Does Directed Innovation Mitigate Climate Damage? Evidence from US Agriculture*

Jacob Moscona† and Karthik A. Sastry‡

July 5, 2022

Abstract

This paper studies how innovation reacts to climate change and shapes its economic impacts, focusing on US agriculture. We show in a model that directed innovation can either mitigate or exacerbate climate change's potential economic damage depending on the substitutability between new technology and favorable climatic conditions. To empirically investigate the technological response to climate change, we measure crop-specific exposure to damaging extreme temperatures and crop-specific innovation embodied in new variety releases and patents. We find that innovation has re-directed since the mid 20th century toward crops with increasing exposure to extreme temperatures. Moreover, this effect is driven by types of agricultural technology most related to environmental adaptation. We next show that US counties' exposure to induced innovation significantly dampens the local economic damage from extreme temperatures. Combining these estimates with the model, we find that directed innovation has offset 20% of potential losses in US agricultural land value due to damaging climate trends since 1960, and that innovation could offset 13% of projected damage by 2100. These findings highlight the vital importance, but incomplete effectiveness, of endogenous technological change as a source of adaptation to climate change.

*We thank Daron Acemoglu, George-Marios Angeletos, Pierre Azoulay, Clare Balboni, Abhijit Banerjee, Dave Donaldson, Arnaud Costinot, Joel Flynn, Solomon Hsiang, Amir Jina, Joshua Lev Krieger, Josh Lerner, Dávid Krisztián Nagy, Ruiqing Miao, Teresa Molina, Frances C. Moore, Nathan Nunn, Ben Olken, Ariel Ortiz-Bobea, Elias Papaioannou, Jacquelyn Pless, Michael Roberts, James A. Robinson, Tobias Salz, Wolfram Schlenker, Alp Simsek, Andrei Shleifer, and Rob Townsend for advice and comments. We also thank seminar participants at MIT, Harvard Business School, the University of Hawaii, the 2020 Berkeley Climate Economics Workshop, the 2021 NBER Summer Institute Economic Growth Meeting, the 2021 NBER Summer Institute Environmental and Energy Economics Meeting, and UC Berkeley for helpful feedback.

†Harvard University and J-PAL, email: `moscona@fas.harvard.edu`

‡Massachusetts Institute of Technology, email: `ksastry@mit.edu`

1 Introduction

This paper studies how technological progress, possibly the most important engine for productivity growth in human history, responds to climate change, possibly the biggest looming threat to productivity growth in the near future. Our area of focus is US agriculture, where both forces have had tangible effects in recent times. The last century has witnessed transformative progress in agricultural biotechnology, evidenced by an explosion of private-sector research spending and the emergence of now ubiquitous high-yielding plant varieties. The same period has also seen rising temperatures dramatically alter agricultural productivity (Lobell and Field, 2007; Schlenker and Roberts, 2009; Lobell, Schlenker and Costa-Roberts, 2011). Yet little is known about how the pace and focus of agricultural innovation has shifted in response to temperature change or shaped the economic consequences of an increasingly extreme environment. Understanding the process by which technological solutions emerge in response to changing and increasingly extreme temperature patterns is essential for assessing economic resilience to global warming, which will continue over the 21st century even under optimistic scenarios for reducing greenhouse gas concentrations.

Historically, innovation has been a critical part of the American agricultural sector's response to new environmental challenges. Olmstead and Rhode (2008, 2011) describe how biological innovation fueled the early expansion of US agriculture, and historians acknowledge the importance of novel hybrid seeds for withstanding early 20th century droughts (Crow, 1998; Sutch, 2008, 2011). Today, agricultural biotechnology firms employ a similar narrative to promote their investments in climate-resistant technology. The most prominent item on Syngenta's website reads "*Helping farmers. Fighting climate change.*" and links to a "growth plan" that promotes, among other goals, developing new innovations for "making agriculture more resilient" in the face of climate change's "existential threat" (Figure A1). The sustainability chief of Monsanto, quoted in a 2017 news article, emphasized that "making sure our products can withstand extreme weather" is a top priority to meet growing "demand for seeds that can thrive [in] more extreme environments" (Gupta, 2017).

This paper empirically investigates how technological progress has reacted to modern temperature change and shaped its economic impact in the US agricultural sector. We answer two specific questions. First, has innovation re-directed toward crops most exposed to climate distress and the technologies most suited to boosting climatic resilience? Second, how has any shift in the direction of innovation affected the agricultural sector's resilience to climate extremes? We use our answers to quantify the extent to which technology has mitigated the economic damage of climate change in the past and to project future damages after accounting for endogenous technological change.

We begin with a theoretical model that describes how climate change might shift market incentives for innovation, and in turn how directed innovation might shape the economic effects of climate change. We model equilibrium in a single market (e.g., the agricultural sector) with spatially heterogeneous production, centralized technology development by a profit-maximizing monopolist, and a climate shock that reduces aggregate production possibilities. Our results convey the economic logic by which directed innovation could either mitigate or exacerbate aggregate climate damage depending on underlying features of technology and demand. If technological advances *substitute* for favorable climatic conditions on average—for example, by making crops increasingly heat and drought resistant—then equilibrium technology development unambiguously increases in response to climate distress and reduces the economic impact of a worsening climate. Higher prices for distressed crops intensify this mechanism in general equilibrium. Conversely, if technological advances *complement* favorable climatic conditions on average—for example, by increasing average yields at the cost of making environmental requirements more exact—then directed innovation can exacerbate climate damages. Profit incentives guide innovators away from propping up "ecological losers" and toward pushing forward "ecological winners," consistent with the intuition that innovation concentrates in the largest, most productive sectors (e.g., Schmookler, 1966).

To determine the role of technological progress in shaping the economic consequences of climate change, it is therefore essential to turn to the data. The first part of our empirical analysis compares technology development since 1960 across crops that have experienced different productivity shocks due to changing temperature realizations. To measure temperature-induced productivity shocks, we start with county-level data on daily temperature realizations. We combine these data with expert-elicited estimates of the maximum growing temperature for individual plant species from the UN Food and Agriculture Organization's EcoCrop database to measure the potential exposure of a given plant to extreme heat in a given location over a specific period of time.[1] Focusing on temperature extremes is consistent with the literature following Schlenker and Roberts (2009) that identifies the increased likelihood of extreme heat as the dominant channel through which climate change affects staple-crop yields, as well as similar findings across a larger panel of crops in our county-level data.[2] Finally, we average local crop-specific extreme-heat exposure over each crop's planting locations in a pre-analysis period to obtain a given crop's aggregate exposure to extreme heat. The change in this measure over time is our measure of exposure to damaging temperature change. The cross-crop variation in this measure, and hence the identification of parameters in our empirical design, derives from interacting the essentially random variation in the geography of warming across the US with pre-determined differences in both crops' planting locations and physiology.

To measure innovation, we compile comprehensive data of all for-sale plant varieties and their time of introduction from the USDA's *Variety Name List*, obtained via a Freedom of Information Act (FOIA) request. This measure has the benefits of (i) an unambiguous mapping to our productivity shocks, which are measured at the crop level, and (ii) homogeneous coverage over a period of heterogeneous intellectual property rights for plant biotechnology (Moscona, 2021). We complement the *Variety Name*

[1]EcoCrop is frequently used in research at the intersection of agronomics and climate change to estimate crop-specific climate tolerance (see, for instance, Hijmans et al., 2001; Ramirez-Villegas, Jarvis and Läderach, 2013; Kim et al., 2018).

[2]Recent developments in agricultural science identify, as a physiological mechanism, that temperature directly damages plant tissue via heat stress, hinders plant photosynthesis, and induces water stress. See, for more details, studies by Lobell et al. (2013) and Schauberger et al. (2017). In Online Appendix D, we document that extreme-heat exposure as we measure it has large, negative effects on crop yields, and explains a large share of the overall impact of temperatures on crop production.

List with two additional data sources. A database of all Plant Variety Protection (PVP) certificates, a weak form of intellectual property protection for seeds introduced in 1970, allow us to replicate our main findings on an independently collected dataset and investigate more detailed characteristics of inventors. A database of crop-specific patents in agricultural patent classes allow us to study effects outside of biotechnology and explore the characteristics of inventions.

Our first main result is that biotechnology development since 1960, measured by new variety releases in the *Variety Name List*, has been directed toward crops that have become more exposed to extreme heat over time. The mean crop in our sample sees about a 20% increase in variety development caused by changing extreme-heat exposure. This result is robust to controlling for crop-level proxies for market size, pre-period trends in innovation, and pre-period climatic characteristics. The result is quantitatively similar when the outcome is measured using the PVP certificate data. Using a decadal panel-data model, we find that the largest effects of extreme temperatures on innovation appear within the decade, with some lagged effects and no evidence of anticipation.

We next probe the mechanisms that underpin the baseline finding by studying its heterogeneity across crops, types of inventor, and types of invention. First, we find that the elasticity of innovation to extreme-heat exposure is higher for more widely planted crops, but find limited evidence that it differs across natural instruments for price elasticity or ease of crop switching. Next, using the PVP certificate data that record the developer of each variety, we find that the redirection of technology is stronger in the private sector than in the public sector. This is consistent with our theoretical model based on profit incentives and with narrative evidence emphasizing the importance of private biotechnology firms for adaptive innovation. Finally, using the patent data, we find that increased extreme-temperature exposure predicts a higher number and share of patents that directly mention keywords related to climate change, heat, and drought. By contrast, there is no significant relationship with patents that do not mention these keywords. These results suggest that climate change does not uniformly induce all types of agricultural innovation, for instance through a channel of raising crop prices and demand for all inputs, but instead more precisely induces innovation related to adaptation for hotter and drier conditions.

We also explore alternative channels for the effect of the climate on agricultural innovation. We first show that, conditional on changes in extreme-heat exposure, changes in extreme-cold exposure have no discrenible effect on innovation and changes in drought exposure measured by the Palmer Drought Severity Index (PDSI) have an imprecise and comparatively small effect. The latter result is consistent with findings in the agronomic literature that extreme heat is itself an important cause of water stress (e.g., Lobell et al., 2014). Next, using data on changes in planting patterns over time, we find (i) that the extent of observed crop switching does not attenuate the relationship between temperature change and innovation and (ii) that temperature-induced expansions in total planted area have an independent positive effect on technology development. Finally, using international data on hourly temperature realizations and planting patterns, we find that trends in non-US extreme-heat exposure have essentially no relationship with either trends in our US measure or the direction of US innovation. This result reminds that adaptive innovation in the US may not translate to addressing climatic threats elsewhere in the world.

Having established the direction of technology's response to temperature change, we turn next toward quantifying the extent to which technology has mitigated temperature changes' economic harms. Previous studies have tried to identify overall adaptation to climate change by comparing short and long-run responses of economic outcomes to temperature change (Dell, Jones and Olken, 2012; Burke and Emerick, 2016). By contrast, we use a different approach based on locations' exposure to directed innovation. We measure both (i) a county-level measure of local extreme-heat exposure, taking into account both its temperature realizations and the temperature sensitivity of its crop mix, as well as (ii) a county-level measure of innovation exposure, the extreme-heat exposure of the county's crop mix across all other counties growing each crop. The previous set of findings on the re-direction of technology documented that counties with higher innovation exposure have more climate-induced technology at their disposal. Our regression model, derived from the theory, allows innovation exposure to affect the sensitivity of local agricultural outcomes to county-level extreme-heat exposure via an interaction term. Our interest is whether more innovation-exposed counties have a significantly greater or smaller sensitivity of local agricultural outcomes to extreme heat.

We find that higher innovation exposure significantly mutes the negative effect of extreme heat on agricultural land values. The effect of an additional crop-specific degree-day of extreme heat per year is a -0.010 percent decrease in land value if a county's crop composition has the (area-weighted) median exposure to innovation, compared with -0.003 percent at the 75th percentile of the same distribution and -0.015 percent at the 25th percentile. The results are very similar using agricultural revenues and profits, rather than land values, as the outcome variable and are robust to directly controlling for changes in output prices and county-level average temperatures. Finally, the results are strongest in counties that cultivate crops with larger national market size, consistent with our previous finding that those crops also had a stronger innovative response to extreme temperatures.

The last part of the paper studies how much of the aggregate economic damage from climate change has been mitigated by innovation. We show how a special case of the model allows us to estimate the counterfactuals of interest directly from our empirical panel data model. The counterfactual also has the following more heuristic interpretation: a world without innovation holds the heat-to-damage relationship constant, while a world with innovation sees this relationship "flatten" in proportion to induced innovation. Our baseline estimate is that innovation has mitigated 19.9% (95% confidence interval: 15.3% to 24.5%) of the potential economic damage from temperature change in agriculture over the last 50 years. We show that this result is not overly sensitive to alternative assumptions about resource constraints for research investment and about crop switching. Quantitatively, the economic damage mitigated by technology development amounts to about $24 billion in current USD or 1.7% of total US agricultural land value.

We repeat the same analysis for future climate scenarios in order to estimate the extent to which climate damages over the 21st century might be dampened by technological progress. Our projections use the model ensemble method of Rasmussen, Meinshausen and Kopp (2016), which averages the predictions of a number of leading climate models that are forced by the same standardized pathway for greenhouse gas concentrations (the IPCC's Representative Concentration Pathways). Under the model ensemble forecast forced by RCP 4.5, an intermediate scenario, innovation mitigates 15.1% of damage by 2050 (95% CI: 9.8% to 20.5%) and 13.0% by 2100 (95% CI: 7.6% to 18.5%). These savings correspond, respectively, to $218 billion and $1.05 trillion current USD (assuming 3% annual inflation), and to 1.9% and 2.8% of all agricultural land value in the respective forecasts. These sums, while economically significant, are far from suggesting that technology is capable of absorbing *all* the risks associated with climate change, even in a wealthy and research-intensive country.

Our study on the role of technology for adapting to climate damage contributes to a large literature about directed technological change and the environment. While existing work has mostly focused on endogenous development of low-emission or "clean" technology (Newell, Jaffe and Stavins, 1999; Popp, 2002, 2004; Acemoglu et al., 2012, 2016; Aghion et al., 2016), we focus instead on the role of innovation in mitigating climate damage. Three exceptions which also study the relationship of environmental distress with innovation are Miao and Popp (2014), who study the innovative response to natural disasters across countries; Miao (2020), who studies how insurance mediates the innovative response to drought; and Moscona (2022), who studies the innovative response to the American Dust Bowl and its consequences. Our main result is consistent with these papers' findings that innovation responds positively to climate distress, by different definitions and in different contexts.[3]

Existing work studying adaptation to climate change has focused on the theoretical benefits of reallocating production across space. Costinot, Donaldson and Smith (2016), Rising and Devineni (2020), and Sloat et al. (2020) study these questions for agricultural crop choice.[4] Our approach, by contrast, focuses on the response of production technology itself, in theory and in practice.

