Risk, Insurance, and Natural Disasters

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Motivation

Risk

Low Income economies are characterized by a high degree of risk

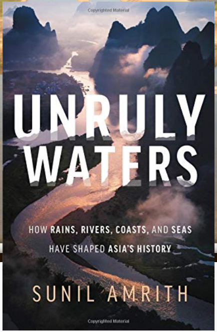
Risk

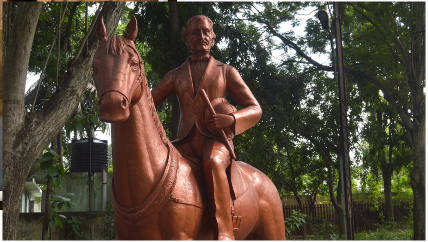
Low Income economies are characterized by a high degree of risk

- Rain-fed agriculture
- Commodity booms and busts
- Lack of formal social insurance programs

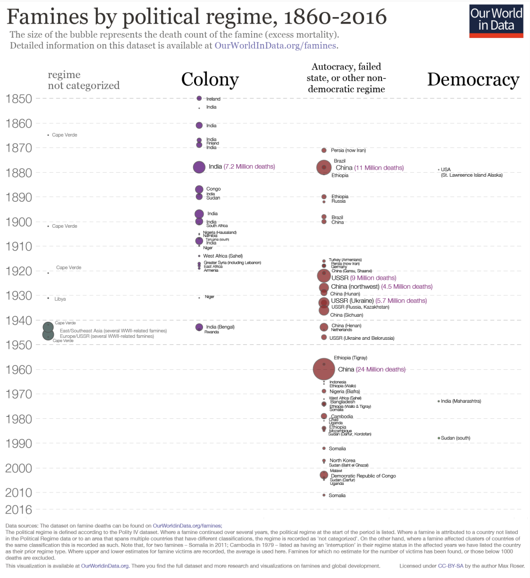
What are the implications for production and consumption?

Arthur Cotton and the Godavari Delta

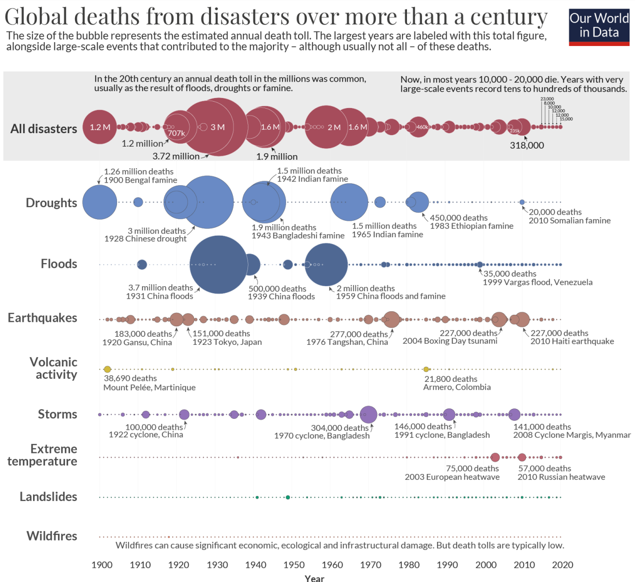




Famine: A Historical Perspective



Not Just Famine



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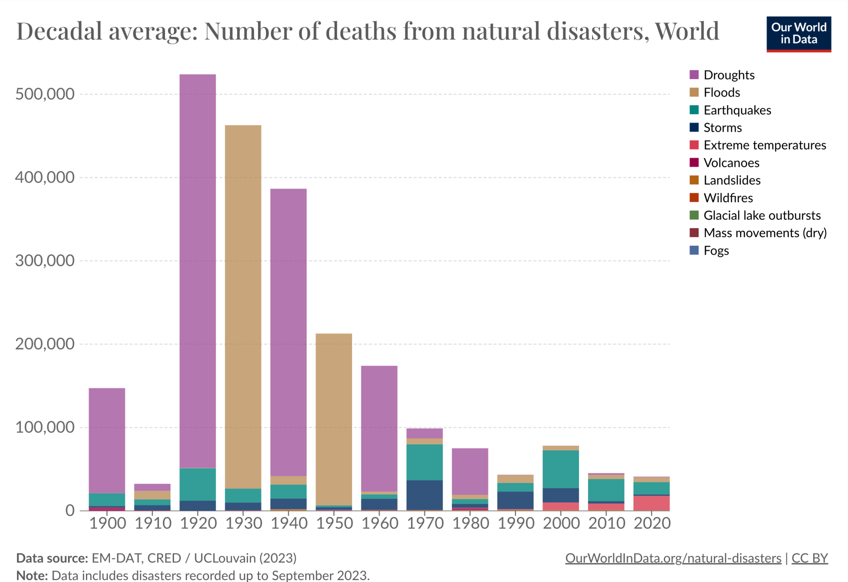

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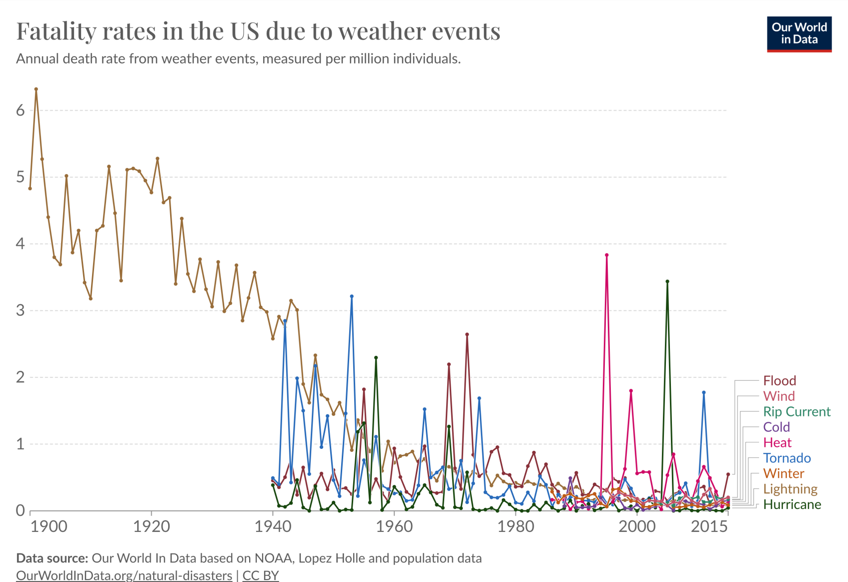
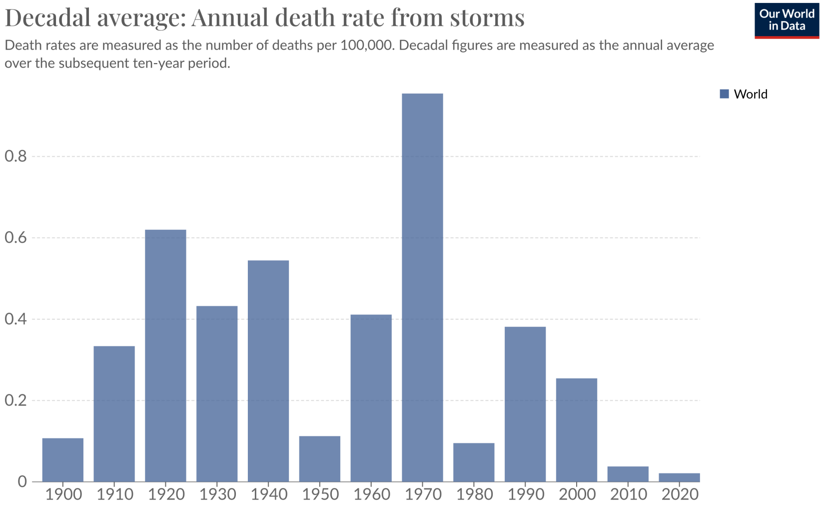


