Some Reflections on the Economics of Climate Change

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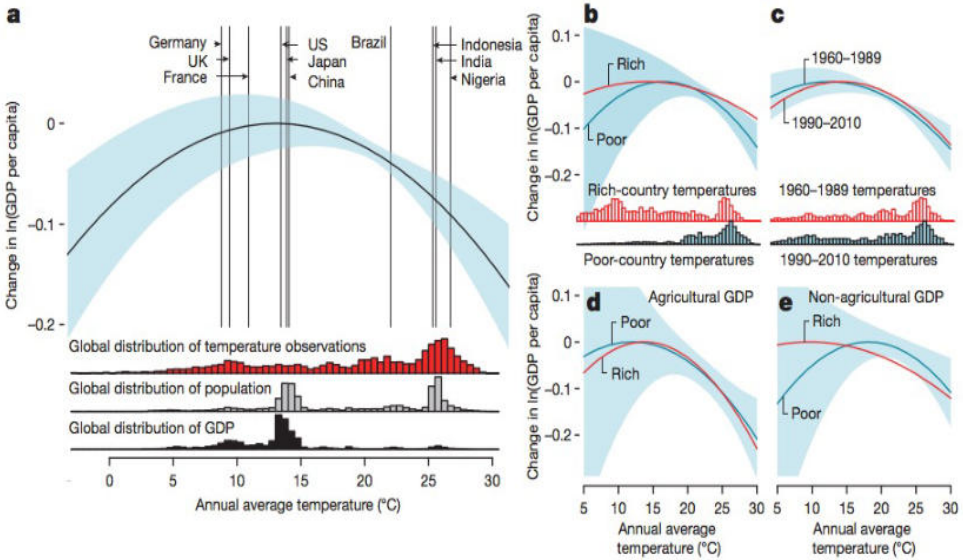
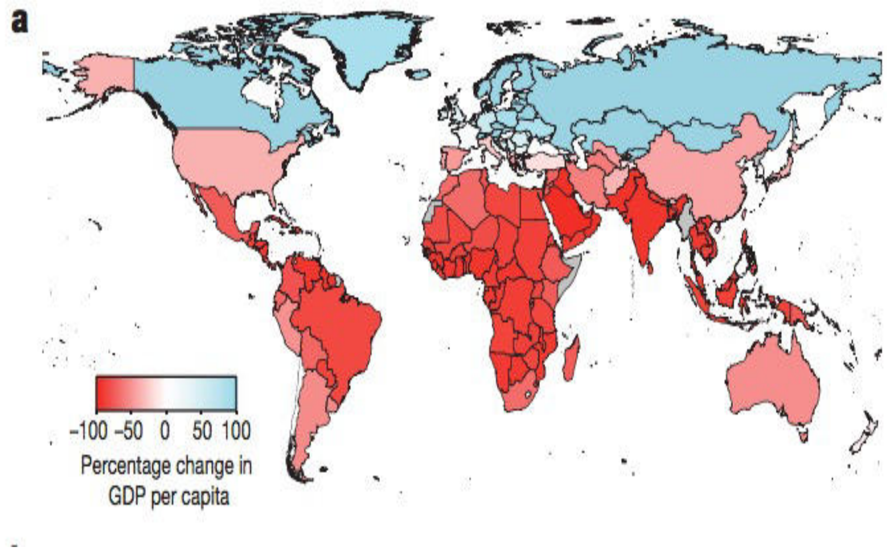
Climate as an Economic Shock





Effect of annual average temperature on economic production - M Burke ***et** al.* 1-5 (2015) doi:10.1038/nature15725

Economic Impact of Climate Change:

