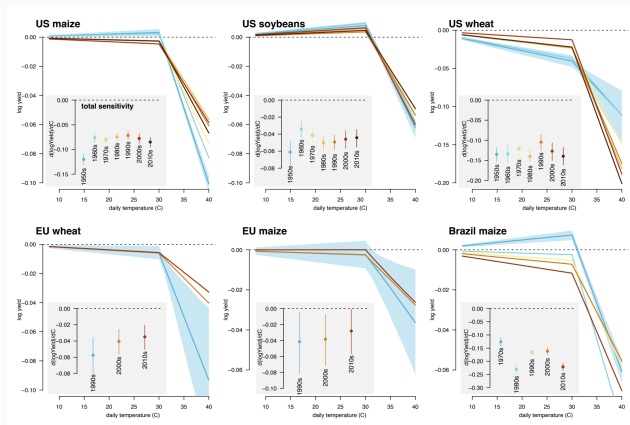
TABLE 1—REGRESSION RESULTS

	Corn		Soybeans	
	(1a)	(1b)	(2a)	(2b)
Moderate heat	0.398*** (0.139)	0.401*** (0.148)	0.577*** (0.088)	0.542*** (0.098)
× fraction insured		−0.006 (0.109)		0.113 (0.086)
Extreme heat	−0.476*** (0.053)	−0.369*** (0.054)	−0.623*** (0.053)	−0.526*** (0.052)
× fraction insured		−0.249*** (0.092)		−0.228** (0.095)
Precipitation	0.896*** (0.225)	1.584*** (0.320)	1.443*** (0.232)	1.661*** (0.307)
× fraction insured		−1.590** (0.679)		−0.473 (0.445)
Precipitation squared	−0.643*** (0.179)	−1.038*** (0.212)	−0.937*** (0.159)	−1.027*** (0.223)
× fraction insured		0.917* (0.520)		0.186 (0.317)
R^2	0.2246	0.2363	0.3232	0.3260
Observations	39,702	39,702	34,958	34,958
Counties	1,717	1,717	1,505	1,505

How widespread are adaptation frictions?

Burke et al - Are We Adapting to Climate Change?

- Same approach as Barecca et al with a bunch of outcome variables



Are We Adapting to Climate Change?

	outcome	period	exposure	Δ Total sensitivity (%/yr)
Agriculture	US maize	1950–2019	+1°C growing season	-0.5
	US soybeans	1950–2019	+1°C growing season	-0.1
	US wheat	1950–2019	+1°C growing season	-0.1
	EU wheat	1990–2019	+1°C growing season	-1.9
	EU maize	1990–2019	+1°C growing season	-2.3
	Brazil soy	1970–2019	+1°C growing season	2.3
	Brazil maize	1970–2019	+1°C growing season	0.8
	India wheat	1990–2019	+1°C growing season	-0.7
Mortality	Global Ag TFP	1960–2019	+1°C growing season	0.2
	US mortality – temperature	1968–2019	+1°C monthly	-0.7
	EU mortality – temperature (annual)	1990–2019	+1°C annual	-5.3
	EU mortality – temperature (weekly)	2000–2019	+1°C weekly	-7.4
Output	US mortality – cyclones	1952–2015	+1 m/s wind speed	4.8
	Global GDP – temperature	1961–2019	+1°C annual	-0.0
	US income – temperature	1968–2019	+1°C annual	-0.5
	Global GDP – cyclones	1965–2019	+1 m/s wind speed	1.3
Violence	US damages – floods	1988–2017	+1sd monthly rainfall	0.4
	African conflict	1989–2019	+1°C annual	3.4
	US violent crime	1980–2019	+1°C monthly	-1.3
	US injury mortality	1968–2019	+1°C monthly	-2.4
	US suicide	1968–2019	+1°C monthly	0.6

Key: p-value, change==0

<0.01 <0.05 <0.1 >0.1



Carleton et al (2022)

- Global study with 24,000 regions - 40 countries, 38% of global population
- Going to try to account for not just adaptation effects on mortality but also costs of adaptation – heterogeneity by long-run climate and income
- Result will be a ‘partial’ SCC – accounts for mortality costs

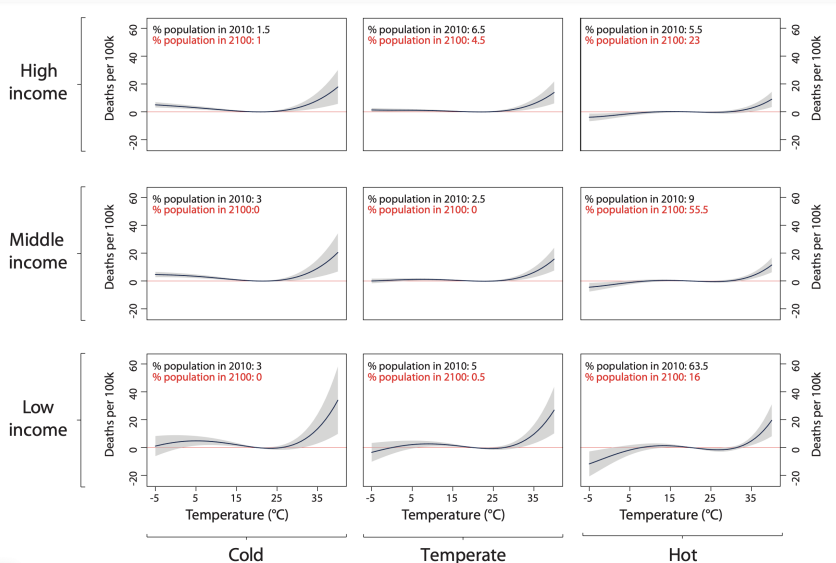
Estimating Equation

$$M_{acit} = g_a(T_{it}, Climate_i, Income_{it}) + q_{ca}(R_{it}) + \alpha_{ai} + \delta_{act} + e_{ait} \quad (6)$$