Fewer Storm Deaths?



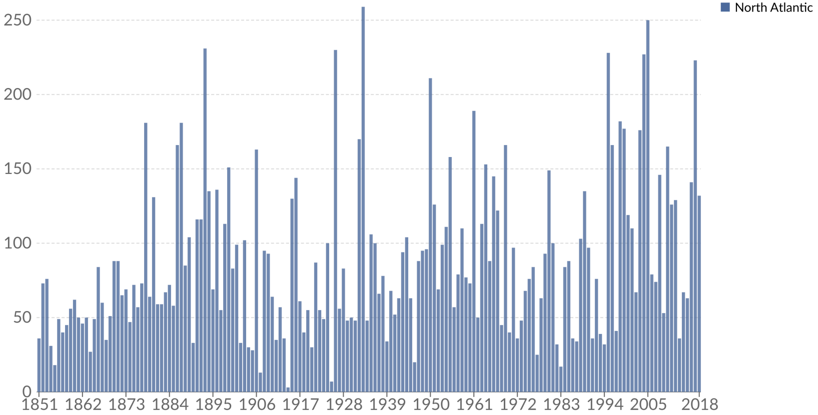
Data source:

Note: Decadal figures are measured as the annual average over the subsequent ten-year period. This means figures for '1900' represent the average from 1900 to 1909; '1910' is the average from 1910 to 1919 etc. Data includes disasters recorded up to September 2023.

Despite Increasing Storm Severity

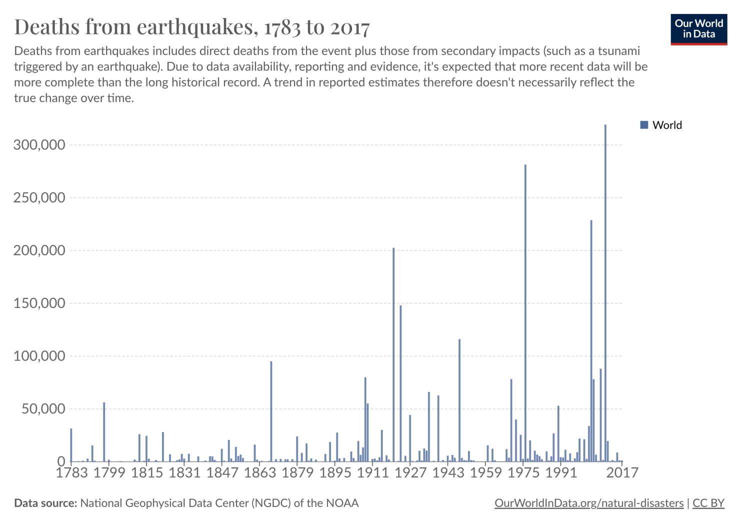
Accumulated cyclone energy of North Atlantic hurricanes

Accumulated cyclone energy (ACE) is an index used to measure the activity of a cyclone/hurricane season. It combines the number of hurricane systems, how long they existed and how intense they became. It is calculated by squaring the maximum sustained surface wind in the system every six hours that the cyclone is a Named Storm and summing it up for the season.



Data source: Hurricane Database HUDRAT (NOAA)

Some Exceptions



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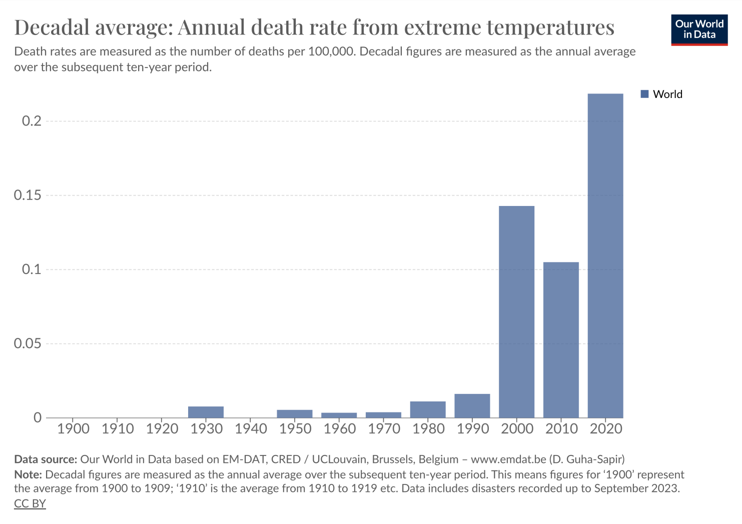
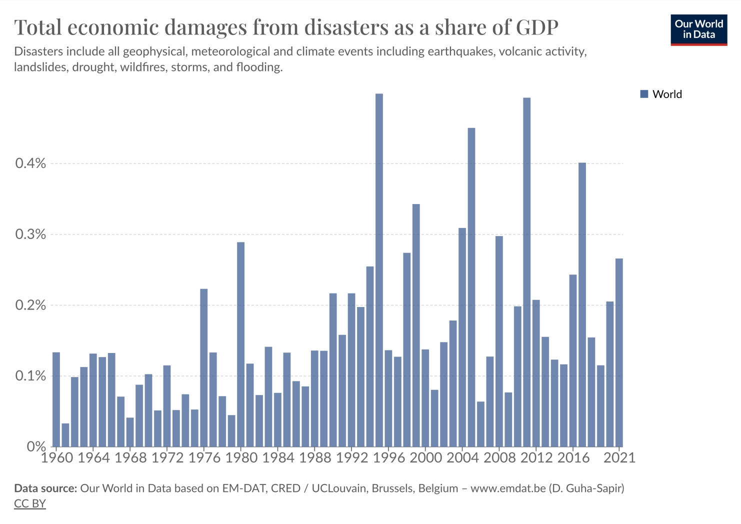