Hedonic Approach

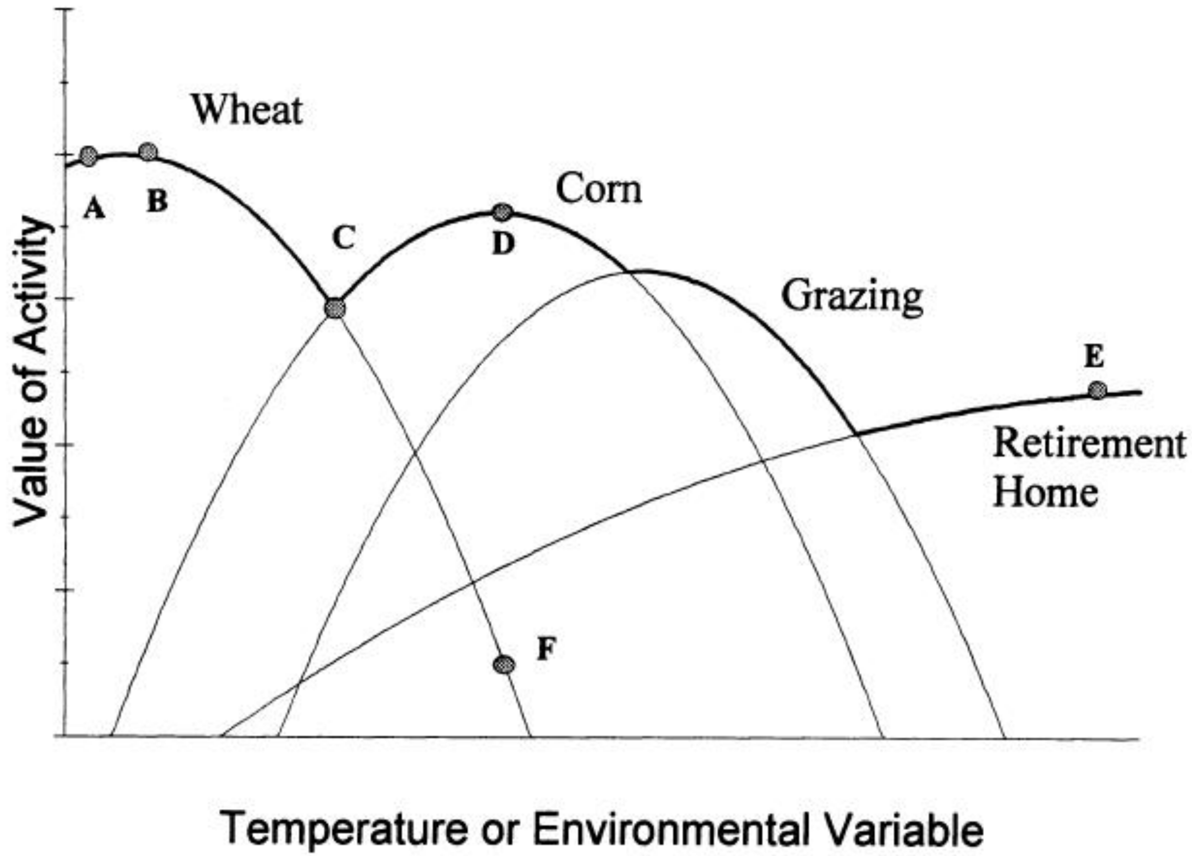


FIGURE 1. BIAS IN PRODUCTION-FUNCTION STUDIES

Mendelsohn et al. 1994

Switching Regression Model of Adaptation
(Di Falco et al., 2011; Di Falco and Veronesi, 2013)

$$A_i^* = \mathbf{Z_i}\boldsymbol{\alpha} + \eta_i \qquad A_i = \begin{cases} 1 & if \quad A_i^* > 0 \\ 0 & otherwise \end{cases}$$

$$y_{1i} = \mathbf{X_{1i}}\boldsymbol{\beta}_\mathbf{1} + \varepsilon_{1i} \quad if \quad A_i = 1$$

$$y_{2i} = \mathbf{X_{2i}}\boldsymbol{\beta}_\mathbf{2} + \varepsilon_{2i} \quad if \quad A_i = 0$$

$$\Sigma = \begin{bmatrix} \sigma_\eta^2 & . & . \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix}$$

$$E\left[\varepsilon_{1i} \mid A_i = 1\right] = \sigma_{1\eta} \frac{\phi(\mathbf{Z_i}\boldsymbol{\alpha})}{\Phi(\mathbf{Z_i}\boldsymbol{\alpha})} = \sigma_{1\eta}\lambda_{1i}$$

$$E\left[\varepsilon_{2i} \mid A_i = 0\right] = -\sigma_{2\eta} \frac{\phi(\mathbf{Z_i}\boldsymbol{\alpha})}{1 - \Phi(\mathbf{Z_i}\boldsymbol{\alpha})} = \sigma_{2\eta}\lambda_{2i}$$

Cross section, Short and Long Differences

$$y_i = \alpha + \beta \mathbf{C}_i + \gamma \mathbf{X}_i + \varepsilon_i,$$

Mendelsohn et al. 1994

$$y_{it} = \beta \mathbf{C}_{it} + \gamma \mathbf{Z}_{it} + \mu_i + \theta_{rt} + \varepsilon_{it}.$$

Deschenes and Greenstone (2011)

$$y_{id} = \beta \mathbf{C}_{id} + \gamma \mathbf{Z}_{id} + \mu_i + \theta_{id} + \varepsilon_{id}.$$

Dell, Jones, and Olken, 2012

Burke and Emerick 2016

Comparison of Long and Short

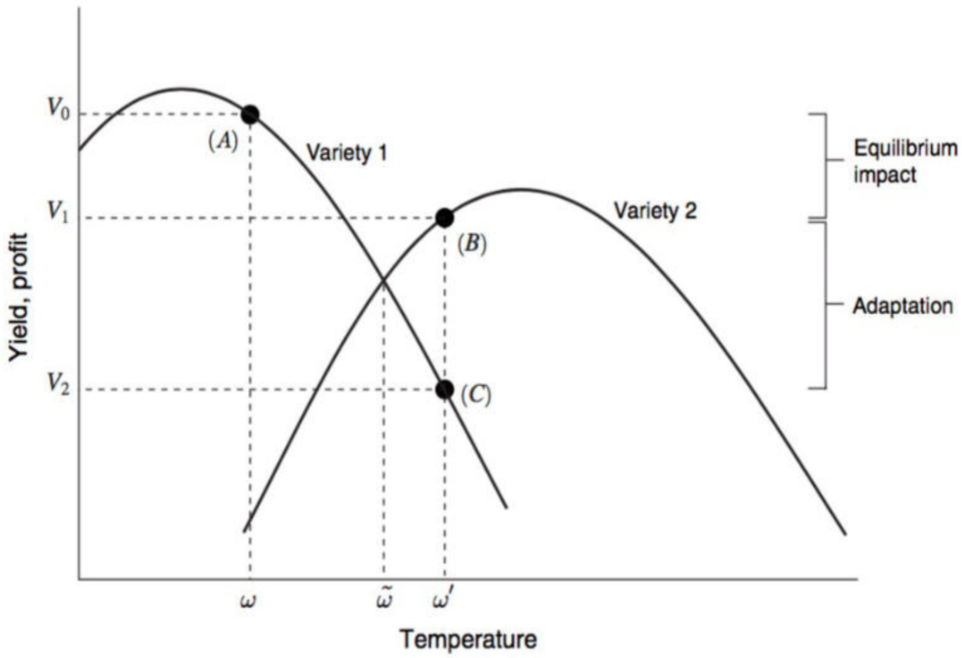
1. Instead of looking at annual shocks, one can examine average impacts over longer time horizons

