Moscona and Sastry (2023)
"Does Directed Innovation Mitigate Climate Damage? Evidence from U.S. Agriculture"

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Reading Group Env.Climate

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Outline

Introduction

Mitigating impact on climate change or of climate change?

- Mitigation of impact on climate change
  - lowering or outsourcing production (Shapiro, 2021)
  - advancing clean technology (Acemoglu et al., 2012; Aghion et al., 2016)
- Adaptation to impact of climate change
  - reallocating production across space or variety (Costinot et al., 2016)
  - advancing adaptation technology (This paper!)

$\Rightarrow$ RQ: climate change $\rightarrow$ adaptation technology $\rightarrow$ agricultural outcome

Climate change on adaptation technology

- Climate substitute technology makes crop increasingly heat- and drought-resistant
  - Climate change increases S-tech
- Climate complement technology increases average yields at the cost of making environmental requirements more exact
  - Climate change increases C-tech if price effect is strong; decreases C-tech if price effect is weak
    - Higher price of agricultural output makes C-tech more valuable.

<table>
<tr><th></th><th>Climate-Substituting Technology</th><th>Climate-Complementing Technology</th></tr>
<tr><td>Price Effects Weak</td><td rowspan="2">(a) Innovation ↑ and Resilience ↑</td><td>(b) Innovation ↓ and Resilience ↑</td></tr>
<tr><td>Price Effects Strong</td><td>(b) Innovation ↑ and Resilience ↓</td></tr>
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Model

1. Production: Farm i produce a crop, sell in a competitive market
   - Production function: $Y_i = \alpha^{-\alpha}(1-\alpha)^{-1} \cdot G(A_i, \theta)^{\alpha} T_i^{1-\alpha}$
   - $G(A_i, \theta) : \mathbb{R}_+^2 \to \mathbb{R}_+$ total productivity of tech inputs
     - $A_i \in [\underline{A}, \bar{A}]$ local productivity capturing i's suitability for crop production
     - θ tech quality
   - T_i quantity of tech inputs with price q
   - Farm i maximizes profits over T_i for given (A_i, θ, p, q)

$$\max_{T_i} pY_i - qT_i \tag{1}$$

$\Rightarrow T_i^* = \alpha^{-1} p^{\frac{1}{\alpha}} q^{-\frac{1}{\alpha}} G(A_i, \theta)$

2. Innovation: A monopoly innovator determines tech price q and quality θ

$$\max_{q,\theta} \int_A [q - (1-\alpha)] T_i^* \, \mathrm{d}F(A) - c(\theta) \tag{2}$$

3. Demand: $p = P(Y) = P(\int Y_i(A) \, \mathrm{d}F(A))$

Model

Def: S-tech iff $G_{12} \leq 0$ and C-tech iff $G_{12} \geq 0$.

Direction of Technoloty: Fixed Prices

Assume that prices are fixed, or $P(Y) \equiv \bar{p}$. If the climate shifts in a damaging way,

1. θ weakly increases in equilibrium if technology is a climate substitute.
2. θ weakly decreases in equilibrium if technology is a climate complement.

Direction of Technoloty: Flexible Prices

Assume equilibrium quantities lie along a nonincreasing demand curve, or $p = P(Y)$ for a nonincreasing $P(\cdot)$. If the climate shifts in a damaging way,

1. θ weakly increases in equilibrium if technology is a climate substitute.
2. θ may increase or decrease in equilibrium if technology is a climate complement.

Model

- $\Pi(A, p, \hat{\theta})$ as equilibrium profits
- $R(A, p, \hat{\theta}) = -\frac{\partial}{\partial A}\Pi(A, p, \hat{\theta})$ as Resilience to climate damage

Resilience

Consider the general environment of flexible prices and a damaging climate shift that moves equilibrium technology from θ to θ'. Then the following properties hold for all (A, p):

1. $R\left(A, p, \theta'\right) \geq R(A, p, \theta)$ if technology is a climate substitute.
2. $R\left(A, p, \theta'\right) \geq R(A, p, \theta)$ if technology is a climate complement and $\theta' \leq \theta$.
3. $R\left(A, p, \theta'\right) \leq R(A, p, \theta)$ if technology is a climate complement and $\theta' \geq \theta$.