Finally, there has been a long-standing interest in the impact of temperature change on the agricultural sector. Mendelsohn, Nordhaus and Shaw (1994), Schlenker, Hanemann and Fisher (2005), Schlenker, Hanemann and Fisher (2006), Deschênes and Greenstone (2007) and Fisher et al. (2012) estimate reduced-form relationships between changing temperatures on agricultural economic outcomes. Several studies, focusing on specific crops, investigate fluctuations in the relationship between extreme heat and yields in order to infer the potential importance of adaptation.[5] Our study takes the

[3] A strand of the general literature on directed technological change studies the conditions under which factor scarcity encourages innovation, in theory (Acemoglu, 2010) and in practice (Hanlon, 2015). We revisit this connection in Section 2.3.

[4] Desmet and Rossi-Hansberg (2015), Alvarez and Rossi-Hansberg (2021), and Conte et al. (2020) study production reallocation in response to climate change in multi-sector models.

[5] See, for example, Roberts and Schlenker (2010), Roberts and Schlenker (2011), Lobell et al. (2014), Burke and Emerick (2016), and Keane and Neal (2020), who study corn and soybeans. Auffhammer and Schlenker (2014) reviews the related literature on this topic for agricultural economics. A different literature in agronomics and geography, including Rodima-Taylor, Olwig and Chhetri (2012) and Zilberman et al. (2018), has highlighted the potential for adaptation through new technology but not been able to quantify its effects.

broader, sector-wide view of the first set of papers while using crop-specific variation to measure the adaptive response of innovation. In so doing, we also extend a classic literature on the role of innovation in shaping US agricultural productivity and overcoming ecological barriers (e.g., Griliches, 1957; Hayami and Ruttan, 1970; Olmstead and Rhode, 1993, 2008) to the study of modern climate change.

The rest of the paper is organized as follows. Section 2 describes a theoretical model that guides measurement and interpretation of results. Section 3 describes data and measurement. Sections 4 and 5 present our main results on directed innovation and the downstream impact of temperature change and technological progress. Section 6 quantifies the aggregate effects of innovation. Section 7 concludes.

2 Model

In this section we present a model in which agricultural technology endogenously responds to productivity shocks induced by climate change. Our main results describe primitive conditions on production technology and equilibrium price responses under which technology development (i) increases or decreases in response to climate damage and (ii) increases or decreases the resilience of agricultural production to climate shocks. We preview these results using heuristic language in Figure 1. This section's theoretical results fill in the logic of these results and structure our subsequent empirical analysis and quantification. All detailed derivations and proofs are in Appendix B.

2.1 Set-up

There are two goods, an agricultural crop and a numeraire. The crop is produced by a unit measure of farms indexed by $i \in [0,1]$. Each farm has a productivity $A_i \in [\underline{A}, \overline{A}]$, which describes the location's suitability for crop production and has cumulative distribution function F across locations.

There is a single crop-specific *technology* in our model (e.g., improved seed varieties). Each farm uses $T_i \in \mathbb{R}_+$ of this input. The input's productivity in location i depends on an endogenous, aggregate state variable $\theta \in \mathbb{R}_+$ summarizing technological advancement, and the local productivity A_i. The farm maximizes profits, taking as given crop price p and technology price q, and using the following production function:

$$Y_i = \alpha^{-\alpha}(1-\alpha)^{-1}G(A_i,\theta)^{\alpha}T_i^{1-\alpha} \tag{2.1}$$

in which $\alpha \in [0,1]$ parameterizes the relative importance of the technological input (and the normalization $\alpha^{-\alpha}(1-\alpha)^{-1}$ is for convenience); and $G : \mathbb{R}^2 \to \mathbb{R}_+$ captures the productivity of the technological input as a function of the climate and quality of the technology. We assume that G is concave in θ, twice continuously differentiable, and satisfies $G_1 \geq 0$ and $G_2 \geq 0$ so that more A_i and θ increase production. It would be straightforward to add other factors of production, like mechanical inputs, labor, or different types of improved seeds, as long as (2.1) represented the production function conditional on these choices. This simple and specific production function allows us to focus on the

Figure 1: Summary of Model Cases

In a sector damaged by climate change...

	Climate-Substitute Technology	Climate-Complement Technology
Price Effects Weak	(a) Innovation $\uparrow$ and Resilience $\uparrow$	(b) Innovation $\downarrow$ and Resilience $\uparrow$
Price Effects Strong		(c) Innovation $\uparrow$ and Resilience $\downarrow$

economic mechanisms of interest and derive equilibrium comparative statics.

The solution of each farm's profit maximization problem gives the technology demand function

$$T_i = \alpha^{-1} p^{\frac{1}{\alpha}} q^{-\frac{1}{\alpha}} G(A_i, \theta) \tag{2.2}$$

which is isoelastic in the input price and linear in $G(A_i, \theta)$.

A representative innovator determines both the price of the technological input (q) and the quality of technology (θ). They face a marginal production cost $1-\alpha$ for the input and a convex, differentiable quality development cost $C : \mathbb{R}_+ \to \mathbb{R}_+$, satisfying $\frac{\mathrm{d}}{\mathrm{d}\theta} C(0) = 0$. Because technology demand is isoelastic, and we have made a convenient normalization for marginal costs, the optimal technological input price is $q = 1$. Thus the innovator's choice of quality can be re-stated more simply as the following maximization of aggregate technology demand over quality θ:

$$\max_{\theta} p^{\frac{1}{\alpha}} \int G(A, \theta) \, \mathrm{d}F(A) - C(\theta) \tag{2.3}$$

To close the model, we assume that demand for each of the goods is represented by a (crop-specific) inverse demand function $p = P(Y)$, where $Y = \int Y_i(A) \, \mathrm{d}F(A)$ is total production, and $P : \mathbb{R}_+ \to \mathbb{R}_+$ is continuous and non-increasing. We therefore define equilibrium in terms of aggregates as a tuple of technology levels, prices, and total production (p, θ, Y) such that farms and technologists optimize and the output price lies along the aforementioned demand curve.

The focus of our analysis will be comparative statics when varying the productivity distribution. We equate the "climate" with the productivity distribution across space F, which in the background might depend on both temperature realizations and plant biology. We define *damaging climate change* as a shift from distribution F to F' such that the former first-order stochastic dominates the latter. Under our normalization of $G_1 \geq 0$, this definition is sufficient for damaging climate change to reduce aggregate production of each crop holding fixed all other inputs and technology.

2.2 The Climate Substitutability of Technology

To structure our results, we introduce two cases for the relationship between technology and the climate in the farm's production function:

Definition 1 (Climate Substitutability of Technology)**.** *Technological advances are climate substitutes if* $G_{12} \leq 0$ *and climate complements if* $G_{12} \geq 0$*.*

Technological advances are *climate substitutes* if they reduce the marginal impact of climatic conditions on output. For example, this case is natural if the technological frontier is to develop less heat or drought sensitive crops that remain productive even in harsher environments. On the other hand, technological advances are *climate complements* if they increase the marginal impact of climatic conditions on output. This is the case, for example, if improved biotechnology is more finely tuned to a particular set of ecological conditions and therefore less tolerant to fluctuations.[6]

2.3 Theoretical Results

2.3.1 The Equilibrium Direction of Innovation

Our first result shows how, in a small open economy case of the model which fixes the crop price at $\overline{p} > 0$, the direction of technological change hinges on the climate substitutability of innovation:

Proposition 1 (Direction of Technology: Fixed Prices)**.** *Assume that prices are fixed, or* $P(Y) \equiv \overline{p}$*. If the climate shifts in a damaging way,*

1. *θ weakly increases in equilibrium if technology is a climate substitute.*

2. *θ weakly decreases in equilibrium if technology is a climate complement.*

The direction of technological change in the model depends on whether farmers are more or less willing to pay for technological improvements in the new, poorer climate. In the climate substitutes case, farmers are more willing to pay for technological improvements in the poorer climate because such improvements are more useful; in the climate complements case, the opposite is true. Note that in *both* cases the partial-equilibrium (i.e., fixed θ) effect of the damaging climate shock on production and technological input demand is negative. Thus the climate substitutes case allows innovation to concentrate in a "shrinking" market because the market nonetheless becomes more receptive on the margin to technological improvement.[7] The climate complements case, on the other hand, embodies the idea that the smaller market may also be less receptive to new technology.[8]

[6] Lobell et al. (2014) describe such an idea as a "general notion that as farmers become more adept at removing all non-water constraints to crop production, the sensitivity to drought generally increases" (p. 519). See Morgan et al. (2014) for a discussion and example of this idea in harvester technology.

[7] A similar logic underlies the case in which labor scarcity encourages innovation in Acemoglu (2010).

[8] In Acemoglu (2002), the positive relationship between the fixed factor and amount of innovation is interpreted as a "market size effect." These results are driven by an assumed complementarity between the fixed factor and new technologies.

We now allow for price adjustment. A damaging climate shock, holding fixed technology and inputs, creates crop scarcity and increases prices. This is, from the farmers' perspective, a *price hedge* against the negative shock. It also increases the value marginal product of technology and hence the marginal return to improvement from the innovator's perspective. In an endogenous technology equilibrium, this leads to a *technology hedge* against the shock that operates on top of the considerations in Proposition 1. We formalize that this force confirms the sign prediction for technology under the substitutes case and possibly over-turns the prediction under the complements case:

Proposition 2 (Direction of Technology: Flexible Prices)**.** *Assume equilibrium quantities lie along a non-increasing demand curve, or $p = P(Y)$ for a non-increasing $P(\cdot)$. If the climate shifts in a damaging way,*

1. *θ weakly increases if technology is a climate substitute.*

2. *θ may increase or decrease if technology is a climate complement.*

2.3.2 Innovation and Resilience

The previous results described when technology development increased or decreased in response to climate damage. We now describe the related but subtly different conditions under which directed technology decreases or increases the sensitivity of production to further climatic shifts.

To this end, we first define $\Pi(A, p, \hat{\theta})$ as the equilibrium profits or land rents of a farm with productivity A when the price is p and the technology level is $\hat{\theta}$ and $R(A, p, \hat{\theta})$, or "Resilience," as the negative of profits' sensitivity to the weather:

$$R(A, p, \hat{\theta}) = -\frac{\partial}{\partial A}\Pi(A, p, \hat{\theta}) \tag{2.4}$$

When Resilience increases, the same climate shock has a smaller absolute-value effect on profits. A similar definition is introduced by Lobell (2014) as the "adaptation" attributable to a new production technology. Our result signs the change in Resilience between equilibria as a function of the model case.

Corollary 1 (Resilience)**.** *Consider the general environment of Proposition 2 and a damaging climate shift which moves equilibrium technology from θ to θ'. Then the following properties hold for all (A, p):*

1. *$R(A, p, \theta') \geq R(A, p, \theta)$ if technology is a climate substitute.*

2. *$R(A, p, \theta') \geq R(A, p, \theta)$ if technology is a climate complement and $\theta' \leq \theta$.*

3. *$R(A, p, \theta') \leq R(A, p, \theta)$ if technology is a climate complement and $\theta' \geq \theta$.*

The climate-substituting case features a feedback loop between a negative climate shock increasing the marginal product of technology and expanding technology decreasing the marginal effects of climate shocks. New technology "substitutes" for the climate in production and renders the latter less important on the margin.

The climate-complementing case is more complicated due to the potential misalignment of marginal product effects and the direction of innovation. If technology contracts because price effects are weak, directed innovation magnifies the average effect of climate change on the agricultural economy but reduces the marginal effects. The regress of technology (e.g., "downgrading" high-yielding seeds to something more weather-robust) is like reducing a complementary input to the climate, and therefore also makes production less sensitive to the climate. If technology expands due to strong price effects, however, the opposite is true. New technology is more productive on average and thus reduces the level of climate damage; however, it is also more sensitive to climate stress and thus increases the marginal effect of damaging climate shifts on agricultural production. This result would be consistent with the field-level study of Lobell et al. (2014), which shows increasing sensitivity of corn yields to drought conditions over time in Iowa, Illinois, and Indiana.

This result emphasizes that fully understanding the role of innovation as a mediating force for climate damage requires independently measuring both the redirection of technology and the induced change in resilience. In other words, neither a mitigating response of directly-measured innovation nor a pattern of increased resilience fully identifies a model case in Figure 1, which is the level of precision required for quantifying the effect of directed innovation on aggregate economic outcomes (e.g., profits or production).

2.4 Extensions: Welfare and Endogenous Focus

The model has simple normative properties driven by a single market failure, the innovator's monopoly power. In Appendix C.1, we show how monopoly power leads to under-provision of technology and insufficient research in equilibrium. But the direction of technological change is always optimal in equilibrium, in the sense that the planner's solution has the same directional comparative statics for θ as the competitive equilibrium. Moreover, the optimal policy to implement the first-best is a simple subsidy for the technological good that offsets the monopoly distortion.

In the same Appendix, we explore richer normative predictions in a variant model with a dynamic externality that stylizes the uninternalized benefits of research today on technological advancement tomorrow. In this case the planner also internalizes the dynamic externality and incorporates this into the optimal subsidy. In principle, equilibrium technology can redirect in the "wrong direction" relative to the planner's preference because of its sub-optimal inertia via the dynamic externality.

In the main analysis, we defined technological progress as either climate substituting or climate complementing. In Appendix C.2, we study a variant of the model in which the innovator makes separate choices to improve climate-complementary or climate-substituting technologies. We find that damaging climate induces innovation in the climate substituting technology and contracts innovation in the climate-complementing technology. These results could explain, for example, why

Midwestern US corn, which to date has been relatively unexposed to damaging heat trends, shows evidence of increasing temperature sensitivity over time (Lobell et al., 2014). In Section 4.3.4, we will present empirical evidence on the redirection of technology toward *a priori* more climate-substitutable technology classes.

2.5 Mapping to Estimation

The previous results show that both the direction and downstream impact of endogenous innovation in response to climate change is an empirical question, since a number of different scenarios are possible in the theory. We now describe a specialization of the model that maps directly to our subsequent empirical analysis.

We allow for multiple crops, indexed by $k \in \{1, \ldots, K\}$, and assume that a unit measure of farmers grow each crop k. Production has the same form indicated in Equation 2.1. The climate realizations A_i have cross-sectional distribution $F_k(\cdot)$ among farms growing crop k. Technology, characterized by price and quantity (θ_k, q_k), is produced by a crop-specific innovator with the production technology as described above. And prices lie on crop-specific inverse demand curves $P_k(Y_k)$ where Y_k is production of that crop. Propositions 1 and 2 and Corollary 1 hold in the multi-crop economy due to the separability of production, demand, and technology development decisions across crops.[9]

We next assume that, for each farm i, the productivity function $G(\cdot)$ has the form

$$\log G(A, \theta) = g_0 + g_1(\overline{A} - A) + (g_{20} + g_{21}(\overline{A} - A)) \log \theta \tag{2.5}$$

This captures a form of climate substitutability and complementarity depending on the sign of g_{21}.[10] We assume that the innovator's cost is $C(x) = \frac{x^{1+\eta}}{1+\eta}$ for some $\eta \geq 0$. And we assume that the inverse demand curve is $P_k(x) \equiv p_0 x^{-\varepsilon}$ for some $\varepsilon \geq 0$ and for each crop k.

We solve the model up to approximation around a long-run average climate. Details are provided in Appendix B.5. We show that aggregate innovation and local agricultural profits satisfy two estimable regression equations and write their coefficients in terms of model primitives.