2. Or, one can focus on a particular permanent shocks and trace out their impacts over many years (Hornbeck, 2012)

3. Combine these methods with short-run panel estimation, one can explicitly compare the same event at different time scales to assess the degree of adaptation

Adaptation

- Changes in land allocation as result of climatic shock (Aragon et al. 2021)
- They showed how land allocation to a staple crop opposed to other crops increased as result of shock exposure
- Avdeenko and Frölich (2025) Study a pre-disaster adaptation program where households are randomly given training, information, or basic equipment to prepare for floods.



Combine RCTs and Structural Models?

- RCTs identify causal effects of specific interventions, but:
  - Limited to observed policy variation
  - Cannot evaluate untried or future program designs
  - Short time horizons; limited dynamics
- Structural models allow counterfactual analysis, but require assumptions about behaviour, constraints, and expectations.
- Structural models + RCT data = credible behavioural models with real counterfactual power.
- RCTs discipline the structure → prevent overfitting.
- Structural models extend the experiment → simulate new policies and long-run outcomes.

How it works

- Use RCT **control group** or **treatment group** as *holdout samples* for **out-of-sample validation**.
- Treatment variation helps identify behavioural parameters (e.g., preferences, constraints).
- Once validated, model we can simulate:
  - Alternative benefit levels
  - Different roll-out speeds
  - Long-run dynamics
  - General equilibrium effects
  - Heterogeneity and targeting

Benefits for Adaptation Studies

- Many adaptation decisions are dynamic, anticipatory, and constrained

—not observable in a single RCT.

- Combining designs:
- Captures behaviour under risk and constraints
- Allows evaluation of policies not yet implemented
- Provides welfare measures (not only LATEs)
- Enables simulation of future climate states

- RCTs tell us what really happened.
- Structural models tell us what *could* happen.
- Together, they provide a fuller economics of adaptation.
- “The best of both Worlds”

Todd, Petra E., and Kenneth I. Wolpin. 2023.

“The Best of Both Worlds: Combining Randomized Controlled Trials with Structural Econometric Models.”

Journal of Economic Literature, 61(3): 643–705.

- Adaptation occurs through direct behavior & technology choices, and indirectly through markets & institutions (Di Falco et al. 2011; Burke and Emerick, 2016; Carleton et al., 2024)
- Climate hazards push people to move
- Floods & storms → forced displacement
- Drought & heat → voluntary moves for work

Social Responses to Climatic Shocks: Migration as Adaptation Response

- Human mobility is likely an important strategy to cope with climatic changes as migration is used to smooth consumption when farm income is low (Morten, 2019)
- Marchiori et al. 2012: Climate anomalies induce rural- urban migration and international migration
- Total movement of 5 million people in net terms during the period 1960-2000

How Climate Shocks Affects Time Allocation?

- Non-farm entrepreneurship is at least as important as temporary migration as a consumption smoothing strategy and way larger than wage labor (Kochar, 1999)
- We focus on the role of non-farm entrepreneurship to smooth consumption following shocks and markets are incomplete (De Giorgi, Di Falco and Pietrobon, 2025)
- Quantify how rural households react to agricultural productivity shocks (rainfall dips) by reallocating their time
- Farm labor, increases in non-farm enterprise (NFE) work, and temporary migration

Our question

- How transitory reductions in agricultural productivity driven by weather fluctuations push farm households to change their engagement in:

1. Farm activities

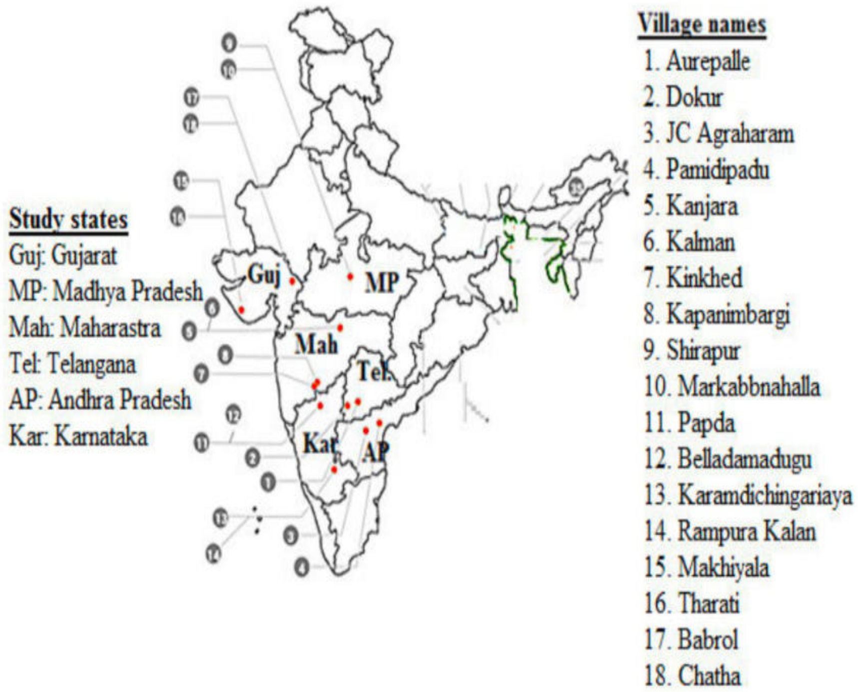
2. Non-farm entrepreneurship

2. Temporary migration

ICRISAT Village Level Studies (VLS)

