Online Appendix for

Does Directed Innovation Mitigate Climate Damage? Evidence from US Agriculture

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A Additional Tables and Figures

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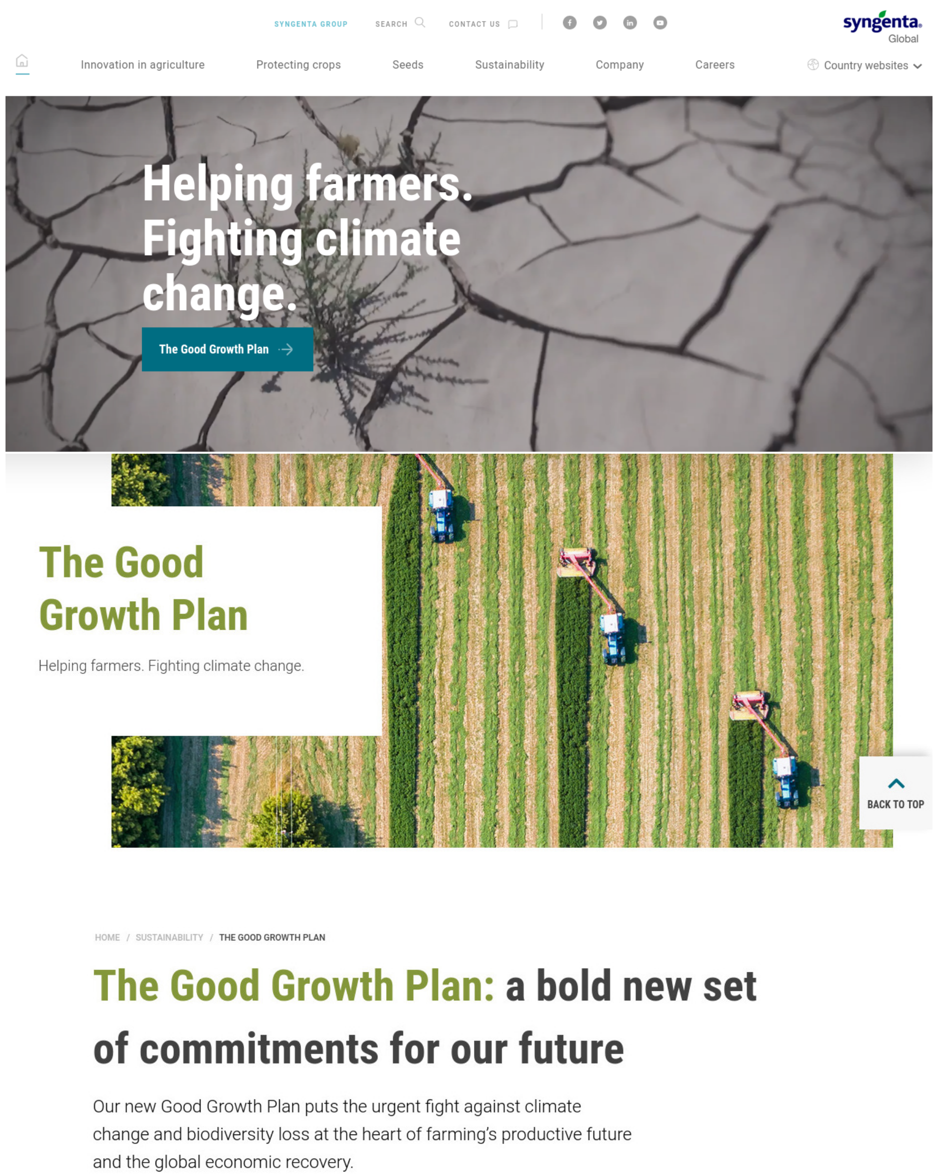
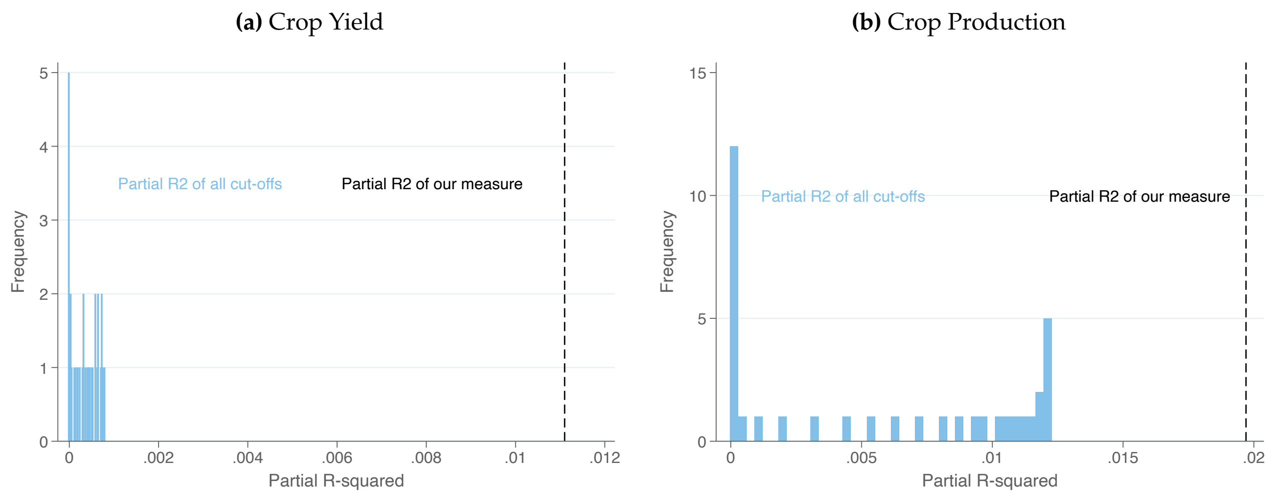
Figure A1: Climate Change Focus in Agricultural Biotechnology



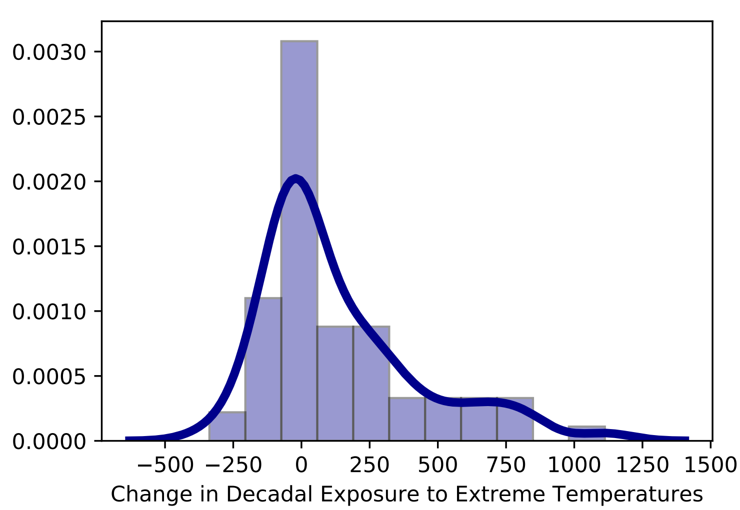
Notes: The Syngenta homepage (top) and landing page for the Good Growth Plan (bottom), accessed on January 19, 2021.

Figure A2: Explanatory Power of ExtremeExposure vs. Uniform Temperature Cut-Offs



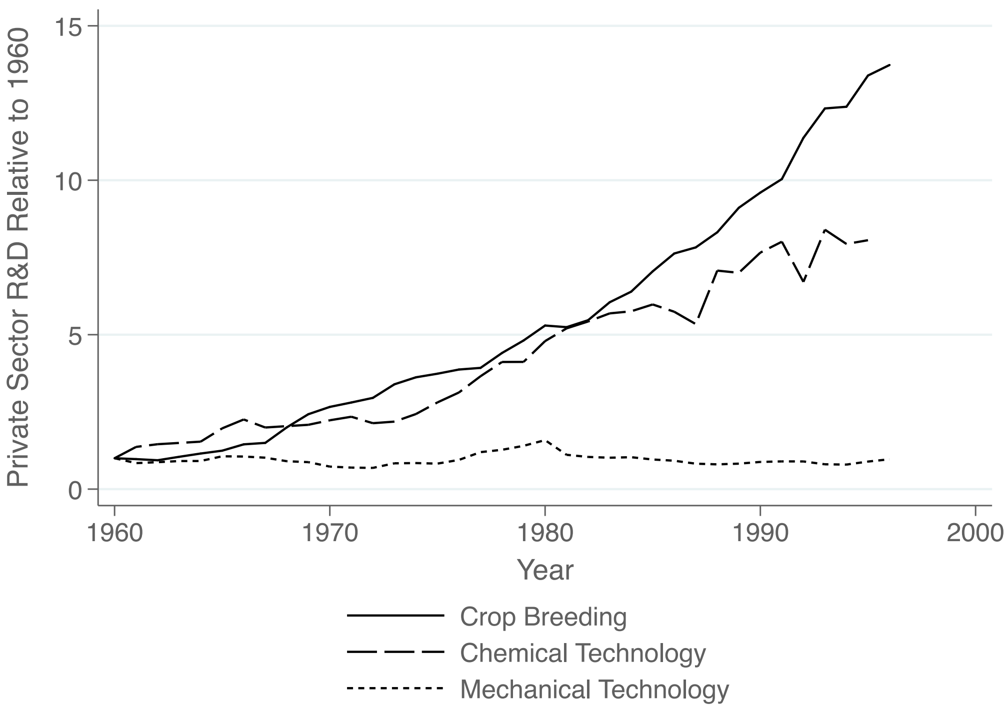
Notes: The blue bars are from a histogram of within-R-squared measures for the relationship between crop yields (A2a) or production (A2b) and exposure to temperatures above each temperature cut off from 10 to 45 degrees Celsius. The specification also includes crop fixed effects. The dotted black line reports the within-R-squared from the same specification in which our measure of extreme-heat exposure is included on the right hand side.

Figure A3: Changes in Extreme Exposure over the Sample



Notes: This figure displays the distribution of crop-level changes in ExtremeExposure between the 1950s and the 2010s.

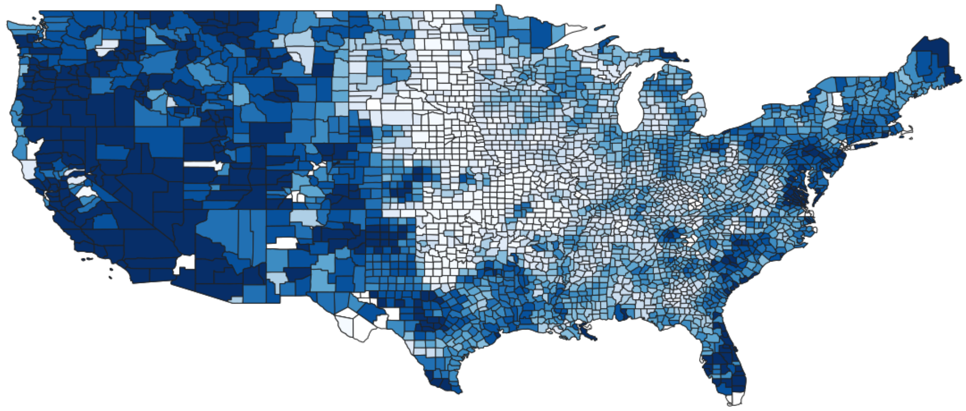
Figure A4: Trends in Private Sector R&D Investment



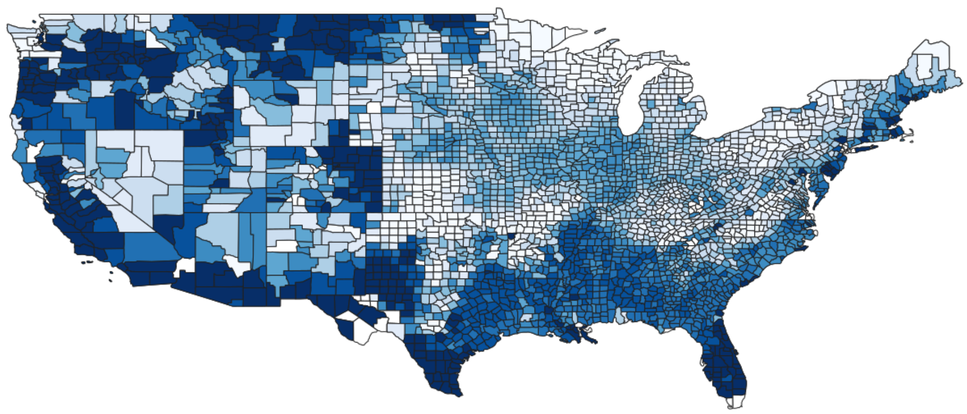
Notes: Values are ratios relative to 1960, all estimated in 1996 USD. Data were compiled from Klotz et al. (1995) and Fernandez-Cornejo (2004).

Figure A5: Distribution of Extreme-Heat Exposure and Innovation Exposure Across Counties

(a) Local Extreme Exposure (1950s-2010)

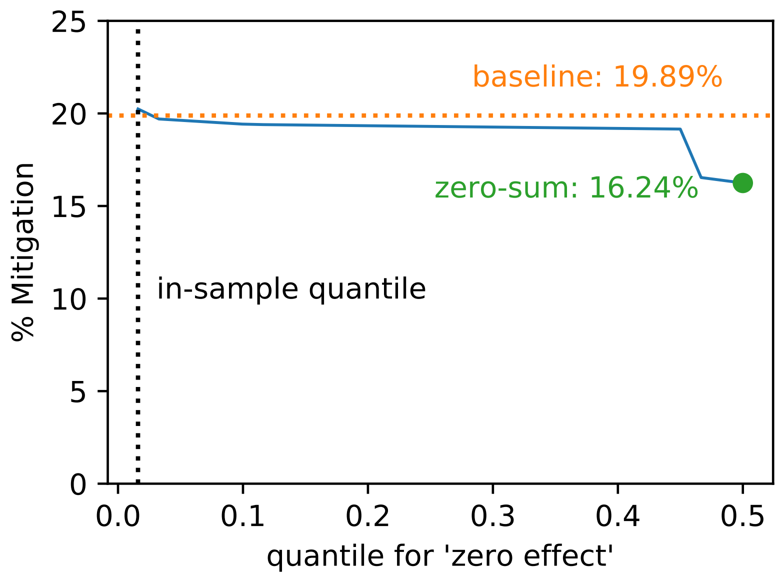


(b) Innovation Exposure (1950s-2010s)



Notes: Counties are color coded by decile, with darker colors indicating higher deciles.

Figure A6: Historical Damage Mitigation as a Function of “Zero Choice”



Notes: The x-axis indicates what area-weighted quantile value of extreme exposure among crops was used as the “zero effect” for the innovation counterfactual, as discussed in the main text. The baseline estimate treats zero extreme exposure as the zero effect. The “zero-sum” effect uses the area-weighted median across crops.