Proposition 3 (Regression Equations)**.** *Technological quality for each crop k is given by*

$$\log \theta_k = \log \theta_0 + \delta \cdot (\overline{A} - A_k) \tag{2.6}$$

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

$$\log \Pi_i = \log \Pi_0 + \beta \cdot (\overline{A} - A_i) + \gamma \cdot (\overline{A} - A_k) + \phi(\overline{A} - A_i)(\overline{A} - A_k) \tag{2.7}$$

[9] In Section 6.2, we discuss the content of these separability assumptions in the context of our quantitative counterfactuals and what happens when they are relaxed.

[10] Technically, the form of substitutability captured here is in log and not level terms. Our derivation in Appendix B.5 demonstrates how the notions are interchangeable up to suitable approximation.

where k is the locally grown crop, $\beta = g_1$, $\gamma = -\tau(g_1 + \delta)$, *and* $\phi = g_{21}\delta$.

Our theoretical results about whether innovation increases or decreases in response to the productivity shock translate in Equation 2.6 to the cases $\delta > 0$ and $\delta < 0$, respectively. Our main empirical specification will measure crop-specific technology by the count of crop-specific plant varieties. In this interpretation, the climate-substitutability g_{21} and inverse elasticity of supply η should be interpreted as features of this technology class. A prediction is that less climate-substitutable technology classes, or those with lower g_{21}, should have a smaller δ. We will explore this prediction by conducting our main analysis for multiple types of technology.

Our theoretical results about whether innovation increases or decreases resilience translate in Equation 2.7 to the cases $\phi > 0$ and $\phi < 0$, respectively. If $\delta > 0$, which will prove to be the empirically relevant case for crop varieties, then this prediction is equivalent to testing $g_{21} > 0$ versus $g_{21} < 0$ (climate substitutes versus climate complements) or differentiating cases (a) and (c) of Figure 1.

Our counterfactual analysis in Section 6 will be based on mapping our estimates back to this specialization of the model. In that section, we will discuss the parameter-stability assumptions that underlie our extrapolation of in-sample findings to out-of-sample counterfactuals via the model.

3 Data and Measurement

To study our questions of interest empirically, we require measurements of exposure to damaging climate change (both location-specific and aggregate), crop-specific biotechnological innovation, and local economic outcomes. This section outlines these data in detail.

3.1 Data Sources

Temperature. We use daily, grid-cell level (2.5 mile × 2.5 mile) temperature data since 1950 from the PRISM ("Parameter-elevation Regressions on Independent Slopes Model") Climate Group.[11] We use temperature data during an April to October growing season. Daily data will be important in light of evidence that crop productivity depends on realizations of extreme weather (e.g., Hodges, 1990; Grierson, 2001; Schlenker and Roberts, 2009), discussed in greater detail below.

Crop-specific Temperature Sensitivity. We compile estimates of crop-specific temperature tolerance from the EcoCrop Database, published by the United Nations Food and Agriculture Organization (FAO). The EcoCrop Database provides information about crop-specific growing conditions, including numerical tolerance ranges for temperature, rainfall, and pH, for over 2,500 plants. The data were compiled from expert surveys and textbook references during the early 1990s. As an example, the EcoCrop data sheet for soybeans (*Glycine max*) cites 21 references including numerous textbooks (e.g., the *Handbook of Legumes of World Economic Importance* by Duke (1981) and *Tropical Pasture and Fodder*

[11] In particular, we use the format of these data that is available on Wolfram Schlenker's website: `http://www.columbia.edu/~ws2162/links.html`, accessed on March 14, 2020.

Plants (Grasses and Legumes) by Bogdan (1977)) and one communication with an agricultural scientist. The list of crops included in the analysis, alongside their species names, is reported in Table A1.

The piece of information we use in our main analysis is EcoCrop's reported upper temperature threshold for optimal growing.EcoCrop's data on temperature tolerance is frequently used in agronomics and climate science to estimate crop-specific tolerance to climate change (e.g. Hijmans et al., 2001; Ramirez-Villegas, Jarvis and Läderach, 2013; Kim et al., 2018; Hummel et al., 2018). In our context, crop-specific temperature tolerances will allow us to incorporate the fact that crops are differentially affected by heat exposure into our main measure of climate-induced productivity shocks. Concretely, we will be able to measure how the same temperature change in a fixed location induces different productivity shocks for different crops.

In principle, a given plant's reported temperature threshold could combine innate, physiological differences across plant species, as well as advancements in agricultural technology. Importantly, therefore, the EcoCrop database is designed to capture the persistent and large differences in temperature sensitivity that exist across crop species. The upper threshold temperatures among our studied crops vary widely, ranging from 17°C to 36°C with a standard deviation of 5.0, representing far greater differences in heat tolerance than could be affected by technology developed in recent decades (and far greater temperature differences than those caused by climate change). Moreover, as the aforementioned example references suggested, EcoCrop is based on survey references with a global and broad temporal scope, rather than field trials of new, advanced varieties. Nevertheless, when we turn to our main empirical analysis we replicate our findings controlling directly for the crop-specific temperature threshold, as well as using a version of crop-level temperature change exposure with a uniform temperature threshold across crops.

Innovation. We use several complementary measures of crop-specific innovation. Our main measure of biotechnology development is from the United States Department of Agriculture (USDA) *Variety Name List*. The *Variety Name List*, obtained through a Freedom of Information Act (FOIA) request by Moscona (2021), is a list of all released crop varieties known to the USDA since the start of our sample period. According to the USDA, it is compiled "from sources such as variety release notices, official journals, seed catalogs, and seed trade publications, as well as names cleared for use by seed companies"; the goal is to be as comprehensive as possible.[12] This data set has several key features. First, it tracks new seeds and plant varieties overtime which, both anecdotally and for agronomic reasons, were and remain the primary technology used to adapt agricultural production to extreme temperatures. Second, the data set is structured by crop and it is straightforward to link individual technologies to crops, the units of observation in our empirical analysis (e.g., a corn seed is a corn innovation). Our main analysis using the *List* consists of 69 crops, covering all the main grains, oilseeds, and feed crops as well as a large portion of vegetables grown in the US. Missing

[12]Moreover, breeders have an incentive to report new biotechnology to the USDA for inclusion in the list because farmers check the *List* to make sure that varieties they purchase were cleared.

are a number of fruits and tubers, which are not covered. Finally, this data set makes it possible to track biotechnology innovation during a period of inconsistent and changing intellectual property law governing seeds and plant varieties, which makes direct measurement from patent data impossible.[13]

We complement this main data set with data on all Plant Variety Protection (PVP) certificates. Plant variety protection is a form of intellectual property protection for seeds that is weaker than utility patent protection and introduced in the middle of our sample period by the United States Government, with the Plant Variety Protection Act (PVPA) of 1970.[14] The key shortcomings of this measure are that PVP certificates exist for only a part of our sample period, and the set of certificates is likely a selected sample due to subsequent changes in patent law. However, the PVP certificates, unlike the *List*, contain systematic information on the identity of the applicant, allowing us to investigate which types of inventors drive the main estimates. We compiled all certificates from the USDA Agricultural Marketing Service (AMS), and use the number of certificates issued by crop as a complementary and independently generated measure of crop-level biotechnology development.

Finally, to measure crop-specific innovation across all technology classes, we use US patent data. Using the patent database *PatSnap*, we computed the number of patents in Cooperative Patent Classification (CPC) classes A01B, A01C, A01D, A01F, A01G, A01H, and A01N (i.e., CPC classes that relate to non-livestock agriculture) that were associated with each crop. To match patents to crops, we searched for the name of each crop in the *Variety Name List* in all patent titles, abstracts, and descriptions. Thus, unlike the *Variety Name List*, a downside to the patent data is that it is less straightforward to link individual technologies to crops and this linking progress is undoubtedly noisier. We also, within these patent classes, collect data on patents that mention keywords related to climate change, heat tolerance, and drought tolerance.[15] This allows us to separately measure, within each crop, patented technologies that are and are not related to climate change.

Geography of Production. We use the 1959 round of the US Census of Agriculture to measure planted area for all of our studied crops in each US county.[16] These data are pre-determined relative to the innovative outcomes we study. We repeat the same data construction process using the 2012 round of the Census of Agriculture, for robustness checks and our analysis of production reallocation.

Agricultural Outcomes. Finally, we combine and harmonize all rounds of the US Census of Agriculture from 1959-2017 to measure local agricultural outcomes. The key outcome of interest is the value of agricultural land per acre, which summarizes the local returns to holders of the fixed factor in our

[13]Patent protection for seeds was not introduced until 1985 following the *Ex Parte Hibberd* ruling; even after 1985, identifying seed patents from patent classification metrics is very challenging (see, e.g., Graff et al., 2003).

[14]In order to be granted a certificate, a variety must be new, distinct, uniform and stable; thus, as with patent protection, there is a minimum quality threshold that all certified varieties must meet. A plant variety protection certificate does *not* prevent farmers from saving protected seeds of prevent protected seeds from being used in breeding.

[15]Our keyword search is to require at least one of the following terms, where the asterisk indicates a wildcard, in the title, abstract, or description: climate change, global warming, drought, heat resist*, heat toler*, extreme temperature, extreme heat, extreme weather.

[16]Where possible, we use reported "planted area" in the Census of Agriculture. When these data are not available, we use "harvested area." Discrepancies between the two, when they are both reported, are generally small.

model, net of costs.Using these data, we construct a decadal panel linking data from the agricultural census to features of the climate averaged over the entire decade. When there are two Censuses from within the same decade, we use the later observation (e.g., for the 2010s decade we use data from the 2017 Census of Agriculture rather than 2012). We also collect data on crop revenue, non-crop revenue, and profits to use as outcomes in robustness checks.

3.2 Measuring Extreme-Heat Exposure

Our main task to estimate an empirical analogue of "climate distress for crop k in location i at time t." Our starting point is the finding in the agronomic literature that exposure to extreme heat is the quantitatively largest effect of temperature, and modern warming trends, on output (Schlenker and Roberts, 2009). It is also understood that the relevant "cut-off" temperature beyond which crop productivity declines can be vastly different across crops (Ritchie and Nesmith, 1991). Empirical estimates of these temperature cut-offs and the non-linear response of productivity only exist for a small set of staple crops—for instance, Schlenker and Roberts (2009) study only corn, soybeans, and cotton. To extrapolate this extreme-heat-exposure approach to our larger panel of crops, we leverage both our fine-grained temperature data and our measurement of crop-specific "maximum optimal temperatures" from expert assessments collected in EcoCrop.

The first step is to measure county-specific heat exposure. In the main analysis, we measure heat exposure in the agronomically standard unit of *degree days*, or the integral of temperature in excess of a specified threshold T over time.[17] We focus on a summer growing season from April to October, which is the period in which the overwhelming majority of extreme-heat exposure occurs.[18] For each US county i, time period (e.g., decade) t, and temperature threshold T, we define the number of realized, growing-season degree days above the threshold as $\text{DegreeDays}_{i,t}(T)$. Appendix D.1 describes in more detail the mechanics of this calculation from the PRISM data.

We next incorporate the crop-specific information via EcoCrop's reported "maximum optimal temperature," which we denote by T_k^{Max} for each crop k. Specifically, we define extreme-temperature exposure for county i, time-period t, and crop k as degree-days above this cutoff:

$$\text{ExtremeExposure}_{i,k,t} := \text{DegreeDays}_{i,t}(T_k^{\text{Max}}) \tag{3.1}$$

Our main measurements of crop- and location-level Extreme Exposure, introduced respectively in Sections 4.1 and 5.1, are area-weighted averages of the above.

The underlying variation in this measure comes from two sources. The first is the spatial pattern

[17] For instance, relative to the threshold 30° C, a single day at a constant temperature 35° C contributes 5 degree days. Five days at the temperature 31° C also contribute, in total, 5 degree days. Any number of days at temperature 29° C contributes zero degree days.

[18] Averaging over all counties and summing over entire 1950-2019 sample, 99.88% of all degree-days over 30° occur from April to October. That number is 98.23% for degree-days over 23°, the high temperature for wheat, and 99.99% for degree-days over 36°, the high temperature for cotton.

of temperatures across the United States. The second is the variation in crop physiology and how different plants respond to this extreme heat to our best agronomic knowledge. For instance, in a fixed period, Dunklin County, Missouri, and Stutsman County, North Dakota, will have different extreme-heat exposures for soybeans ($T_k^{\text{Max}} = 33$) because they experience different weather. But even within Dunklin County, the same weather patterns induce different extreme exposure for soybeans and cotton ($T_k^{\text{Max}} = 36$), since the latter is biologically more heat tolerant.

Validation. In order to show directly that this measure of exposure to damaging heat affects crop productivity, we estimate the relationship between extreme-heat exposure during the 1950s decade and crop yields at the crop-by-county level using the 1959 Census of Agriculture, which we treat as our pre-analysis period throughout the analysis. In particular, we estimate:

$$\log \text{yield}_{i,k,1959} = \xi \cdot \text{ExtremeExposure}_{i,k,1950} + \alpha_i + \alpha_k + \varepsilon_{ik} \tag{3.2}$$

where i indexes counties and k indexes crops. Our findings are reported in Table A2 and convey that extreme-heat exposure, by our measure, substantially reduces crop yields. The results are similar both using the full sample of crops recorded in the Census (columns 1-3) and restricting attention to the staple crops corn, wheat, and soybeans, which have been the focus of prior work (column 4). In column 4, the within-R^2 of our measure (i.e., the R^2 after excluding the effect of crop and county fixed effects) is 0.083, indicating that our measure generates substantial variation in yields. We also show in Section D.2 that this one-dimensional measure of heat exposure explains a large share of the overall effect of temperature on staple crop yields by comparing it to a more flexible estimation approach.

We next show that our measure, which incorporates crop-specific cutoffs, explains a much larger share of variation in crop yields and production than any strategy based on a uniform, crop-invariant cut-off. In particular, we estimate versions of (3.2) without county fixed effects, and after replacing $\text{ExtremeExposure}_{i,k}$ with the exposure to degree-days greater than a single cut-off temperature, for all temperatures between 10 and 45 degrees Celsius. The within-R-squared of the effect of our measure on either crop yields or production is substantially larger than the within-R-squared of the effect of exposure to degree-days above any single cut-off temperature (Figure A2). These estimates are also described in greater detail in Appendix Section D.2.

4 Results: Climate Change and Induced Innovation

We now empirically study how exposure to damaging climate change affects innovation. We find that increasing exposure to extreme temperatures causes biotechnology development. We then explore in greater detail the timing of this innovative response; its heterogeneity across crops, inventors, and types of technology; its relationship with geographic reallocation of production; and the effects of temperature damage in the rest of the world.

4.1 Empirical Model

We estimate an empirical model that tests, in the spirit of Propositions 1 and 2, whether new crop-level biotechnology development responds positively or negatively to crop-level climate distress.