- Rural households in semi-arid regions of India
- Household panel 2001–2010
- Covers **annual and seasonal rounds** of data collection
- Observes both **short-term responses** (e.g., to a drought) and **medium-run dynamics** (e.g., learning-by-doing, wealth accumulation)

ICRISAT data



- Tracks labor allocation, migration, and climate exposure
- Time use: farm labor, non-farm, temporary migration
- Rainfall data matched at village level
- Income, assets, consumption, education, credit access

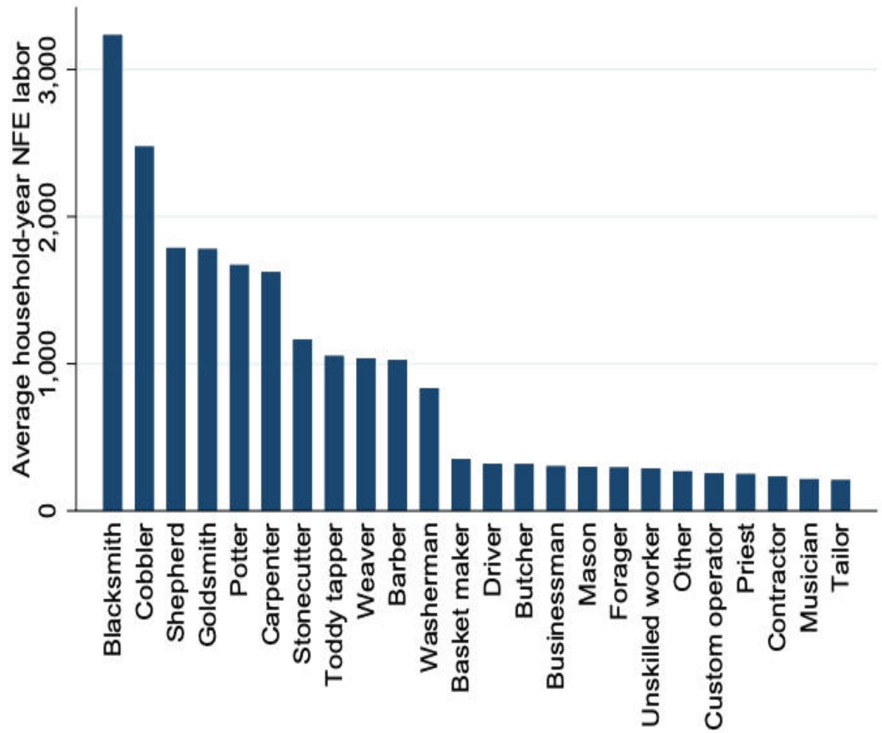
Table: Summary statistics

Variable	Obs.	Avg.	S.d.	Min	Max
Household size	4,330	4.98	2.32	1	24
# adult males	4,330	1.76	0.93	0	6
Landholdings (acres)	4,330	4.68	6.78	0	66
Farm labor (hours)	3,214	639.94	566.06	0	4,789
Non-farm labor (hours)	4,319	1,223.82	1,687.97	0	15,032
NFE	4,319	0.59	0.49	0	1
Migration	4,319	0.16	0.37	0	1
Farm income	3,160	5,576.19	11,706.16	-13,160.2	199,382.7
Non-farm income	4,319	11,377.23	23,907.62	-11,134.82	374,864.5
Migration income	4,319	589.92	2,076.19	-132.26	45,541.09

The unit of analysis across all columns is the household-year. NFE and Migration are dummy variables, where NFE equals 1 if a household operates an NFE in a given year, and Migration equals 1 if a household engages in temporary migration in a given year. All money values are in 1975 Indian rupees.

Facts about NFEs in the Data

- In our sample, over 50% of farm households report operating NFEs at least once between 2010 and 2014
- Average NFE income is almost twice as much as average farm income