- Age-country-year and age-region FEs
 - Note that average effect of climate, income is captured by α_{ai} .
- R: second order polynomial of precipitation, interacted with country and age group dummies
- T: fourth order polynomial of daily average temps, interacted with log GDP and mean temps

So what is the identifying variation?

Results: Adaptation by Income and Climate



Projecting into the Future

Now we can use projections of future income and climate to look at adaptation

Mortality Cost of Climate Change:

$$\Delta M_{it} = g(T_{it}, Climate_{it}, Income_{it}) - g(T_{i0}, Climate_{i0}, Income_{it}) \quad (7)$$

Without Adaptation:

$$\Delta M_{it} = g(T_{it}, Climate_{i0}, Income_{it}) - g(T_{i0}, Climate_{i0}, Income_{it}) \quad (8)$$

Without Adaptation or Income Growth:

$$\Delta M_{it} = g(T_{it}, Climate_{i0}, Income_{i0}) - g(T_{i0}, Climate_{i0}, Income_{i0}) \quad (9)$$

(10)

What assumptions does this require?

- Spatial Extrapolation: Need estimates in regions without mortality data
 - Assume that estimated relationship can be extrapolated to these other regions
 - They do cross-validation
- Temporal Extrapolation: In future, climate change will put average temperature outside support of data
 - Put constraints on estimated projections to make sure they are sensible
- Monte Carlo across climate and income projections, as well parameter standard errors to estimate uncertainty

Extrapolations

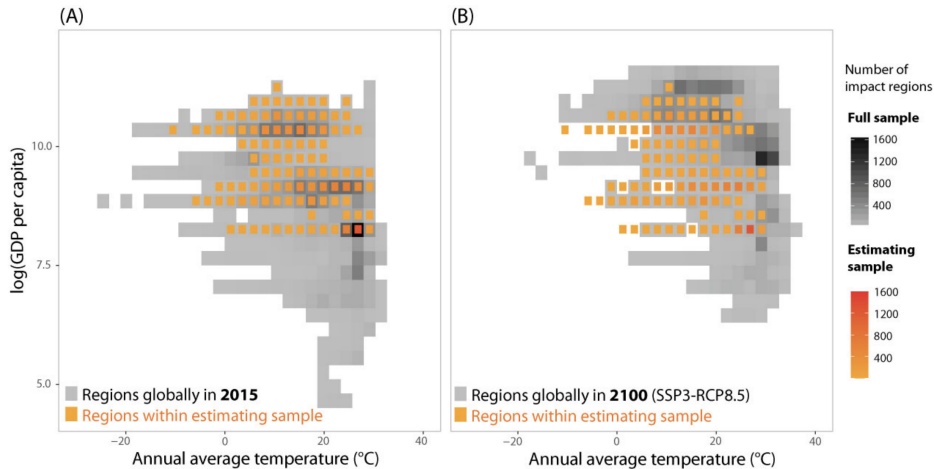


FIGURE II

Joint Coverage of Income and Long-Run Average Temperature for Estimating and Full Samples

Extrapolations: Spatial

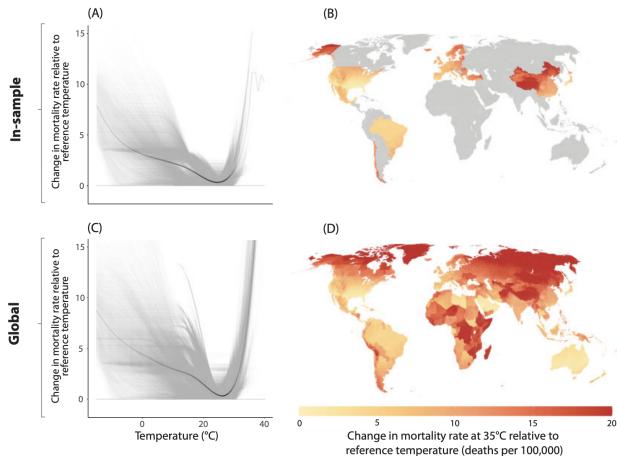


FIGURE III

Using Income and Climate to Predict Current Response Functions Globally (Age > 64 Mortality Rate)