Model This:


Total economic damages from disasters as a share of GDP
Disasters include all geophysical, meteorological and climate events including earthquakes, volcanic activity, landslides, drought, wildfires, storms, and flooding.
Our World in Data
World
0.4%
0.3%
0.2%
0.1%
0%
1960 1964 1968 1972 1976 1980 1984 1988 1992 1996 2000 2004 2008 2012 2016 2021
Data source: Our World in Data based on EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be (D. Guha-Sapir)
CC BY

Outline for Today

Focus on Transitory Shocks

- Private Adaptation: Networks, Insurance, Migration
- Public Adaptation: Public Investments and Infrastructure
- Expectations: The Value of Forecasts

Next time: Climate Change Adaptation (or not)

- Start to think about why it might be different

Risk and Private Adaptation

How do people cope with risk?

Monsoon rains in Mumbai

How do people cope with risk?

Timing	Production	Consumption
ex ante		
ex post		

How do people cope with risk?

Timing	Production	Consumption
ex ante	Technology choice, diversification, Occupational choice(s), Location choice	Save, Buy formal insurance, Network insurance
ex post	Work supply, Migration	Borrow, Sell assets

Deaton (1991)

A simple model:

$$V = \max_{c} \sum_{t=0}^{\infty} \beta^t u(c_t) \tag{1}$$

$$x_{t+1} = R(x_t - c_t) + Y_t$$

$$x_t > 0$$

$$Y \sim N(0, \sigma^2)$$

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma}$$

An extremely brief review of dynamic programming

We want to solve for a consumption policy function: $c(x_t)$. Notice that

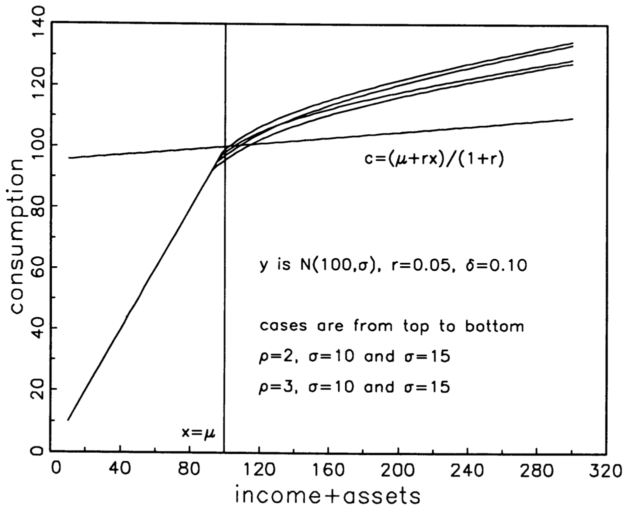
$$\begin{aligned} V(x_t) &= \max_c u(c_t) + \beta E[V(x_{t+1})] \\ V(x_t) &= \max_c u(c_t) + \beta E[V(R(x_t - c_t) + Y_t)] \end{aligned} \tag{2}$$

Value Function Iteration:

- First guess that $V(x_t) = 0$.
- Make a grid of points for x_t.
- Solve for above at each grid point.
- Take left side and plug in on right side.
- Repeat until convergence.

Consumption Smoothing

Contrast with permanent income model: $c_t = E(Y_t)$.



Testing for incomplete insurance

The Townsend Regression (Townsend 1994):

$$log(c_{it}) = \beta \log Y_{it} + \mu_i + e_{it} \tag{3}$$

Other variants:

$$log(c_{it}) = \beta \log Y_{it} + \mu_i + \gamma_{vt} + e_{it}$$
$$log(c_{it}) = \beta \log Y_{it} + \mu_i + \gamma_{ct} + e_{it}$$

What is the interpretation of β?

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What is the interpretation of β?

Typical values of β range from .1 to .3

But few bank accounts, formal insurance contracts, so how are people smoothing?

Marriage and Migration

Problem: Agricultural income risk has a strong spatial dimension

- If I get a bad shock, likely that my neighbors did too.
- This makes mutual insurance schemes difficult.
- At the same time, hard to insure with people further away, because more difficult to observe their income.

Rosenzweig and Stark (JPE 1989): Consumption Smoothing, Migration, and Marriage: Evidence from Rural India

- Rural to Urban migration is low
- Rural to Rural migration is high (9% of men born outside village, 94% of women)

Rosenzweig and Stark 1989

The greater distance between villages, the less correlated their rainfall:

	Village Correlations between:		
Variable	Daily Rainfall*	Mean Profits†	Wages‡
Distances between villages ($\text{km} \times 10^{-3}$)	−.122	−.0912	−.0998
	(5.44)	(2.48)	(1.96)
Constant	1.05	.665	1.17
	(8.84)	(3.42)	(4.33)
R^2	.694	.322	.227
F	29.5	6.27	3.82
Number of observations	15	15	15

Note.—Dependent variable = $.5 \ln[(1 + r)/(1 - r)]$, where r is the correlation coefficient. t-ratios are in parentheses beneath coefficients.

* Averages for the months of July–October.

† For all sample farm households, in 1975 rupees.

‡ Daily wages for male agricultural workers, in 1975 rupees.

Rosenzweig and Stark 1989

Determinants of Variability in Real Food Expenditures in Farm Households, 1975–84

Variable	(1)	(2)	(3)
Profit variance	.114	.229	.227
	(14.9)	(7.91)	(7.18)
Inherited wealth × profit variance (× 10^{-6})	−.147	−.107	−.197
	(4.08)	(4.97)	(4.53)
Number of married women × profit variance	. . .	−.0346	−.0340
		(2.82)	(1.97)
Marriage distance × profit variance	. . .	−.000228	−.000231
		(4.31)	(4.33)
Number of migrants × profit variance	. . .	−.00719	−.00695
		(1.32)	(1.03)
Number of adult male market workers × profit variance	. . .	. . .	−.0003
			(1.24)
Number of adult female market workers × profit variance	. . .	. . .	−.0708
			(1.34)
Shirapur village (× 10^5)	11.0	11.1	11.4
	(4.29)	(3.75)	(3.50)
Kanzara village (× 10^5)	3.37	6.18	6.89
	(1.39)	(2.10)	(2.14)
Constant (× 10^5)	1.10	−1.64	−1.20
	(.59)	(.64)	(.44)
R^2	.764	.846	.852
F	63.3	43.4	33.9

Note.—t-ratios are in parentheses beneath coefficients.