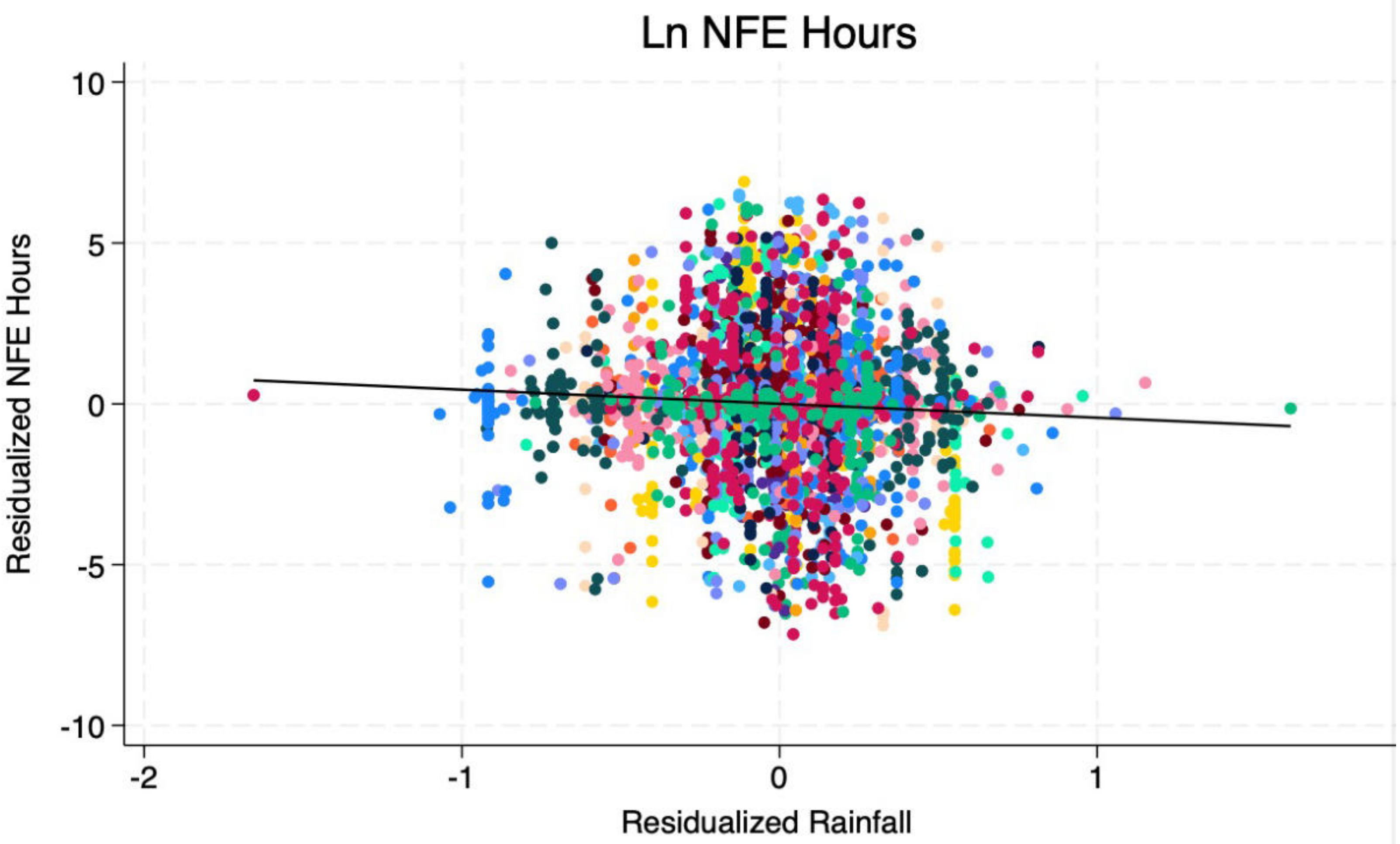
Using the ICRISAT: Findings

When rainfall is low, households:

1. decrease their farm labor supply
2. are more likely to operate NFEs
3. increase their non-farm labor supply
4. are more likely to engage in temporary migration

- Unlike temporary migration, we find that learning by doing in non-farm entrepreneurship
- is very important
- Households operating NFEs accumulate skills that increase their non-farm productivity

Reduced Form: NFE hours and rainfall



Agricultural Productivity: Effective Rainfall

- Rainfall data are at the village level
- The effect of village-level precipitation on household-level agricultural yields is mediated by plot characteristics
- Same amounts of rainfall to have heterogeneous effects on different households within the same village
- Deeper soils retain more water than shallower soils [Rahimi (2012), Rajakaruna and Boyd (2019)
- Effective rainfall-depth: $\pi_{it}^{\text{depth}} = \overline{\text{depth}}_{it} \times \pi_{v(i)t}$

No Price Effect

Table: Effect of effective rainfall-depth on price index

Dep. var.	Price index
Coef.	0.0000614
S.e.	(0.0001068)
Observations	90
R^2	0.5696
Avg.	3.28

Regression of price index on avg. effective rainfall-depth. The unit of analysis is the village-year. The regression includes village and year fixed effects. Standard errors are clustered at the village level.

Core Evidence of Household Behavior

Table 1: Occupational choices and labor supply decisions on effective rainfall-depth

Dep. var.	Log farm hours	Log NFE hours	NFE	Migration
Coef.	0.1381**	−0.4361***	−0.0648***	−0.0283*
	(0.0688)	(0.1106)	(0.0165)	(0.0148)
Obs.	4,253	4,244	4,244	4,244
R^2	0.8594	0.7328	0.6936	0.6080
Avg.	4.47	4.25	0.59	0.16

Regression of various outcomes of interest on $\log\left(\pi_{it}^{\text{depth}}\right)$. The unit of analysis across all columns is the household-year. NFE and Migration are dummy variables, where NFE equals 1 if a household operates an NFE in a given year, and Migration equals 1 if a household dispatches a temporary migrant in a given year. All regressions include household and year fixed effects. Standard errors in parentheses are clustered at the household level.

- Households reallocate labor immediately under climate stress

Reallocation is Persistent

Table 14: Regression of NFE on NFE in the previous year

Dep. var.	NFE
NFE in the previous year	0.086***
	(0.026)
Observations	3,388
R^2	0.7324
Adjusted R^2	0.6408

Note: NFE is a dummy variable that equals 1 if a household operates an NFE in a given year. Household and year fixed effects are included. Standard errors in parentheses are clustered at the household level.