Extrapolations: Temporal

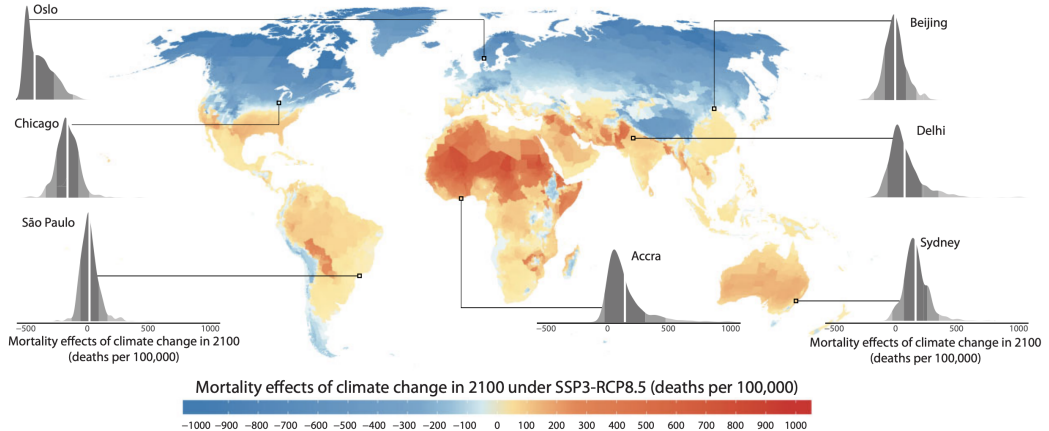


FIGURE IV

The Mortality Effects of Future Climate Change

Importance of Adaptation

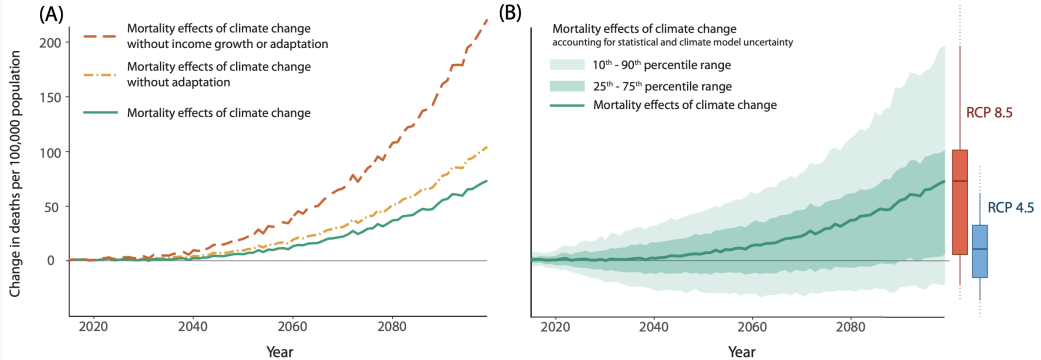


FIGURE V
Time Series of Projected Mortality Effects of Climate Change

But Adaptation also has Costs...

A = adaptation costs, b = behaviors, f = mortality

$$\underbrace{\frac{dA}{db}}_{\text{Adaptation Costs}} = -VSL \underbrace{\frac{df}{db}}_{\text{Reduction in Mortality}} \quad (11)$$

Going to infer adaptation from differential responses to T in places with different climates

- Effect of a hot day in Seattle is much greater than Houston (Houston has AC)

$$\frac{dA}{db} = -VSL \frac{dE[g]}{dClimate} \quad (12)$$

Sum these marginal changes over time following climate projections

- VSL is also a function of income, so increases over time

The Mortality Costs of Climate Change

GLOBAL AND REGIONAL ESTIMATES OF THE FULL MORTALITY RISK OF CLIMATE CHANGE IN 2100 (HIGH-EMISSIONS SCENARIO, RCP8.5)

	No income growth or adaptation	Benefits of income growth	Benefits of climate adaptation	Mortality effects of climate change	Costs of climate adaptation	Full mortality risk of climate change	
	Eq. (2a') deaths/100k (1)	Eq. (2b')–Eq. (2a') deaths/100k (2)	Eq. (2')–Eq. (2b') deaths/100k (3)	Eq. (2') deaths/100k (4)	Eq. (7) deaths/100k (5)	Eq. (3') deaths/100k (6)	% of GDP (7)
<i>Panel A: Global estimates</i>							
Mean effects	220.6	–116.5	–31.0	73.1	11.7	84.8	3.2
Full uncertainty IQR	[76.4, 258.8]	[–149.4, –39.2]	[–60.1, 3.8]	[5.6, 101.4]	[0.2, 19.4]	[17.4, 116.4]	[–5.4, 9.1]
<i>Panel B: Regional estimates</i>							
China	112.0	–81.8	–28.8	1.4	17.7	19.1	1.9
United States	14.8	–13.2	–1.8	–0.2	10.2	10.1	1.0
India	334.4	–248.2	–25.6	60.6	2.1	62.7	6.0
Pakistan	589.1	–161.7	–105.0	322.4	53.6	376.0	27.5
Bangladesh	382.5	–89.3	–79.3	213.8	34.7	248.5	18.5
Europe	–14.3	–6.2	–74.8	–95.5	90.8	–4.7	0.1
Sub-Saharan Africa	232.5	–77.4	–34.5	121.3	10.5	131.8	8.4