Model to Estimation

- Crops $k = 1, 2, \cdots, K$
- $\log G(A, \theta) = g_0 + g_1(\bar{A} - A) + \left(g_{20} + g_{21}(\bar{A} - A)\right) \log \theta$
- $C(\theta) = \frac{\theta^{1+\eta}}{1+\eta}$ and $P(Y_k) = p_0 Y_k^{-\varepsilon}$

Regression

Technology quality for each crop k is given by

$$\log \theta_k = \log \theta_0 + \delta \cdot (\bar{A} - A_k) \tag{3}$$

where $A_k = \int A \, \mathrm{d}F_k(A), \delta = \frac{g_{21} - \tau g_1}{1+\eta+\tau}$, and $\tau = \frac{\varepsilon}{\alpha + \varepsilon(1-\alpha)}$. Local profits are given by

$$\log \Pi_i = \log \Pi_0 + \beta \cdot (\bar{A} - A_i) + \gamma \left(\bar{A} - A_k\right) + \phi \cdot \left(\bar{A} - A_i\right) \left(\bar{A} - A_k\right) \tag{4}$$

where $\beta = g_1, \gamma = -\tau(g_1 + \delta)$, and $\phi = g_{21}\delta$.

Data

US Agriculture, County level i, time t from 1950

- A_{ikt}: county i's suitability for crop k at time t
  - Temperature: PRISM, $2.5 \times 2.5 miles$ grid
  - Crop k's growing temperature: EcoCrop
- θ_{kt}: crop k's technology at time t
  1. USDA's Variety Name List: all released crop varieties in the US
  2. Plant Variety Protection (PVP) certificates: crop varieties' certificate time + inventor info
  3. Patent from PatSnap: all agricultural patents in the US + whether the patent's related to climate change
- Π_{it}: county i's land profit at time t
  1. Rent of agri land per acre: US Cencus of Agriculture, 1959–2017
  2. Land revenues or profits

Regression: $\log \theta_k = \log \theta_0 + \delta \cdot (\bar{A} - A_k)$

A_{kt} is the weighted A_{ikt} across all i in the US.

- $A_{ikt} \Rightarrow \text{ExtremeExposure}_{ikt} = \text{DegreeDays}_{it}(T_k^{Max})$
- $A_{kt} \Rightarrow \text{ExtremeExposure}_{kt} = \sum_i [\frac{Area_{ik}^{Pre}}{\sum_i Area_{ik}^{Pre}} \text{ExtremeExposure}_{ikt}]$

$$y_k = \exp\left\{\delta \cdot \Delta \text{ ExtremeExposure }_k + \Gamma X_k' + \varepsilon_k\right\} \tag{5}$$

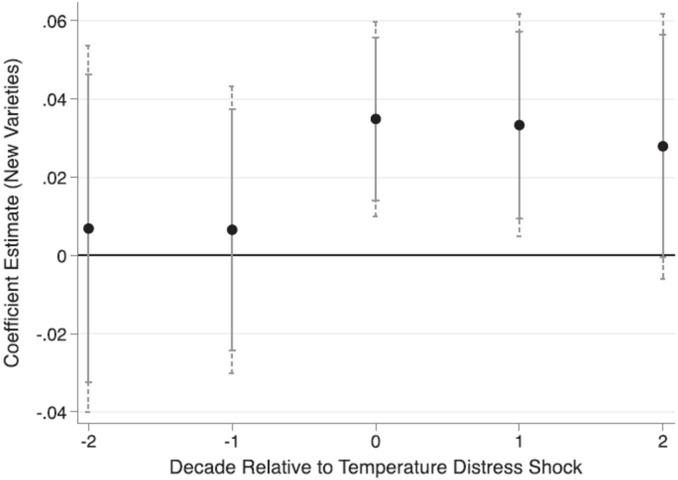
where y_k is the number of new varieties of crop k btw 1960–2016, Δ ExtremeExposure $_k$ is the change in extreme exposure btw 1960–2016.