Table A1: List of Crops in Main Sample and Summary Statistics

Crop Name	*Species Name*	*log total land area*	*Δ Extreme Exposure (1950s-2010s)*	*Δ Extreme Exposure (1950s-2010s), Rank*	*Δ Predicted Extreme Exposure (2010s-2090s)*	*Δ Predicted Extreme Exposure (2010s-2090s), Rank*
escarole endive and chicory	Cichorium endivia	9.3	1112.2	1	2278.7	9
lettuce and romaine	Lactuca sativa var. capitata	12.2	831.1	2	2233.5	10
collards	Brassica oleracea var. viridis	7.0	803.1	3	2584.5	7
radishes	Raphanus sativus var. radicula	10.0	800.3	4	2043.2	12
green onions and shallots	Allium fistulosum	7.7	695.9	5	1472.4	23
carrots	Daucus carota	11.3	663.3	6	1526.7	22
kale	Brassica oleracea var. acephala	6.4	657.0	7	1932.8	13
chewings fescue seed	Festuca rubra var. commutata	10.1	565.3	8	1916.4	14
celery	Apium graveolens var. dulce	10.3	527.5	9	771.2	35
ladino clover seed	Trifolium repens	9.7	462.7	10	2724.5	4
spinach	Spinacia oleracea	10.6	413.6	11	2976.1	2
cabbage	Brassica oleracea var. capitata	11.6	393.2	12	1719.5	18
alsike clover seed	Trifolium hybridum	9.9	325.7	13	1408.8	24
bentgrass seed	Agrostis stolonifera	10.0	318.3	14	801.3	31
dry onions	Allium cepa	11.5	304.3	15	1644.7	20
lupine seed	Lupinus angustifolius	9.3	300.7	16	3723.3	1
broccoli	Brassica oleracea var. italica	10.3	294.6	17	1084.9	29
white clover seed	Trifolium repens	10.1	252.7	18	452.7	44
perennial ryegrass seed	Lolium perenne	10.7	226.3	19	118.6	54
hairy vetch seed	Vicia villosa sp. varia	10.2	212.4	20	242.9	49
beets	Beta vulgaris	9.7	196.9	21	1111.3	28
vetch seed	Vicia sativa ssp. nigra	11.3	187.2	22	1638.6	21
cauliflower	Brassica oleracea var. botrytis	10.0	185.3	23	1220.1	26
other vetch seed	Astragalus cicer	8.8	180.0	24	245.9	48
sugar beets	Beta vulgaris var. saccharifera	13.6	171.5	25	689.9	39
muskmelons	Cucumis melo	11.8	129.1	26	1150.2	27
squash	Cucurbita mixta	10.6	120.8	27	582.5	40
barley	Hordeum vulgare	16.5	102.1	28	1687.2	19
lentils	Lens culinaris	10.6	79.1	29	131.4	53
asparagus	Asparagus officinalis	12.0	56.4	30	216.6	50
crimson clover seed	Trifolium incarnatum	10.9	52.6	31	931.5	30
green lima beans	Phaseolus lunatus	11.3	51.1	32	515.2	43
common ryegrass seed	Lolium multiflorum	11.7	46.6	33	5.7	68
sudangrass seed	Sorghum x drummondii	10.4	23.6	34	111.7	56
sorghum	Sorghum bicolor	16.5	8.4	35	47.0	63
cotton	Gossypium hirsutum	16.5	4.7	36	17.0	66
dry field and seed peas	Vigna unguiculata	12.7	4.2	37	1.2	69
watermelons	Citrullus lanatus	12.5	0.9	38	60.5	61
emmer and spelt	Triticum spelta	10.9	-0.2	39	2636.3	6
eggplant	Solanum melongena	8.2	-1.6	40	37.3	64
birdsfood trefoil seed	Lotus corniculatus	8.9	-1.7	41	1727.5	16
sunflower seed	Helianthus annuus	9.5	-6.3	42	24.7	65
green peas	Pisum sativum	9.7	-9.7	43	2674.1	5
cowpeas	Vigna unguiculata	11.2	-14.2	44	7.9	67
coastal bermuda grass	Cynodon dactylon	11.7	-21.9	45	538.0	41
rice	Oryza sativa	14.3	-32.1	46	717.4	37
okra	Hibiscus sabdariffa	9.8	-33.1	47	529.7	42
corn	Zea mays	18.3	-33.7	48	72.2	60
soybeans	Glycine max	16.9	-34.9	49	86.0	59
tall fescue seed	Festuca arundinacea	11.8	-36.1	50	2507.9	8
turnips	Brassica campestris	9.0	-36.2	51	170.2	52
buckwheat	Fagopyrum esculentum	10.8	-37.4	52	380.0	45
mung beans	Vigna radiata	9.5	-45.0	53	51.7	62
rye	Secale cereale	14.1	-48.5	54	2848.7	3
pumpkins	Cucurbita maxima	8.9	-55.1	55	101.2	57
tobacco	Nicotiana tabacum	13.9	-57.0	56	321.8	47
peanuts	Arachis hypogaea	13.0	-72.9	57	112.5	55
alfalfa and alfalfa mixtures	Medicago sativa	17.1	-76.7	58	773.9	34
redtop seed	Panicum virgatum	11.1	-89.4	59	211.0	51
orchardgrass seed	Dactylis glomerata	10.9	-91.4	60	92.0	58
oats	Avena sativa	17.1	-121.1	61	2228.9	11
wheat	Triticum aestivum	17.3	-124.3	62	1790.9	15
lespedeza	Lespedeza cuneata	14.9	-143.9	63	1720.6	17
popcorn	Sapium sebiferum	11.7	-145.1	64	693.7	38
durum wheat	Triticum durum	13.9	-149.6	65	793.2	33
sweetclover seed	Melilotus albus	11.6	-155.1	66	797.5	32
flaxseed	Linum usitatissimum	14.8	-203.4	67	757.4	36
bluegrass (junegrass) seed	Poa pratensis	10.8	-214.0	68	360.1	46
bromegrass seed	Bromus inermis	10.4	-337.3	69	1241.8	25

Notes: This table reports the crop name; species name (from EcoCrop); log of planted area in 1959; change in extreme exposure from the 1950s-2010s; rank in change in extreme exposure from the 1950s-2010s; predited change in extreme exposure from the 2010s-2090s (RCP 4.5); and rank in predited change in extreme exposure from the 2010s-2090s (RCP 4.5), for all crops in the baseline analysis.

Table A2: Temperature Distress and Crop Yields

	(1)	(2)	(3)	(4)
	log Yield			
	All Crops			Staples (Corn, Wheat, Soy)
ExtremeExposure / 1000	-0.0915***	-0.0774***	-0.0891***	-0.131***
	(0.0179)	(0.0178)	(0.0172)	(0.0383)
County Fixed Effects	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes
Only East of 100th Meridian	No	Yes	No	No
Crop Fixed Effects x East of 100th Meridian	No	No	Yes	Yes
Observations	26,566	22,621	26,566	5,556
R-squared	0.937	0.947	0.942	0.959

Notes: The unit of observation is a crop-county. The outcome variable is crop yield measured in the 1959 US Census of Agriculture. In column 4, we restrict the sample to corn, wheat, and soy. The fixed effects included in each specification are noted at the bottom of each column. Standard errors are clustered by state and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A3: Temperature Distress and Crop Varieties: Plant Variety Protection Certificates

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is Plant Variety Protection (PVP) Certificates				
Δ ExtremeExposure	0.0161*	0.0209*	0.0184**	0.0397***	0.0410***
	(0.00933)	(0.0111)	(0.00887)	(0.0148)	(0.0144)
Log area harvested	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes
Pre-period PVP certificates (1970-1980)	No	No	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	No	No	No	Yes	Yes
Average Temperature Change	No	No	No	No	Yes
Observations	62	62	62	62	62

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific plant variety protection (PVP) certificates released since 1980. ExtremeExposure is similarly computed as the change in the number of crop-specific extreme GDDs between the 1980s and 2010s, while the pre-period is defined as 1970-1980 since PVP was intrduced in 1970. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A4: Temperature Distress and Crop Varieties: GDDs in Excess of 30° C

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is New Crop Varieties				
	Panel A: Extreme Exposure as Growing Degree Days over 30C				
Δ ExtremeExposure (GDD over 30 C)	0.00443***	0.00476***	0.00347**	0.00361**	0.00362*
	(0.00163)	(0.00158)	(0.00148)	(0.00164)	(0.00208)
	Panel B: Growing Degree Days over 30C Alongside Baseline Measure				
Δ ExtremeExposure (GDD over 30 C)	0.00115	0.00113	6.01e-05	-0.00226	-0.00178
	(0.00240)	(0.00243)	(0.00205)	(0.00234)	(0.00245)
Δ ExtremeExposure (our measure with crop-level variaiton)	0.0137*	0.0143*	0.0135**	0.0244***	0.0267***
	(0.00748)	(0.00778)	(0.00591)	(0.00840)	(0.00902)
Log area harvested	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes
Pre-period PVP certificates (1970-1980)	No	No	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	No	No	No	Yes	Yes
Average Temperature Change	No	No	No	No	Yes
Observations	69	69	69	69	69

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released. In Panel A, the independent variable of interest is the change in the number of growing degree days (GDDs) in excess of 30 degrees Celsius. In Panel B, our baseline measure of Δ ExtremeExposure that incorporates crop-level variation in temperature sensitivity is included alongside the number of growing degree days (GDDs) in excess of 30 degrees Celsius. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A5: Temperature Distress and Crop Varieties: Crop Area Measurement Sensitivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Crop Varieties					
Sample Period	1950-2016					1980-2016
	Panel A: Crop-by-County Areas from the 1955 Census of Agriculture					
Δ ExtremeExposure	0.0213***	0.0214***	0.0156***	0.0200***	0.0253***	0.0318***
	(0.00420)	(0.00457)	(0.00416)	(0.00559)	(0.00710)	(0.00866)
	Panel B: Average Between 1955 and 1959 Measures					
Δ ExtremeExposure	0.0196***	0.0193***	0.0144***	0.0185***	0.0224***	0.0321***
	(0.00437)	(0.00453)	(0.00398)	(0.00545)	(0.00690)	(0.00870)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes	Yes
Pre-period 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	65	65	65	65	65	65

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released and the sample period for each specification is listed at the top of each column. ExtremeExposure was computed using crop-by-county areas from the 1955 Census of Agriculture in Panel A, and using the average of 1955 and 1959 in Panel B. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A6: Temperature Distress and Crop Varieties: Geographic Controls

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is New Crop Varieties				
Δ ExtremeExposure	0.0241***	0.0288***	0.0231***	0.0254***	0.0355***
	(0.00749)	(0.00815)	(0.00651)	(0.00733)	(0.00894)
Log area harvested	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	Yes	Yes	Yes	Yes	Yes
Pre-period varieties	Yes	Yes	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	Yes	Yes	Yes	Yes	Yes
Average Temperature Change	Yes	Yes	Yes	Yes	Yes
Area-weighted latitude and longitude	Yes	Yes	No	No	Yes
Area-weighted latitude and longitude squared	No	Yes	No	No	Yes
State shares for ten most agticultural states	No	No	Yes	No	Yes
Share cropland irrigated	No	No	No	Yes	Yes
Observations	69	69	69	69	69

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released. The controls included in each specification are noted at the bottom of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A7: Temperature Distress and Crop Varieties: East of the 100th Meridian

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Crop Varieties					
Sample Period	1950-2016					1980-2016
Δ ExtremeExposure	0.00157***	0.00173***	0.00123***	0.00140***	0.00142**	0.00158**
	(0.000451)	(0.000467)	(0.000441)	(0.000525)	(0.000590)	(0.000652)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes	Yes
Pre-period 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

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released and the sample period for each specification is listed at the top of each column. ExtremeExposure was computed using only production and temperature data from East of the 100th meridian. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A8: Temperature Distress and Crop Varieties: Economic Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is New Crop Varieties						
Δ ExtremeExposure	0.0226***	0.0931***	0.0902***	0.0282***	0.0133*	0.0187***	0.0188***
	(0.00669)	(0.0268)	(0.0292)	(0.00912)	(0.00777)	(0.00686)	(0.00631)
US Experiment Station Exposure (area-weighted)	✓						
log Insured Acres		✓					
log Total Subsidies ($)			✓				
log Exports - log Imports				✓			
Share global cropland in the US					✓		
Profits per farm (area-weighted)						✓	
log total profits (area-weighted)							✓
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period varieties	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average Temperature Change	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69	18	18	27	35	69	69

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released. The controls included in each specification are noted at the bottom of each column. Data on the location of US crop experiment stations are from Kantor and Whalley (2019). Farm profits were computed from the US Census of Agriculturein the baseline year (1959). Data on crop-level trade and global production are from FAO STAT and data on insurance coverage and subsidies are from the USDA Risk Management Agency's (RMA) Summary of Business Reports, which we digitized. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A9: Temperature Distress and Crop Varieties: Panel Estimates

	(1)	(2)	(3)	(4)
	Dependent Variable is New Crop Varieties			
EE, *second lead*			0.000341	
			(0.00272)	
EE, *first lead*		0.000657	0.000745	0.00135
		(0.00187)	(0.00233)	(0.00169)
EE, *current decade*	0.00349***	0.00432***	0.00465**	0.00263**
	(0.00127)	(0.00166)	(0.00227)	(0.00115)
EE, *first lag*				0.00308**
				(0.00152)
Crop & Year Fixed Effects	Yes	Yes	Yes	Yes
log Area Harvested x Year Fixed Effects	Yes	Yes	Yes	Yes
Pre-Period Varieties x Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	483	414	345	345

Notes: The unit of observation is a crop-decade pair. Standard errors, clustered by crop, are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A10: Temperature Distress and Crop Varieties: Heterogeneity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is New Crop Varieties							
Δ ExtremeExposure	0.00438	0.0237***	0.0187***	0.0215**	0.0235***	0.0325***	0.0135**	0.0145***
	(0.00510)	(0.00667)	(0.00622)	(0.00854)	(0.00866)	(0.00912)	(0.00604)	(0.00545)
Δ ExtremeExposure x								
Above Median US Area (=1)	0.0258***							
	(0.00741)							
Above Median as Share of Global Area (=1)		-0.00948						
		(0.0112)						
Above Median Net Exports (=1)			-0.00283					
			(0.0113)					
Above Median "Switchability" (=1)				0.00111				
				(0.00900)				
Annual Crop (=1)					0.00561			
					(0.00920)			
Cold-Weather Crop (=1)						-0.0162*		
						(0.00883)		
Not Perishable (=1)							0.00130	
							(0.0123)	
US Experiment Station Exposure								0.213
								(0.169)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period varieties	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cuf-off temp. and cut-off temp sq.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69	35	35	69	69	69	69	69

Notes: The unit of observation is a crop. The outcome vairable is the number of crop-specific varieties. Each column in includes an interaction term between crop-level extreme heat exposure and a different crop-level variable, noted in the leftmost column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A11: Temperature Distress and Crop Varieties: Effects by Type of Inventor

	(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

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific plant variety protection (PVP) certificates released since 1980 awarded to the noted type of inventor. ExtremeExposure computed as the change in the number of crop-specific extreme GDDs between the 1980s and 2010s, while the pre-period is defined as 1970-1980 since PVP was intrduced in 1970. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A12: Temperature Distress and Crop Varieties: Within-Inventor Re-Direction of Technology

	(1)	(2)	(3)
	Dependent Variable is Plant Variety Protection Certificates		
Sample:	All Applicants	Applicants with >5 Certificates	Applicants with >10 Certificates
Δ ExtremeExposure	0.0408***	0.0466***	0.0525***
	(0.0147)	(0.0158)	(0.0169)
Applicant Fixed Effects	Yes	Yes	Yes
All Baseline Controls	Yes	Yes	Yes
Observations	45,689	12,200	7,198

Notes: The unit of observation is a crop-by-applicant. The outcome variable is the number of crop-specific plant variety protection (PVP) certificates released by each applicant since 1980. ExtremeExposure is similarly computed as the change in the number of crop-specific extreme GDDs between the 1980s and 2010s, while the pre-period is defined as 1970-1980 since PVP was intrduced in 1970. Standard errors, double-clustered by crop and applicant, are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A13: Temperature Distress and Patenting, by Class

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable is change in:					
	Planting and Pre-Harvest				Harvest	Post-Harvest
	Crop Varieties (Baseline)	Fertilizing, Planting, and Sowing Patents (A01C)	Soil Working Patents (A01B)	All Planting and Soil Working Patents (A01B & C)	Harvester and Mower Patents (A01D)	Post-Harvest Technology Patents (A01F)
Δ ExtremeExposure	0.0136***	0.00930**	0.00860	0.00939**	0.000824	-0.00496
	(0.00372)	(0.00406)	(0.00623)	(0.00439)	(0.00426)	(0.00728)
All Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69	69	69	69	69	69