A Partial SCC

Need to estimate costs per unit of emissions, and a discount rate

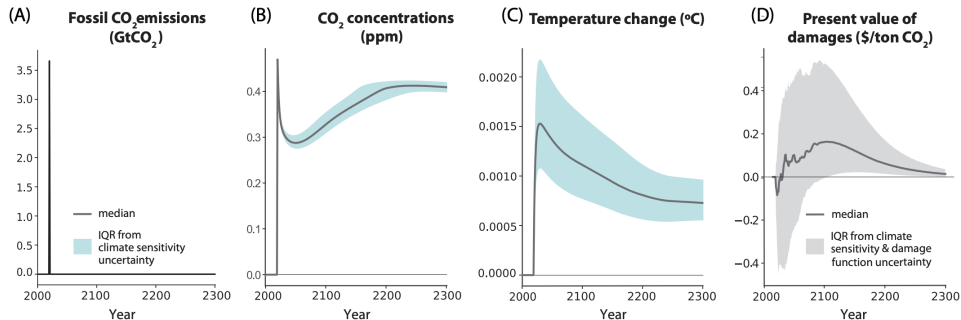


FIGURE VIII

Change in Emissions, Concentrations, Temperature, and Damages Due to a Marginal Emissions Pulse in 2020

TABLE III
ESTIMATES OF THE MORTALITY PARTIAL SOCIAL COST OF CARBON (SCC)

	Annual discount rate			
	$\delta = 1.5\%$ (1)	$\delta = 2\%$ (2)	$\delta = 3\%$ (3)	$\delta = 5\%$ (4)
<i>Panel A: Mortality partial SCC</i>				
Moderate-emissions scenario (RCP4.5)	28.5	17.1	7.9	2.9
Full uncertainty IQR	[-35.6, 88.5]	[-24.7, 53.6]	[-15.2, 26.3]	[-8.5, 11.5]
High-emissions scenario (RCP8.5)	66.4	36.6	14.2	3.7
Full uncertainty IQR	[-2.8, 126.5]	[-7.8, 73.0]	[-11.4, 32.9]	[-8.9, 13.0]
<i>Panel B: Alternative approaches to calculating the mortality partial SCC</i>				
Excluding adaptation costs (RCP8.5)				
Central estimate	66.9	37.7	15.1	4.1
Full uncertainty IQR	[-3.1, 114.6]	[-6.7, 66.4]	[-9.6, 29.8]	[-8.2, 11.5]
Accounting for risk aversion (RCP8.5)				
Central estimate (risk neutral)	88.4	47.7	17.2	3.7
Certainty equivalent (risk averse)	375.3	192.4	59.2	8.6

Takeaways

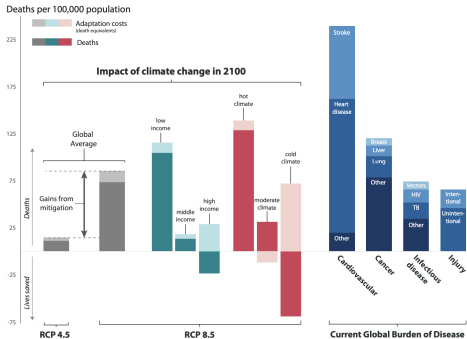


FIGURE IX

The Mortality Effects of Climate Change in 2100 are Comparable to Contemporary Leading Causes of Death

- Not significantly different from zero!
- Right skewed
- Still many limitations

Trade and Migration

Other Margins of Adaptation: Trade and Migration

Why might we want a quantitative spatial model of global warming?

- Damages from climate change heterogeneous across space
- If regions can reallocate through trade and migration, this could mitigate damages
- Costinot, Donaldson, Smith (2016) covered in last class

Cruz and Rossi-Hansberg - The Economic Geography of Global Warming

- A spatial IAM covering the world at 1 degree x 1 degree grid cell resolution
- Multiple margins of adaptation: trade, migration, innovation

Cruz and Rossi Hansberg: Ingredients

- Local Production (requires labor, land, and energy) and Consumption (one good per region plus location specific amenities)
- Endogenous population growth
- Trade, Migration, Innovation and Diffusion, Agglomeration
- Clean and carbon based energy inputs with imperfect substitutability
- Cost of fossil fuel extraction and clean energy changing over time
- Global carbon cycle → local temperatures
- Temperatures damage productivity and amenities

The Economic Geography of Global Warming

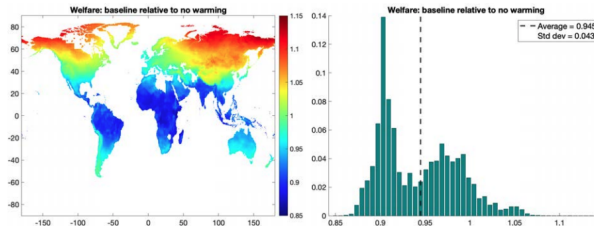


Figure 8: Welfare losses due to global warming.

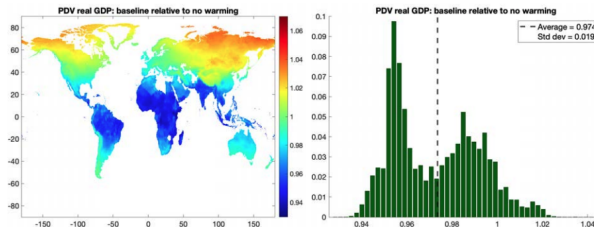


Figure 9: Real GDP losses due to global warming.