Learning by doing

Table 2: NFE income on NFE in the previous year controlling for contemporaneous non-farm labor

Dep. var.	NFE income
NFE in the previous year	2424.34***
	(731.33)
non-farm labor	8.90***
	(0.68)
Observations	3,399
R^2	0.8695
Adjusted R^2	0.8249

Regression of NFE income on a dummy variable that equals 1 if a household operated an NFE in the previous year, controlling for contemporaneous non-farm labor. Household and year fixed effects are included. Standard errors in parentheses are clustered at the household level.

Why a Structural Model

- Counterfactual analysis and Policy simulations
- Mechanism Identification: how and why households reallocate labor under climate stress
- Dynamic Feedbacks: Captures learning effects and path dependence in skill accumulation
- Heterogeneous Effects: Estimates differential responses by landholding, skill, and demographic group
- Welfare Evaluation: Quantifies losses from shocks and potential gains from interventions

Structural Model

- Build and estimate a dynamic model of household labor supply decisions under incomplete consumption insurance
- Analyze the relationship between agricultural productivity and:

1. Allocation of time between farm h_{it}^{f} and non-farm activities h_{it}^{e}
2. Temporary migration m_{it}

- Risk-averse households can't fully insure and are ex-ante heterogeneous in

1. Landholdings L_i
2. Demographic characteristics z_i

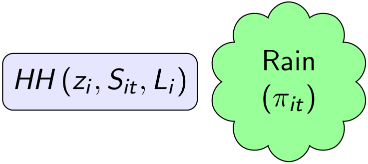
- Learning by doing: households engaged in non-farm activities increase their non-farm productivity making them ex-post heterogeneous in non-farm skills S_{it}
- Because of limited insurance, agricultural productivity ↓ consumption ↓ MU of consumption ↑ NFE labor ↑

Model: A graphical representation

$HH\,(z_i, S_{it}, L_i)$

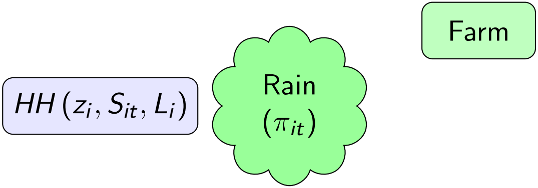
▸ Farm technology ▸ non-farm technology ▸ migration technology

Model: A graphical representation



▸ Farm technology ▸ non-farm technology ▸ migration technology

Model: A graphical representation



▸ Farm technology ▸ non-farm technology ▸ migration technology

Model: A graphical representation

$y_{it}^{f} = \mathcal{T}^{f}\left(\pi_{it} + L_i\right)\left(h_{it}^{f}\right)^{\sigma}$

κ^{f}: marginal disutility of farm labor

Farm

$HH\left(z_i, S_{it}, L_i\right)$

Rain $\left(\pi_{it}\right)$

▸ Farm technology ▸ non-farm technology ▸ migration technology

Model: A graphical representation

$y_{it}^{f} = \mathcal{T}^{f} \left(\pi_{it} + L_i \right) \left(h_{it}^{f} \right)^{\sigma}$

κ^{f}: marginal disutility of farm labor

Farm

$HH \left(z_i, S_{it}, L_i \right)$

Rain
$\left(\pi_{it} \right)$

NFE

Farm technology | non-farm technology | migration technology

Model: A graphical representation

$HH\,(z_i, S_{it}, L_i)$

Rain (π_{it})

Farm

$$y^f_{it} = \mathcal{T}^f\,(\pi_{it} + L_i)\,\left(h^f_{it}\right)^\sigma$$

κ^f: marginal disutility of farm labor

NFE

$$y^e_{it} = \mathcal{T}^e\,(\varepsilon_{it} S_{it})\,(h^e_{it})^\gamma$$

κ^e: marginal disutility of NFE labor

$\iota\,(z_i)$: setup utility cost

Farm technology · non-farm technology · migration technology

Model: A graphical representation

$y_{it}^{f} = \mathcal{T}^{f}\left(\pi_{it} + L_i\right)\left(h_{it}^{f}\right)^{\sigma}$

κ^{f}: marginal disutility of farm labor

Farm

$HH\left(z_i, S_{it}, L_i\right)$

Rain $\left(\pi_{it}\right)$

$y_{it}^{e} = \mathcal{T}^{e}\left(\varepsilon_{it} S_{it}\right)\left(h_{it}^{e}\right)^{\gamma}$

κ^{e}: marginal disutility of NFE labor

$\iota\left(z_i\right)$: setup utility cost

NFE

$S_{it+1} = S_{it} + 1$: learning by doing

ϕ: separation rate

▸ Farm technology ▸ non-farm technology ▸ migration technology

Model: A graphical representation

$$y_{it}^{f} = \mathcal{T}^{f}\left(\pi_{it} + L_i\right)\left(h_{it}^{f}\right)^{\sigma}$$

κ^{f}: marginal disutility of farm labor

Farm

$HH\left(z_i, S_{it}, L_i\right)$

Rain $\left(\pi_{it}\right)$

$$y_{it}^{e} = \mathcal{T}^{e}\left(\varepsilon_{it} S_{it}\right)\left(h_{it}^{e}\right)^{\gamma}$$