Notes: The unit of observation is a crop. The dependent variable in each specification is noted at the top of each column; in each case, it is a different technology type, either seed varieties (column 1) or patent grants from a particular patent class, with the CPC class noted in the technology description (columns 2-6). Baseline controls are included in each specification, and the pre-period innovation control in each column corresponds to the number of variety releases or patent grants from 1900-1960 corresponding to the technology class(es) of the dependent variable. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A14: The Effects of Drought and Extreme Cold on Innovation

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is New Crop Varieties				
Δ ExtremeHeatExposure	0.0200***	0.0202***	0.0160***	0.0214***	0.0225***
	(0.00486)	(0.00447)	(0.00434)	(0.00598)	(0.00722)
Δ DroughtExposure	0.358*	0.493*	0.286	0.284	0.258
	(0.216)	(0.264)	(0.355)	(0.327)	(0.382)
Δ ExtremeColdExposure	0.000653	-0.000427	-0.00245	-0.00352	-0.00305
	(0.00321)	(0.00384)	(0.00343)	(0.00331)	(0.00382)
Log area harvested	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	Yes
Pre-period varieties	No	No	Yes	Yes	Yes
Cut-off temp. and cut-off temp sq.	No	No	No	Yes	Yes
Average Temperature Change	No	No	No	No	Yes
Observations	69	69	69	69	69

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released and the sample period for each specification is listed at the top of each column. The controls included in each specification are noted at the bottom of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A15: County-Level Estimates: Direct Effect of Temperature Distress

	(1)	(2)	(3)
Dependent Variable:	log Land Value per Acre	Revenue per Acre from Crop Production	Revenue per Acre from Non-Crop Production
County-Level Extreme Exposure	-0.437***	-147.9***	0.0634
	(0.104)	(54.72)	(39.19)
County Fixed Effects	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes
Observations	6,000	5,880	5,876
R-squared	0.988	0.654	0.606

Notes: The unit of observation is a county-year. All columns include county and state-by-census round fixed effects. Standard errors are double clustered at the county and state-by-decade levels and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A16: County-Level Estimates: Crop Revenue and Farm Profits

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is:					
	log Crop Revenue per Acre		Total Agricultural Profits		Agricultural Profits per Acre	
County-Level Extreme Exposure	-0.829**	-2.029***	-1,278**	-4,143***	-8.451*	-4.457*
	(0.358)	(0.411)	(498.4)	(1,449)	(5.045)	(2.678)
	[0.446]	[0.509]	[612.6]	[1,818]	[6.051]	[3.299]
County-Level Extreme Exposure x Innovation Exposure	0.234**	0.570***	339.7***	1,252***	2.687	0.923
	(0.114)	(0.113)	(128.6)	(450.4)	(1.694)	(0.783)
	[0.139]	[0.135]	[134.4]	[560.6]	[2.068]	[0.875]
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weighted by Agricultural Land Area	No	Yes	No	Yes	No	Yes
Observations	5,880	5,880	5,986	5,986	5,982	5,982
R-squared	0.979	0.985	0.727	0.814	0.698	0.886

Notes: The unit of observation is a county-year. Standard errors, double clustered at the county and state-by-decade levels, are reported in parentheses, and standard errors clustered by state are reported in brackets, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A17: County-Level Estimates: No State Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
County-Level Extreme Exposure	-0.768***	-1.756***	-0.690***	-1.023***	-0.797***	-0.200	-0.330**
	(0.199)	(0.347)	(0.198)	(0.195)	(0.206)	(0.127)	(0.162)
	[0.258]	[0.464]	[0.253]	[0.247]	[0.259]	[0.0890]	[0.137]
County-Level Extreme Exposure x Innovation Exposure	0.306***	0.643***	0.251***	0.319***	0.270***	0.0925**	0.136***
	(0.0858)	(0.124)	(0.0674)	(0.0788)	(0.0675)	(0.0371)	(0.0439)
	[0.112]	[0.164]	[0.0834]	[0.102]	[0.0830]	[0.0291]	[0.0368]
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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-squared	0.986	0.987	0.986	0.986	0.986	0.968	0.972

Notes: The unit of observation is a county-year. Standard errors, double clustered at the county and state-by-decade levels, are reported in parentheses, and standard errors clustered by state are reported in brackets, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A18: County-Level Estimates: Controlling for Higher Order Terms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
County-Level Extreme Exposure	-0.861***	-1.550***	-0.838***	-0.872***	-0.798***	-0.232**	-0.391***
	(0.211)	(0.238)	(0.203)	(0.238)	(0.226)	(0.107)	(0.132)
	[0.265]	[0.301]	[0.245]	[0.305]	[0.279]	[0.105]	[0.103]
County-Level Extreme Exposure x Innovation Exposure	0.259***	0.445***	0.247***	0.261***	0.240***	0.0923***	0.130***
	(0.0755)	(0.0718)	(0.0725)	(0.0786)	(0.0757)	(0.0315)	(0.0320)
	[0.0942]	[0.0885]	[0.0876]	[0.0988]	[0.0921]	[0.0251]	[0.0239]
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LocalEE Squared	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-squared	0.989	0.991	0.989	0.989	0.989	0.979	0.984

Notes: The unit of observation is a county-year. All columns include local extreme exposure squared on the right hand side of the regression. Standard errors, double clustered at the county and state-by-decade levels, are reported in parentheses, and standard errors clustered by state are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A19: County-Level Estimates: Sample East of 100th Meridian

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Sample is Restricted to Counties East of the 100th Meridian						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
County-Level Extreme Exposure	-0.880***	-1.229***	-0.751***	-0.845***	-0.656**	-0.210*	-0.260**
	(0.263)	(0.278)	(0.233)	(0.290)	(0.272)	(0.121)	(0.129)
	[0.339]	[0.360]	[0.285]	[0.383]	[0.346]	[0.128]	[0.105]
County-Level Extreme Exposure x Innovation Exposure	0.311***	0.408***	0.269***	0.295***	0.245**	0.0960**	0.127***
	(0.103)	(0.0990)	(0.0934)	(0.106)	(0.0972)	(0.0373)	(0.0381)
	[0.133]	[0.125]	[0.117]	[0.139]	[0.123]	[0.0299]	[0.0273]
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x 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	4,852	4,852	4,842	4,852	4,842	16,956	16,956
R-squared	0.991	0.993	0.991	0.991	0.991	0.981	0.987

Notes: The unit of observation is a county-year. The estimation sample is restricted to counties East of the 100th Meridian in all specifications. Standard errors, double clustered at the county and state-by-decade levels, are reported in parentheses, and standard errors clustered by state are reported in brackets, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A20: County-Level Estimates: "Leave State Out" Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	InnovationExposure is Computed Excluding the State in which the County is Located						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
County-Level Extreme Exposure	-0.707***	-1.293***	-0.693***	-0.699***	-0.651***	-0.204*	-0.368***
	(0.208)	(0.220)	(0.194)	(0.226)	(0.214)	(0.109)	(0.140)
	[0.261]	[0.273]	[0.232]	[0.287]	[0.261]	[0.104]	[0.0998]
County-Level Extreme Exposure x Innovation Exposure	0.192**	0.339***	0.187**	0.188**	0.181**	0.0830**	0.121***
	(0.0770)	(0.0752)	(0.0719)	(0.0772)	(0.0735)	(0.0322)	(0.0333)
	[0.0966]	[0.0931]	[0.0866]	[0.0965]	[0.0885]	[0.0259]	[0.0261]
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x 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	20,966	20,966
R-squared	0.989	0.991	0.989	0.989	0.989	0.979	0.984

Notes: The unit of observation is a county-year. Innovation exposure is calculated after excluding from the sample all counties in the same state as the county of interest. Standard errors, double clustered at the county and state-by-decade levels, are reported in parentheses, and standard errors clustered by state are reported in brackets, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A21: County-Level Estimates: Alternative Standard Error Clusters

	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient t-statistic for kernel cut-off distance (km):					State-level cluster
	250	500	1000	1500	2000	
County-Level Extreme Exposure	4.828	3.812	3.797	4.825	8.404	3.22
County-Level Extreme Exposure x Innovation Exposure	3.894	3.233	2.808	2.957	4.065	2.64
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Coefficient estimate t-statistics from the baseline county-level specification (Table 3, Column 1) with alternative standard error clustering strategies. Columns 1-5 follow Hsiang (2010)'s implementation of Conley (2008) standard errors, for five different values of the kernel cut off distance (measured in km). In column 6, standard errors are clustered by state.

Table A22: County-Level Estimates: Heterogeneity by Crop Mix Market Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is log Land Value per Acre						
	Long Difference Estimates (1950s-2010s)					*Panel Estimates*	
(County-Level Extreme Exposure) x (Innovation Exposure) x (Crop Mix Market Size)	0.178***	0.140*	0.192***	0.179***	0.190***	0.0800***	0.104***
	(0.0490)	(0.0838)	(0.0509)	(0.0479)	(0.0507)	(0.0268)	(0.0325)
	[0.0568]	[0.108]	[0.0547]	[0.0553]	[0.0542]	[0.0183]	[0.0231]
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x 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-squared	0.989	0.991	0.989	0.989	0.989	0.979	0.984

Notes: The unit of observation is a county-year. Standard errors, double clustered at the county and state-by-decade levels, are reported in parentheses, and standard errors clustered by state are reported in brackets, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A23: Climate Change Damage, With and Without Innovation: All Projection Estimates

	(1)	(2)	(3)	(4)	(5)
Scenario	End Decade	Damage with Innovation (Percent)	Damage without Innovation (Percent)	Mitigated By Innovation (Percent of Damage)	Present Value of Savings (billion USD)
RCP 4.5	2050s	10.7	12.6	15.2	218.1
	2090s	18.9	21.7	13.0	1047.1
RCP 6.0	2050s	7.4	8.8	15.8	159.6
	2090s	21.6	25.3	14.4	1344.3
RCP 8.5	2050s	16.1	19.2	16.0	347.2
	2090s	39.3	59.2	33.6	7350.5

Notes: The concentration pathway for each projection is noted in the leftmost column. Column 1 lists the decade used to estimate the end period climate. Columns 2 and 3 report percent damage in counterfactuls with and without innovation respectively. Columns 4 and 5 report the percent of climate damage mitigated by directed innovation and the net present value (in billion USD) of savings due to directed technology.

Table A24: Climate Change Damage, With and Without Innovation: All Projection Estimates with Predicted Future Areas

	(1)	(2)	(3)	(4)	(5)
Scenario	End Decade	Damage with Innovation (Percent)	Damage without Innovation (Percent)	Innovation (Percent of Damage)	Present Value of Savings (billion USD)
RCP 4.5	2050s	9.8	11.6	15.5	249.4
	2090s	18.2	21.0	13.1	1233.3
RCP 6.0	2050s	6.7	8.0	16.5	181.9
	2090s	20.7	24.0	13.6	1462.5
RCP 8.5	2050s	15.1	17.9	15.4	385.8
	2090s	49.7	56.3	11.8	3088.3

Notes: All estimates use predicted crop switching patterns from our empirical model. The concentration pathway for each projection is noted in the leftmost column. Column 1 lists the decade used to estimate the end period climate. Columns 2 and 3 report percent damage in counterfactuls with and without innovation respectively. Columns 4 and 5 report the percent of climate damage mitigated by directed innovation and the net present value (in billion USD) of savings due to directed technology.

B Omitted Proofs and Derivations

B.1 Derivation of Expressions in Main Text

We first derive Equation 2.2 starting with the farm's profit maximization problem:

$$\max_{T_i} p \cdot \alpha^{-\alpha}(1-\alpha)^{-1} G(A_i, \theta)^{\alpha} T_i^{1-\alpha} - qT_i \tag{B.1}$$

This is a concave problem, so its optimum is characterized by the first-order condition:

$$0 = p \cdot \alpha^{-\alpha} G(A_i, \theta)^{\alpha} T_i^{-\alpha} - q \tag{B.2}$$

which re-arranges to $T_i = \alpha^{-1} p^{\frac{1}{\alpha}} q^{-\frac{1}{\alpha}} G(A_i, \theta)$, as desired.

We next derive Equation 2.3. The first step is to solve for the technology firm's optimal price. Substituting the technology demand of Equation 2.2 into the innovating firm's profit-maximization problem gives the program:

$$\max_{q,\theta} \left(q - (1-\alpha)\right) \alpha^{-1} p^{\frac{1}{\alpha}} q^{-\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) - C(\theta) \tag{B.3}$$

It is straightforward to verify that this program is concave in both q and θ under our maintained assumptions that G is concave in θ and $\alpha \in [0, 1)$. The first-order condition for q, which is necessary and sufficient for optimality, is

$$\left(q^{-\frac{1}{\alpha}} - \frac{1}{\alpha} q^{-\frac{1}{\alpha}-1}(q - (1-\alpha))\right) \alpha^{-1} p^{\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) = 0 \tag{B.4}$$

This is satisfied for any θ if

$$q^{-\frac{1}{\alpha}} - \frac{1}{\alpha} q^{-\frac{1}{\alpha}-1}(q - (1-\alpha)) = 0 \tag{B.5}$$

which in turn re-arranges to $q = 1$. Plugging this back into the outer profit maximization problem and simplifying yields the desired expression

$$\begin{aligned} &(1 - (1-\alpha)) \, \alpha^{-1} p^{\frac{1}{\alpha}} 1^{-\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) - C(\theta) \\ &= p^{\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) - C(\theta) \end{aligned}$$

B.2 Proof of Proposition 1

Consider a damaging shift in the climate from F to F', meaning that $F \succeq_{FOSD} F'$. Let (θ, θ') respectively be the technology levels in each equilibrium. It is necessary and sufficient for the original equilibrium technology level to be optimal for the innovating firm, or satisfy

$$\theta \in \operatorname{argmax} \, \overline{p}^{\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) - C(\theta) \tag{B.6}$$

Because $G(\cdot)$ is concave and twice continuously differentiable in θ, $C(\cdot)$ is convex and differentiable in θ, $\frac{\mathrm{d}}{\mathrm{d}\theta}C(0) = 0$, and $G_2 \geq 0$ for any (A, θ), a necessary and sufficient condition is the first-order condition

$$\overline{p}^{\frac{1}{\alpha}} \int G_2(A, \theta)\,\mathrm{d}F(A) = \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) \tag{B.7}$$

and similarly, for the second equilibrium,

$$\overline{p}^{\frac{1}{\alpha}} \int G_2(A, \theta')\,\mathrm{d}F'(A) = \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta') \tag{B.8}$$

If $G_{12} \leq 0$, then $A \mapsto G_2(A, \theta)$ is a decreasing function. Since $F \geq_{FOSD} F'$, we have

$$\int G_2(A, \theta)\,\mathrm{d}F(A) \leq \int G_2(A, \theta)\,\mathrm{d}F'(A) \tag{B.9}$$

Now we show that $\theta \leq \theta'$. Consider the contradictory case that $\theta > \theta'$. Because $G(\cdot)$ is concave in its second argument, we have $G_2(A, \theta) \leq G_2(A, \theta')$ for all A and therefore

$$\int G_2(A, \theta)\,\mathrm{d}F'(A) \leq \int G_2(A, \theta')\,\mathrm{d}F'(A) \tag{B.10}$$

Combined with the previous expressions, this implies,

$$\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) = \int G_2(A, \theta)\,\mathrm{d}F(A) \leq \int G_2(A, \theta)\,\mathrm{d}F'(A) \leq \int G_2(A, \theta')\,\mathrm{d}F'(A) = \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta')$$

But the initial claim $\theta > \theta'$, owing to the strict convexity of $C(\cdot)$, implies $\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) > \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta')$. This is a contradiction. Therefore $\theta' \geq \theta$.