Regression: $\log\theta_k = \log\theta_0 + \delta\cdot(\bar{A} - A_k)$

	Dependent variable is new crop varieties					
Sample period	1950–2016					1980–2016
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ExtremeExposure	0.0167***	0.0171***	0.0136***	0.0184***	0.0226***	0.0338***
	(0.00424)	(0.00436)	(0.00372)	(0.00541)	(0.00668)	(0.00745)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
Preperiod climate controls	No	Yes	Yes	Yes	Yes	Yes
Preperiod varieties	No	No	Yes	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	No	No	No	Yes	Yes	Yes
Average temperature change	No	No	No	No	Yes	No
Observations	69	69	69	69	69	69

- $\delta > 0$: 1 SD increase in climate distress led to 0.2 SD increase in new varieties.

Regression: $\log\theta_k = \log\theta_0 + \delta\cdot(\bar{A} - A_k)$



- No anticipation effect: δ is not significant before extreme exposure.

Regression: $\log \theta_k = \log \theta_0 + \delta \cdot (\bar{A} - A_k)$

	(1)	(2)	(3)	(4)
	Plant Variety Protection Certificates Awarded to:			
	Private Sector Firms	Public Sector	Universities	None of the Above
Δ ExtremeExposure	0.0476***	0.00424	0.00217	0.0194**
	(0.0181)	(0.0147)	(0.0128)	(0.00831)
Log area harvested	Yes	Yes	Yes	Yes
Pre-period climate controls	Yes	Yes	Yes	Yes
Pre-period PVP certificates (1970-1980)	Yes	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	Yes	Yes	Yes	Yes
Observations	62	62	62	62

- The redirection of technology is mainly driven by the private sector due to profit incentives.

Regression: $\log \theta_k = \log \theta_0 + \delta \cdot (\bar{A} - A_k)$

Dependent variable:	Patents not related to the climate (1)	Patents related to the climate (2)
Δ ExtremeExposure	0.00335	0.0118**
	(0.00458)	(0.00552)
All baseline controls	Yes	Yes
Observations	69	69

- Innovation redirecting toward climate-related technologies without crowding out other technologies.
  - Price impact incentives non-climate change patents, thus no crowding out.

Regression: $\log \theta_k = \log \theta_0 + \delta \cdot (\bar{A} - A_k)$

Many other robustness checks

- Heterogeneous Effects across Crops
  - market size
  - crop switching
  - reallocation across locations and seasons
  - proximity to US experiment stations
- Effects of Creating New Markets
  - farmers switch from more exposed crop to less exposed crop, but in small magnitude.
- Response to Global Damages
  - No.

Regression: $\log \Pi_i = \cdots + \phi \cdot (\bar{A} - A_i)(\bar{A} - A_k)$

- $\text{ExtremeExposure}_{it} = \sum_k [\frac{Area^{Pre}_{ik}}{\sum_k Area^{Pre}_{ik}} \text{ExtremeExposure}_{ikt}]$
- $\text{InnovationExposure}_{it} = \sum_k [\frac{Area^{Pre}_{ik}}{\sum_k Area^{Pre}_{ik}} \sum_{j \neq i} [\frac{Area^{Pre}_{jk}}{\sum_{j \neq i} Area^{Pre}_{jk}} \text{ExtremeExposure}_{jkt}]]$

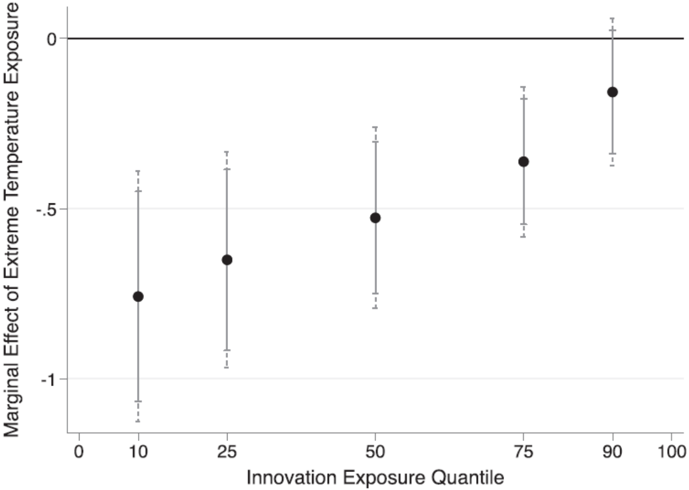
$$\begin{aligned} \log \text{AgrLandPrice}_{i,t} = \delta_i + \alpha_{s(i),t} + \beta \cdot \text{ ExtremeExposure }_{i,t} + \gamma \cdot \text{ InnovationExposure }_{i,t} \\ + \phi \cdot (\text{ ExtremeExposure}_{i,t} \times \text{ InnovationExposure }_{i,t}) + \Gamma X'_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