Urban-Rural Migration in India

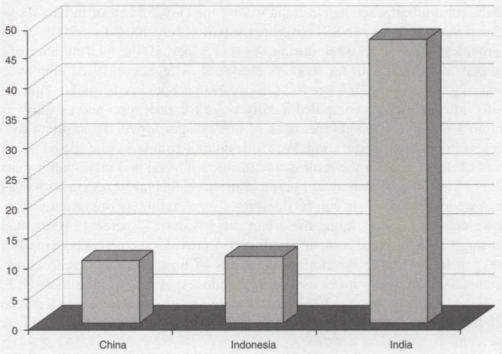


FIGURE 1. RURAL-URBAN WAGE GAP, BY COUNTRY

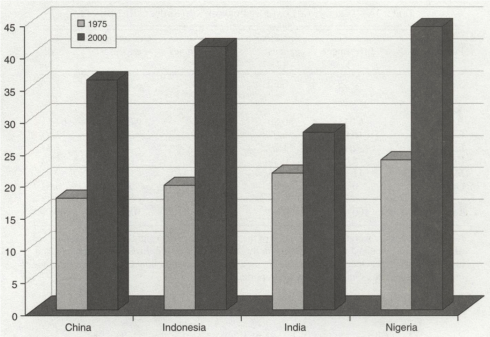


FIGURE 4. CHANGE IN PERCENT URBANIZED, BY COUNTRY, 1975–2000

A Model of Migration and Informal Insurance

Assumptions: Households have preference over the mean and variance of their incomes:

$$M_A = \lambda_{M_A} M_r < M_u \tag{4}$$

$$\text{Migrate if: } U(M_u, V_u) > U(M_r, V_r)$$

$$\frac{dV_r}{dN_r} < 0$$

3 Predictions:

- Income is redistributed within castes
- Wealthy households within castes should be more likely to have migrant members
- Households with higher V_r are *less* likely to migrate

Redistribution and Migration within Castes

TABLE 5—INCOME AND CONSUMPTION WITHIN THE CASTE

	ICRISAT			REDS 2006			
	Relative income	Relative consumption	Consumption-income ratio	Relative income	Relative consumption	Consumption-income ratio	Migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relative income class							
1	0.119	0.460	3.871	0.316	0.843	2.665	0.032
2	0.281	0.625	2.224	0.416	0.854	2.052	0.034
3	0.373	0.626	1.680	0.513	0.871	1.697	0.051
4	0.510	0.673	1.319	0.627	0.887	1.413	0.046
5	1.000	1.000	1.000	1.000	1.000	1.000	0.051

Notes: Income classes are defined by quintiles within each caste. Income and consumption are measured relative to the highest (fifth) income class. REDS 2006 income and consumption are inputed from ICRISAT data. REDS data consists of 100 castes, while ICRISAT data consist of 7 castes. Sample-size restriction is at least 30 households per caste with REDS data and 20 households per caste with ICRISAT data.

Munshi and Rosenzweig (AER 2016)

Migration vs Income Risk

Table 6—Reduced-Form Migration Estimates

	Migration					
	(1)	(2)	(3)	(4)	(5)	(6)
Household income	0.0059	0.0051	0.0026	0.0025	0.0021	0.0021
	(0.0024)	(0.0024)	(0.0033)	(0.0033)	(0.0030)	(0.0033)
Caste income	−0.016	−0.018	−0.022	−0.024	−0.025	−0.017
	(0.0043)	(0.0055)	(0.008)	(0.0107)	(0.0107)	(0.014)
Income risk	—	−0.00038	−0.00037	−0.00053	−0.00053	−0.00053
		(0.00015)	(0.00016)	(0.00017)	(0.00017)	(0.00011)
Village income			0.007	0.006	—	—
			(0.011)	(0.013)	—	—
Village/caste income					0.0073	0.0088
					(0.013)	(0.027)
Village fixed effects	No	No	No	No	No	Yes
Infrastructure variables	No	No	No	Yes	Yes	No
Joint sig. of infrastructure variables						
$\chi 2$	—	—	—	16.14	16.59	—
	—	—	—	[0.0011]	[0.00090]	—
Observations	19,362	19,362	19,362	19,362	19,362	19,362

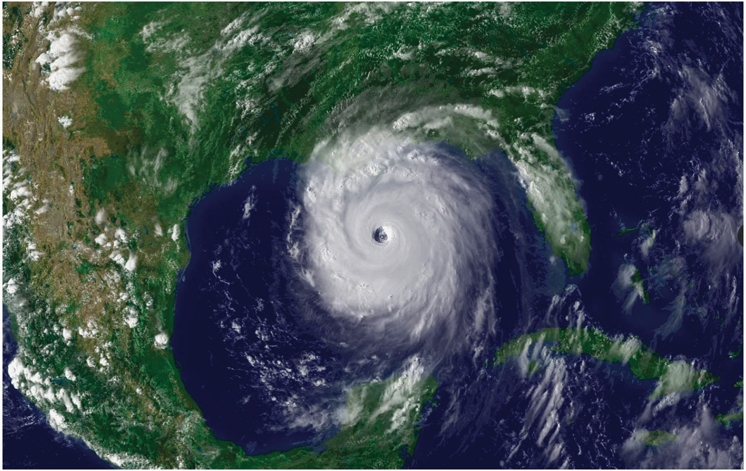
Notes: Bootstrapped standard errors in parentheses are clustered at the caste level in columns 1, 2, and 6 and two-way clustered at the caste and village level in columns 3–5. Income measured in lakhs of rupees, (1 lakh = 100,000). Infrastructure variables: whether there is a bank, secondary school, health center, or bus station in the village, as well as distance to the nearest town. χ^2 p-value reported in square brackets. Sample-size restricted

Takeaways

- Households care about mean *and* variance of consumption
- Variety of methods for smoothing shocks:
  - Loans: Udry (1994)
  - Durable Assets (Livestock): Rosenzweig and Wolpin (1993)
  - Remittances: Yang (2006)
  - Brideprice: Tapsoba (2022)
- How would better formal insurance affect migration? Caste-networks? Marriage markets?

What is the effect of getting hit by a hurricane?