If $G_{12} \geq 0$, then the previous argument is reversed. Note first that, because $A \mapsto G_2(A, \theta)$ is an increasing function,

$$\int G_2(A, \theta')\,\mathrm{d}F(A) \geq \int G_2(A, \theta')\,\mathrm{d}F'(A) \tag{B.11}$$

using first-order stochastic dominance. Now we will verify that $\theta' \leq \theta$. Consider the contradictory case that $\theta' > \theta$. Because $G(\cdot)$ is concave in its second argument, we have $G_2(A, \theta) \geq G_2(A, \theta')$ for all A and

$$\int G_2(A, \theta)\,\mathrm{d}F'(A) \geq \int G_2(A, \theta')\,\mathrm{d}F'(A) \tag{B.12}$$

Combined with the previous expressions, this implies,

$$\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) = \int G_2(A, \theta)\,\mathrm{d}F(A) \geq \int G_2(A, \theta)\,\mathrm{d}F'(A) \geq \int G_2(A, \theta')\,\mathrm{d}F'(A) = \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta')$$

But the initial claim $\theta' > \theta$, owing to the strict convexity of $C(\cdot)$, implies $\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta') > \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta)$. This is a contradiction. Therefore $\theta' \leq \theta$.

B.3 Proof of Proposition 2

Consider a damaging shift in the climate from F to F', meaning that $F \succeq_{FOSD} F'$. Let (θ, θ') respectively be the technology levels in each equilibrium and (p, p') respectively be the prices. As argued in the proof of Proposition 1, necessary conditions for equilibrium under each climate are respectively

$$p^{\frac{1}{\alpha}} \int G_2(A,\theta)\,\mathrm{d}F(A) = \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) \tag{B.13}$$

and similarly, for the second equilibrium,

$$p'^{\frac{1}{\alpha}} \int G_2(A,\theta')\,\mathrm{d}F'(A) = \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta') \tag{B.14}$$

A second necessary condition in each case is that the price lies on the demand curve. Denote the price level, as a function of the technology level and productivity distribution, as $p^*(\theta, F(\cdot))$ which solves the following fixed-point equation for p:

$$p = P\left(\alpha^{-1}(1-\alpha)^{-1}p^{\frac{1}{\alpha}-1}\int G(A,\theta)\,\mathrm{d}F(A)\right) \tag{B.15}$$

and observe that equilibrium requires $p = p^*(\theta, F(\cdot))$ (and likewise $p' = p^*(\theta', F'(\cdot))$).

Let us argue first that $p^*(\cdot)$ is weakly decreasing in θ and $F(\cdot)$, the latter via the FOSD order. See that, for any fixed $(F(\cdot), \theta)$, the right-hand-side of (B.15) is a continuous, non-increasing function of p on the range $[0, \infty]$. The left-hand-side is a continuous function that increases without bound from 0. Thus, the fixed point solution exists and is unique. Moreover, increasing θ (in the standard order) or $F(\cdot)$ (in the FOSD order) increases the term $\int G(A,\theta)\,\mathrm{d}F(A)$ under the global assumptions that $G_1 \geq 0$ and $G_2 \geq 0$, which decreases for every p the value of the right-hand-side of (B.15). Thus the unique solution is non-increasing in these arguments.

We next make an argument similar to that in Proposition 1 to show that $\theta' \geq \theta$, for all crops, when the climate worsens and $G_{12} \leq 0$. We split the argument based on conjectures for the price. Consider first the case in which $p = p^*(\theta, F(\cdot)) \geq p^*(\theta', F'(\cdot)) = p'$. This is only possible if $\theta' \geq \theta$ owing to the previously demonstrated monotonicities of p^*, which proves the desired claim. Consider next the case in which $p = p^*(\theta, F(\cdot)) \leq p^*(\theta', F'(\cdot)) = p'$. If $G_{12} \leq 0$, then $A \mapsto G_2(A,\theta)$ is a decreasing function. Since $F \succeq_{FOSD} F'$, we have

$$\int G_2(A,\theta)\,\mathrm{d}F(A) \leq \int G_2(A,\theta)\,\mathrm{d}F'(A) \tag{B.16}$$

Observe in this case that

$$\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) = p^{\frac{1}{\alpha}} \int G_2(A,\theta)\,\mathrm{d}F(A) \leq p'^{\frac{1}{\alpha}} \int G_2(A,\theta)\,\mathrm{d}F'(A) \tag{B.17}$$

by combining (B.16) with the previous claim.

We now establish $\theta' \geq \theta$ by, as in the proof of Proposition 1, ruling out the case $\theta > \theta'$ by contradiction. If $\theta > \theta'$, then

$$p'^{\frac{1}{\alpha}} \int G_2(A,\theta)\,\mathrm{d}F'(A) \leq p'^{\frac{1}{\alpha}} \int G_2(A,\theta')\,\mathrm{d}F'(A) \tag{B.18}$$

by weak concavity of $G(\cdot)$. Combining this with (B.17) implies that $\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) \leq \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta')$. But the conjecture $\theta > \theta'$ and the strict convexity of $C(\cdot)$ implies $\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) < \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta')$. This is a contradiction. Therefore, $\theta' \geq \theta$ as desired.

To establish the second point, it suffices to have an example of each case. The example of technology decreasing is given in Proposition 1, as the rigid price case is nested in the more general model. The example of technology increasing is given here. Consider an economy in which $C(\theta) = \theta$; $P(Y) = Y^{-\varepsilon}$ for all k and some $\varepsilon \geq 0$; and $G(A,\theta) = A\theta^{\beta}$ for some $\beta \in (0,1)$. The original distribution of productivity places a Dirac mass on productivity A, and the new distribution places a Dirac mass on $A' \leq A$. The first-order condition for equilibrium technology is

$$\beta p^{\frac{1}{\alpha}} A\theta^{\beta-1} = 1 \tag{B.19}$$

The equilibrium price is $p = M_0 \cdot (A\theta^{\beta})^{-\frac{\varepsilon}{1+\varepsilon(1/\alpha-1)}}$ up to a positive constant M_0 which depends on α and ε. The solution to the fixed point equation which identifies θ is therefore

$$\theta = M_1 \cdot A^{\frac{\alpha(1-\varepsilon)}{\alpha(1-\beta)+\varepsilon(1-\alpha(1-\beta))}} \tag{B.20}$$

up again to a positive constant which depends on α and ε. By the same token, $\theta' = M_1 \cdot (A')^{\frac{\alpha(1-\varepsilon)}{\alpha(1-\beta)+\varepsilon(1-\alpha(1-\beta))}}$. See that $\theta \geq \theta'$ if and only if $\varepsilon \in (0,1)$. Thus, if $\varepsilon > 1$, we have an example economy in which $G_{12} \geq 0$ but equilibrium technology decreases, for all crops, when the climate gets worse.

B.4 Proof of Corollary 1

We first derive the profits of each farmer. Using the expression for technology demand in Equation 2.2, we write the farmer's profit as

$$\Pi_i = p \cdot \alpha^{-\alpha}(1-\alpha)^{-1} G(A_i,\theta)^{\alpha} (\alpha^{-1} p^{\frac{1}{\alpha}} q^{-\frac{1}{\alpha}} G(A_i,\theta))^{1-\alpha} - q(\alpha^{-1} p^{\frac{1}{\alpha}} q^{-\frac{1}{\alpha}} G(A_i,\theta)) \tag{B.21}$$

Combining terms and simplifying, this is

$$\begin{aligned} \Pi_i &= (1-(1-\alpha)) \cdot p \cdot \alpha^{-\alpha}(1-\alpha)^{-1} G(A_i,\theta)^{\alpha} (\alpha^{-1} p^{\frac{1}{\alpha}} q^{-\frac{1}{\alpha}} G(A_i,\theta))^{1-\alpha} \\ &= p\alpha Y_i = (1-\alpha)^{-1} q^{1-\alpha} p^{\frac{1}{\alpha}} G(A_i,\theta) \end{aligned} \tag{B.22}$$

where Y_i is the farm's production in physical units.[1] Moreover, the sensitivity of this to climatic productivity is

$$\frac{\partial}{\partial A_i}\Pi_i = M_0 p^{\frac{1}{\alpha}} G_1(A_i,\theta) \tag{B.23}$$

[1]In this context, profits are also the return to the implicit "fixed factor" in a constant-returns-to-scale re-writing of the production function. From this logic, it is immediate that the fixed factor earns share α of income.

where $M_0 = (1-\alpha)^{-1} q^{1-\alpha} > 0$ is invariant across equilibria of the model (as $q \equiv 1$ from the monopolist's pricing problem and α is primitive).

We now prove the result. Let us start with case 1. By the fundamental theorem of calculus, with differentiable G,

$$\begin{aligned}\Delta R(A, p) &= M_0 p^{\frac{1}{\alpha}} \cdot (G_1(A, \theta) - G_1(A, \theta')) \\ &= -M_0 p^{\frac{1}{\alpha}} \int_{\theta}^{\theta'} G_{12}(A, z)\, \mathrm{d}z\end{aligned} \tag{B.24}$$

By the assumption $G_{12} \leq 0$ and the result from Proposition 2 that $\theta' \geq \theta$, we know the integrand is non-positive along the entire path. Moreover, the constant $-M_0 p^{\frac{1}{\alpha}}$ is strictly negative. Thus $\Delta R(A, p) \geq 0$ for any (A, p).

Consider next case 2. Proposition 2 tells us that we could have either $\theta' \geq \theta$ or the opposite. If $\theta' \geq \theta$, $\Delta R(A, p) \leq 0$ by following the argument above and noting that $G_{12} \geq 0$. If $\theta' \leq \theta$, then we revise the first argument to integrate from the lower to the higher technology level

$$\Delta R_i = M_0 p^{\frac{1}{\alpha}} \int_{\theta'}^{\theta} G_{12}(A, z)\, \mathrm{d}z \tag{B.25}$$

and observe that non-negativity of the constant and G_{12} implies $\Delta R(A, p) \geq 0$.

B.5 Proof of Proposition 3

We begin with the first-order condition of the innovator for crop k. See that the partial derivative of $G(\cdot)$ in θ, evaluated at (A_i, θ_k), is

$$\frac{\partial}{\partial \theta} G(A_i, \theta_k) = \frac{G(A_i, \theta_k)}{\theta_k} (g_{20} + g_{21}(\overline{A} - A_i)) \tag{B.26}$$

We approximate this around the point at which $A_i = \tilde{A} \in [\underline{A}, \overline{A}]$, $\theta_k = \tilde{\theta}$, and $G(A_i, \theta) = \tilde{G} := G(\tilde{A}, \tilde{\theta})$ for each crop. Since the scale of $\tilde{G}$ and $\tilde{\theta}$ is arbitrary, we make the convenient normalizations that $g_{20} + g_{21}(\overline{A} - \tilde{A}) = 1$ and $g_0 + g_1(\overline{A} - \tilde{A}) = 0$ (i.e., $G(\tilde{A}, \theta) = \theta$).

The first-order condition for the innovator's choice of θ_k is, applying the approximation to set $\frac{G(A_i, \theta_k)}{\theta_k} \approx \frac{\theta_k}{\theta_k} = 1$, is

$$\theta_k^{\eta} == p_k^{\frac{1}{\alpha}} \int_0^1 \frac{G(A_i, \theta_k)}{\theta_k} \left(g_{20} + g_{21}(\overline{A} - A_i)\right) \mathrm{d}F(A_i) \approx p_k^{\frac{1}{\alpha}} \int_0^1 \left(g_{20} + g_{21}(\overline{A} - A_i)\right) \mathrm{d}F(A_i) \tag{B.27}$$

We approximate the log of the integral as

$$\log \int_0^1 \left(g_{20} + g_{21}(\overline{A} - A_i)\right) \mathrm{d}F(A_i) = \int_0^1 \left(\left(g_{20} + g_{21}(\overline{A} - A_i)\right) - 1\right) \mathrm{d}F(A_i) \tag{B.28}$$

since the integrand is close to one. Applying this approximation to the first-order condition, and taking logs, we get

$$\eta \log \theta_k = (g_{20} - 1) + \frac{1}{\alpha} \log p_k + g_{21}(\overline{A} - A_k) \tag{B.29}$$

in which we define the crop-level shock

$$A_k := \int_0^1 A \, \mathrm{d}F_k(A) \tag{B.30}$$

We now solve for equilibrium prices. Prices, in logs, lie on the following demand curve:

$$\log p_k = \log p_0 - \varepsilon \log Y_k \tag{B.31}$$

The output of a farm i growing crop k, based on substituting the technology demand of Equation 2.2 into the production function, is

$$Y_i(A_i, \theta_k, p_k) = (\alpha(1-\alpha))^{-1} p_k^{\frac{1}{\alpha}-1} G(A_i, \theta_k) \tag{B.32}$$

and the expression for total output of crop k is

$$Y_k = \int Y_i(A_i, \theta_k, p_k) \, \mathrm{d}F(A_i) = (\alpha(1-\alpha))^{-1} p_k^{\frac{1}{\alpha}-1} \int_0^1 G(A, \theta_k) \, \mathrm{d}F_k(A) \tag{B.33}$$

Taking a log and substituting this into Equation B.31 gives

$$\log p_k = \log p_0 - \varepsilon \left(\frac{1}{\alpha} - 1\right) \log p_k + \varepsilon \log(\alpha(1-\alpha)) - \varepsilon \log \int_0^1 G(A, \theta_k) \, \mathrm{d}F_k(A) \tag{B.34}$$

We again apply an approximation around $\tilde{G}$. Specifically, we do the log-linearization

$$\log \int_0^1 \frac{G(A, \theta_k)}{\tilde{G}} \, \mathrm{d}F_k(A) \approx \int_0^1 \log\left(\frac{G(A, \theta_k)}{\tilde{G}}\right) \mathrm{d}F_k(A) \tag{B.35}$$

Using the approximation, and the fact that $\log \tilde{G} = \log \tilde{\theta}$ under the normalization, we write

$$\begin{aligned} \log p_k = {} & \log p_0 - \varepsilon \left(\frac{1}{\alpha} - 1\right) \log p_k + \varepsilon \log(\alpha(1-\alpha)) - \varepsilon g_0 - \varepsilon g_1(\overline{A} - A_k) \\ & - \varepsilon \left((g_{20} + g_{21}(\overline{A} - A_k)) \log \theta_k\right) + \varepsilon \log \tilde{\theta} \end{aligned} \tag{B.36}$$

We finally approximate the second order term in the price equation around the point at which $A_i \equiv \tilde{A}$:

$$(\overline{A} - A_i) \log \theta \approx (\overline{A} - \tilde{A}) \log \theta \tag{B.37}$$

This is required to obtain a closed-form solution for prices. We then write, using this substitution and the aforementioned normalization that $g_{20} + g_{21}(\overline{A} - \tilde{A}) = 1$,

$$\log p_k = (\log p_0 + \varepsilon \log \tilde{\theta}) + \varepsilon \left(\log(\alpha(1-\alpha)) - g_0 - g_1(\tilde{A} - A_k) - \left(\frac{1}{\alpha} - 1\right) \log p_k - \log \theta_k\right) \tag{B.38}$$

Solving for p_k, we get

$$\log p_k = \frac{\alpha}{\alpha + \varepsilon(1-\alpha)} \left(\log p_0 + \varepsilon \log \tilde{\theta} + \varepsilon \log(\alpha(1-\alpha)) - \varepsilon \left(g_0 + g_1(\overline{A} - A_k) + \log \theta_k \right) \right) \tag{B.39}$$