Crop-Level Extreme-Heat Exposure. To estimate crop-level exposure to extreme heat in the entire US market, we sum the location-by-crop-by-time measure $\text{ExtremeExposure}_{i,k,t}$ over all counties, weighting each county by its share of total planted area for that crop in the United States:

$$\text{ExtremeExposure}_{k,t} = \sum_i \left[\frac{\text{Area}^{\text{Pre}}_{i,k}}{\sum_j \text{Area}^{\text{Pre}}_{j,k}} \cdot \text{ExtremeExposure}_{i,k,t} \right] \tag{4.1}$$

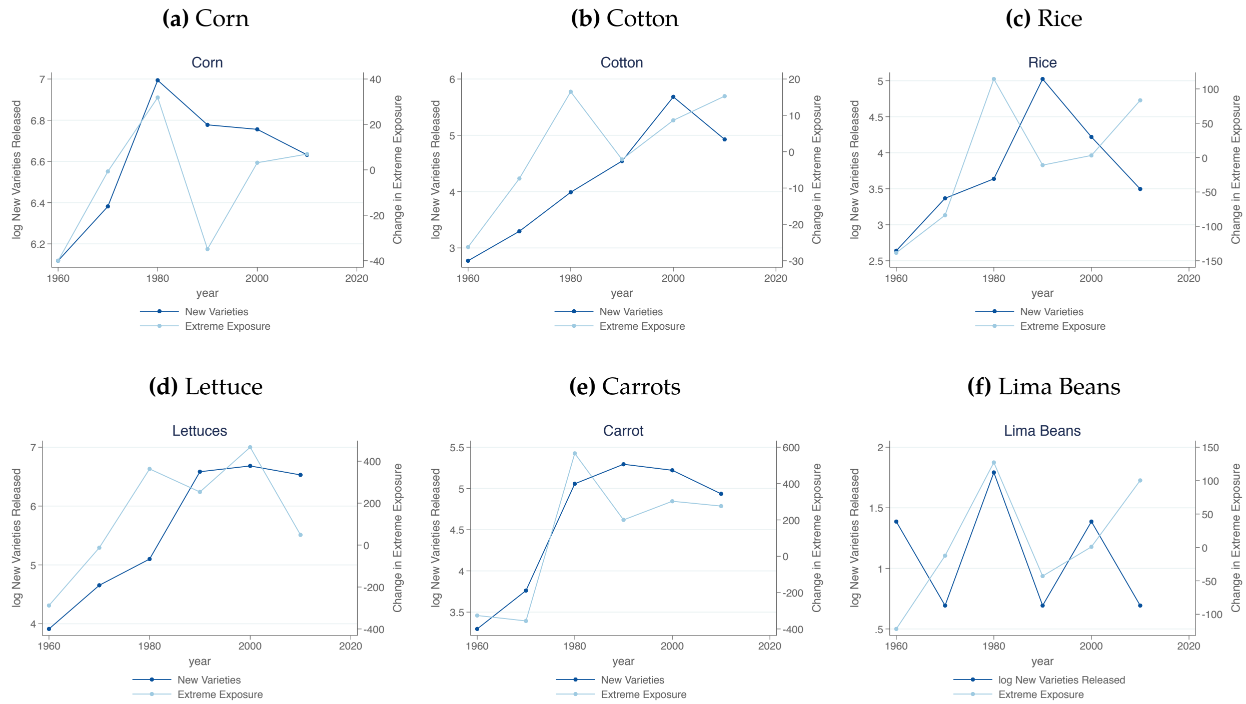
where $\text{Area}^{\text{Pre}}_{i,k}$ is the area devoted to crop k in county i prior to our sample period, in 1959.[19] As foreshadowed earlier, the ExtremeExposure measure varies across crops in a given decade, owing to variation in both the distribution of temperature realizations across space and the crop-specific temperature cutoffs. In our regression framework below, exogeneity of crop-level $\Delta\text{ExtremeExposure}_k$ is due to the exogeneity of change in temperature realizations across locations (Meehl, Arblaster and Branstator, 2012; Burke and Emerick, 2016).[20] The changes in extreme-heat exposure for each crop in the sample between the 1950s and 2010s and between the 1980s and 2010s are reported in Table A1; the sample consists of all crops included in both the Census of Agriculture and the *Variety Name List*.

Before turning to our main empirical framework, Figure 2 displays changes across decades in both $\text{ExtremeExposure}_{k,t}$ and in new variety releases for a subset of crops. Changes in $\text{ExtremeExposure}_{k,t}$ are displayed as the light blue line (left y-axis) and changes in the number of new varieties released are displayed with the dark blue line (right y-axis). Even in the raw data crop-by-crop, changes in variety development seem to coincide with (or slightly lag) changes in extreme-temperature exposure. Moreover, although most crops experienced an increase in exposure to extreme heat over the full sample period (Figure A3), the timing of this increase varies across crops. Moreover, for some crops, exposure to extreme heat did not increase in all decades, and the magnitude of changes in extreme heat exposure varied substantially across crops and decades. These patterns highlight the variation underpinning our analysis and convey the complementarity between our main long-difference empirical approach, described in the next section, and the a panel approach, which we turn to in Section 4.3.1.

[19] We use land area to weight the average since it is more stable (and weather-independent) than variables like physical production and because output data are missing in the early Census of Agriculture for a large portion of our studied crops. For the crops for which we have both area and production, the elasticity of physical production to planted area in the cross-section of the 1959 Census of Agriculture, for all crops for which data are available (and in a regression with crop fixed-effects, to capture differential yields), is 1.04 with standard error .002.

[20] Recent work has documented that variation in heat exposure across different parts of the continental US is due to natural climate variability and, in particular, the heterogeneous consequences of rising temperatures over the Pacific Ocean (Meehl, Arblaster and Branstator, 2012). Related prior work has also assumed the exogeneity of changes in extreme-heat exposure across locations in the US (e.g., Burke and Emerick, 2016). While exogeneity of temperature realizations is sufficient for identification, we also show that all of our main results are very similar after controlling directly for the other component of $\Delta\text{ExtremeExposure}_k$, crop-level variation in the maximum cut-off temperature.

Figure 2: Changes in Extreme Exposure and Variety Releases Across Decades: Examples



Notes: Each graph reports the change in $\text{ExtremeExposure}_{k,t}$ (light line, left y-axis) and the change in the (log of the number of) new varieties released (dark line, right y-axis) across decades.

Estimation Framework. Our baseline regression equation is the following:

$$y_k = \exp\{\delta \cdot \Delta\text{ExtremeExposure}_k + \Gamma X_k' + \varepsilon_k\} \tag{4.2}$$

and is the empirical analogue to Equation 2.6, in differences.[21] y_k is the number of novel seed varieties developed for crop k during the period 1960-2016 and $\Delta\text{ExtremeExposure}_k$ is the change in crop-level extreme heat exposure between our starting and ending decades. X_k' is a series of crop-level controls, which we vary across specifications to probe the sensitivity of our estimates, and includes total land under cultivation, trends in pre-period innovation, and pre-period climate measures. The former two controls are natural to hold fixed initial market size. The last ameliorates concerns that our estimates capture pre-existing trends. Since Equation 4.2 is a long-difference regression, each control captures *trends* in the impact of that control, since all level differences across crops are differenced out.

An estimate of $\delta > 0$ implies that biotechnology development has been directed toward crops that have been more exposed to extreme temperature; $\delta < 0$ implies that biotechnology development has been directed away from crops that have been more exposed to extreme temperature.

[21]For consistency with the literature in innovation economics (which follows Hausman, Hall and Griliches, 1984), we use a Poisson pseudo maximum likelihood estimator. Whenever results from a Poisson model are reported, we use pseudo-maximum likelihood estimators in order to ensure appropriate standard error coverage; see Wooldridge (1999).

Table 1: Temperature Distress Induces Crop Variety Development

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is New Crop Varieties					
Sample Period	1950-2016					1980-2016
Δ ExtremeExposure	0.0167***	0.0171***	0.0136***	0.0184***	0.0226***	0.0338***
	(0.00424)	(0.00436)	(0.00372)	(0.00541)	(0.00668)	(0.00745)
Log area harvested	Yes	Yes	Yes	Yes	Yes	Yes
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. 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.

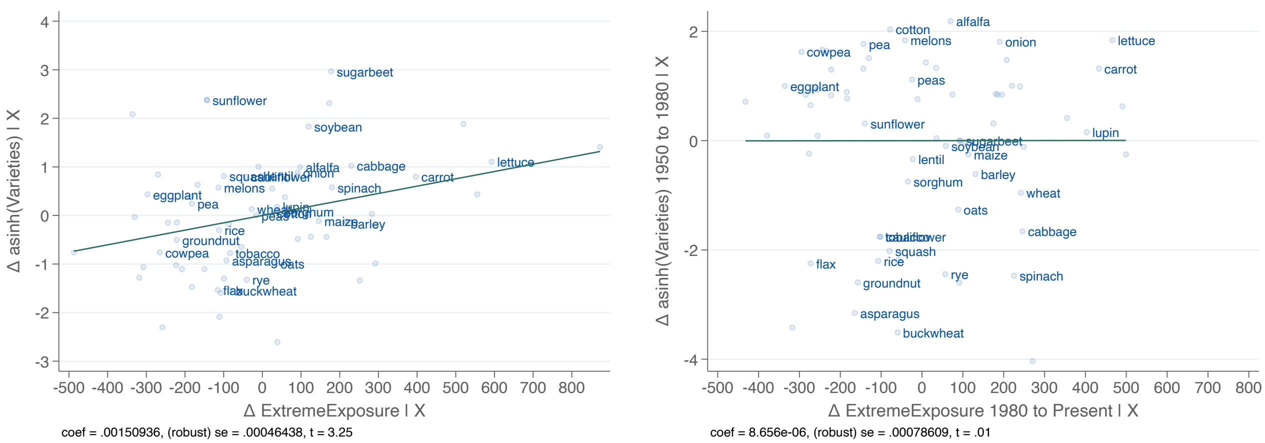
4.2 Results: Temperature Distress and Variety Development

Table 1 presents our baseline estimates of Equation 4.2. In the first column, only ExtremeExposure_k and the log of total area harvested, our proxy for crop-level market size, are included as predictors. We find that $\delta > 0$; innovation in variety development was directed toward crops that were more damaged by temperature change. The point estimate implies that a one standard deviation increase in climate distress led to an about 0.2 standard deviation increase in new varieties. Moreover, the mean change in extreme exposure across crops corresponds to a 20% increase in new variety development.

The remaining columns explore the sensitivity of the estimates. In column 2, we control for the average temperature and average precipitation on land devoted to each crop during the pre-period and in column 3, we add the number of varieties released for each crop from 1900-1960, equivalent to the pre-trend in variety development for the long difference specification; the coefficient of interest remains very similar. In column 4 we control directly for each crop's cut-off temperature, T_k^{Max}, and cut-off temperature squared—again, the coefficient of interest is similar, suggesting that the estimates are not driven by fixed differences in crop-level sensitivity, which could affect trends in technology development or the extent to which crop production can shift across seasons. The similar estimates also indicate that the findings are not driven by differences across crops in ideal planting and harvesting dates, which could vary depending on heat sensitivity. In column 5, we control for the change in the average temperature for each crop over the sample period—this is constructed analogously to (4.1), except rather than weight crop allocations by extreme-heat exposure we weight by county-level average temperature (°C). The inclusion of this control has little impact on our coefficient of interest, validating our extreme exposure measure as a strong crop productivity shock operating

Figure 3: Extreme Exposure and Variety Development: Partial Correlation Plot (OLS)

(a) Partial Correlation Plot (t = 3.25) **(b)** Placebo Partial Correlation Plot (t = 0.01)



Notes: The unit of observation is a crop and the full set of baseline controls are included on the right hand side in each specification, including log of pre-period area, pre-period temperature, pre-period precipitation, and (asinh of) pre-period variety releases. The coefficient estimate, standard error, and t-statistic are reported at the bottom of each graph.

independently from changes in mean temperature. Last, column 6 documents that the result is very similar if we restrict our analysis to decades since 1980.

We visualize the relationship between extreme exposure and innovation in Figure 3a, the (ordinary least squares) partial correlation plot of $\Delta\text{asinh(Varieties)}_k$ against $\Delta\text{ExtremeExposure}_k$ after partialling out all control variables. The relationship is positive, strongly statistically significant ($t = 3.25$), and does not appear to be driven by outlier observations. In Figure 3b, we plot the relationship between extreme-temperature exposure from 1980-present and $\Delta\text{asinh(Varieties)}_k$ from 1950-1980. If this relationship were positive, it could indicate that our main results are driven by pre-existing trends in temperature change and innovation. However, the relationship is almost exactly zero and statistically insignificant ($t = 0.01$). The null result in this falsification exercise is consistent with a causal interpretation of our findings and with no anticipation effects in the long run.

Sensitivity Analysis: Measurement. Table A3 replicates our baseline results using an alternative and independently constructed measure of new plant varieties measured from the Plant Variety Protection certificates. The specifications are identical to columns 1-5 of Table 1, except the sample period is from 1980 to the present and pre-period innovation is measured from 1970-1980, since the PVPA authorizing the certificates was passed in 1970. The sample size is also slightly smaller since asexually propagating crops were excluded from the PVPA. We find that the impact of extreme-temperature exposure on biotechnology development is positive and significant using this alternative strategy to measure the dependent variable.

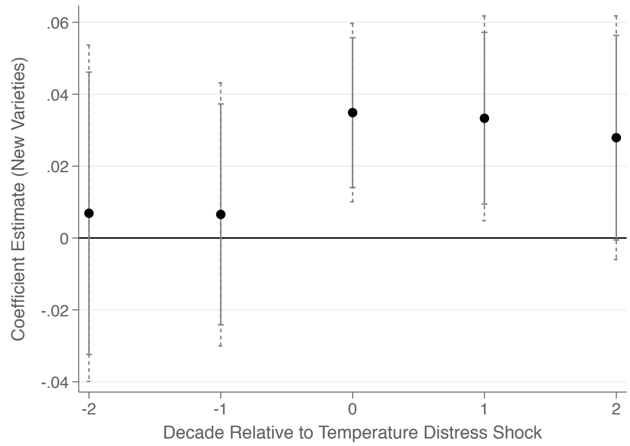
We next show in Table A4 that the results are qualitatively similar using GDDs in excess of 30°C for all crops as the key independent variable (Panel A), a strategy which does not rely on the crop-specific temperature tolerances from EcoCrop. Our baseline measure of ΔExtremeExposure that incorporates crop-specific temperature tolerances is, however, a stronger predictor of technology development when the two are included in the same regression (Panel B). This finding, consistent with our earlier finding for disaggregated production and yield data (Section 3.2), suggests that our new strategy for incorporating crop-level differences in temperature sensitivity is important for precisely measuring the crop-level productivity shock. Finally, we show in Table A5 that the results are very similar if we construct the main independent variable using crop-by-county areas from the 1955, instead of 1959, Census of Agriculture, or the average of the two.