Diff in Diff: Benefits of Adaptation Technology =

$$\Delta W(\Delta T, \text{Adaptation}) - \Delta W(\Delta T, \text{No Adaptation}) \quad (13)$$

- Increase migration costs by 25% increases damages from climate change by 33%
- Increasing trade costs much more minor
- More innovation (lower costs of innovating) actually *increases* the damages of global warming
 - Destination regions in global north benefit less from migration when agglomeration forces are lower (and origin regions are hurt less by population outflows)
 - Overall welfare is lower, but the difference with climate change is smaller

Friction 1: Trade and the 'food problem'?

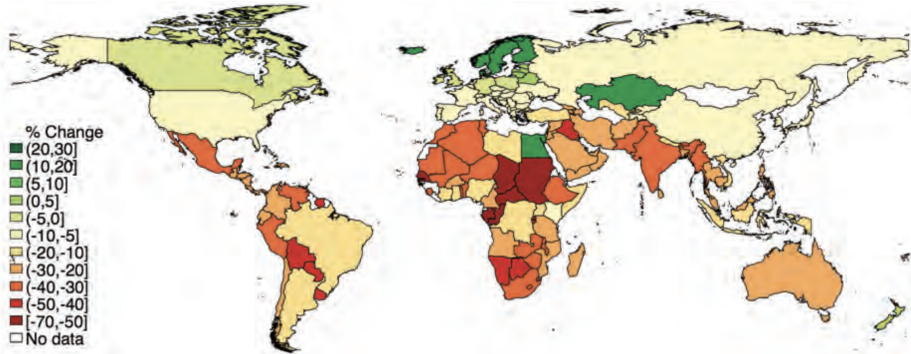
Nath - The Food Problem and the Aggregate Productivity Consequences of Climate Change

Trade is beneficial for adaptation if:

1. Climate damages are heterogeneous
2. Regions can specialize in their comparative advantage

Climate damages are heterogeneous:

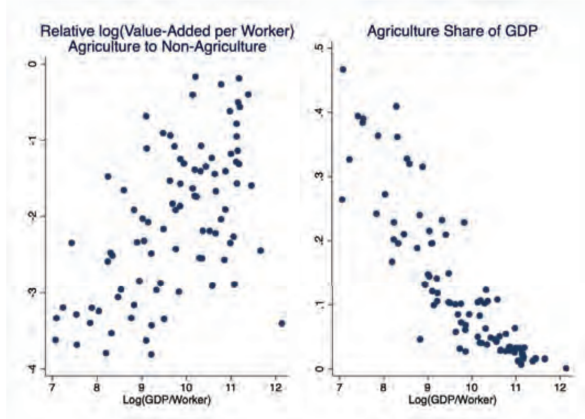
Figure 1: Cline (2007) Projected Impact of Climate Change on Agricultural Productivity, 2080-2099



Notes: Figure shows the projected change in revenue per acre from producing grains, vegetables, fruits, and livestock according to analysis by Cline (2007).

Comparative advantage and the 'food problem'

Figure 2: Comparative Advantage and Specialization in Agriculture



Notes: Figure shows data from Tombe (2015) that adjusts for prices for the global cross-section in 2005. Poor countries specialize heavily in agriculture despite low productivity relative to other sectors.

Non-homothetic Preferences

A key ingredient in models of structural transformation:

$$U = \left(\sum_{i \in \{a, m, s\}} \alpha_i^{\frac{1}{\sigma}} C_i^{\frac{\sigma-1}{\sigma}} I^{\frac{e_i}{\sigma}} \right)^{\sigma} \quad (14)$$

Ratio of expenditure between agriculture and manufacturing:

$$\frac{X_a}{X_m} = \frac{p_a C_a}{p_m C_m} = \left(\frac{\alpha_a}{\alpha_m} \right)^{\frac{1}{\sigma}} \left(\frac{P_a}{P_m} \right)^{1-\sigma} I^{\frac{e_a - e_m}{\sigma}} \quad (15)$$

Notice that if $e_a = e_m$ this does not depend on income.

- If $\sigma = 1$ (Cobb-Douglas): $\alpha_i = X_i$
- If $\sigma < 1$ (low substitution): $\uparrow P_i$ leads to $\uparrow X_i$

Non-homothetic Preferences

A key ingredient in models of structural transformation:

$$U = \left(\sum_{i \in \{a, m, s\}} \alpha_i^{\frac{1}{\sigma}} C_i^{\frac{\sigma-1}{\sigma}} l_i^{\frac{e_i}{\sigma}} \right)^{\sigma} \quad (14)$$

Expenditure share on sector i :

$$X_i = \frac{p_i C_i}{I} = \alpha_i^{1/\sigma} \left(\frac{P_i}{\mathbf{P}} \right)^{1-\sigma} \left(\frac{l_i}{\mathbf{P}} \right)^{e_i - (1-\sigma)} \quad (15)$$

This gives us a regression equation in logs:

$$\log X_i = \frac{\log \alpha_i}{\sigma} + (1 - \sigma) \log \frac{P_i}{\mathbf{P}} + (e_i - (1 - \sigma)) \log \frac{l_i}{\mathbf{P}} \quad (16)$$