Deryugina, Kawanao, and Levitt (AEJ: Applied 2018): The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns



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Deryugina et al (2018)

An event study with administrative tax data

$$Y_{it} = \sum_{t=1999}^{2013} \beta_t D_t D_i^{NO} + \alpha_i + \lambda_t + e_{it} \tag{5}$$

- What exactly are we measuring? (external validity)
- What are threats to identification? (internal validity)

Deryugina et al (2018)

An event study with administrative tax data

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- What exactly are we measuring? (external validity)
- What are threats to identification? (internal validity)
- Propensity score matching:
  - Usually we are worried about unobservables - they have very rich data (age, marital status, children, homeownership, employment, wages, total income...)
  - NOLA is unique: draw donor pool from 10 comparison cities
  - For more details on state of the art see Abadie 2021 NBER Summer Institute Methods Lecture: Synthetic Controls

Results: Income and Social Insurance

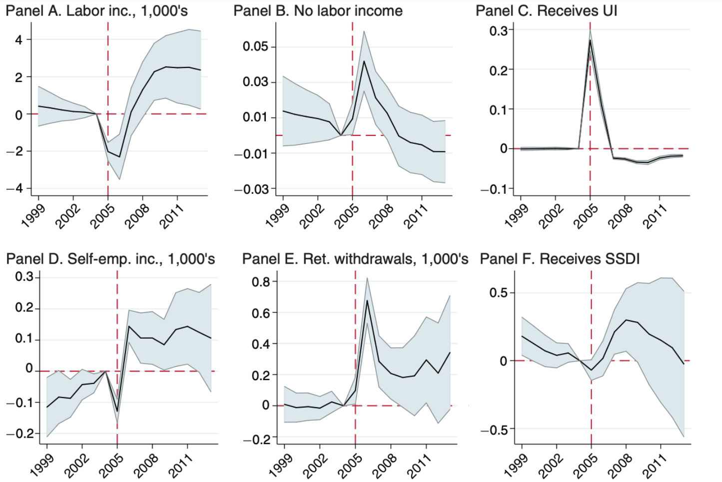
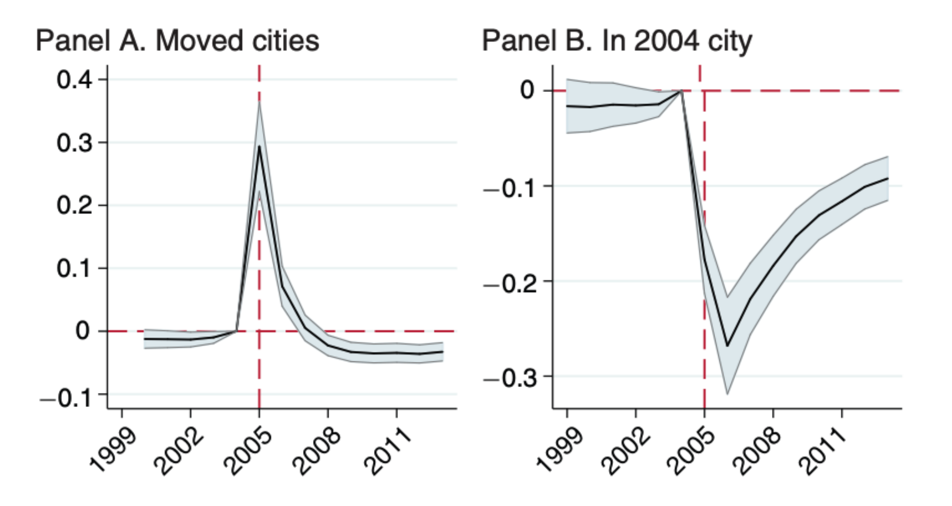


FIGURE 3. AVERAGE ECONOMIC EFFECTS OF HURRICANE KATRINA

Results: Migration



Takeaways and Reflections:

Why didn't they move before the storm? Is income = welfare?

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Why didn't they move before the storm? Is income = welfare?

- Nominal income vs real income (Housing prices grew faster than in other cities)
- Fixed costs of moving
- Other amenities (think back to previous papers)

Adaptation Policy

How can policy support adaptation?

Do public investments substitute or complement private actions?

Moral Hazard and Adverse Selection

Wagner (2022 AEJ EP): Adaptation and Adverse Selection in Markets for Natural Disaster Insurance

- Moral Hazard: In the US, subsidized flood insurance means that coastal homeowners do not bear full cost of location decisions
  - "As a result of cumulative damages from recent hurricanes, the NFIP is currently over $20 billion in debt, despite regularly borrowing from the Treasury."
  - Proposed reform: remove subsidies

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    - "As a result of cumulative damages from recent hurricanes, the NFIP is currently over $20 billion in debt, despite regularly borrowing from the Treasury."
    - Proposed reform: remove subsidies
- Adverse selection: Homeowners can take private actions to reduce risk. This reduces their WTP for insurance $\Longrightarrow$ those remaining in insurance pool have higher (unobserved) risk.
    - Akerlof (1970) Market for Lemons.

Adaptation

Model

WTP for insurance (D) defined implicitly by expected damages (f):

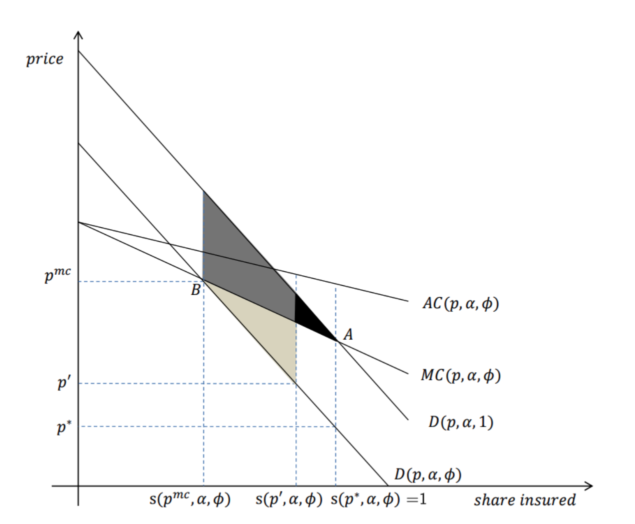
$$u(y_i - D(s_i, \alpha, \phi_i)) = \phi_i E[u(y_i - f(s_i, \alpha))|s_i] \tag{6}$$

- α is adaptation,
- ϕ is 'behavioral frictions'
- s_i is other private information

Insurer's costs (normalize $s \sim U(0,1)$):

$$AC = \frac{1}{s(p, \alpha, \phi)} \int_0^{s(p,\alpha,\phi)} E[f(s_i, \alpha)] ds_i \tag{7}$$

Downard sloping MC = Adverse selection on unobservables.