Sensitivity Analysis: Potential Confounding Forces. The temperature trends we measure are unavoidably correlated with geography. Hence, one possible source for spurious correlation are geographic trends in agricultural conditions and/or innovation. We first show that our baseline results are stable when controlling for polynomials in crop-level area-weighted latitude and longitude, the share of cropland in each of the ten largest agricultural states, and the share of cropland under irrigation (Table A6). Schlenker, Hanemann and Fisher (2006) and Schlenker and Roberts (2009) emphasize that the predominance of irrigation in Western states necessitates different agronomic modeling of outcomes in the East and West US. When we follow these authors' suggestions of measuring climate damage only east of the 100th meridian, we find similar effects of damage on total US innovation (Table A7). These findings underscore that our results are not driven differences in geography or, more specifically, by differences in temperature change and agricultural production between the Eastern and Western parts of the US.

In addition to differences in geographic characteristics, crops also differ along a range of economic dimensions that have a major impact on agricultural production, including trade and agricultural policy. To study whether our findings are influenced by broader aspects of the agricultural economy, we measure crop-specific exposure to five potentially relevant variables: proximity to US experiment stations (Kantor and Whalley, 2019), insurance coverage, subsidy payments, trade exposure, and the wealth of producers. We re-produce our main estimates controlling for each of these variables in Table A8, and our main coefficient of interest is stable across specifications.

Sensitivity Analysis: Inference. We finally report results that use statistical inference techniques that are more robust to other, unmeasured and unmodeled confounders. First, we calculate the standard errors of Adao, Kolesár and Morales (2019), clustered by state, for our main OLS regression model underlying Figure 3a. The Adao, Kolesár and Morales (2019) method provides more correct inference when there are unmodeled shocks at the level of our "share" variable, the crop area weights. In particular, they allow for county-level confounding shocks, arbitrarily correlated among themselves at the state level, which cause potential outcomes for crops grown in common locations to be correlated. We obtain reassuringly similar precision to the baseline estimates (SE: 0.0058). We also use randomization inference as an alternative strategy to investigate statistical significance. In

Figure 4: Extreme Exposure and Variety Development: Panel Estimates



Notes: Each point reports a coefficient estimate from separate estimations of (4.3). The solid and dashed lines are 90% and 95% confidence intervals. Standard errors are clustered by crop.

the specification with all baseline controls, randomization inference implies that $p = 0.007$ in the case of the Poisson estimate and $p = 0.003$ in the case of the OLS estimate.

Narrative Evidence. In Online Appendix E, we provide narrative evidence that corroborates and contextualizes our result the biotechnology development responds to modern climate change. As concrete examples, we describe in detail the scientific underpinning and development history of two lines of heat-resistant corn, Pioneer's Optimum AQUAmax and Monsanto's DroughtGard. In each case, the plant breeders themselves emphasize how hot and dry conditions in corn-growing areas motivated product development. This analysis foreshadows our subsequent analysis showing that agricultural patents corresponding to more heat-exposed crops are also become more likely, over time, to mention key words related to climate change, heat, and drought (Section 4.3.4).

4.3 Additional Results and Mechanisms

4.3.1 Timing of Technological Response

We have focused on long-difference specifications because both temperature change and innovation are long-run processes. However, it is important also to know how quickly innovation responds to temperature change and whether innovative activity has anticipated future changes or lagged past ones. Figure 2 displayed the substantial variation in extreme-heat exposure and innovation across decades during our sample period and was a preliminary indication that technology development has reacted in the same decade as the change in temperature, or in some cases with a lag.

To investigate these questions systematically, we estimate the following panel-data model:

$$y_{kt} = \exp\left\{\sum_{\tau \in \mathrm{T}} \delta_{t+\tau} \cdot \text{ExtremeExposure}_{k,t+\tau} + \Gamma X'_{kt} + \alpha_k + \omega_t + \varepsilon_{kt}\right\} \tag{4.3}$$

where the outcome variable now is new varieties released for crop k in decade t, and both crop and decade fixed effects are included. The set of leading or lagged values of extreme-temperature exposure is denoted by T. Figure 4 shows our dynamic estimates graphically. Each point is the coefficient from a separate regression estimate of Equation 4.3, in which T includes both the relevant lead or lagged value and the contemporaneous value of the temperature shock. We find no evidence of an anticipation effect, consistent also with our null result in Figure 3b. Variety development increases markedly during the decade of the temperature shock and persists during the decade that follows. Table A9 reports additional estimates of Equation 4.3. Across specifications, which include varying numbers of leads and lags, leading values are small in magnitude and statistically insignificant, while the contemporaneous and lagged temperature shocks have a positive effect on technology development.

4.3.2 Heterogeneous Effects Across Crops

Our baseline estimates treated all crops as symmetric. In practice crops vastly differ in market size and production technology, and our model described how these differences can affect the relationship between climate damage and innovation (see Proposition 3). Here, we study heterogeneity in the relationship between extreme-heat exposure and innovation. Our findings are reported in Table A10.

We first study whether our baseline effects are heterogeneous based on baseline market size, as proxied by planted area. We find strong evidence that larger-market crops see a more pronounced response to climate distress (column 1). However, we do not find evidence of larger effects on crops for which, using international production and trade data, the United States is a relatively large producer (column 2) or a relatively large net exporter (column 3). These estimates foreshadow our findings reported below in Section 4.3.7 that US innovation reacts predominately to crop-level temperature damage in the US and not the rest of the world. Thus, large markets in the US have the largest pull on innovation, even if they are not large as a share of global production.

We next study whether the response of innovation depends on the relative impracticality of crop switching. In our model, a more easily "switchable" crop could have a higher or lower elasticity of technology development to climate distress, depending on whether it has a higher or lower climate substitutability of technology. We formalize this link, and the ambiguity of the sign prediction, in Online Appendix C.3. As a first proxy for "switchability," we compute the average share of county cropland devoted to each crop among counties where it is cultivated. Higher values of this measure imply that the crop is more constrained in terms of where it can be planted. We find no evidence of heterogeneous effects along this margin (column 4). We also find very little heterogeneity based on whether a crop is annual or perennial (column 5). Annual crops are re-planted every year, and as a result are easier to shift across locations. Together, these results suggest that ease of crop switching, and its net effect on climate substitutability, is not an important mediating factor in our analysis.

In response to extreme heat, crop production may shift not only across locations but also across seasons. To investigate whether the response of innovation depends on the possibility of shifting production toward colder months, we construct an indicator that equals one if a crop has a below-median value for its lower-bound temperature according to EcoCrop. Consistent with this hypothesis, we find some evidence that crops that can withstand lower temperatures see a less pronounced response to climate distress (column 6). We also investigate the potential role of differences in price responsiveness (ε) across crops. We use whether or not a crop is perishable as a proxy for the strength of the price response. However, we do not detect heterogeneous effects along this margin (column 7).

We finally investigate whether proximity to US experiment stations, which could plausibly increase the elasticity of research supply η^{-1}, leads to a greater response of technology to extreme-heat exposure. In particular, we study whether the results are heterogeneous based on the share of land area in the same county as an experiment station (column 8). We do find a larger effect for crops that are grown, on average, closer to US experiment stations; however, the estimate is imprecise and we therefore interpret it with caution.

4.3.3 Heterogeneous Effects Across Inventors

Our baseline estimates pool technology development across all inventors. However, different parts of the innovation ecosystem could react differently to new technology demand that results from temperature change. While the *Variety Name List* does not collect systematic data on inventor identify throughout the sample period, the PVP data do. Using the applicant name associated with each PVP certificate, we classify each applicant as either a private sector firm, a public sector entity, a university, or none of the above.[22] In Table A11 we re-produce our baseline estimates separately for PVPs from each applicant category. We find large, positive effects for private sector applicants (column 1). While the effect is also positive for public sector and university applicants, the effect sizes are smaller and statistically indistinguishable from zero (columns 2-3). These findings indicate that the re-direction of technology underlying our main results is driven by the private sector, consistent with our model of innovation in response to profit incentives and changing farmer demand (Section 2.1).

A related question is whether temperature distress shifts patterns of innovation across crops *within inventor* or whether it leads to the entry of new inventors to meet the demand for new climate-resistant technology. To investigate this question, we estimate a crop-by-applicant regression that

[22]We make this classification using keyword searches of applicant names. We identify private sector applicants as those with word fragments INC, LLC, LC, CO, CORP, BV, COMPANY, LP, or LTD in the applicant name. We identify public sector applicants as those with word fragments USDA, US GOVERNMENT, RESEARCH SERVICE, or EXPERIMENT STATION in the applicant name. We identify colleges and universities as those with UNIVERSITY, COLLEGE, or INSTITUTE in the applicant name. By our measure, the average crop in the sample has received since 1980 144.2 total PVP certificates, 116.5 private sector PVP certificates, 9.6 public sector PVP certificates, 11.2 college or university PVP certificates, and 11.2 unclassified PVP certificates. Unclassified certificates could be capturing individual inventors in any sector, or small firms.

Table 2: Temperature Distress and Climate-Related Patenting

Dependent Variable:	(1) Patents *not* related to the climate	(2) Patents related to the climate
Δ ExtremeExposure	0.00335	0.0118**
	(0.00458)	(0.00552)
All Baseline Controls	Yes	Yes
Observations	69	69

Notes: The unit of observation is a crop and both columns report Poisson pseudo-maximum likelihood estimates. The outcome variables are the number of crop-specific agricultural patents that are not related to the climate (column 1) and the number of crop-specific agricultural patents related to the climate (column 2). All baseline controls are included in both specifications. Robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

includes applicant fixed effects:

$$y_{ka} = \exp\{\delta_w \cdot \Delta\text{ExtremeExposure}_k + \Gamma X_k' + \alpha_a + \varepsilon_{ka}\} \tag{4.4}$$

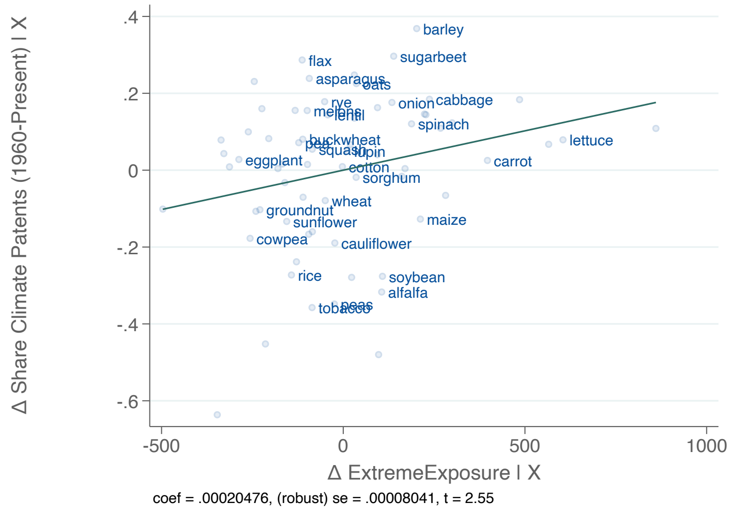
where a indexes PVP applicants, y_{ka} is the number of PVP certificates awarded to applicant a for crop k since 1980, and α_a are applicant fixed effects. The coefficient δ_w captures the within-applicant redirection of technology. Estimates of (4.4) are reported in Table A12 and we find that δ_w is positive, statistically significant, and statistically indistinguishable in magnitude from our baseline estimates. These findings indicate that the results are driven by individual firms and organizations re-directing technology development toward more distressed crops. They are also consistent with our narrative evidence about the refocusing of crop breeding within large biotechnology firms on heat- and drought-resistance (Online Appendix E).

4.3.4 Heterogeneous Effects Across Types of Technology

Our model predicted that the reallocation of agricultural innovation toward climate-distressed crops should be stronger for climate-substitutable technologies (i.e., those with higher g_{21}). We test this prediction using two schemes of technology classification in our crop-specific patent data.

Our first strategy for measuring the climatic specificity of patents is to measure whether or not each patent mentions climate-related key words, as introduced in Section 3.1. We re-estimate our long-difference economic model (Equation 4.2) using *non*-climate-identified patents and climate-identified patents as separate outcomes in Table 2. We find a small and insignificant effect on the first, and positive and significant effect on the second, consistent with innovation redirecting toward climate-related technologies without crowding out other technologies. Figure 5 visualizes the positive and

Figure 5: Temperature Distress and the Share of Climate-Related Patents



Notes: This figure reports the partial correlation plot between $\Delta\text{ExtremeExposure}_k$ and the share of crop-specific patented technologies released since 1960 that are related to the climate. The full set of baseline controls are included, including the relevant pre-period dependent variable in this context: the share of climate-related patented technologies developed between 1900-1960. The coefficient estimate, standard error, and t-statistic are reported at the bottom of the figure.

significant relationship between crop-level climate distress and the share of new crop-level patented technologies that are related to the climate. These results convey that temperature change has directly increased the development of new technologies related to climate change, while leaving the development of other technologies relatively unchanged. This is also consistent with qualitative evidence on the directed search for climate-resistant traits and varieties (see Online Appendix E). Moreover, in light of our model, the null response of non-climate patents is inconsistent with strong price effects driving incentives for innovation. This case would create incentives for all categories of technology, not just the more climate-adaptive categories (see Propositions 2 and 3).

As a secondary strategy, we investigate the impact of exposure to extreme temperatures on patenting in each major Cooperative Patent Classification (CPC) class associated with crop agriculture.[23] The results are reported in Table A13. We find positive effects on fertilizing, planting, and sowing technologies (CPC Class A01C; column 2) and soil working technologies (A01B; column 3), which are statistically significant for the former and for their sum (column 4). The coefficients, up to statistical precision, have comparable magnitude to our baseline effect on crop varieties (reprinted in column 1). However, we find small and statistically insignificant effects of climate distress on innovation in harvester and mower technologies (column 5) or post-harvest and processing technology (column 6). These results are consistent with arguments in the economic and historical literature that fertilizer,

[23]We omit patents in A01G, which covers both agriculture and horticulture, and A01H, which did not have consistent relevance for all plant species over our sample period due to legal changes in the patentability of plants.

planting, and soil modification technology have been crucial in the face of environmental constraints (Olmstead and Rhode, 2008; Baveye et al., 2011), while mechanical harvesting technology has not (Hayami and Ruttan, 1971; Ruttan and Hayami, 1984). Moreover, in our own data 30% of patents related to fertilizing, planting, and sowing mention at least one of the climate-related keywords, while only 7% of harvest and post-harvest patents do so.

4.3.5 Effects of Other Climate Shocks

Our main analysis focuses on the impact of extreme heat, which has been documented in prior work (Schlenker and Roberts, 2009) and our own validation analysis (Appendix D.2) to be the main channel through which temperature affects crop production. We now investigate the relationship between other measures of climate distress and innovation: extreme cold and drought. To measure crop-level exposure to extreme cold, we use the *lower* bound temperature cut-off from the EcoCrop database to measure, for each crop, and compute exposure to temperatures below this threshold:

$$\text{Extreme Cold Exposure}_{k,t} = \sum_i \left[\frac{\text{Area}^{\text{Pre}}_{i,k}}{\sum_j \text{Area}^{\text{Pre}}_{j,k}} \cdot \text{DaysBelowLowerBound}_{i,k,t} \right] \tag{4.5}$$

To measure crop-level exposure to drought, we measure:

$$\text{Drought Exposure}_{k,t} = \sum_i \left[\frac{\text{Area}^{\text{Pre}}_{i,k}}{\sum_j \text{Area}^{\text{Pre}}_{j,k}} \cdot \text{PDSI}_{i,t} \right] \tag{4.6}$$

where $\text{PDSI}_{i,t}$ is the Palmer Drought Severity Index (PDSI) measure in county i and decade t. Drought itself is often caused by evapotranspiration that results from exposure to extreme heat (Hanson, 1991; Cheng et al., 2019). Thus, exposure to drought is unlikely to be independent from exposure to extreme heat, and instead may capture one channel through which extreme heat affects crop production and hence demand for new technology.