\mathbf{P} is the price index

Agriculture biased shocks

Consider this expression:

$$\log X_i = \log \alpha_i + (1 - \sigma) \log \frac{P_i}{\mathbf{P}} + (e_i - (1 - \sigma)) \log \frac{I}{\mathbf{P}} \quad (17)$$

A negative shock biased to agricultural productivity has two effects:

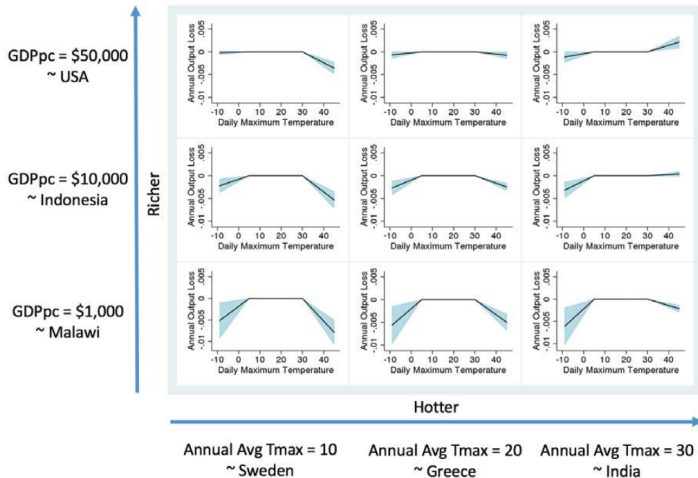
1. Increases price of agriculture relative to other goods. Consumers substitute away from ag, but expenditure share increases if $\sigma < 1$.
2. Decreases wealth - depends on sign of $e_a - (1 - \sigma)$

In contrast, production will shift away from agriculture

- Unless trade costs are too high, and food needs to be produced domestically

Effects of Climate on Manufacturing

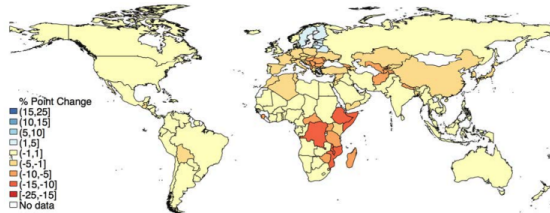
Figure 3: Predicted Heterogeneous Response of Annual Manufacturing Revenue per Worker to Daily Maximum Temperature



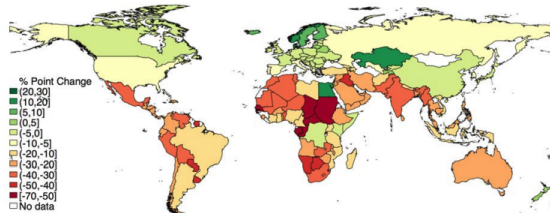
Agricultural Biased Shocks

Figure 8: Projected Impact of Climate Change on Productivity

(a) Manufacturing

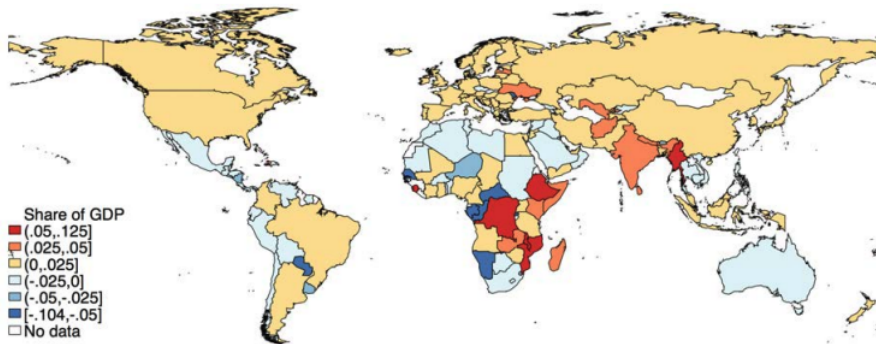


(b) Agriculture Relative to Manufacturing



Effect of Climate Change on Agriculture Share of GDP

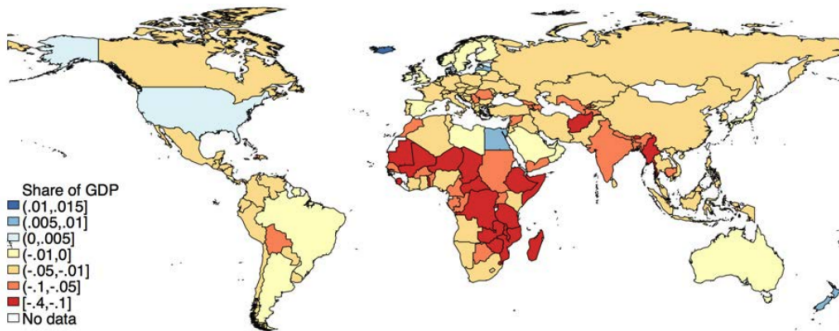
Figure 10: Projected Impact of Climate Change on Agricultural GDP Share



Notes: Map shows the model simulations of the change in the agriculture share of GDP driven by climate change.