Empirical Tests

$$y_{it} = \rho p_{it} + \beta \mathbf{1}[adapted_i = 1] + \lambda_{zt} + \nu_{zdf} + \tau_{fdt} + e_{it} \tag{8}$$

- Impressive data collection (FOIA requests to get p_{it})
- Adapted $=$ 1 for houses subject to minimum elevation requirements
- Instrument for price with congressional reform that increased prices for non-adopted houses

Results: Selection on Observables

Adapted Houses less likely to insure

	Any Policy (1)	Building Policy (2)	Contents Policy (3)
Panel A: Differences-in-Differences			
Adapted × $1[t \geq 2013]$	0.019***	0.018***	0.008**
	(0.005)	(0.005)	(0.004)
Adapted	-0.108***	-0.106***	-0.051***
	(0.016)	(0.015)	(0.013)
Panel B: Instrumental Variables			
Price	-0.027***	-0.025***	-0.012**
	(0.006)	(0.006)	(0.006)
Adapted	-0.148***	-0.144***	-0.069***
	(0.022)	(0.022)	(0.020)
Non-Adapted Dep. Var. Mean	0.619	0.615	0.423
K-P F−stat	487	487	487
N		13,433,549	
Zip code × Year FE	✓	✓	✓
Decade Built × Flood Severity Controls	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results: Selection on Unobservables

No relationship between price and likelihood of claim

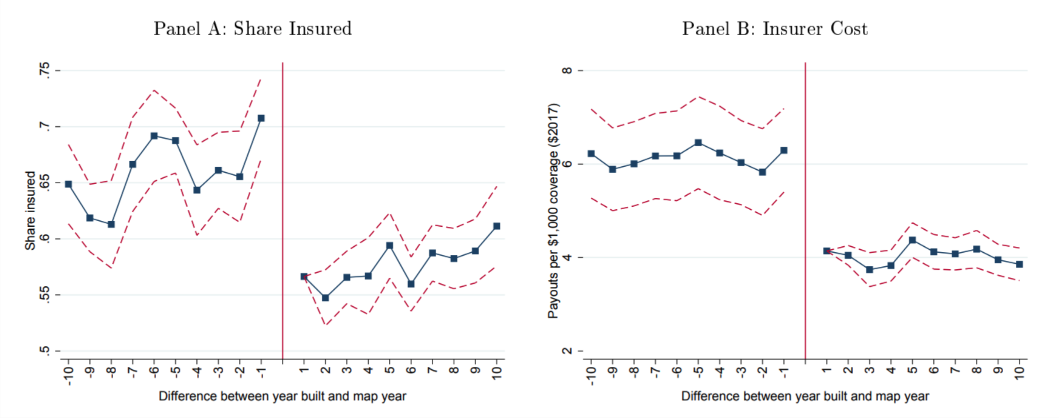
Table 5: Effects of Prices and Adaptation on Insurer Costs

	Any Claim (1)	Average Cost (2)
Panel A: Differences-in-Differences		
Adapted × $1[t \geq 2013]$	0.020	0.234
	(0.073)	(0.469)
Adapted	-0.418***	-2.211***
	(0.067)	(0.470)
Panel B: Instrumental Variables		
Price	-0.028	-0.326
	(0.101)	(0.652)
Adapted	-0.455**	-2.641**
	(0.179)	(1.224)
Non-Adapted Dep. Var. Mean	2.481	8.535
K-P $F-$stat	332	332
N	11,983,183	
Zip code × Year FE	✓	✓
Decade Built × Flood Severity Controls	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Adverse Selection

Adapted Houses Less Likely to Be Insured and less costly to insure



Takeaways

She also quantifies take-up frictions: WTP for insurance is 30% below expected costs

- This means we can't use WTP to infer welfare effects of price change

Adverse selection means raising prices *increases* average costs to insurer

In this setting, welfare optimal policy is to mandate insurance!

What about Infrastructure?

Hsiao: Sea Level Rise and Urban Adaptation in Jakarta

Quantitative Spatial Models: Allow us to study how policies affect spatial distribution of economic activity, as well as spatial margins of adaptation (trade, migration)

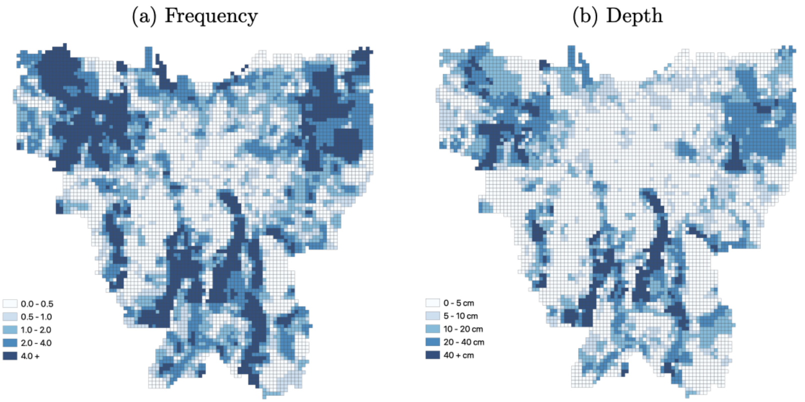
- High resolution spatial data (satellites)
- Advances in structural estimation in IO and Trade - see references in this paper

Recent Examples:

- Tsivanidis: Evaluating the Impact of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio
- Cruz and Rossi-Hansberg: The Economic Geography of Global Warming

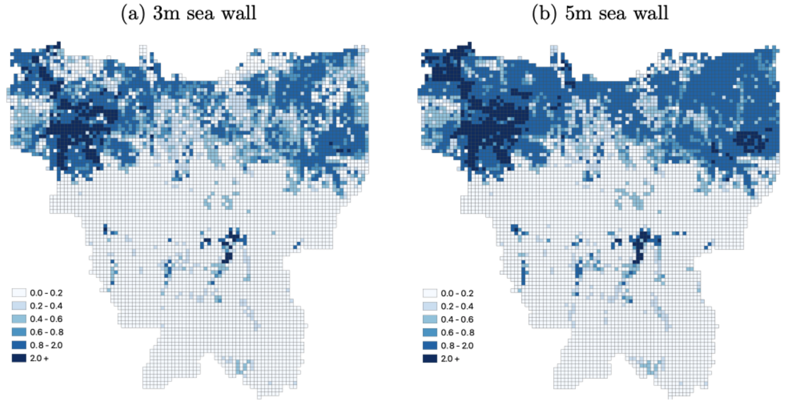
Sea levels are rising and Jakarta is sinking