We now solve for the equilibrium level of technology by combining (B.29) and (B.39). Direct substitution gives

$$\eta \log \theta_k = \frac{\log p_0 + \varepsilon \log \tilde{\theta} + \varepsilon \log(\alpha(1-\alpha)) - \varepsilon \left(g_0 + g_1(\overline{A} - A_k) + \log \theta_k \right)}{\alpha + \varepsilon(1-\alpha)} + (g_{20} - 1) + g_{21}(\overline{A} - A_k) \tag{B.40}$$

We first solve the above for $A_k = \tilde{A}$ to derive the constant

$$\log \tilde{\theta} = \frac{\tau}{\eta} \left(\frac{1}{\varepsilon} \log p_0 + \log(\alpha(1-\alpha)) \right) \tag{B.41}$$

where we define the parameter

$$\tau = \frac{\varepsilon}{\alpha + \varepsilon(1-\alpha)} \tag{B.42}$$

We then observe that we can write

$$\log \theta_k = \log \theta_0 + \delta(\overline{A} - A_k) \tag{B.43}$$

where $\log \theta_0 = \log \tilde{\theta} - \delta(\overline{A} - \tilde{A})$ and slope

$$\delta := \frac{g_{21} - \tau g_1}{1 + \eta + \tau} \tag{B.44}$$

We finally consider equilibrium rents. Log rents for farm i, growing crop k, are

$$\log \Pi_i = -\log(1-\alpha) + \frac{1}{\alpha} \log p_k + \log G(A_i, \theta_k) \tag{B.45}$$

Using the assumed form of $\log G$ from (2.5), p from (B.39), and θ from (B.43),

$$\begin{aligned} \log \Pi_i = & -\log(1-\alpha) \\ & + \tau \left(\frac{1}{\varepsilon} \log p_0 + \log \tilde{\theta} + \log(\alpha(1-\alpha)) - \left(g_0 + g_1(\overline{A} - A_k) + (\log \theta_0 + \delta(\overline{A} - A_k)) \right) \right) \\ & + g_0 + g_1(\overline{A} - A_i) + (g_{20} + g_{21}(\overline{A} - A_i))(\log \theta_0 + \delta(\overline{A} - A_k)) \end{aligned} \tag{B.46}$$

which simplifies, as desired, to

$$\log \Pi_i = \log \Pi_{0,i} + \beta \cdot (\overline{A} - A_i) + \gamma \cdot (\overline{A} - A_{k(i)}) + \phi(\overline{A} - A_i)(\overline{A} - A_{k(i)}) \tag{B.47}$$

with coefficients

$$\begin{aligned}\beta &= g_1 \\ \gamma &= -\tau(g_1 + \delta) \\ \phi &= g_{21}\delta\end{aligned} \tag{B.48}$$

and constant

$$\log \Pi_{0,i} = -\log(1-\alpha) + \tau\left(\frac{1}{\varepsilon}\log p_0 + \log\tilde{\theta} + \log(\alpha(1-\alpha)) - g_0 - \log\theta_0\right) + g_0 + g_{20}\log\theta_0 \tag{B.49}$$

B.6 Proof of Corollary 2

The stated assumptions translate to $g_{20} = 0$ and $\varepsilon = 0$. The latter implies $\tau = 0$. See, under these conditions, that the regression coefficients in representation (B.48), from the derivation in Appendix B.5, are $\beta = g_1$, $\gamma = 0$, and $\phi = g_{21}\delta$.

Let us now consider the counterfactual scenarios. Denote by regular notation quantities under the intial climate, by primes quantities under the later climate, and by double primes quantities under the counterfactual scenario. Given the mapping

$$\begin{aligned}\log\Pi_i &= \log \mathrm{AgrLandPrice}_i \\ A_i &= \mathrm{LocalEE}_i \\ A_{k(i)} &= \mathrm{InnovationExposure}_i\end{aligned}$$

we want to show that $\log\Pi_i''$ corresponds with each of the expressions in Equations 6.1 and 6.2 under the assumed conditions.

In the counterfactual without climate change, the climate is instead $A_i'' = A_i$ and $A_k'' = A_k$ in the second period. See that

$$\begin{aligned}\log\Pi_i'' &= \log\Pi_{0,i} + \beta\cdot(\overline{A} - A_i'') + \gamma\cdot(\overline{A} - A_{k(i)}'') + \phi(\overline{A} - A_i'')(\overline{A} - A_{k(i)}'') \\ &= \log\Pi_{0,i} + \beta\cdot(\overline{A} - A_i) + \gamma\cdot(\overline{A} - A_{k(i)}) + \phi(\overline{A} - A_i)(\overline{A} - A_{k(i)}) \\ &= \log\Pi_i\end{aligned}$$

or that the two scenarios are identical. This validates the counterfactual.

In the counterfactual without innovation, technology is held counterfactually at $\theta_k'' = \theta_k$ while the climate satisfies $A_{i,k}'' = A_{i,k}'$ and $A_k'' = A_k'$ for all locations and crops. Using (B.46) from the derivation in Appendix B.5, and substituting in $\varepsilon = 0$ (which implies $\tau = 0$) and $g_{20} = 0$, we have

$$\log\Pi_i'' = -\log(1-\alpha) + g_0 + g_1(\overline{A} - A_i') + (g_{20} + g_{21}(\overline{A} - A_i'))(\theta_0 + \delta(\overline{A} - A_{k(i)})) \tag{B.50}$$

See that this corresponds with

$$\log\Pi_i'' = \log\Pi_{0,i} + \beta\cdot(\overline{A} - A_i') + \gamma\cdot(\overline{A} - A_{k(i)}) + \phi\cdot(\overline{A} - A_i')(\overline{A} - A_{k(i)}) \tag{B.51}$$

given the expressions for the coefficients in Equation B.48 and, in particular, the fact that $\varepsilon = 0$ and $\tau = 0$ implies that $\gamma = 0$.

C Model Extensions

C.1 Efficiency

In this section, we explore the efficiency properties of the model. For simplicity, we focus on the fixed-price variant of the model.

C.1.1 Static Baseline

We begin with the main static model introduced in the text. We first fully specify the consumer block of the model. In addition to the agricultural good (the "crop"), there is a second numeraire good which can be interpreted as leisure (i.e., negative labor).[2] The agent has an endowment $\overline{z}$ of this good and consumes at level z. The consumer's problem is

$$\begin{aligned} &\max_{c,z} \overline{p}c + z \\ &\text{s.t. } z + pc \leq W + \overline{z} \end{aligned} \tag{C.1}$$

where $\overline{p} > 0$ is a constant, c is consumption of the crop, and W is the agent's total income from owning the farms and the innovative firm. See, from the first-order conditions for consumer optimization, that demand is completely elastic at $p = \overline{p}$.

The social planner's objective is to maximize the representative household's income subject to feasibility constraints. It is straightforward to show that the social planner's problem can be written as

$$\begin{aligned} &\max_{Y,T(\cdot),\theta} \overline{p}Y + \overline{z} - C(\theta) - (1-\alpha)\int_0^1 T(A)\,\mathrm{d}F(A) \\ &\text{s.t. } Y \leq \alpha^{-\alpha}(1-\alpha)^{-1}\int_0^1 T(A)^{1-\alpha}G(A,\theta)^{\alpha}\,\mathrm{d}F(A) \end{aligned} \tag{C.2}$$

after substituting in feasibility constraints. Let λ be the Langrange multiplier on the production constraint, and note immediately that $\lambda = \overline{p}$ in the solution (if the constraint binds at equality). The remaining first order conditions are

$$\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) = \overline{p}\alpha^{1-\alpha}(1-\alpha)^{-1}\int_0^1 T(A)^{1-\alpha}G(A,\theta)^{\alpha-1}G_2(A,\theta)\,\mathrm{d}F(A) \tag{C.3}$$

for θ; and

$$(1-\alpha) = \overline{p}\alpha^{-\alpha}T(A)^{-\alpha}G(A,\theta)^{\alpha} \tag{C.4}$$

for each $T(A)$. See that (C.4) coincides with decentralized technology demand (2.2) and (C.3) corresponds with decentralized quality choice (2.3) if $q = 1-\alpha$, or technology is priced at marginal cost. Thus the singular source of inefficiency in the decentralized allocation is the monopoly power of the technology producer, which could be fixed by leveraging an appropriate subsidy of rate α (i.e., having consumers face price $(1-\alpha)q$). Moreover, the effect of the monopoly power is to unambigu-

[2]For the simplifying reason of ignoring non-negativity constraints, we allow for negative consumption of this good.

ously reduce the amount of technology used by each firm ($T(A)$ for all $A \in [\underline{A}, \overline{A}]$) and the level of technology θ. This is clear from the combination of (C.3) and (C.4) which gives the socially optimal level of technology:

$$\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) = (1-\alpha)^{-\frac{1}{\alpha}}\overline{p}^{\frac{1}{\alpha}} \int G_2(A,\theta)\,\mathrm{d}F(A) \tag{C.5}$$

which differs from the equilibrium condition (B.7), in the proof of Proposition 1 in Appendix B.2, by the scaling $(1-\alpha)^{-\frac{1}{\alpha}} > 1$ on the marginal benefit. Under the established assumptions that G is concave in θ and C is convex in θ, it is immediate that the socially optimal level of technology exceeds the equilibrium level.

Note finally that, since correcting the externality affects technology demand only up to a scaling factor, the comparative static in Proposition 1 continues to hold as a comparative static for the planner's preferred allocation. This can be verified by going through the steps of the proof in Proposition B.2 under a different definition for $\overline{p}$, which is also a scaling factor. Therefore, the "direction" of technological change is not different in the planner's solution and the equilibrium allocation.

C.1.2 With Dynamic Externalities

We now discuss a model extensions that stylizes a second possible source of under-investment in technology: the dynamic returns to scale in idea production, which are emphasized in classic models of endogenous technological change (e.g., Romer, 1990), and in this setting reflect the extent to which agricultural research can build on past discoveries.

Consider an extension of the model with two periods populated with distinct "generations" of consumers, farmers, and technology producers. We will use primes to distinguish quantities and prices in the second period. The only primitive difference is that, at period $t = 1$, the cost of producing technological quality (or "conducting research") is lower when quality was higher in the last period. We model this by having the cost given by $f(\theta)C(\theta')$, where $f(\cdot) : \mathbb{R}_+ \to \mathbb{R}_+$ is a decreasing, differentiable, and convex function; $1 - f(\theta)$ are the "percentage cost savings" associated with a given level θ of research in the first period.[3]

Using the same arguments in the main text, see that the decentralized equilibrium in the first period is characterized by the following first-order condition for technology quality

$$\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) = \overline{p}^{\frac{1}{\alpha}} \int G_2(A,\theta)\,\mathrm{d}F(A) \tag{C.6}$$

while the equilibrium in the second period is characterized by

$$f(\theta)\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta') = \overline{p}^{\frac{1}{\alpha}} \int G_2(A,\theta')\,\mathrm{d}F'(A) \tag{C.7}$$

Consider now the problem of a social planner who maximizes total utility of agents across periods with discount factor β.[4] It is straightforward to show, extending the results above, that optimal

[3]In this formulation, the "savings" could be positive or negative.
[4]This implies Pareto weights 1 and β, respectively, on each generation.

investment at $t = 0$ and $t = 1$ satisfy the following system of equations:

$$\begin{aligned} \frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta) - \beta\left(\frac{\mathrm{d}}{\mathrm{d}\theta}f(\theta)\right)C(\theta') &= (1-\alpha)^{\frac{1}{\alpha}}p^{\frac{1}{\alpha}}\int G_2(A,\theta)\,\mathrm{d}F(A) \\ f(\theta)\frac{\mathrm{d}}{\mathrm{d}\theta}C(\theta') &= (1-\alpha)^{\frac{1}{\alpha}}p^{\frac{1}{\alpha}}\int G_2(A,\theta')\,\mathrm{d}F'(A) \end{aligned} \tag{C.8}$$

See that the social planner now wants both to cancel the monopoly markup and to make the first period producers internalize the value of their technological progress on lowering research costs at $t = 1$. A sufficient instrument is a subsidy on research effort at $t = 0$ proportional to

$$\beta \cdot \frac{\mathrm{d}}{\mathrm{d}\theta}f(\theta) \cdot \frac{C(\theta')}{C(\theta)}$$

evaluated at the social planner's optimum allocation. This naturally increases in the technological requirements of the second period and decreases in the technology produced in the first period.

Observe that, in contrast to the previous section's analysis with only the monopoly distortion, the planner's problem and the (autarkic) equilibrium allocation differ by more than a scaling factor. Therefore, the "direction of technological change" or sign of $\theta' - \theta$ may generally differ in the planner's solution and the equilibrium solution under different scenarios for the input distributions F and F'. The intuition is that the social planner may want to boost research in the first period for the sake of exploiting the dynamic externality—that is, the planner may want the economy so well prepared for eventual climate damage *ex ante*, that a large redirection of technology is not necessary *ex post*.

C.2 Multiple Types of Technology

We now explore a variant model in which whether technology is climate substituting or complementing is an endogenous outcome of the directed innovation process. This recovers the intuition that climatic change can also push technology toward a climate-mitigating focus even within a specific studied crop.

C.2.1 Equilibrium and Comparative Statics

The farm continues to consume a scalar technological good in quantity T_i, but this good has two different "qualities" θ and τ. The production function is

$$Y_i = \alpha^{-\alpha}(1-\alpha)^{-1}G(A_i,\theta,\tau)^{\alpha}T_i^{1-\alpha}$$

in which we assume

1. Higher A_i corresponds to good climate, or $G_1 \geq 0$;

2. Both technological qualities improve output, or $G_2 \geq 0$ and $G_3 \geq 0$;

3. The technology embodied by θ is climate substituting while the technology embodied by τ is climate complementing, or $G_{12} \leq 0$ and $G_{13} \geq 0$;

4. The two technologies are substitutes for one another, or $G_{23} \leq 0$.

5. Each technology has a decreasing return, or $G_{22} \leq 0$ and $G_{33} \leq 0$.

An innovative firm produces the technological input at marginal cost $1 - \alpha$; sets the price of this input; and chooses research in each area, or (θ, τ), subject to an additive cost $C(\theta) + K(\tau)$, where $C(\cdot)$ and $K(\cdot)$ are differentiable and convex.

Let us focus on the fixed-price economy. Essentially identical logic to that underpinning Proposition 1 shows that the first-order conditions determining the quality of each technology are the following:

$$\begin{aligned} \frac{\mathrm{d}}{\mathrm{d}\theta} C(\theta) &= \overline{p}^{\frac{1}{\alpha}} \int G_2(A, \theta, \tau) \, \mathrm{d}F(A) \\ \frac{\mathrm{d}}{\mathrm{d}\theta} K(\tau) &= \overline{p}^{\frac{1}{\alpha}} \int G_3(A, \theta, \tau) \, \mathrm{d}F(A) \end{aligned} \tag{C.9}$$

Consider now a damaging shift in the climate, as in Proposition 1, to a new productivity distribution $F(A)$. This induces a weak increase in the climate-substituting technology θ and a weak decrease in the climate-mitigating technology τ. Informally, this shift has increased the demand for climate-substituting technologies while decreasing the demand for climate-complementing technologies, *and* the substitutability of two inputs intensifies this force. This shows how our model can accomodate directed technological change *within* specific crops. The remainder of this subsection gives the more detailed proof of the claim.