κ^{e}: marginal disutility of NFE labor

$\iota\left(z_i\right)$: setup utility cost

NFE

$S_{it+1} = S_{it} + 1$: learning by doing

ϕ: separation rate

Migrate

Farm technology non-farm technology migration technology

Model: A graphical representation

$y^f_{it} = \mathcal{T}^f \left(\pi_{it} + L_i\right) \left(h^f_{it}\right)^\sigma$
κ^f: marginal disutility of farm labor

Farm

$HH\left(z_i, S_{it}, L_i\right)$

Rain
$\left(\pi_{it}\right)$

$y^e_{it} = \mathcal{T}^e \left(\varepsilon_{it} S_{it}\right) \left(h^e_{it}\right)^\gamma$
κ^e: marginal disutility of NFE labor
$\iota\left(z_i\right)$: setup utility cost

NFE

$S_{it+1} = S_{it} + 1$: learning by doing
ϕ: separation rate

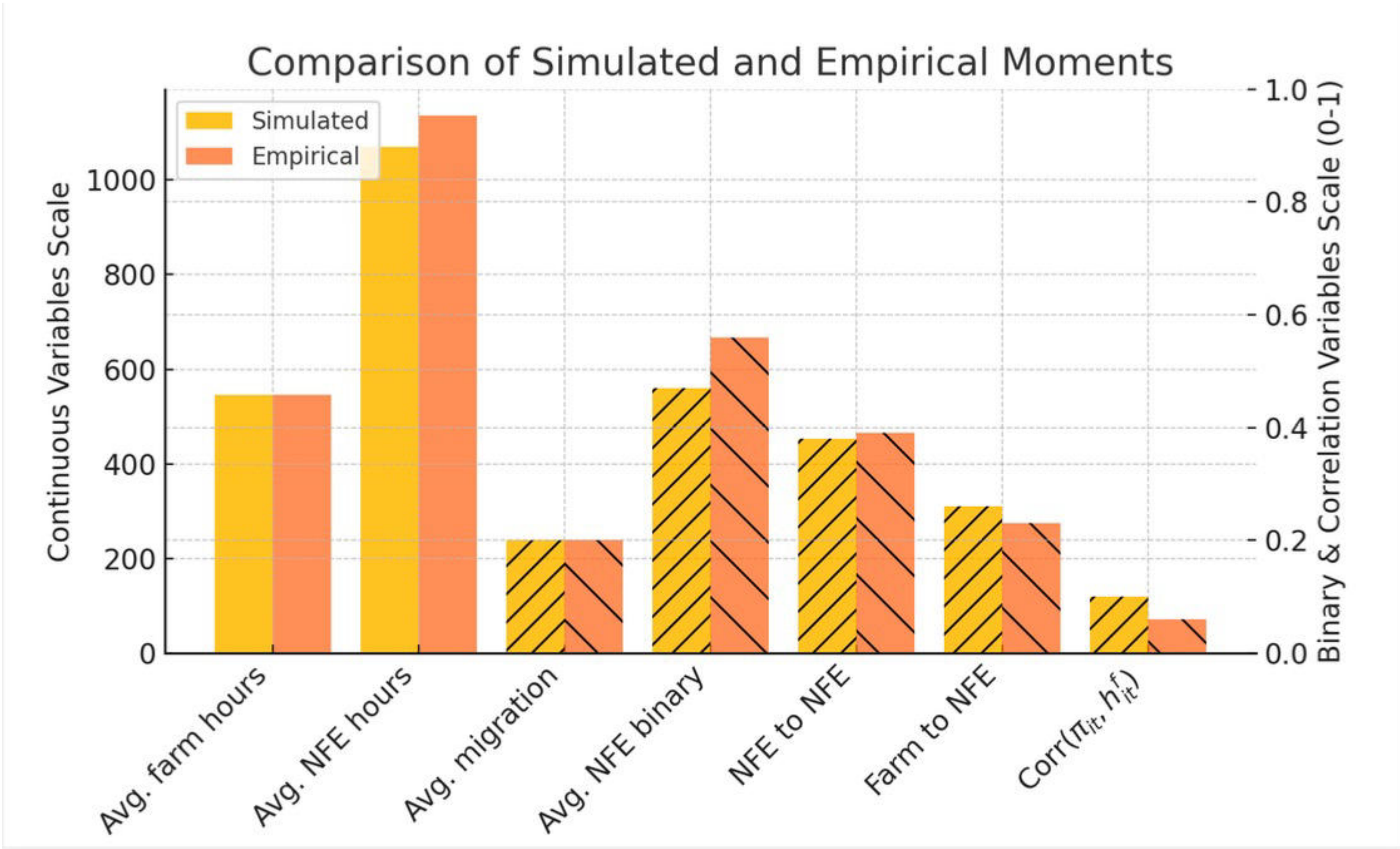
Migrate

$y^m_{it} = w$
δ: disutility of migrating

Farm technology | non-farm technology | migration technology

Comparison of Simulated and Empirical Moments

Moment	Simulated	Empirical
Avg. farm hours	546.52	546.13
Avg. NFE hours	1069.10	1134.78
Avg. migration rate	0.20	0.20
NFE participation rate	0.47	0.56
NFE persistence (t→t+1)	0.38	0.39
Corr(rain→farm hours)	–0.28	–0.06
Corr(rain→NFE participation)	–0.20	–0.07
Corr(rain→migration)	–0.05	–0.09