Figure 1: Flooding (2013-2020)



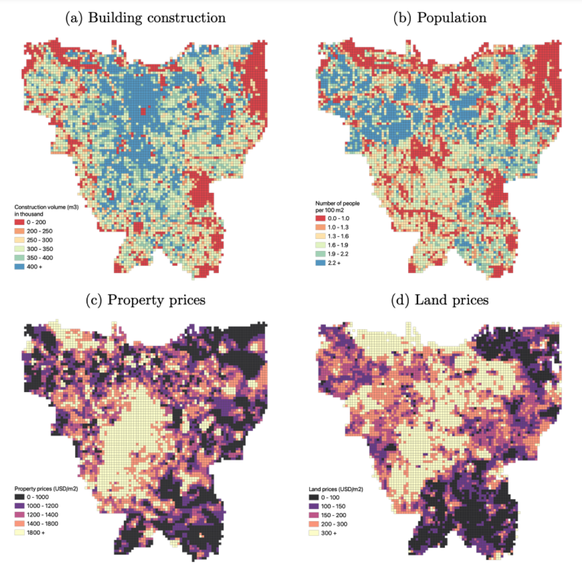
A seawall could help

Figure 4: Reductions in flooding

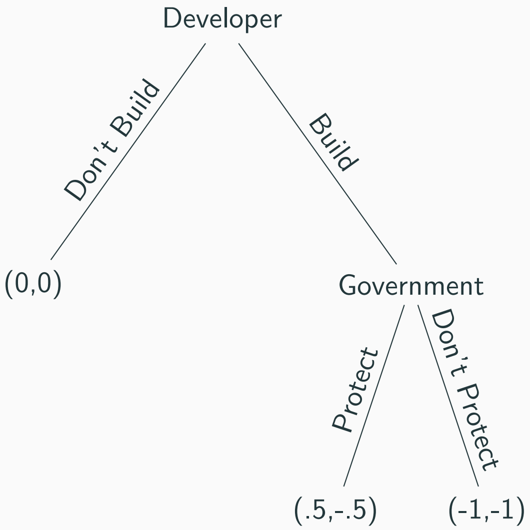


I map reductions in flood frequency, as measured in months per year, following the construction of a sea wall. I use the trained hydrological model to simulate the sea wall, raising elevation by 3m and 5m in the figures above, then I compute predicted changes in flood frequency over space.

Hsiao: Sea Level Rise and Urban Adaptation in Jakarta

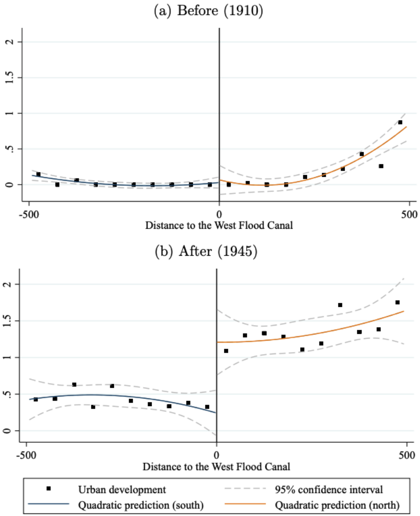


Government's Commitment Problem



And Development's Response

Figure 3: Land development and the West Flood Canal



Model: Demand

This should look familiar:

$$U_{ijk} = \underbrace{\alpha r_k + \phi f_k + x_k' \gamma + \epsilon_k}_{\delta_k} + \tau m_{jk} + e_{ijk} \tag{9}$$

Choose parameters to match fraction of residents in each grid cell:

$$p_{jk}^{res} = \frac{\exp(\delta_k - \tau m_{jk})}{\sum_k \exp(\delta_k - \tau m_{jk})} \tag{10}$$

For IO folks, this is basically BLP (Berry, Levinsohn, Pakes 1995)

Model: Supply

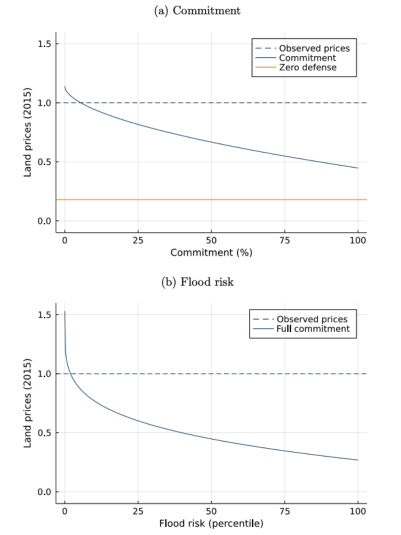
Developer Bellman:

$$V(D, L, \omega_{kt}) = r(D, \omega_{kt}) - c(d, l) + \beta E[V(D + d, L - l, \omega_{kt+1})]$$
$$\omega kt = \{x_{kt}, \epsilon_{kt}, \mathbf{D}, \mathbf{L}, G_t\}$$

- Similar to demand, we will find parameters of V by matching moments (predicted development to observed development)
- However, this is tricky, because for each set of parameters, you need to solve for the value function, which is computationally intensive
- Kalouptsidi (2014): In some cases you can estimate the value function directly from prices!
    - Won't go into this today, but you should take IO if interested in learning these techniques.

Developers are expecting protection

Figure 6: Observed coastal land prices (2015)



Takeaways

- Political economy can hinder adaptation
- Protective investments can create moral hazard
- Quantitative Spatial Models can be fun and not scary
- What about alternative instruments? Tax on development?

Changing Expectations

Changing Expectations

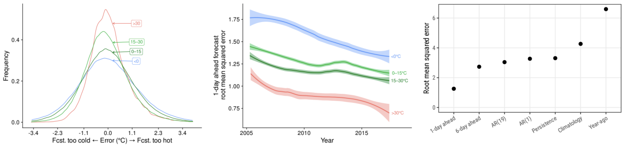
So far we have focused on adaptive behaviors to deal with future uncertain shocks.

What if we can make those shocks less uncertain...