Formally, we show the claim by contradiction. Consider first the possibility in which τ strictly increases and θ weakly increases. If the strictly increasing technology is τ, then under this conjecture $\frac{\mathrm{d}}{\mathrm{d}\tau} K(\tau') > \frac{\mathrm{d}}{\mathrm{d}\tau} K(\tau)$. But

$$\frac{\mathrm{d}}{\mathrm{d}\tau} K(\tau) = \int G_3(A, \theta, \tau) \, \mathrm{d}F(A) \geq \int G_3(A, \theta, \tau) \, \mathrm{d}F'(A)$$

because $G_{13} \geq 0$ and $F \geq_{FOSD} F'$; and

$$\int G_3(A, \theta, \tau) \, \mathrm{d}F'(A) \geq \int G_3(A, \theta', \tau) \, \mathrm{d}F'(A) \geq \int G_3(A, \theta', \tau') \, \mathrm{d}F'(A) = \frac{\mathrm{d}}{\mathrm{d}\tau} K(\tau')$$

by $G_{23} \leq 0$ (inputs are substitutes) and concavity of $G(\cdot)$. This implies $\frac{\mathrm{d}}{\mathrm{d}\tau} K(\tau) \geq \frac{\mathrm{d}}{\mathrm{d}\tau} K(\tau')$ which contradicts the assumption.

Identical and reverse logic rules out the case that θ strictly decreases and τ weakly decreases, finding the contradiction in the first-order condition for θ.

We finally rule out the possibility that θ strictly decreases and τ weakly increases. By increasing differences of $(-\theta, \tau)$ in A, implied by our assumptions $G_{12} \leq 0$ and $G_{13} \geq 0$, the positive demand shift from (θ, τ) to (θ', τ') must be larger in the less damaging climate or

$$G(A', \theta', \tau') - G(A', \theta, \tau) \leq G(A, \theta', \tau') - G(A, \theta, \tau)$$

for any $A' \geq A$. The optimality of (θ', τ') in the new climate implies that this choice generates more profit that (θ, τ), or

$$\overline{p}^{\frac{1}{\alpha}} \int G(A, \theta', \tau')\, \mathrm{d}F'(A) - C(\theta') - K(\tau') \geq \overline{p}^{\frac{1}{\alpha}} \int G(A, \theta, \tau)\, \mathrm{d}F'(A) - C(\theta) - K(\tau)$$

while increasing differences and $F' \geq_{FOSD} F$ implies that (θ', τ') would have been strictly better improvement over (τ, θ) under the old climate, or

$$\overline{p}^{\frac{1}{\alpha}} \int G(A, \theta', \tau')\, \mathrm{d}F(A) - \overline{p}^{\frac{1}{\alpha}} \int G(A, \theta, \tau)\, \mathrm{d}F(A) > \overline{p}^{\frac{1}{\alpha}} \int G(A, \theta', \tau')\, \mathrm{d}F'(A) - \overline{p}^{\frac{1}{\alpha}} \int G(A, \theta, \tau)\, \mathrm{d}F'(A)$$

Together, however, these statements imply

$$\overline{p}^{\frac{1}{\alpha}} \int G(A, \theta', \tau')\, \mathrm{d}F(A) - C(\theta') - K(\tau') > \overline{p}^{\frac{1}{\alpha}} \int G(A, \theta, \tau)\, \mathrm{d}F(A) - C(\theta) - K(\tau)$$

which contradicts the optimality of (θ, τ) under the old climate. Therefore this case is impossible.

The only remaining case has θ weakly increase and τ weakly decrease as desired.

C.2.2 Dynamic Externalities and Lock-In

We conclude with a brief discussion of how the previous model of endogenous *climate complementarity* of technology interacts with the issue of dynamic externalities raised in C.1.2. Consider a variant of the two-technology model with two periods and myopic agents, as earlier. The cost of investing in θ in the second period is $f(\theta)C(\theta')$, where $f(\cdot) : \mathbb{R}_+ \to \mathbb{R}_+$ is a decreasing, differentiable, and convex function as before; and the cost of investing in τ in the second period is $f(\tau)C(\tau')$. It is immediate that the social planner contemplates separate subsidies for the development of each type of technology to allow innovators in the first period to internalize the dynamic externality.

Now map this exercise to a world in which the climate worsens in the second period relative to the first. An immediate implication is that the equilibrium allocation may relatively over-invest in climate-complementing technologies in the first period due to not internalizing the value of "preparedness" for climate change in the second period, or having lower costs for climate-substituting technologies which are relatively more useful in the second period.

C.3 Variable Utilization

In this section, we introduce a tractable variant of the model which illustrates variable utilization or a form of switching from a given crop to an outside option. Let $Z_i \in [0, 1]$ be a *utilization level* of a given tract of land. In the model with utilization, the farm's production function is now given by $Y_{i,k} = Z_i^{1-\alpha} \alpha^{-\alpha} (1-\alpha)^{-1} G(A_i, \theta_k)^{\alpha} T_{i,k}^{1-\alpha}$. Utilization Z_i entails an additive cost $\phi(Z_i)$, where $\phi(\cdot)$ is convex and twice differentiable, and satisfies $\phi'(0) = 0$ and $\phi'(1) = \infty$ to ensure an interior solution for utilization. This is a reduced form for transforming land from non-agricultural use or from planting other crops. It is straightforward to show that the farm's demand for technology now includes an endogenous utilization term (substituting in the immediately verifiable assumption that $q_k = 1$):

$$T_{i,k} = \alpha^{-1} p_k^{\frac{1}{\alpha}} Z^*(A_i, \theta_k, p_k) G(A_i, \theta_k) \tag{C.10}$$

where optimal utilization solves

$$Z^*(A_i, \theta_k, p_k) \in \underset{Z_i \geq 0}{\operatorname{argmax}}\ Z_i \cdot \alpha^{-1}(1-\alpha)^{-1} p_k^{\frac{1}{\alpha}} G(A_i, \theta_k) - \phi(Z_i) \tag{C.11}$$

Let us now revisit the environment of Proposition 1, with fixed prices. It is immediate that the results of Proposition 1 go through as long as the relevant cross-partial properties are satisfied by the function $(A_i, \theta_k) \mapsto Z^*(A_i, \theta_k, \overline{p}_k) G(A_i, \theta_k)$, or climate and technology are appropriately "complements" or "substitutes" after endogenous utilization is taken into account. We can be more specific about what this means by calculating this directly.

Let $\tilde{G}(A_i, \theta_k) := Z^*(A_i, \theta_k, \overline{p}_k k) G(A_i, \theta_k)$ be the aforementioned product (supressing dependence on $\overline{p}_k$), let $\psi(\cdot)$ denote the (by assumption, well-defined) inverse of $\phi'(\cdot)$, and normalize for convenience $\alpha^{-1}(1-\alpha)^{-1}\overline{p}_k^{\frac{1}{\alpha}} = 1$. See that optimal utilization is given by

$$Z^* = \psi(G(A_i, \theta_k)) \tag{C.12}$$

which is, by assumption, an increasing function. Depending on the shape of $\psi(\cdot)$, or more primitively the shape of $\phi'(\cdot)$, this function can be concave, convex, or neither.

The cross-partial derivative of $\tilde{G}$ is the following

$$\frac{\partial^2}{\partial A_i \partial \theta_k} \tilde{G}(A_i, \theta_k) = G_{12}\left(Z^* + \psi'(G)\right) + (2\psi'(G) + \psi''(G)) G_1 G_2 \tag{C.13}$$

The first term is the familiar term which reflects the "raw" complementarity in $G(\cdot)$ and the indirect effect via Z^*. The second, under the going assumptions that $(G_1, G_2) \geq 0$, inherits its sign from the sign of $2\psi' - \psi''$.

Consider first the case in which ψ is not too concave or $2\psi' > -\psi''$. Then, endogenous utilization can result in $\frac{\partial^2}{\partial A_i \partial \theta_k} \tilde{G}(A_i, \theta_k) \geq 0$ even when $G_{12} \leq 0$. In this sense, endogenous utilization "fights against case 1 and fights for case 2," referring to the cases of Proposition 1. This embodies the economic intuition that farmers respond to bad climate shocks by planting less. Even if conditional on "digging in their heels" and planting they demand more technology, lower planting can be the dominant effect when utilization is very sensitive to productivity (high ψ').

If ψ is very concave, or $2\psi' < -\psi''$, then the sign of the cross partial will be negative as long as $G_{12} \leq 0$. This is a slightly perverse case in which negative shocks increase the marginal product of technology because they make the utilization decision more sensitive to productivity. Concretely, when the climate is good the farm does not adjust much; when the climate is poor, farms adjust more on all margins, so new technology has an outsized effect on decisions. In this sense, the basic idea that land adjustments dampen the force of case 1 in Proposition 1 is *not* a fully robust one.

C.4 Capacity Constraints for Research

In our baseline model, the allocation of research effort had no capacity constraints or restrictions *across sectors*. The right economic thought experiment was that the innovators were optimally trading off research in each crop with an unmodeled outside option, like research in other areas of chemistry or biotechnology. We now relax this assumption in a particularly tractable way to illustrate the dual process of re-allocation both into agricultural bio-technology and between sectors of this field.

C.4.1 Model

As in Section 2.5, we extend the model to include multiple crops. There are K crops indexed by $k \in \{1, \ldots, K\}$. For each crop, there is a unit measure of locations which produce the crop. We use $(p_k)_{k=1}^K$ to denote each crop's price in terms of the numeraire; $(F_k)_{k=1}^K$ to denote each crop's productivity distribution; and $(\theta_k)_{k=1}^K$ to denote each crop's technology level. The production function for each crop is given by (2.1).

A single representative innovator chooses the price and quality of each technological input. The innovator faces a constraint that their total dollar investment in quality improvement does not exceed some level $\overline{C}$, or $\sum_{k=1}^K C(\theta_k) \leq \overline{C}$. We can think of $\overline{C}$ as the overall size of the innovator's "laboratory." The innovator can then expand the size of their laboratory at some cost given by $\psi(\overline{C})$, where $\psi(\cdot) : \mathbb{R}_+ \to \mathbb{R}_+$ is a differentiable, convex function. The profit maximization problem is therefore:

$$\begin{aligned} \max_{(q_k, \theta_k)_{k=1}^K, \overline{C}} \; & (q_k - (1-\alpha))\, \alpha^{-1} \sum_{k=1}^K p_k^{\frac{1}{\alpha}} q_k^{-\frac{1}{\alpha}} \int G(A, \theta_k)\, \mathrm{d}F_k(A) - \psi(\overline{C}) \\ \text{s.t.} \; & \sum_{k=1}^K C(\theta_k) \leq \overline{C} \end{aligned} \tag{C.14}$$

It is straightforward to show, as in the baseline model (see Appendix B.1), that the profit-maximzing price is $q_k \equiv 1$ for all crops and therefore the problem reduces to

$$\begin{aligned} \max_{(\theta_k)_{k=1}^K, \overline{C}} \; & \sum_{k=1}^K p_k^{\frac{1}{\alpha}} \int G(A, \theta_k)\, \mathrm{d}F_k(A) - \psi(\overline{C}) \\ \text{s.t.} \; & \sum_{k=1}^K C(\theta_k) \leq \overline{C} \end{aligned} \tag{C.15}$$

Let λ denote the Lagrange multiplier on the capacity constraint and

$$D(p_k, \theta_k, F_k) := p_k^{\frac{1}{\alpha}} \int G(A, \theta_k)\, \mathrm{d}F_k(A)$$

denote crop-specific technology demand in a more compact notation. The first-order condition for each choice θ_k is

$$\lambda C'(\theta_k) = D(p_k, \theta_k, F_k) \tag{C.16}$$

Note that, given the concavity of $G(\cdot)$, $D_k(\cdot)$ is a decreasing function of θ_k holding fixed all other inputs. The first-order condition for the constraint, assuming that it binds at equality, is

$$\lambda = \psi'(\overline{C}) \tag{C.17}$$

Therefore, the vector of θ_k solves the following system of equations:

$$\left(\psi'\left(\sum_{k=1}^{K} C(\theta_k)\right)\right) C'(\theta_k) = D(p_k, \theta_k, F_k), \quad \forall k \tag{C.18}$$

See that increasing research in sector k' increases the effective marginal cost of research in sector k, and thus lowers research in sector k. This captures a "soft" capacity constraint.

C.4.2 Tractable Variant

To make more progress, let us specialize to a particularly tractable version of this model. Let $C(x) = x^{1+\eta}/(1+\eta)$ for some $\eta > 0$ and $\psi(x) = (\chi x)^{1+\zeta}/(1+\zeta)$ for some $\chi \geq 0$ and $\zeta > 0$. Finally, assume that $D(p_k, \theta_k, F_k) \equiv D(p_k, F_k)$, so we can solve for θ_k explicitly. The previous system of equations simplifies to

$$\chi^{1+\zeta}\left(\sum_{k=1}^{K} \frac{\theta_k^{1+\eta}}{1+\eta}\right)^{\zeta} \theta_k^{\eta} = D(p_k, F_k), \quad \forall k \tag{C.19}$$

Conjecture that $\theta_k = A \cdot (D(p_k, F_k))^{\frac{1}{\eta}}$ for some $A \geq 0$. Then the above evaluated for any k simplifies to

$$\chi^{1+\zeta} A^{(1+\eta)\zeta}\left(\sum_{k=1}^{K} \frac{(D(p_k, F_k))^{1+1/\eta}}{1+\eta}\right)^{\zeta} = A^{-\eta} \tag{C.20}$$

which implies

$$A = \chi^{-\frac{1+\zeta}{\eta+\zeta+\eta\zeta}}\left(\sum_{k=1}^{K} \frac{(D(p_k, F_k))^{1+1/\eta}}{1+\eta}\right)^{-\frac{\zeta}{\zeta+\eta+\eta\zeta}} \tag{C.21}$$

See that this value of A decreases in the demand for each technology and in the cost shifter χ. We can solve now for the value of the capacity which is

$$\begin{aligned}
\overline{C} &= A^{(1+\eta)} \sum_{k=1}^{K} \frac{(D(p_k, F_k))^{1+1/\eta}}{1+\eta} \\
&= \chi^{-\frac{(1+\eta)(1+\zeta)}{\eta+\zeta+\eta\zeta}}\left(\sum_{k=1}^{K} \frac{(D(p_k, F_k))^{1+1/\eta}}{1+\eta}\right)^{\frac{\eta}{\zeta+\eta+\eta\zeta}}
\end{aligned}$$

See in particular, as $\zeta \to \infty$ or marginal costs of expanding the capacity become sufficiently large, then the model converges to one in which capacity is fixed at $\overline{C} = 1/\chi$.