Estimates of an augmented version of Equation 4.2 that includes both extreme cold exposure and drought exposure are reported in Table A14. We find no statistically significant evidence that exposure to extreme cold affects innovation. We identify a positive but imprecise relationship between drought exposure and innovation. However, across specifications, the magnitude of the effect of drought is substantially smaller than the magnitude of the direct effect of extreme heat. In standardized units, the effect of drought is always below one third the magnitude of the effect of extreme-heat exposure.

4.3.6 Effects of Creating New Markets

Farmers may respond to shifting temperatures by changing the crops that they grow. Such a reallocation in planting across space may have quantitatively important effects on the response of US agriculture to climate change and may also interact with directed innovation. In Online Appendix F, we investigate the extent to which temperature change has induced crop switching and, as a result, affected innovative incentives by changing crop-level market sizes. We briefly summarize our results here.

First, we find that farmers in a given county switch away from more extreme-heat exposed crops and toward crops for which local conditions became more favorable. Second, conditional on crop and county fixed effects, the magnitude of this reallocation is quantitatively small—a one-standard deviation relative increase in crop-by-county extreme-heat exposure leads to only a 0.018 standard deviation decline in planted area. Third, when we control directly for our estimates of *temperature-induced* changes in planted area in our baseline estimating equation (4.2), the estimated relationship between extreme-heat exposure and technology development is unchanged. Thus, endogenous planting reallocation does not bias or mediate our baseline estimates of the relationship between temperature change and technology development. Fourth, we find an independent positive correlation between heat-induced changes in market size and biotechnology development. This demonstrates an additional channel by which temperature change affects agricultural innovation.

4.3.7 Response to Global Damages

While our main analysis focuses on the response of US innovation to temperature distress in the US, in Appendix G we investigate how US innovation has reacted to temperature distress in the rest of the world. To measure the extreme-heat exposure of each crop globally, we combine the gridded, hourly temperature dataset of Muñoz-Sabater et al. (2021), which covers the whole world from 1980 to the present, with geo-coded crop-level planting data from Monfreda, Ramankutty and Foley (2008).[24] Figure G1 reports the relationship between crop-level extreme-heat exposure in the US and in the rest of the world, which we find is essentially flat. This suggests that crop-specific adaptation technology developed for the US may not be meeting the most pressing needs around the world. This also indicates that temperature change outside the US does not bias or mediate our baseline finding.

We next directly investigate how US innovation reacts to changes in temperature distress in the rest of the world by estimating an augmented version of Equation 4.2 that includes crop-level extreme-heat exposure outside of the US. We find no evidence that US technology responds to extreme-heat exposure elsewhere in the world, and document that this is not an artifact of our global measurement strategy by replicating our baseline, within-US results using the new data. These results are consistent with existing findings of high home bias in biotechnology innovation (Costinot et al., 2019; Moscona and Sastry, 2022). While a full analysis of global innovation is beyond the scope of this paper, understanding which markets do and do not shift incentives to develop climate adaptation technology, and which parts of the world are more or less able to benefit from technological spillovers from research-intensive markets like the US, seems like an important area for future research.

[24] The Monfreda, Ramankutty and Foley (2008) dataset was created by combining national, state, and county level census data with crop-specific suitability data, to construct a 5-by-5 minute grid of the area devoted to each crop circa 2000.

5 Results: Induced Innovation and Damage Mitigation

The previous section's results demonstrated that technology development has re-directed toward crops more exposed to extreme heat in recent history. In this section, we investigate the extent to which induced innovation has mitigated economic damage from temperature change. Our empirical strategy, suggested by the model, is to estimate the marginal impact of county-level extreme-heat exposure as a function of predicted innovation exposure. We find significant evidence that innovation exposure has mitigated the economic impacts of temperature distress.

5.1 Empirical Model

Extreme-Heat Exposure for Counties. To measure extreme-heat exposure for each county i, we estimate the average crop-specific extreme-heat exposure across all crops grown in the county, weighting by crop-specific planted areas in the pre-analysis period:

$$\text{County-Level Extreme Exposure}_{i,t} = \sum_k \left[\frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \cdot \text{ExtremeExposure}_{i,k,t} \right] \tag{5.1}$$

$\text{Area}_{i,k}^{\text{Pre}}$ is the land area devoted to crop k in county i in 1959 and $\text{ExtremeExposure}_{i,k,t}$ is measure of extreme-heat exposure defined in Section 3.2. County-Level Extreme $\text{Exposure}_{i,t}$ thus incorporates crop-specific variation in heat sensitivity, departing from previous work on county-level climate damages that treat all counties the same and estimate the effect of different temperature realizations across space (e.g., Schlenker, Hanemann and Fisher, 2006). In the model, the measure $\overline{A} - A_i$ sufficed to measure local climate distress for the single grown crop (Proposition 3); since US counties grow many crops, our empirical analogue is simply the weighted average across crops. Figure A5a displays the the change in County-Level Extreme $\text{Exposure}_{i,t}$ from the 1950s to the 2010s across US counties.

To validate this measure of county-level temperature distress, we estimate county-level relationship between the change in County-Level Extreme $\text{Exposure}_{i,t}$ from the 1950s to the 2010s and the change in log of agricultural land values over the same period. This estimate is reported in column 1 of Table A15; it is negative and highly significant, consistent with County-Level Extreme $\text{Exposure}_{i,t}$ capturing damage from climate change that translates into lower rents. In columns 2 and 3 we present the relationship between the change in County-Level Extreme $\text{Exposure}_{i,t}$ and the change in revenue per acre from crop and non-crop production respectively. We find a large, negative effect on revenues from crop production but no effect on revenues from non-crop production, suggesting our measure finely targeted to the productivity of crop production.

Innovation Exposure for Counties. We next calculate each county's *innovation exposure* as the average across all crops' national extreme-heat exposure—our main crop-level measure of temperature distress—weighted by planted areas:

$$\text{Innovation Exposure}_{i,t} = \sum_k \left[\frac{\text{Area}^{\text{Pre}}_{i,k}}{\sum_{k'} \text{Area}^{\text{Pre}}_{i,k'}} \cdot \sum_{j \neq i} \left[\frac{\text{Area}^{\text{Pre}}_{j,k}}{\sum_{j \neq i} \text{Area}^{\text{Pre}}_{j,k}} \cdot \text{ExtremeExposure}_{j,k,t} \right] \right] \tag{5.2}$$

We make only the small change of calculating this variable leaving out the county i to avoid any mechanical correlation. This measure will allow us to investigate the role of endogenous technological progress because, as documented in the first part of the paper, it is a strong predictor of innovation and hence the existence of new, climate-induced technology that can be used for production in county i. Equation 5.2 is again the empirical analogue of our model-derived expression for innovation exposure, $\overline{A} - A_{k(i)}$, modified to incorporate multiple crops and purge the measure of national crop-level damage driven by the county in question (see Proposition 3). Figure A5b displays the change in $\text{InnovationExposure}_{i,t}$ from the 1950s to the 2010s across US counties.

Estimation Framework. As our primary dependent variable, we use the price of agricultural land. Let $\text{AgrLandPrice}_{i,t}$ be the agricultural land price per acre of cultivated land, measured from the Census of Agriculture in decade t in location i.[25] The agricultural land price captures the net present value of profits from agricultural production and has the benefit of capturing both the benefits of new technology alongside its potentially higher cost. To investigate the role of innovation in mitigating economic damages from temperature change, we estimate versions of the following equation:

$$\begin{aligned} \log \text{AgrLandPrice}_{i,t} = \delta_i + \alpha_{s(i),t} + \beta \cdot \text{Extreme Exposure}_{i,t} + \gamma \cdot \text{InnovationExposure}_{i,t} \\ + \phi \cdot \left(\text{Extreme Exposure}_{i,t} \times \text{InnovationExposure}_{i,t} \right) + \Gamma X'_{it} + \varepsilon_{i,t} \end{aligned} \tag{5.3}$$

where δ_i is a county fixed effect and $\alpha_{s(i),t}$ is a state-by-time fixed effect. Our coefficients of interest are β and ϕ, which capture the direct effect of temperature distress and the heterogeneous effect of temperature distress depending on each county's "innovation exposure." This specification is the empirical analogue of Equation 2.7, derived in Proposition 3 of the model.

We estimate Equation 5.3 with two main specifications: a two-period "long difference," with $t \in \{1959, 2017\}$, and a decadal panel. We focus on testing the hypothesis that $\phi > 0$. Through the lens of the simple model taxonomy in Figure 1, combined with our previous finding that climate distress induced positive innovation, this hypothesis compares case (a) in which mitigation (driven by the marginal product force) corresponds with increased resilience, against case (c), in which mitigation (driven by price effects) corresponds with decreased resilience.

Table 3: Innovation and Resilience to Climate Damage

	(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	-0.851***	-1.519***	-0.825***	-0.862***	-0.786***	-0.232**	-0.390***
	(0.211)	(0.240)	(0.203)	(0.238)	(0.226)	(0.107)	(0.132)
	[0.264]	[0.304]	[0.244]	[0.305]	[0.279]	[0.105]	[0.103]
County-Level Extreme Exposure x Innovation Exposure	0.249***	0.425***	0.237***	0.251***	0.230***	0.0912***	0.128***
	(0.0757)	(0.0745)	(0.0728)	(0.0791)	(0.0762)	(0.0315)	(0.0321)
	[0.0945]	[0.0921]	[0.0881]	[0.0995]	[0.0929]	[0.0253]	[0.0243]
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State 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.

5.2 Results: Local Adaptation and Resilience

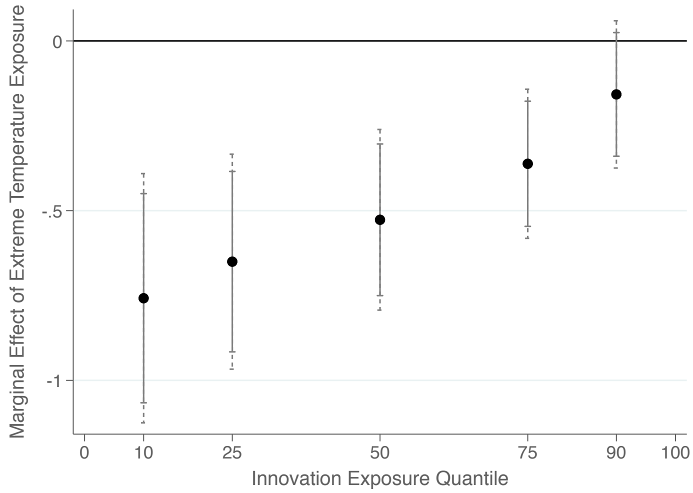
Estimates of Equation 5.3 are reported in Table 3. In column 1, the baseline long-difference specification with no added controls, we find that $\phi > 0$ and that this relationship is highly statistically significant. The estimates are very similar when each county is weighted by its pre-period agricultural land area (column 2), or when either the unweighted or weighted specification is estimated on a decadal panel of counties (columns 6-7). Combined with our estimates of the relationship between temperature distress and innovation, this result indicates that technological progress is directed toward damaged crops and leads to increased resilience.

To visualize the findings, Figure 6 reports the marginal impact of exposure to extreme heat (y-axis) for quantiles of the innovation exposure distribution (x-axis), using the specification from column 1. On the left side of the figure is the marginal effect of extreme-heat exposure for counties that are relatively less exposed to induced innovation and on the right side of the figure is the marginal effect of extreme-heat exposure for counties that are relatively more exposed to induced innovation. The difference in marginal effects between the 75th and 25th percentile is 60% of the median effect, and the difference from the 90th and 10th percentiles is 115% of the median effect. In the counties most exposed to induced innovation, we detect no significant impact of extreme heat on land values.

Sensitivity: Alternative Measurement Strategies. While our baseline estimates use the (log of) agricultural land values as the main dependent variable, Table A16 documents that our findings are very similar if we instead use in-sample agricultural revenues or profits as the dependent variable.

[25]The price of land reported in the Census includes the price of the land itself plus buildings and improvements. We include state-by-time fixed effects in our baseline specification, which soak up any variation in building and improvement prices that is varies at the state level (as assumed, for instance, by Donaldson and Hornbeck, 2016).

Figure 6: Marginal Effect of County-Level Extreme Exposure as a Function of Innovation Exposure



Notes: This figure reports marginal effect of extreme-temperature exposure on (log of) agricultural land values for quantiles of the innovation exposure distribution. The solid and dashed lines are 90% and 95% confidence intervals respectively.

In columns 1-2 the dependent variable is (log of) crop revenue per acre, in columns 2-3 it is total agricultural profits, and in column 3 it is total agricultural profits per acre; while we are able to measure revenue specific to crop production, spending is not broken down by crop and non-crop production and so we are only able to measure profits from all agricultural activities, Nevertheless, in all specifications we find that $\beta < 0$ and that $\phi > 0$.

Sensitivity: Potential Confounding Forces. A potential concern with our approach is that our innovation exposure measure might be correlated with national crop prices and that prices have non-log-linear effects on agricultural land values. In the model of Section 2.5, prices have only a log-linear impact on land values because of the Cobb Douglas structure, and in this case the relationship between output prices and land values do not bias our estimates of ϕ. Nevertheless, in practice, the relationship between prices and land values might be more complicated because input shares are not fixed. To ameliorate these concerns, we directly measure and control for the change in output prices of the crops produced in each county. Using data on national crop-level producer prices from the USDA, we construct a measure of the price of each county's output bundle in decade t as:[26]

$$\text{Output Price}_{it} = \sum_k \frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \cdot \log(\text{Producer Price}_{k,t}) \tag{5.4}$$

[26]Producer price information is not available for the full set of crops in the baseline analysis. The crops for which national producer price data exist during the period of analysis are: wheat, rye, rice, tobacco, sorghum, soybeans, corn, alfalfa, cotton, sugar beets, oats, cranberries, peanuts, flax, hay, beans, and hops.

where Producer Price$_{k,t}$ is the national producer price for crop k in averaged over decade t as recorded by the USDA. Column 3 of Table 3 reports estimates of Equation 5.3 in which we control for both this county-level output price measure, as well as its interaction with County-Level Extreme Exposure$_{i,t}$. Estimates of our coefficient of interest are virtually unchanged.