Weather Forecasts are getting better

Shrader, Bakkensen, Lemoine. Fatal Errors: The Mortality Value of Accurate Weather Forecasts

Figure 1: Forecast Errors and Comparison With Alternatives



(a) Forecast Error Density (b) Accuracy (c) NWS fcst. vs. alternatives

Other forthcoming work:

- Molina and Rudik. The Social Value of Predicting Hurricanes
- Burlig et al: The value of forecasts: Experimental evidence from developing-country agriculture

Shrader, Bakkensen, Lemoine: Model

First the intuition:

- If people use forecasts, and take protective actions based on them, errors in either direction might affect mortality.
- So we think mortality might be *convex* in forecast errors.
- Further, we think this might be worse when forecasts are off at the extremes
  - If it is forecast to be hot, I might take some protective actions.
  - If realized temperature is lower, nothing too bad happens.
  - If it is forecast to be mild, I don't take protective actions.
  - If the realization is hot, bad things can happen.

Model: Adaptation and Expectations

Marginal Costs of Adaptation equal Marginal Benefits:

$$c'(A^*) = E[h(T, A^*(T))]VSL \tag{11}$$

Expected mortality on a day with temperature T is

$$\bar{h} = E_{e|T}[h(T, A^*(T + e)] \tag{12}$$

Taylor expansion around e = 0:

$$\bar{h} \approx E_{e|T}\Big[h(T, A^*(T)) + \frac{dh(T, A^*(T))}{de}(e) + \\ \frac{1}{2}\frac{d^2 h(T, A^*(T))}{de^2}e^2\Big]$$

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Therefore if $\frac{d^2 h(T, A^*(T))}{de^2} > 0$, reducing the variance of forecast errors will reduce mortality risk. This will depend on whether adaptation is *appropriate* or *protective*.

Estimating Equation

$$y_{ct} = \sum_{\ell=0}^{L}\Big[\sum_{j=1}^{J} 1\{f_{c,t-\ell} \in B_j\}\Big(\beta_{0,\ell,j} + \beta_{1,\ell,j} \cdot e^{low}_{j,c,t-\ell} +$$

$$\beta_{2,\ell,j} \cdot e^{high}_{j,c,t-\ell} + \beta_{3,\ell,j} 1\{e_{c,t-\ell} > \tilde{e}_j\}\Big)\Big] +$$

$$\sum_{\ell=0}^{L}[g_{1,\ell}(T_{c,t-\ell}) + g_{2,\ell}(P_{c,t-\ell})] + X_{ct}\Gamma + \alpha_{cm} + \rho_t + \epsilon_{ct}$$

- L: leads and lags for dynamics; J: Forecasted Temperature bins
- Bottom line: Flexible controls for realized temperature, precipitation, fixed effects
- Top 2 lines: Effects of forecast error, when forecast is in a given T bin (allowed to vary depending on whether higher or lower than median error).

Estimating Equation

Check for understanding: Why not linear in e?

$$y_{ct} = \sum_{\ell=0}^{L}\Big[\sum_{j=1}^{J} 1\{f_{c,t-\ell} \in B_j\}\Big(\beta_{0,\ell,j} + \beta_{1,\ell,j} \cdot e_{j,c,t-\ell}\Big)\Big] +$$

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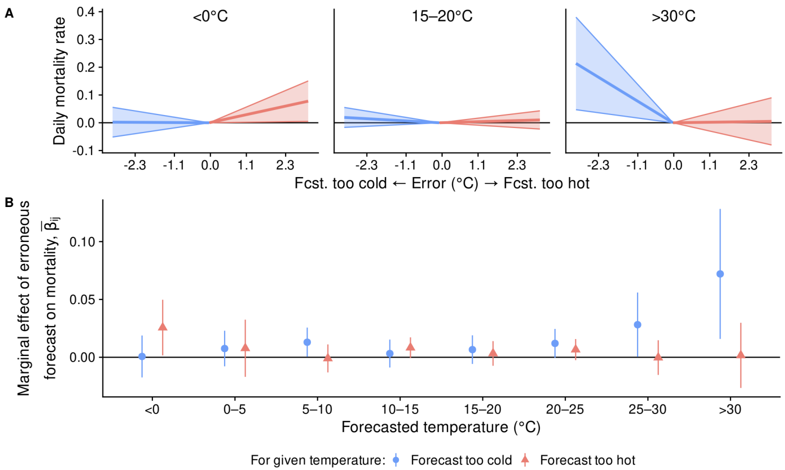
Estimated Effects

Figure 2: Forecast Errors Increase Mortality



Evidence for Mechanisms

On hot days, hotter forecasts cause people to substitute away from leisure activites towards work and home production. On cold days the opposite (holding T constant).

	(1)	(2)	(3)	(4)
	Time use (minutes/day)			Log electricity demand
	Work	Home prod.	Leisure	
$< 0°C \times$ Forecast error	3.94	-2.03	-1.91	0.00029
	(4.41)	(4.00)	(7.16)	(0.00026)
0 to 15°C $\times$ Forecast error	0.53	-5.84***	5.31**	-0.00029
	(2.57)	(1.99)	(2.51)	(0.00020)
15 to 30°C $\times$ Forecast error	3.95	-1.63	-2.32	0.00014
	(2.78)	(2.45)	(2.52)	(0.00019)
$> 30°C \times$ Forecast error	12.5	27.6***	-40.1***	0.0014***
	(8.07)	(10.1)	(7.37)	(0.00033)
LHS mean	189.8	263.8	986.4	
N	144,234	144,234	144,234	7,104
Clusters	100	100	100	48

Takeaways

- Reducing the standard deviation of forecasts errors by 1 degree C would save 5,400 lives per year
- Can monetize this based on VSL to inform how much we should spend on weather research
- Molina and Rudik find that improvements in hurricane forecasts over last decade are worth more than NOAA's entire budget
- Burlig et al provide farmers in Bangladesh with more accurate Monsoon forecasts, find that it changes planting behavior

Next Time: Climate Change

"Throughout Asia, one of the ways in which communities have coped with extreme weather has been to move...For regions that are threatened by climate change and water-related risks, borders create barriers to mobility. 'Climate refugees' are much discussed in current legal and political debates... Many of the region's migrants today come from places and communities that have been mobile in the past...Forced immobility can be as dangerous, as traumatic as forced migration. Controls on mobility have intensified...and they are likely to harden"

–Sunil Amrith, Unruly Waters

Final Thoughts for Next Class

"Many of the measures taken to secure India against the vagaries of the monsoon...have, through a cascade of unintended consequences, destabilized the monsoon itself. When the geographers of the early 20th century wrote of 'monsoon Asia' they saw the monsoon as sovereign – it shaped the lives of hundreds of millions of people... Monsoon Asia means something quite different now, when the monsoon's behavior, increasingly erratic, responds to human intervention."

–Sunil Amrith, Unruly Waters