Regression: $\log \Pi_i = \cdots + \phi \cdot \left(\bar{A} - A_i\right)\left(\bar{A} - A_k\right)$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
County-level extreme exposure	-0.851^{***}	-1.519^{***}	-0.825^{***}	-0.862^{***}	-0.786^{***}	-0.232^{**}	-0.390^{***}
	(0.211)	(0.240)	(0.203)	(0.238)	(0.226)	(0.107)	(0.132)
	[0.264]	[0.304]	[0.244]	[0.305]	[0.279]	[0.105]	[0.103]
County-level extreme exposure × innovation exposure	0.249^{***}	0.425^{***}	0.237^{***}	0.251^{***}	0.230^{***}	0.0912^{***}	0.128^{***}
	(0.0757)	(0.0745)	(0.0728)	(0.0791)	(0.0762)	(0.0315)	(0.0321)
	[0.0945]	[0.0921]	[0.0881]	[0.0995]	[0.0929]	[0.0253]	[0.0243]
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × decade fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by agricultural land area	No	Yes	No	No	No	No	Yes
Output prices and interactions	No	No	Yes	No	Yes	No	No
Avg. temp. (°C) and interactions	No	No	No	Yes	Yes	No	No
Observations	6,000	6,000	5,990	6,000	5,990	20,931	20,931
R^2	0.989	0.991	0.989	0.989	0.989	0.979	0.984

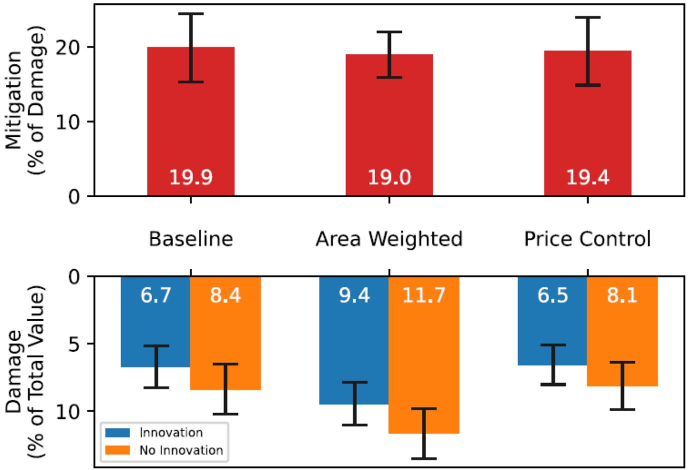
- $\phi > 0$: Technological progress is directed toward damaged crops and leads to increased resilience.

Regression: $\log \Pi_i = \cdots + \phi \cdot (\bar{A} - A_i)(\bar{A} - A_k)$



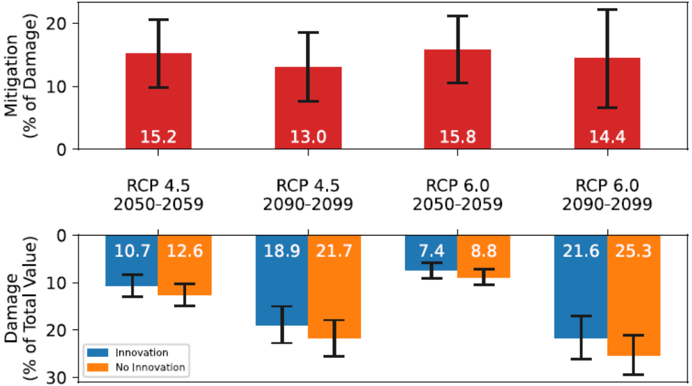
- Non-linear resilience
- In the counties most exposed to induced innovation, no significant impact of extreme

Aggregate damage mitigation from directed innovation



- Historical damage mitigation: 19.9% by directed innovation.

Aggregate damage mitigation from directed innovation



- Future damage mitigation: 13%–16% by directed innovation.

Conclusion

- Climate change incentives substitute innovation
    - Mean change in extreme exposure across crops corresponds to a 20% increase in new variety development.
- Directed innovation mitigates 20% damage from climate change btw 1960–2016; 13%–16% in the future.

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