Another potential question is whether the estimates are capturing amenity value effects of changing temperature rather than the productivity consequences of climate change (Fisher et al., 2012). While we are less worried about this issue since our temperature distress measure captures not only the distribution of temperature changes but also the distribution of crop production and physiology, in column 4 of Table 3 we control directly for county-level temperature (in degrees Celsius), counties' crop mix exposure to average temperature changes, and the interaction of the two. Our results remain very similar. Column 5 includes both the full set of price controls and the full set of temperature controls and the results are again very similar.

We conduct a series of additional checks that our findings are not driven by features of the baseline specification. The results are very similar using decade fixed effects in place of state-by-decade fixed effects (Table A17) and controlling directly for non-linear effects of extreme-heat exposure (Table A18), which suggests that innovation exposure is not capturing higher order terms of county-level extreme-temperature exposure. The results are also similar after dropping counties West of the 100th meridian (Table A19) and removing the effect of local spillovers by estimating a version of innovation exposure that excludes any variation in crop distress that occurs in other counties in the same state (Table A20). These findings indicate that the results are not driven by differences in climate change or innovation between the Eastern and Westerns parts of the US, or the effect of within-state production spillovers

Sensitivity: Inference. One potential concern is that both climate realizations and the value of land are spatially correlated. While Table 3 shows that our estimates are precise when we cluster by state, which is a large geographic unit, in Table A21 we investigate the role of spatial correlation more systematically. In particular, we estimate Hsiang (2010)'s implementation of Conley (1999) standard errors, for several possible choices of the kernel cut-off distance. Reassuringly, the results are very similar across specifications, even after allowing for spatial correlation across long distances.

Technology as the Mechanism: Exploiting Variation in Market Size. We found earlier that the impact of temperature distress on technology development was stronger for crops with a larger pre-period market size (see Table A10). If innovation were the mechanism driving the county-level estimates, we would expect the results in Table 3 to be driven by counties that cultivate crops with a larger national pre-period market size since these were the crops that benefited from the most induced innovation. To measure the average market size of the crops grown in each county we compute the following measure of the average, national market size of crops grown in i:

$$\text{CropMixMarketSize}_i = \sum_k \frac{\text{Area}_{i,k}^{\text{Pre}}}{\sum_{k'} \text{Area}_{i,k'}^{\text{Pre}}} \cdot \log\left(\text{National Area Harvested}_k^{\text{pre}}\right) \tag{5.5}$$

We then estimate an augmented version of Equation (5.3) that includes a triple interaction between (i) County-Level Extreme Exposure$_{i,t}$, (ii) InnovationExposure$_{i,t}$, and (iii) CropMixMarketSize$_i$. If the adaptive role of innovation were driving the results, we would expect the coefficient on the triple interaction to be positive.

Table A22 reports estimates of this specification. In all columns, we find that the triple interaction is positive and statistically significant. Thus, the crops toward which innovation was directed most strongly are also the crops driving the mitigating impact of "innovation exposure" on land value decline. This is consistent with our estimates of ϕ capturing the effect of innovation.

6 Aggregate Damage Mitigation From Directed Innovation

We now combine our empirical estimates and model to quantify the aggregate effect of innovation on climate damage mitigation, both in and out of sample.

6.1 Methods

Definitions. For each US county i in period t, we use our regression model from Equation 5.3 along with the coefficient estimates thereof, to predict a location's land value per acre as a function of climate realizations. We define two scenarios, letting t_0 and t_1 represent our pre-period and post-period, respectively. We first define a *No Climate Change* (NCC) scenario in which CountyLevelExtremeExposure$_{i,t}$ and InnovationExposure$_{i,t}$ are fixed at their t_0 values, or

$$\begin{aligned}\log \text{AgrLandPrice}_{i,t_1}^{\text{NCC}} = \hat{\delta}_i + \hat{\alpha}_{s(i),t_1} + \hat{\beta} \cdot \text{CountyLevelExtremeExposure}_{i,t_0} + \hat{\gamma} \cdot \text{InnovationExposure}_{i,t_0} \\ + \hat{\phi} \cdot \left(\text{CountyLevelExtremeExposure}_{i,t_0} \times \text{InnovationExposure}_{i,t_0}\right)\end{aligned} \tag{6.1}$$

We next define a *No Innovation* (NI) scenario in which the interactive effect of innovation exposure is based on the t_0 climate

$$\begin{aligned}\log \text{AgrLandPrice}_{i,t_1}^{\text{NI}} = \hat{\delta}_i + \hat{\alpha}_{s(i),t_1} + \hat{\beta} \cdot \text{CountyLevelExtremeExposure}_{i,t_1} + \hat{\gamma} \cdot \text{InnovationExposure}_{i,t_1} \\ + \hat{\phi} \cdot \left(\text{CountyLevelExtremeExposure}_{i,t_1} \times \text{InnovationExposure}_{i,t_0}\right)\end{aligned} \tag{6.2}$$

We aggregate the local predictions to a national total value of agricultural land, in (contemporaneous) dollars, using the pre-determined agricultural land areas in each US county. This translates local counterfactuals into their aggregate national counterparts $\text{AgVal}_{t_1}^{\text{NCC}}$ and $\text{AgVal}_{t_1}^{\text{NI}}$, the total value of US cropland in counterfactual scenarios without climate change and with climate change but no directed innovation. We compare these with the aggregate obtained from the in-sample fitted values AgVal_{t_1} (i.e., a scenario with both climate change *and* directed innovation) to calculate the following three statistics of interest. The first and second are the damage due to climate change in scenarios with and without innovation, expressed as a percentage of the total possible value absent climate change:

$$\text{PctDamage}^{\text{I}} := 100 \cdot \frac{\text{AgVal}_{t_1} - \text{AgVal}_{t_1}^{\text{NCC}}}{\text{AgVal}_{t_1}^{\text{NCC}}} \quad \text{PctDamage}^{\text{NI}} := 100 \cdot \frac{\text{AgVal}_{t_1}^{\text{NI}} - \text{AgVal}_{t_1}^{\text{NCC}}}{\text{AgVal}_{t_1}^{\text{NCC}}} \tag{6.3}$$

The third is the damage abated by directed technology, as a percentage of counterfactual damage from climate change absent innovation:

$$\text{PercentMitigation} := 100 \cdot \left(\frac{\text{PctDamage}^{\text{NI}} - \text{PctDamage}^{\text{I}}}{\text{PctDamage}^{\text{NI}}} \right) \tag{6.4}$$

Model Interpretation. Equations 6.1 and 6.2, and hence the aggregate statistics based upon them, have a structural interpretation in the model of Section 2.5 under the following conditions:[27]

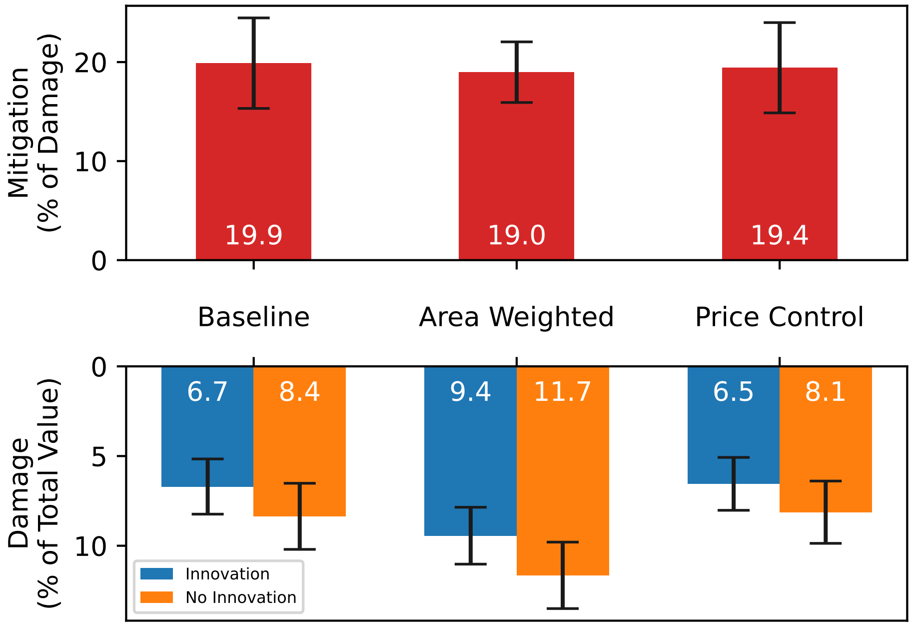
Corollary 2. *The counterfactual calculations correspond with the model's counterfactuals if (i) prices are perfectly rigid, or $\varepsilon = 0$, and (ii) climate-induced technology has zero marginal benefit when climate is "ideal" or $\text{ExtremeExposure}_i = 0$.*

A formal derivation is given in Online Appendix B.6. The first assumption is to set the price response across counterfactuals to zero. To justify this assumption, we are reassured by our findings above suggesting that price effects have not been an important mechanism driving technology development (Section 4.3.4) and that they play little role in our county-level estimates, even when included as an endogenous control (Table 3). The second is to assume that climate-induced technology has zero effect on land values when the county experiences zero climate distress. This normalization biases our results for damage mitigation toward zero.

The model also provides structural interpretations for the counterfactual-relevant estimated coefficients (β, γ, ϕ) as functions of the following deep parameters: the climate substitutability g_{21}, the direct productivity effect of extreme exposure g_1, the farm profit share α, the inverse elasticity of crop demand ε, and the inverse elasticity of technology supply η. The internal validity of our counterfactual estimates relies on these deep parameters, and hence the (β, γ, ϕ), being stable across the two scenarios. This assumption might be violated, for instance, if climate change alters market structure in either upstream technology markets or downstream crop markets. Modeling such forces is ultimately outside the scope of our analysis. Another important assumption is the separability of

[27]The state-by-time fixed effects have no structural interpretation in our model, and thus we hold them constant. In numerical experiments corresponding to each result presented below, however, in which we randomize the value of each state-by-time fixed effect based on the observed distribution, our results are stable. This suggests that the distribution of state trends does not drive our findings.

Figure 7: Historical Damage Mitigation Via Innovation



Notes: The top panel displays the percent of economic damage from historical temperature change, since 1960, mitigated by innovation across three model specifications: (i) the baseline (unweighted, only fixed effects as controls), (ii) the agricultural-land-area-weighted estimate (only fixed effects as controls), and (iii) the estimate that controls directly for the output prices and interactions (in addition to all fixed effects). The bottom panel shows the aggregate economic damage from temperature change (%) in each model, both with (blue) and without (orange) directed innovation. Standard errors were computed via a bootstrap and 95% confidence intervals are reported.

innovation supply across crops. We discuss strategies to relax this assumption, using an extension of the model, below.

6.2 Results: Historical Damage Mitigation

Figure 7 reports our estimates of the extent to which temperature damages since 1960 have been mitigated by innovation (top panel), along with the extent of aggregate damage both with and without innovation (bottom panel). The first column shows our baseline estimates, which treat the 1960s climate as the "no-climate-change" baseline and use our empirical estimates from the panel specification in column 6 of Table 3. We show error bars corresponding to 95% confidence intervals from a bootstrap procedure.[28] Innovation has mitigated 19.9% of damage from climate change in our sample. The savings amount to 1.7% of total agricultural land value in the US, or about 24 billion in current USD.

[28]The data were bootstrapped 1000 times clustering by county. Coefficient estimates from (5.3) were re-calculated and the procedure described in Section 6.1 repeated for each pseudo-sample. The standard deviation of the set of aggregated measures across pseudo-samples was used to generate the standard error of each value in Figure 7.

The second column reports the same results if instead we use our coefficient estimates from the area-weighted specification in Table 3. These findings suggest larger damages (9.4% in the observed scenario with innovation) but very comparable percent mitigation (19.0%). The last column uses the version of the model that controls directly for prices and thus allows us to more directly implement our assumption of rigid prices in the counterfactual.[29] Reassuringly, this scenario implies almost identical damage and mitigation to the baseline (6.6% and 19.4%, respectively).

Robustness: Alternative Counterfactual Trends for Innovation. Our baseline analysis assumes that there is no aggregate resource constraint for innovation across crops. Thus, firms are not forced to reduce investment in innovation in crop k when they want to increase investment in crop k'; instead, they substitute away from other (non-agricultural) activities. We do not consider this assumption extreme within the studied sample for two reasons. First, agricultural R&D investment, and investment in biotechnology in particular, experienced unprecedented growth during our sample period. From 1960 to 2000, private sector R&D investment in crop breeding increase nearly 1500% (Figure A4). Second, much of the historical increase in agricultural biotechnology research was redirected from other adjacent fields. Monsanto, now a ubiquitous player in seed development, started as a non-agricultural chemical company specializing in food additives, cleaning products, and pharmaceuticals. The companies that would become Syngenta began with a focus on pharmaceutical research and chemical production.

Nevertheless, we investigate the extent to which our baseline estimate is sensitive to relaxing this separability assumption. In Appendix C.4, we introduce a variant of our model in which research investment across crops cannot exceed a threshold (e.g., the total research capacity of the biotechnology sector), and this aggregate threshold can be increased at some cost. When this cost of increasing the aggregate threshold is zero, we get back our baseline model. When this cost is infinitely convex, we get a model with an immutable capacity for research and hence a purely "zero-sum" redistribution of research in response to incentives. In all models in-between, there is a marginal crop that sees no induced innovation when the climate shifts, and this marginal crop has a technology demand shock less than or equal to some measure of central tendency of damages across crops.

We replicate this exercise in the numerical counterfactual in the following parameteric way. We calculate area-weighted quantiles $q \leq 0.5$ of the observed distribution of crop-level exposures and re-solve the model under the assumption that the crop with exposure q has zero induced innovation. Our upper bound of $q = 0.5$ simulates a "zero-sum" case, where increasing research investment in crop k requires removing research investment from some crop(s) k'. Appendix Figure A6 shows damage mitigation as a function of q. For choices of q between 0 and 0.45, estimated damage mitigation is almost identical to our baseline result. In the extreme, zero sum benchmark ($q = 0.5$), innovation still mitigates 16.2% of damages; As expected, this is lower than our baseline estimate, but still far from zero. The reason this number is still positive is that transferring innovation from less to more affected

[29]We do this, in a very slight variant of Equations 6.1 and 6.2, by holding prices fixed at their observed values.

crops dampens the most extreme climate damages.

Robustness: Crop Switching. We discussed how accounting for endogenous crop switching may or may not change our estimates for directed innovation in response to climate damage in Section 4.3.6 and Appendix F. We found in the data that an *ex ante* proxies for "switchability" had limited bite for predicting innovation (Table A10) and that exposure to extreme temperatures induced relatively little crop switching (Appendix F). Nonetheless, it may be important to take into account crop switching as an alternative angle for adaptation in our counterfactual scenarios.

We explore two counterfactual scenarios that take into account crop switching. In the first, we impose observed modern crop areas instead of pre-period areas to calculate heat exposure. This intuitively provides an upper bound for the effects of land re-allocation on our main results, since it retroactively assumes an (infeasible) allocation of crops from the future in the past. A disadvantage is that modern crop allocations are clearly not pre-determined with respect to our regressors of interest, and so the estimates come with all the associated caveats. This exercise yields lower estimates of the *level* of climate damage, but a comparable number for damage mitigation (14.5%).