Takeaways: Costs of climate change much higher

Figure 11: Willingness-to-Pay to Avoid Climate Change



Notes: Map shows model simulations of the willingness-to-pay to avoid the effects of climate change as a share of GDP.

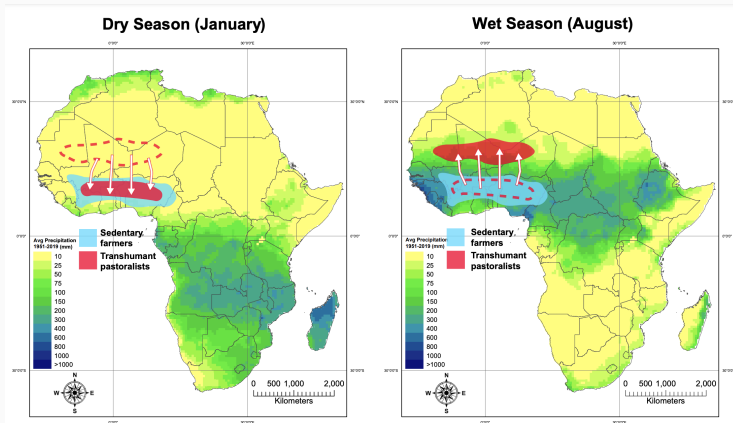
Takeaways: Trade is a much more important adaptation strategy

Table 9: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Rwanda	-.434	-.387	-.086
Central African Republic	-.428	-.356	-.037
Chad	-.25	-.226	-.032
Malawi	-.225	-.225	-.119
Zimbabwe	-.223	-.212	-.074
Zambia	-.208	-.199	-.001
Ethiopia	-.171	-.169	-.091
Sierra Leone	-.13	-.164	-.105
India	-.085	-.082	-.013
Poorest Quartile	-.092	-.088	-.029
World	-.018	-.017	-.013

Friction 2: Migration and adaptation externalities

McGuirk and Nunn - Transhumant Pastoralism, Climate Change and Conflict in Africa



(a) Rainfall and migration during the dry season.

(b) Rainfall and migration during the wet season.

Figure 1: Rainfall and seasonal migration in Africa.

McGuirk and Nunn: The Story

Stories are models too...

- Historically symbiotic relationship between transhumant pastoralists (Muslim) and sedentary agriculturalists (Christian)
 - Fertilizer for fodder
- As long as seasonal migration occurs after the harvest...

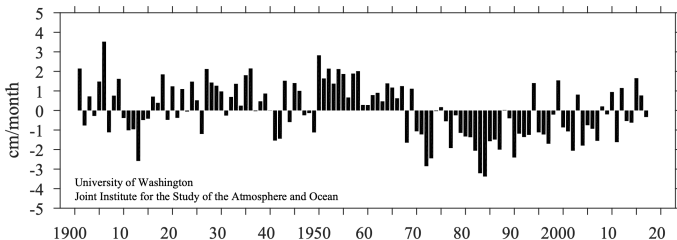


Figure 2: Climate change and historical precipitation in the Sahel. *Source:* Sahel Precipitation Index. University of Washington. June through October averages over 20°-10°N, 20°W-10°E. 1900–2017. <http://research.jisao.washington.edu/data/sahel/>

McGuirk and Nunn: The Story

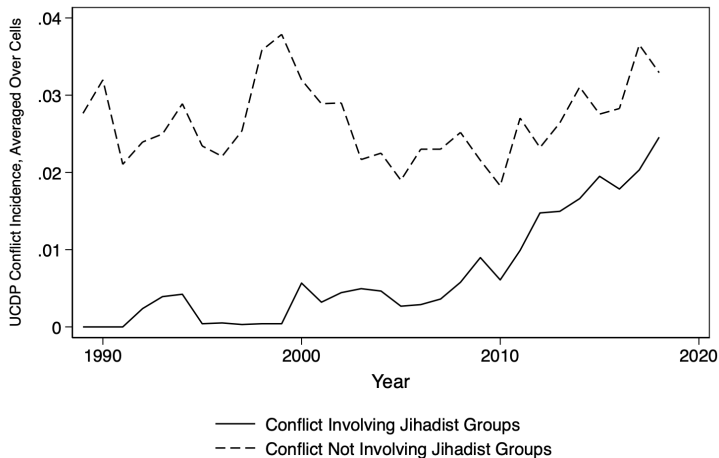


Figure 5: Total Jihadist and non-Jihadist Conflicts over Time in Africa

McGuirk and Nunn: The Story



Nigeria has seen decades of intermittent violence between Berom farmers and Fulani herders (file picture)

At least 86 people have died in central Nigeria after violent clashes broke out between farmers and cattle herders, police in Plateau state said.