This result has also the following implication when read "backward": the assumption that directed innovation has a "zero effect" for a given crop maps to a unique level of the cost χ. Consider now two vectors $(\theta_k)_{k=1}^K$ and $(\theta'_k)_{k=1}^K$ that solve the monopolist's problem respectively for different prices and climate distributions (also denoted with primes, in the second case). Assume that the following condition holds which, in certain units, implies that aggregate demand for technology across crops increased:

$$\sum_{k=1}^{K} (D(p'_k, F'_k))^{1+1/\eta} \geq \sum_{k=1}^{K} (D(p_k, F_k))^{1+1/\eta} \tag{C.22}$$

Now consider a crop that had a positive demand shock or $D(p'_k, F'_k) \geq D(p_k, F_k)$. Note that the growth rate in technology for crop k is, up to A and A',

$$\frac{\theta'_k}{\theta_k} = \frac{A'}{A} \left(\frac{D(p'_k, F'_k)}{D(p_k, F_k)} \right)^{\frac{1}{\eta}} \tag{C.23}$$

and

$$\frac{\theta'_k}{\theta_k} = 1 \quad \Leftrightarrow \quad \frac{A'}{A} = \left(\frac{D(p'_k, F'_k)}{D(p_k, F_k)} \right)^{-\frac{1}{\eta}} \tag{C.24}$$

Plugging into the expression for A, the right hand side is

$$\left(\frac{\sum_{k=1}^{K} D(p'_k, F'_k)^{1+1/\eta}}{\sum_{k=1}^{K} D(p_k, F_k)^{1+1/\eta}} \right)^{-\frac{\zeta}{\zeta+\eta+\zeta\eta}} = \left(\frac{D(p'_k, F'_k)}{D(p_k, F_k)} \right)^{-\frac{1}{\eta}} \tag{C.25}$$

or, taking each side to the power $-\eta$,

$$\left(\frac{\sum_{k=1}^{K} D(p'_k, F'_k)^{1+1/\eta}}{\sum_{k=1}^{K} D(p_k, F_k)^{1+1/\eta}} \right)^{\frac{\eta\zeta}{\zeta+\eta+\zeta\eta}} = \frac{D(p'_k, F'_k)}{D(p_k, F_k)} \tag{C.26}$$

For fixed η, or convexity of crop-specific costs, this is solved by

$$\zeta = \frac{\eta}{\eta+1} \frac{\log \frac{D(p'_k, F'_k)}{D(p_k, F_k)}}{\frac{\eta}{\eta+1} \log \frac{\sum_{k=1}^{K} D(p'_k, F'_k)^{1+1/\eta}}{\sum_{k=1}^{K} D(p_k, F_k)^{1+1/\eta}} - \log \frac{D(p'_k, F'_k)}{D(p_k, F_k)}} \geq 0 \tag{C.27}$$

provided that the crop's demand growth is lower than the appropriate CES average of overall demand growth:

$$\log \frac{D(p'_k, F'_k)}{D(p_k, F_k)} \leq \frac{\eta}{\eta+1} \log \frac{\sum_{k=1}^{K} D(p'_k, F'_k)^{1+1/\eta}}{\sum_{k=1}^{K} D(p_k, F_k)^{1+1/\eta}} \tag{C.28}$$

When this holds at equality, then $\zeta = \infty$ and the model simulates a capacity constraint for research. Thus our approach of normalizing a "zero progress" crop to a measure of central tendency for observed damages at least qualitatively matches the predictions of this model with flexible capacity.

D Extreme Exposure: Measurement and Validation

In this Appendix, we first describe in detail how to calculate Extreme Exposure from the raw temperature data. We then show validation that our measure of crop-specific extreme exposure explains crop yields and, in terms of explanatory power, out-performs non-crop-specific methods based on the same data.

D.1 Construction

We follow the procedure outlined in Schlenker and Roberts (2009) to compute daily temperature averages since 1950 from raw data on daily maximum and minimum temperatures. This includes interpolating the portion of a day that is within a particular temperature range and aggregating to US counties using only grid cells that are identified via satellite data to contain cropland. We thank Wolfram Schlenker for making these data available on his website at the following link: http://www.columbia.edu/~ws2162/links.html.

We now describe the method in more detail. We first define the following object that counts the number of degree days relative to a specific cutoff T in a specific (2.5 mile by 2.5 mile) grid cell:

$$\text{DegreeDays}(T; T_{\text{high},d,g}, T_{\text{low},d,g}) := \begin{cases} 0 & \text{if } T_{\text{high},d,g} < T \\ T_{\text{avg},d,g} - T & \text{if } T_{\text{low},d,g} > T \\ g(T; T_{\text{high},d,g}, T_{\text{low},d,g}) & \text{otherwise} \end{cases}$$

where $T_{\text{avg},d,g} := \frac{T_{\text{low},d,g}+T_{\text{high},d,g}}{2}$ is the midpoint of the high and low temperatures and the specific interpolation function $g(\cdot)$ is given by the following:

$$g(T; T_{\min}, T_{\max}) = \frac{1}{\pi}\left(\left(T_{\text{avg},d,g} - T\right) \cdot \cos^{-1}\left(\frac{T - T_{\text{avg},d,g}}{T_{\text{avg},d,g}}\right) + \left(T_{\text{avg},d,g} \cdot \sin\left(\frac{T - T_{\text{avg},d,g}}{T_{\text{avg},d,g}}\right)\right)\right)$$

This function smoothly interpolates between 0 and $\frac{T_{\text{low},d,g}+T_{\text{high},d,g}}{2}$.

Next, within a given county, we aggregate the previous measure across grid cells that have planted cropland using weights w_g:

$$\text{DegreeDays}_i(T; d) := \left[\sum_{\text{grid } g \in i} w_g \cdot \text{DegreeDays}(T; T_{\text{high},d,g}, T_{\text{low},d,g})\right]$$

The weights w_g on individual grid-cells encode what fraction of the grid-cell is farmland based on satellite data, as done in Schlenker and Roberts (2009).

We sum the previous over all days in the summer growing season April to October, within a given decade (e.g., 1950-59, 1960-69) indexed by t:

$$\text{DegreeDays}_{i,t}(T) := \sum_{\text{day } d \in t} \text{DegreeDays}_i(T; d)$$

The units for this measure are "extreme degree days per decade."

We finally make this measure crop-specific by substituting in the crop-specific maximum optimal temperature from EcoCrop. This step is described in the main text. This discussion connects with the measurement in the main text when we define Extreme Exposure at the location, crop, and time level as degree days in excess of the crop-specific threshold T_k^{Max}:

$$\text{ExtremeExposure}_{i,k,t} := \text{DegreeDays}_{i,t}(T_k^{\text{Max}})$$

D.2 Validation: Extreme Heat Exposure and Crop Yields

We validate this measure of extreme exposure as a shock to crop yields, and also investigate the share of variation in crop yields caused by temperature that it explains. First, as described in the main text, we show that $\text{ExtremeExposure}_{i,k}$ has a significant and substantial negative effect on crop yields. These results are reported in Table A2.

Second, we compare the variation in yields of staple crops (corn, wheat, and soy) explained by our one-dimensional measure to the variation in yields of staple crops explained by a more flexible approach that captures exposure to different parts of the temperature distribution. In particular, in each county we determine the number of days in each five degree bin, with an upper bound of 45 degrees Celsius (that is, our highest bin is the number of days greater than 45 degrees Celsius). We then interact each of these bins with staple crop fixed effects. This vector of interactions captures the effect of exposure to temperatures in all parts of the distribution, and allows its effect to differ for each crop. We then predict crop yields using this full vector of interactions:

$$\log\left(\text{yield}_{i,k}\right) = Z'\Gamma + \alpha_i + \alpha_k + \varepsilon_{ik} \tag{D.1}$$

where Z' is the full set of interactions between the number of days in each temperature bin and crop fixed effects. To gauge the explanatory power of our one-dimensional temperature shock, we compare the within-R^2 of (D.1) to the within-R^2 of (3.2), which only includes $\text{ExtremeExposure}_{i,k}$ on the right hand side (along with crop and county fixed effects). Our main conclusion is that $\text{ExtremeExposure}_{i,k}$ explains a large share of the variation in crop yields caused by temperature; across specifications, its within-R^2 is greater than one third that of the within-R^2 of (D.1), even though (D.1) includes many more variables on the right hand side of the regression. For example, when Z' includes all temperature bins from 15° to 45°+, the within within-R^2 is 0.23, despite the inclusion of 21 regressors, while the within-R^2 from our one-dimensional measure is 0.083.

Third, we compare $\text{ExtremeExposure}_{i,k}$ to alternative measures of exposure to heat that do not take into account variation in crop-level sensitivity. In particular, we estimate:

$$\log\left(\text{yield}_{i,k}\right) = \xi \cdot \text{ExtremeExposure}_{i,k} + \alpha_k + \varepsilon_{ik} \tag{D.2}$$

and recover the within-R^2 of our measure of extreme heat exposure. We then estimate:

$$\log\left(\text{yield}_{i,k}\right) = \xi \cdot \text{DegreeDaysAbove}_i^z + \alpha_k + \varepsilon_{ik} \tag{D.3}$$

where $\text{DegreeDaysAbove}_i^z$ is the total number of degree days above temperature cut-off z in county i. That is, it is analogous to our baseline measure except it uses the same temperature cut-off z for all crops. We estimate Equation D.3 for values of z between 10 and 45 degrees Celsius. In Figure A2, we report the distribution of within-R^2 measures for all estimates of (D.3) as a blue histogram, and we also mark the within-R^2 from (D.2) with a dotted black line. Incorporating variation across crops in temperature sensitivity makes it possible to explain a much larger share of variation in crop yields than any measure that only exploits variation across places in exposure to high temperatures.

E Agricultural Innovation and Climate Stress: Background and Narrative Evidence

In this section, we report case-study evidence from recent advances in biotechnology suggesting that inventors have been directing innovation toward emergent climate threats. To do this, we provide background information on how climate stress affects plants (E.1), discuss examples of how plant breeders develop heat- and drought-resistant varieties (E.2), and provide narrative evidence that the intensity of heat- and drought-resistant breeding has responded to climatic trends (E.3).

E.1 The Effects of Weather Stress on Plants

Weather patterns may affect an individual plant's morphology (i.e., physical structure), physiology (i.e., growth, metabolism, and reproduction processes), and phenotype (i.e., the translation of genes to observed traits) (Raza et al., 2019). All of these features jointly affect agricultural productivity outcomes (e.g., yield of corn per planted acre). Thus, understanding the exact effect of a specific weather feature, like exposure to extreme degree days, on an agricultural productivity outcome, like corn yield, involves jointly modeling multiple aspects of a plant.

As an illustrative example, relevant to our empirical analysis, Lobell et al. (2013) study the effects of exposure to degree-days above 30C on maize. Using a biophysical model, the authors find that a critical pathway from extreme-heat exposure to reduced maize yield is water stress. More specifically, extreme heat increases the rate at which plants draw water from the ground and exhale water through their leaves. This specific biophysical mechanism is necessarily affected by a number of expressed traits by the plant—two examples, in the present case, are how the plant draws water from the ground and how the plant opens and closes pores in its leaves and stems (stomata) to breathe.

E.2 Breeding Heat- and Drought-Resistance

Traditional breeding methods select plants across a number of traits based on empirically observed improvements in the field. The selected traits may influence a number of mechanisms regulating a plant's resistance to physical stress like extreme heat or drought. Moreover, improvements in heat- and drought-tolerance based on these traditional, empirical methods may predate scientific understanding of the exact mechanisms for yield loss due to heat and drought.

As one example, Duvick et al. (2004) survey maize breeding at the private firm Pioneer Hi-Bred International since the early 1930s.[5] The authors describe the firm's methodology for selecting plant lines (germplasm) as decidedly empirical:

> The one consistent feature of the plant breeding group was its pragmatism. If a method or source of germplasm worked, it was used whether or not it fit the current styles in breeding theory. [. . .] Widespread on-farm performance of released hybrids was used to identify the top-performing inbreds, to winnow the best from merely average germplasm.

[5] Today, Pioneer is owned by Corteva Agriscience, which was itself spun off from the agricultural science division of DuPont.

The authors write that severe drought in the 1930s, in the company's early stages, directed breeding efforts toward drought-tolerance as an important secondary objective to the primary goal of increasing grain yield. In their retrospective analysis of seven decades of field-trial data, combined with modern genetic analysis, the authors argue that increased tolerance to biological and physical stress was a primary cause of yield improvements. In particular, they highlight a secular trend of increased tolerance to heat and drought. Subsequent genetic studies have clarified the mechanisms for improved drought resistance in the Pioneer line. For instance, Habben et al. (2014) suggest an important mechanism for drought tolerance in modern corn hybrids, including Pioneer's, is increased catalysis of ethylene production, which interacts with many different biochemical pathways.

An alternative method for breeding stress tolerance is direct genetic modification of organisms. Genetic modification, unlike field-trial breeding, is predicated on understanding how a specific molecule confers a valuable trait, and how insertion of specific genes would make a plant produce that molecule. One example of a genetically modified organism based on this principle is Monsanto's *DroughtGard* maize. As described in the original scientific article by Castiglioni et al. (2008), *DroughtGard* maize is genetically modified to produce "Cold Shock Proteins" or CSPs. These proteins are produced by *E. coli* and *B. subtilis* bacteria in response to cold temperature shocks and are associated with post-shock revival. Castiglioni et al. (2008) describe the process by which the CSP-expression gene was inserted into rice and maize plants, and they show empirically how CSP production is associated with tolerance to heat, cold, and water-deficit shocks in these plants.

E.3 The Response of Innovation to Climatic Shocks

As alluded to earlier in the context of Pioneer's corn breeding, a primary example of private agricultural innovation's response to climatic conditions is the intensification of hybrid plant development in response to widespread droughts in the early 20th century. These droughts notably include the successive droughts of the 1930s that precipitated the Dust Bowl in the US prairies. Crow (1998) and Sutch (2008, 2011) provide detailed historical accounts of early hybrid corn breeding and adoption. Moscona (2022) studies the response of innovation to the US Dust Bowl empirically, across a wider range of crops, as well as the effects on downstream production. While the modern, privatized biotechnology industry emerged primarily after these early 20th century events, agricultural historians also write about climatic stress driving innovation in the centuries prior. Olmstead and Rhode (2011) highlight the important role of state and non-profit breeders in improving heat- and drought-tolerance for North American wheat. Olmstead and Rhode (2008) more broadly survey biological innovation in US agriculture in the two centuries before World War II.

Today, as mentioned in the paper's introduction, agricultural biotechnology companies are "racing to develop products" that address the problem of "rising temperatures" according to news reports (Schulman, 2015). According to Gupta (2017), "Monsanto poured more than $1.5 billion into research and development efforts last year to design better quality corn seeds and products...'In our breeding efforts and biotech efforts, we're making sure our products can withstand that extreme weather,' explains Pam Strier, Monsanto's sustainability chief." In 2019, Syngenta allocated $2 billion toward developing technologies that will "help farmers prepare for and tackle the increasing threats posed by climate change" (Syngenta, 2019). Biotechnology companies also note the fact that demand has grown for climate-resilient seeds—relative to other varieties—because of how essential they are when the environment is unfavorable: "As the Midwest's climate grows hotter, Monsanto notes there's demand for seeds that can thrive in warmer and more extreme environments" (Gupta, 2017).

A particularly illustrative case study was the North American Drought of 2012-2013 in the US Plains. Within two years of the drought, Monsanto released the corn variety Genuity DroughtGard Hybrids and Pioneer-DuPont released Optimum AQUAmax, both of which were designed to remain productive in low-moisture environments. As reviewed earlier in this section, both technologies were based on breeding and scientific advances that took place prior to the drought. Nonetheless, their implementation as marketable products was possibly influenced by the emergent need. In the words of Connie Davis, corn systems technology development manager for Monsanto:

> [We had] great timing to get those hybrids out when we actually saw severe to exceptional drought in the Western Great Plains. We focused on the field corn just because that was the biggest need... (Daniels, 2015)

These specific events are consistent with broader trends of improved drought performance in 2012-2013 compared to a similar drought event in 1988 (Eisenstein, 2013) and, more obviously, relative to the disastrous droughts that instigated the Dust Bowl of the 1930s (Schaper, 2012).

These patterns are not restricted to maize, or even to staple grains and oilseeds. A news report by Daniels (2015) surveys breeding investments by Monsanto and DuPont Pioneer toward developing heat- and drought-resistant fruit and vegetable varieties in California. Genetic modification technology, in particular, allows for feasible transferal of drought-resistance "discoveries" from one crop to another. Raza et al. (2019) surveys several examples of successful traits that have been applied toward many crops. One example already given was the CSP-expression gene essential to *DroughtGard*.

Finally, it is worth noting that the public sector and universities are also involved in this innovative push. In the Request for Applications for the US Department of Agriculture's "Specialty Crop Research Initiative," a recurring grant available for agricultural science, "Climate adaptation" is listed as a targeted "critical need." Researchers at the University of California, Davis, for example, received a $4.5 million grant from the SCRI in 2015 to "support a multidisciplinary research program aimed at leveraging new technologies to sustain the supply of lettuce in spite of changes in climate" (Filmer, 2015). As one additional example, recent advances led by researchers at the University of Chicago in RNA de-methylation, and their application to rice and potato cultivars, potentially drastically increase crop yields as well as tolerance to extreme climate (Yu et al., 2021).