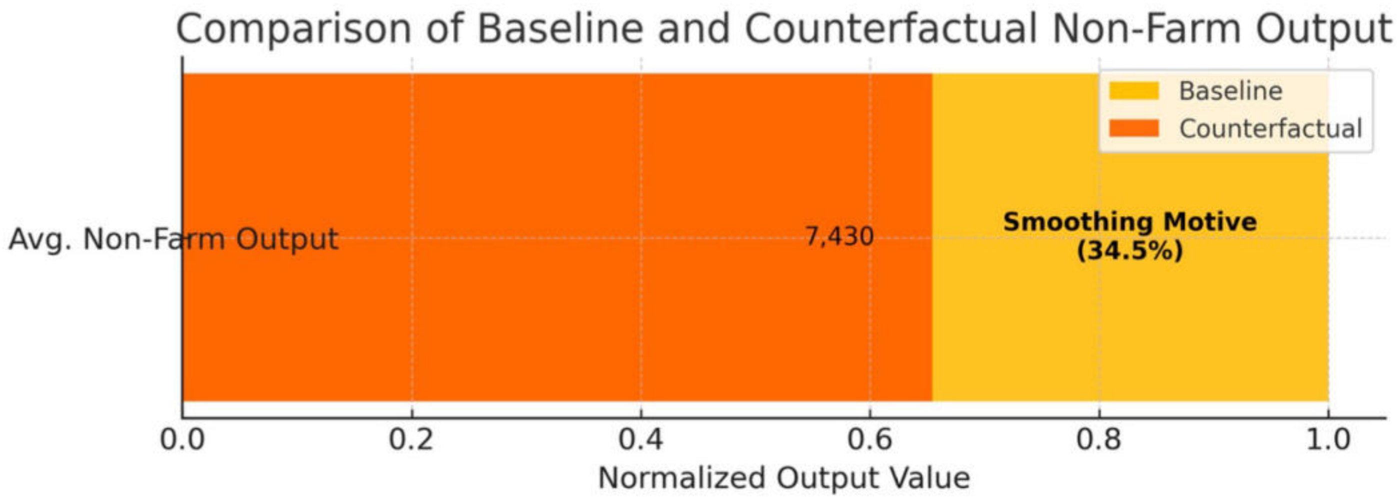


Comparison of Simulated and Empirical Moments
Simulated
Empirical
Continuous Variables Scale
Binary & Correlation Variables Scale (0-1)
0
200
400
600
800
1000
0.0
0.2
0.4
0.6
0.8
1.0
Avg. farm hours
Avg. NFE hours
Avg. migration
Avg. NFE binary
NFE to NFE
Farm to NFE
Corr(π_{it}, h^f_{it})

Counterfactual Analysis

Comparison of average farm and non-farm output in the baseline economy and in counterfactual economies

	Baseline	Counterfactual
Avg. farm output	4118.94	4541.09
Avg. non-farm output	11350.68	7429.58



NFE output would decreases by more than 30%

Self-insurance is a major reason why Indian farm households run NFEs

Improving insurance markets

- How do improvements in insurance markets affect non-farm entrepreneurship and structural transformation?
- This question is part of a broad research interest on financial deepening and economic development [Greenwood and Jovanovic (1990), Townsend and Ueda (2006)]
- Two exercises:

1. Provision of free weather insurance: increases non-farm output by about 70%
2. Implementation of cash transfers: increases non-farm about by about 40%

- Notice: the effect of both policies on non-farm output is a priori ambiguous

Weather insurance

- An insurance contract that pays recipients when rainfall falls below a certain threshold

We consider a contract that pays household *i* avg. farm output per acre × Li when rainfall falls below the first quartile of the village-specific rainfall distribution

Theoretically, weather insurance

1. makes farming more appealing (substitution effect)
2. induces to take on more risk (Arrow, 1971), including NFEs (insurance effect)

Quantitatively, the insurance effect dominates: weather insurance increases non-farm output

Minimum income

We consider a minimum income program paying the equivalent of 90 days of employment, ≈ 1139.53 rupees in 1975 terms

▶ Amount calibrated to MGNREGA, a program that guarantees 90 days of paid employment to every Indian rural household

▶ Theoretically, minimum income guarantees

1. incentivize to supply less labor (income effect)

2. induce to take on riskier activities, including NFEs (insurance

- effect)

▶ Quantitatively, the insurance effect dominates: minimum income guarantees increase non-farm output

Climate change

Climate change may decrease precipitation in the lower part of the rainfall distribution

- Conceptually, we can think of this shift as a “negative weather insurance contract”
- Households face mandatory insurance with negative payouts if rainfall falls below a certain threshold
- This shift in rainfall increases aggregate non-farm output by ≈ 30%
- This finding highlights the potential for climate-induced structural transformation

Final Remarks

- Non-farm entrepreneurship helps rural households to smooth consumption
- Households pushed into non-farm entrepreneurship out of "necessity" learn by doing
- Non-farm entrepreneurship as a self-insurance strategy

adds to our view of how structural transformation happens

- Policy: weather insurance contracts and minimum income guarantees foster structural transformation
- Climate change also will foster the transformation

- First dynamic structural model of effort across farming, enterprise, and migration
- Explicitly incorporates climate risk and incomplete markets
- Highlights enterprise and migration as proactive adaptation tools
- Informs integrated policy design for rural resilience

Thank you

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