$$\begin{aligned} y_{iet} = & \gamma_0^s \text{Rain}_{it}^{\text{Neighbor}} + \gamma_1^s \text{Rain}_{it}^{\text{Neighbor}} \times \text{TranshumantPastoral}_i^{\text{Neighbor}} + \\ & \gamma_2^s \text{Rain}_{et}^{\text{OwnGroup}} + \gamma_3^s \text{Rain}_{et}^{\text{OwnGroup}} \times \text{TranshumantPastoral}_e^{\text{OwnGroup}} + \\ & \gamma_4^s \text{Rain}_{it}^{\text{OwnCell}} + \gamma_5^s \text{Rain}_{it}^{\text{OwnCell}} \times \text{TranshumantPastoral}_e^{\text{OwnGroup}} + \\ & X'_{iet} \Gamma + \alpha_i^s + \alpha_{c(i)t}^s + \eta_{iet}^s \end{aligned}$$

McGuirk and Nunn: Results

	Indicator for the presence of conflict					
	UCDP			ACLED		
	(1) I(Any)	(2) I(State)	(3) I(Nonstate)	(4) I(Any)	(5) I(State)	(6) I(Nonstate)
<u>Nearest Neighboring Ethnic Group</u>						
Rain [γ_0^d]	-0.0005 (0.0006)	0.0001 (0.0006)	-0.0005 (0.0005)	-0.0007 (0.0011)	0.0004 (0.0009)	-0.0008 (0.0011)
Rain \times Transhumant Pastoral [γ_1^d]	-0.0110*** (0.0033)	-0.0121*** (0.0031)	-0.0012 (0.0021)	-0.0096** (0.0038)	-0.0092*** (0.0035)	-0.0096** (0.0038)
<u>Own Ethnic Group</u>						
Rain [γ_2^d]	0.0001 (0.0010)	0.0014 (0.0009)	-0.0002 (0.0007)	0.0007 (0.0013)	0.0014 (0.0010)	0.0005 (0.0013)
Rain \times Transhumant Pastoral [γ_3^d]	-0.0014 (0.0047)	-0.0046 (0.0048)	0.0017 (0.0038)	-0.0011 (0.0065)	-0.0079 (0.0062)	0.0005 (0.0065)
<u>Own Cell</u>						
Rain [γ_4^d]	-0.0002 (0.0007)	-0.0005 (0.0006)	-0.0001 (0.0005)	-0.0004 (0.0010)	-0.0007 (0.0009)	-0.0002 (0.0010)
Rain \times Transhumant Pastoral [γ_5^d]	0.0041 (0.0035)	0.0056* (0.0032)	-0.0008 (0.0024)	0.0046 (0.0051)	0.0052 (0.0039)	0.0032 (0.0051)
<u>Nearest Neighboring Ethnic Group: Additional Calculations</u>						
Effect of 1 Std. Dev. Rain Shock as % of Dep. Var. Mean:						
Rain	-1.88	0.57	-3.51	-0.95	0.83	-1.13
p-value	[0.40]	[0.83]	[0.36]	[0.53]	[0.67]	[0.46]
Rain \times Transhumant Pastoral	-37.51	-57.26	-8.68	-13.60	-20.12	-13.64
p-value	[0.00]	[0.00]	[0.58]	[0.01]	[0.01]	[0.01]
Rain + Rain \times Transhumant Pastoral	-39.39	-56.68	-12.19	-14.55	-19.29	-14.76
p-value	[0.00]	[0.00]	[0.43]	[0.01]	[0.01]	[0.00]
Dep. Var. Mean	0.035	0.025	0.016	0.085	0.055	0.084
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country \times Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Climate-Zone-Year Clusters	420	420	420	322	322	322
Cell Clusters	7,722	7,722	7,722	7,722	7,722	7,722
Observations	231,660	231,660	231,660	177,606	177,606	177,606

Takeaways

- Find that additional 1 std dev rainfall would lower jihadist conflict 31%
- Find no mitigating effects of aid projects
- Find that high amounts of protected areas might exacerbate conflict
- Find that increasing power of pastoralists in national government can mitigate the effect

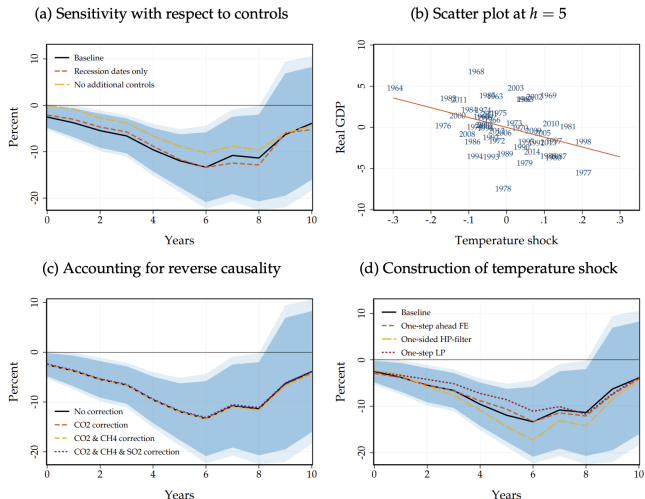
How should we account for these kinds of costs?

A Global Perspective?

Bilal and Kanzig: Global vs Local Temperatures

- Accounts for trade and migration spillovers, but also geophysical spillovers
- Only 60 observations...
- $SCC > \$1,000$

Figure 4: Sensitivity of the Effect of Global Temperature Shocks in the Time Series



What role can economics research play in climate policy?

- Quantifying the costs of damages
- Understanding policy interactions
- R&D for adaptation