F Crop Switching, Market Size, and Innovation

Our main analysis studies the relationship between temperature distress and innovation holding the pre-period distribution of crops fixed. However, farmers may re-allocate land across crops in response to temperature-induced productivity changes. Moreover, the presence of systematic re-allocation of land toward certain crops opens a second potential channel through which temperature change might affect innovation.

In this section we (i) empirically document that this re-allocation has occurred but that re-allocation has been small in magnitude, (ii) show that controlling for predicted and actual changes in crop-level planted area does not affect our baseline results, and (iii) show that nevertheless temperature-induced changes in market size predict crop-level innovation as suggested by the theory.

F.1 County-level Reallocation

The first sub-question that needs to be answered is whether climate incidence predicts re-allocation of land in particular areas away from more damaged crops and toward less-damaged crops. Let $\text{Area}_{k,i}^{1959}$ be the area planted for crop k in county i in 1959 and let $\text{Area}_{k,i}^{2012}$ be the same in 2012. For all county-by-crop observations we estimate the following specification:[6]

$$\text{asinh}(\text{Area}_{k,i}^{2012}) = \alpha_{ks} + \delta_i + \psi \cdot \text{asinh}(\text{Area}_{k,i}^{1959}) + \pi \cdot \Delta\text{ExtremeExposure}_{k,i} + \varepsilon_{k,i} \tag{F.1}$$

where α_{ks} are crop-by-state fixed effects and δ_i are county fixed effects. The inclusion of county fixed effects absorbs the fact that certain countries have become more or less agricultural overall since 1959. The coefficient π measures the extent to which local temperature distress induces switching away from a particular crop. Crucially, since our measure of $\text{ExtremeExposure}_{k,i}$ relies only on temperature realizations and crop-level physiology, ewe can measure $\text{ExtremeExposure}_{k,i}$ for all county-crop pairs *even if the crop is not grown in the county during the pre period*. Thus, the specification allows us to home in on the effect of crop-by-county specific climate distress on production allocation.

If crop allocation choices indeed have reacted to changes in temperature, we would hypothesize that $\pi < 0$. This captures both the fact that production has declined where temperature change has made cultivation less productive and that production has increased where temperature change has made cultivation more productive. We find that π is negative and statistically significant, as predicted, but that it is small in magnitude. A one standard deviation increase in crop-by-county temperature distress reduces planted area by just 0.018 standard deviations. Thus, we find that crop allocation has reacted to temperature distress as we measure it, but the reallocation of production has been limited.

[6]The specialization to counties with more planted area, we found, dramatically increases the fit of this first regression, in part because it removes the "obvious" zeros (e.g., regardless of the effects of climate change, there will not likely by any significant sorghum cultivation in New York County (Manhattan)).

Table F1: Crop Switching and Technology Development

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is New Crop Varieties							
Δ ExtremeExposure	0.0178***	0.0139***	0.0217***	0.0235***	0.0135***	0.00998***	0.0112***	0.0105**
	(0.00486)	(0.00374)	(0.00594)	(0.00687)	(0.00381)	(0.00344)	(0.00402)	(0.00435)
log EE-Predicted Natl. Area	0.536*	0.325	0.523**	0.506**				
	(0.275)	(0.248)	(0.209)	(0.214)				
log Natl. Area *(endogenous control)*					0.268***	0.285***	0.273***	0.275***
					(0.0414)	(0.0546)	(0.0577)	(0.0598)
Log 1959 area harvested	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period climate controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Pre-period varieties	No	No	Yes	Yes	No	No	Yes	Yes
Cut-off temp. and cut-off temp sq.	No	No	No	Yes	No	No	No	Yes
Observations	55	55	55	55	55	55	55	55

Notes : The unit of observation is a crop. In columns 1-4, we include log of crop-level planted area predicted by the empirical model of temperature change induced crop switching. In columns 5-8, we include log of crop-level planted area in 2012 as measured from the Census of Agriculture. The additional controls included in each specification are noted at the bottom of each column. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

F.2 Crop Switching and Innovation

Next, we investigate whether accounting for crop-level changes in planted area affect our baseline estimates. For each county in the sample, we use the estimation of Equation (F.1) to predict the area devoted to each crop in each county in 2012: $\widehat{\text{Area}}_{k,i}^{2012}$. We then aggregate these estimates to compute a measure of "predicted national area" for each crop in 2012 due to changes in extreme temperature exposure:

$$\text{EE-PredictedArea}_k^{2012} := \sum_i \widehat{\text{Area}}_{k,i}^{2012} \tag{F.2}$$

This captures the area harvested for each crop in 2012—our proxy for market size—as predicted by changing crop allocations in response to temperature change. Next, we estimate an augmented version of Equation (4.2) in which we control directly for changes in crop-level market size:

$$\text{New Seeds}_k = \exp\left\{\beta \cdot \Delta\text{ExtremeExposure}_k + \beta^{\text{MS}} \cdot \log\left(\text{EE-PredictedArea}_k^{2012}\right) + \Gamma X_k' + \varepsilon_k\right\} \tag{F.3}$$

Our new coefficient of interest β^{MS} captures the impact of temperature-induced expansions in crop market size on innovative output. The control vector X_k' always includes the log of 1959 area planted for each crop. This ensures that the coefficient β^{MS} measures the effect of expanded market size holding fixed initial market size. Estimates of Equation F.3 are reports in columns 1-4 of Table F1. The first key finding is that controlling for temperature-induced changes in market size have virtually no impact on β, the relationship between temperature distress and variety development. Our baseline estimates are not biased by changes in planted area. The second key finding is that, intuitively, β^{MS} is positive; moreover, it is statistically distinguishable from zero in three of the four specifications. This suggests that temperature-induced market expansion is an independent and potentially important channel through which climate change affects patterns of innovation.

As a final check that our baseline estimates operate independently from crop-level changes in planted area over the sample period, in columns 5-8 of we control directly for the measured changes in the planted area of each crop. While this qualifies as a "bad control" and as a result this specification comes with all the associated caveats, it is reassuring that the relationship between temperature distress and variety development remains very similar after accounting for endogenous changes in planted area.

G Global Analysis

In this section, we describe our investigation of the relationship between global temperature distress and US innovation. We first explain our strategy for measuring crop-level exposure to extreme temperatures around the world, and then we describe our main findings using this global data.

G.1 Measurement

Our strategy for measuring crop-level exposure to changes in extreme temperature consists of combining global temperature data from Muñoz-Sabater et al. (2021) with global geo-coded crop-level planting data from Monfreda et al. (2008). Muñoz-Sabater et al. (2021) is the fifth-generation data set produced by the European Centre for Medium-Range Weather Forecasts, in collaboration with the European Commission and Copernicus Climate Change Service. It is a reanalysis data set that combines weather observations from around the world with model data in order to generate a complete global gridded temperature data set at the hourly level with a grid size of 0.25 degrees. The data are reported from 1979 to the present, and so for our global analysis we focus on long-difference specifications comparing the 1980s to the 2010s.

The Monfreda et al. (2008) data set, also known as the EarthStat Database, was created by combining national, state, and county level census data with crop-specific maximum potential yield data, to construct a 5-by-5 minute grid of the area devoted to each crop circa 2000. Our final sample consists of the 36 crops that are both represented in Monfreda et al. (2008) and our own baseline sample.

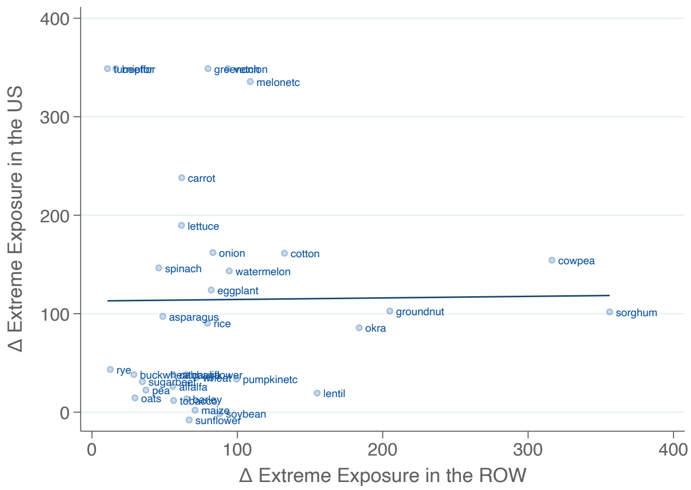
Combining the two sources of data, we measure the change in each crop's extreme-heat exposure in all countries outside of the US ($\Delta \text{ExtremeExposure}_k^{\text{ROW}}$) exactly as described for the US in Section 3.2 of the paper.

G.2 Results

Figure G1 plots the cross-crop relationship between the change in extreme heat exposure in the US and in the rest of the world, which is almost completely flat. The set of crops most damaged by high temperatures in the US is a very different set from that most affected by extreme heat in the rest of the world, suggesting that crop-specific adaptation technology developed for the US may not be meeting the most pressing needs around the world. This finding is a first indication that extreme-heat exposure in the rest of the world does not bias or mediate our baseline estimates since it is uncorrelated with crop-level extreme-heat exposure in the US.

Next, in Table G1, we investigate the impact of exposure to extreme heat outside of the US on new variety development in our baseline specification. In column 1, we re-produce our baseline estimates of the relationship between extreme heat exposure in the US and new variety development using only the restricted sample of crops that are part of the global analysis. The relationship remains positive, significant, and similar in magnitude on this restricted sample. In the second column, we include $\Delta \text{ExtremeExposure}_k^{\text{ROW}}$ in the regression. The estimate of the coefficient on $\Delta \text{ExtremeExposure}_k^{\text{ROW}}$ is statistically indistinguishable from zero and, if anything, negative. Probing the estimate in greater detail, we find that the negative point estimate is driven entirely by the US staple crops wheat, corn,

Figure G1: Crop-Level Extreme-Heat Exposure: US vs. the Rest of the World



Notes: This figure plots the relationship between crop-level ΔExtremeExposure, computed from the 1980s to the 2010s, in the US compared to the rest of the world. To compute both sets of values, we combine temperature data from Muñoz-Sabater et al. (2021) with crop-level planting data from Monfreda et al. (2008).

and soy, which have been the subject of substantial innovation but have been relatively less affected by damaging temperature trends in the rest of the world. When we control for an indicator variable that equals one for these three crops (column 3), the coefficient estimate on $\Delta\text{ExtremeExposure}_k^{\text{ROW}}$ declines by roughly two-thirds and is very close to zero.

The null effect of $\Delta\text{ExtremeExposure}_k^{\text{ROW}}$ is not driven by differences in the data sources and measurement strategy that we use to measure extreme-heat exposure outside of the US. In Panel A of Table G2, we replicate the paper's main results using the measurement strategy described in this section. There is a positive and significant relationship between crop-level extreme-heat exposure in the US and innovation, and the estimate is similar after controlling directly for trends in pre-period innovation (column 2) and the quadratic polynomial in each crop's temperature cut-off (column 3). In Panel B, we show that in the exact same specifications there is no relationship between crop-level extreme-heat exposure outside of the US and technology development.

Taken together, these results indicate that our main estimates are not affected or mediated by crop-level temperature distress outside the US. More speculatively, they instead indicate that US innovation responds substantially more strongly (if not exclusively) to climate distress in the US. This dovetails with a growing body of work that documents strong home bias in technology development (Costinot et al., 2019; Moscona and Sastry, 2022). Moreover, especially since the US represents a large share of global agricultural innovation, these findings indicate that the rest of the world may benefit substantially less from climate-induced adaptation technology and international technological spillovers. While a full analysis of global innovation and technology diffusion is beyond the scope of this paper, these topics strike us as an important area for future research.

Table G1: Temperature Distress and Innovation: US vs. the Rest of the World

	(1)	(2)	(3)
	Dependent Variable is New Crop Varieties		
Δ ExtremeExposure in the US, 1980s-2010s	0.0183***	0.0178***	0.0138**
	(0.00644)	(0.00664)	(0.00674)
Δ ExtremeExposure in the Rest of the World, 1980s-2010s		-0.0226	-0.00787
		(0.0150)	(0.0154)
Log area harvested in the US	Yes	Yes	Yes
Log area harvested in the rest of the world	No	Yes	Yes
US staple crop indicator	No	No	Yes
Observations	36	36	36

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released from 1980 to the present. The controls included in each specification are noted at the bottom of each column. US staple crops are defined as corn, wheat, and soy. In the first column, we estimate the relationship between our baseline measure of extreme heat exposure and new variety releases on the restricted subsample used for the global analysis. In columns 2-3, we also include extreme heat exposure measured in the rest of the world. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table G2: US vs. the Rest of the World: Sensitivity

	(1)	(2)	(3)
	Dependent Variable is New Crop Varieties		
	Panel A: Temperature Distress in the US		
Δ ExtremeExposure in the US, 1980s-2010s	0.0376**	0.0311**	0.0336**
	(0.0147)	(0.0123)	(0.0131)
Observations	34	34	34
	Panel B: Temperature Distress in the Rest of the World		
Δ ExtremeExposure in the Rest of the World, 1980s-2010s	-0.0174	-0.0141	-0.0116
	(0.0179)	(0.0167)	(0.0204)
Observations	36	36	36
Log area harvested from EarthStat	Yes	Yes	Yes
US Staple Crop Indicator	Yes	Yes	Yes
Pre-period varieties	No	Yes	Yes
Cut-off temp. and cut-off temp sq.	No	No	Yes

Notes: The unit of observation is a crop. The outcome variable is the number of crop-specific varieties released from 1980 to the present. The controls included in each specification are noted at the bottom of each column. US staple crops are defined as corn, wheat, and soy. In Panel A, the independent variable of interest is crop-level extreme temperature exposure in the US computed using the ERA-5 temperature data and EarthStat data on crop planting patterns, in Panel B the independent variable of interest is crop-level extreme temperature exposure outside of th US computed using the ERA-5 temperature data and EarthStat data on crop planting patterns. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

H Modeling Crop Choice in the Counterfactual

In this section we explore the possibility that the pattern of crop switching might shape the impact of climate change in future climate scenarios. To project future crop allocations and the extent to which they change as a result of temperature change, we return to our estimates from Section F.1 and use these alongside our measures of predicted future exposure to extreme temperature at the crop-by-county level.

Using measures of extreme exposure $\Delta\text{ExtremeExposure}_{k,i}(d,r)$ for each decade $d \in \{2050, 2090\}$ and for each RCP $r \in \{4.5, 6.0, 8.5\}$ we estimate $\text{Area}_{k,i}(d,r)$ as:

$$\text{asinh}(\text{Area}_{k,i}(d,r)) = \hat{\alpha}_{ks} + \hat{\delta}_i + \hat{\psi} \cdot \text{asinh}(\text{Area}_{k,i}^{2012}) + \hat{\pi} \cdot \Delta\text{ExtremeExposure}_{k,i}(d,r) + \varepsilon_{k,i} \qquad \text{(H.1)}$$

where estimated coefficients (denoted with a hat) are from Equation F.1 and recall $\hat{\pi} < 0$. We use these predicted future areas under each climate scenario in our analysis of how crop switching might affect our estimates of the causal effect of technology development on climate damage. That is, we re-estimate our counterfactuals after assuming that planting patterns correspond to this endogenous allocation as predicted by changing temperature realizations. As reported in Section 4.3.6, we find lower estimates of climate damage under this scenario, but percent mitigation that is comparable to our baseline (18.9%).

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