We next use our empirical model of planting patterns' response to both climate change, outlined in Appendix H, to estimate more realistically the interaction between crop switching and the mitigation effects of technology. Using our empirical model of how temperature change has affected planting allocations, we predict the area devoted to each crop in each county by the post-period. Using predicted post-period planted areas, we again find smaller climate damages than we did using observed planted areas but a comparable percentage mitigation (18.9%).

6.3 Projecting Future Climate Scenarios

In this final subsection, we apply the same methods developed for in-sample counterfactuals to quantify the role of technology for mitigating expected future climate damages.

Methods. This analysis maintains the assumption that, while the relationship between climate distress and local outcomes can change over time as a function of innovation, both the speed of technology's response to climate change and the effectiveness of that technology remain constant. In the language of our model's deep parameters, this requires stability of the climate substitutability g_{21}, the direct productivity effect of extreme exposure g_1, the farm profit share α, the inverse elasticity of crop demand ε, and the inverse elasticity of technology supply η.

This assumption becomes more tenuous as we extend our predictions further into the future. On the one hand, some ecologists and agronomists argue that temperatures may pass critical thresholds beyond which innovation cannot help within biological constraints (Eisenstein, 2013). In the model, this would map to a lower climate substitutability g_{21} and hence a reduction in the responsiveness of technology to climate change, the effectiveness of that technology for boosting resilience, and aggregate damage mitigation. On the other hand, innovation itself may experience a paradigm shift that changes the rate and effectiveness of new technology development. The parallel advances of direct gene editing techniques (e.g., with CRISPR-Cas9 technology), more precise DNA sequencing technologies, and big-data techniques for analyzing both genetic and agricultural data may generate such a paradigm shift (Taranto et al., 2018; Abdelrahman et al., 2018). In the model, this could map to a higher elasticity of supply η^{-1} and hence an increase in the responsiveness of technology to climate change, the effectiveness of that technology for boosting resilience, and aggregate damage mitigation.

We use projections for daily temperature realizations from a surrogate/model mixed ensemble method developed by Rasmussen, Meinshausen and Kopp (2016) and applied in the state-of-the-art regional climate projections of Hsiang et al. (2017).[30] This method averages the predictions of a number of leading climate models (28 to 44, depending on the scenario) that have a common input for greenhouse gas concentrations corresponding to one of the International Panel on Climate Change's (IPCC's) Representative Concentration Pathways. We use this model average to forecast the change in degree days above each relevant cut-off temperature in each US county between a given future decade (2050-2059 or 2090-2099) and the most recent decade (2010-2019).[31] We use crop-level planted areas from the 2012 Census of Agriculture to estimate county-level temperature damage and construct our aggregate damage measures, so that our future exposure measures are more precisely estimated. Finally, we assume that state-level trends grow at a constant rate per year in and out of sample.

For our main projections, we use the ensemble forecast corresponding to two intermediate concentrations scenarios, RCP 4.5 and RCP 6.0. These respectively imply average warming of 1.8 and 2.4 degrees Celsius in the continental United States by the end of the century. They also differ slightly in the timing of the emissions peak, with RCP 6.0 assuming lower concentrations in the early part of the 21st century followed by a more pronounced ramp-up.[32] The correlation between crop-level extreme-heat exposure from the 1950s-2010s and projected extreme head exposure from the 2010s-2090s under RCP 4.5 is 0.46, indicating that, while they are positively correlated, the distribution of projected damages across crops does not exactly match the distribution of damages to date. We print the predicted changes in Extreme Exposure in the second-to-last column of Table A1.

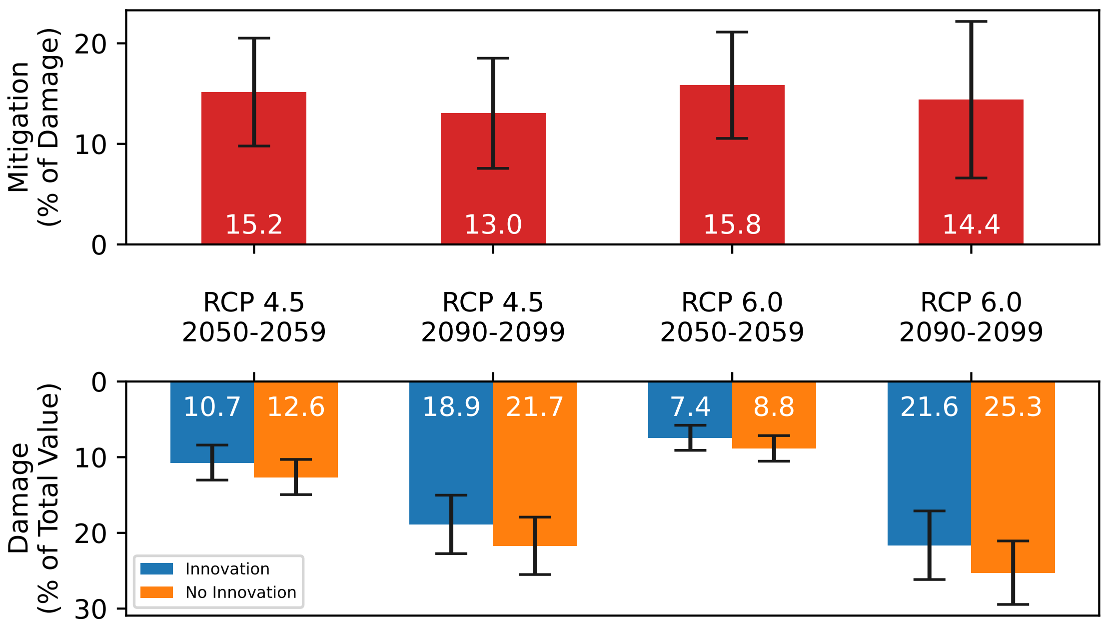
Results: Directed Technology and Future Climate Damage. Figure 8 replicates our main results for percent mitigation and damages with and without innovation for each RCP and two end-points,

[30]We thank James Rising for invaluable advice on how to use these data, which are available at Rasmussen and Kopp (2017). We defer to Rasmussen, Meinshausen and Kopp (2016) and its accompanying documentation for details on data construction, but two points are worth highlighting. First, each model has independent prediction for regional as well as aggregate climate trends. Second, the forecasts use existing relationships between long-run mean temperatures and daily realizations to impute forecasts for daily temperatures. Thus the projections account for broad climatic trends, but do not incorporate the additional possibility of weather extremes becoming more (or less) likely conditional on the same mean temperatures.

[31]We adjust for the distinction between using the entire year for the projections and the growing season April to October for our main analysis by multiplying these projected changes by the fraction of observed degree days, for each cutoff, that occur during the growing season in the historical sample. Finally, we add our estimates of projected changes to our observed degree days in the 2010s to create our forecast in level units.

[32]See the discussion on p. 2030 as well as Figure 5 of Rasmussen, Meinshausen and Kopp (2016) for the specific implications for temperature projections, and Meinshausen et al. (2011) for detailed discussion of the concentration pathways and their interpretation.

Figure 8: Projected Damage Mitigation via Innovation Over the 21st Century



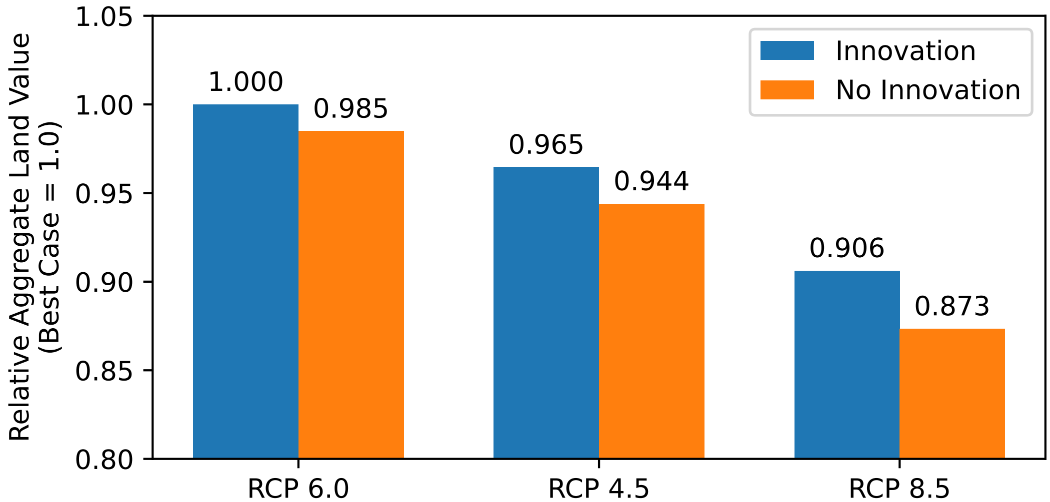
Notes: The top panel displays the percent of economic damage from projected temperature change mitigated by innovation across two climate scenarios and post-periods. The bottom panel shows the aggregate economic damage from temperature change (%) in each model, both with (blue) and without (orange) directed innovation. Standard errors were computed via a bootstrap and 95% confidence intervals are reported.

the middle of the century (2050-2059) and the end of the century (2090-2099). In all cases, innovation mitigates between 13 and 16% of the damage, slightly lower than our in-sample estimates. This damage mitigation implies larger savings in dollar terms (or percentages of total value), however, since climate change escalates over time. Under the projected RCP 4.5 scenario, directed innovation recovers 1.9% and 2.8% of all agricultural land value in the US respectively by mid-century and the end of the century. This translates in present-value terms, if we assume 3% inflation, to $218 billion and $1.05 trillion. Table A23 provides damage estimates under each of these climate scenarios, as well as the more extreme RCP 8.5 scenario (which allows for a ramp-up in emissions that is worse than most reasonable notions of "business as usual").[33] Finally, we estimate projected economic damages from climate change as well as the percent mitigated by technology development after accounting for planted area changes due to crop switching. These estimates are reported in Appendix Table A24 and are very similar to our baseline projections.

The Value of Curbing Climate Change. Figure 9 compares the impact of directed innovation on economic damage from temperature change to the impact of shifting the trend in carbon emissions. We

[33]For the RCP 8.5 scenario in the 2090s, we truncate the maximum value of local GDD exposure at 15,000, which is far beyond even the tails of the observed GDD distribution. This prevents a few large agricultural counties (less than 1% of the sample) from having extreme predictions for the damages from climate change.

Figure 9: Comparing Climate Scenarios, With and Without Innovation



Notes: Each bar represents the value of US agricultural land in 2050-2019 relative to the best case RCP (RCP 6.0) in the scenario with directed technology. Blue bars are scenarios with directed innovation and orange bars are counterfactual scenarios with directed innovation shut down. The RCP used for each projection is noted at the bottom of each pair of bars.

focus on the 2050-2059 end decade, in which RCP 6.0 is the most optimistic concentration pathway, followed by RCPs 4.5 and 8.5 respectively. This comparison between the effects of technological progress *within* a given climate scenario and the effects of moving between the climate scenarios themselves (e.g., via reducing emissions) may be a more interpretable counterfactual than freezing the climate in place, given the existing accumulation of greenhouse gases in the atmosphere.

Comparing the blue columns across RCPs shows that land values are highest under RCP 6.0, 3.5% lower than this under RCP 4.5, and 9.4% lower than this under RCP 8.5. These estimates are substantially larger than our prediction for the damage mitigation due to directed technology within each emissions scenario, which is the difference between the orange and blue column in each pair.

Our estimates in Figure 9 also imply that the losses in percent terms from more damaging concentration pathways increase when innovation is shut off. This suggests a potentially important interaction between social incentives for developing damage-mitigating technologies, as studied in our analysis, and emission-mitigating technologies, which ultimately control greenhouse gas concentrations. In short, damage mitigation and emissions reductions are *social substitutes*: a more damage-resilient economy faces a lower social cost of greenhouse gases, which may reduce incentives to develop emissions reducing technology in the first place. We leave a full model of the endogenous development of both emission-reduction and damage-mitigation technologies to future research.

7 Conclusion

Are some sectors doomed to be ill-fated victims of climate change or do they have the tools to "innovate around" nature's new challenges? We study this question in US agriculture and document that technological progress has reacted dramatically in response to threats posed by temperature change, substantially dampening its economic impact. Combining comprehensive data on US agricultural innovation with a new measure of crop-specific temperature distress, we find that innovation has been directed toward more distressed crops and toward technologies that are potentially relevant for environmental adaptation. We next find that counties exposed to new climate-induced technology development experienced more muted changes in land value as a result of temperature change.

Our best estimates suggest that the re-direction of technology has abated 20% of the economic damage to US agriculture from extreme temperature since 1960, and may abate 13-16% over the coming century. Adaptation via technological progress, according to our estimates, is economically significant but not a panacea. Even in the US, a country that has a comparatively large and wealthy agricultural sector and is a global leader in agricultural R&D, 80% of climate damage as we measure it has been unchecked by technology development.

Our analysis leaves several important issues unexplored. One is the relationship between technological progress in advanced economies and global adaptation to climate change. We found that US innovation responded strongly to within-US climatic distress and did not respond to non-US climatic distress. This finding, combined also with the observation that agricultural innovations are highly attuned to the environments for which they are designed (Moscona and Sastry, 2022), suggests that an innovative response in wealthy, research-intensive countries may not boost global resilience to climate change. In fact, directed innovation concentrated in only a few places could deepen global disparities in agricultural productivity. Direct study of this issue is an important topic for future research.

A second is the interaction between incentives for damage-mitigating innovation and climate-improving (e.g., emission-mitigating) innovation. The two are "social substitutes" in the following sense: improving climate-resilience of production reduces the marginal harm of worse weather, and improving the weather reduces the marginal benefit of climatic resilience. Studying the interaction of these effects, positively or normatively, is an open area for further research.

References

Abdelrahman, Mostafa, Abdullah M Al-Sadi, Alireza Pour-Aboughadareh, David J Burritt, and Lam-Son Phan Tran (2018) "Genome editing using CRISPR/Cas9–targeted mutagenesis: An opportunity for yield improvements of crop plants grown under environmental stresses," *Plant Physiology and Biochemistry*, 131, 31–36.

Acemoglu, Daron (2002) "Directed Technical Change," *The Review of Economic Studies*, 69 (4), 781–809.

——— (2010) "When does labor scarcity encourage innovation?" *Journal of Political Economy*, 118 (6), 1037–1078.

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous (2012) "The environment and directed technical change," *American Economic Review*, 102 (1), 131–66.

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley, and William Kerr (2016) "Transition to clean technology," *Journal of Political Economy*, 124 (1), 52–104.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales (2019) "Shift-share designs: Theory and inference," *The Quarterly Journal of Economics*, 134 (4), 1949–2010.

Aghion, Philippe, Antoine Dechezleprêtre, David Hemous, Ralf Martin, and John Van Reenen (2016) "Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry," *Journal of Political Economy*, 124 (1), 1–51.

Alvarez, José Luis Cruz and Esteban Rossi-Hansberg (2021) "The Economic Geography of Global Warming," Working Paper 28466, National Bureau of Economic Research.

Auffhammer, Maximilian and Wolfram Schlenker (2014) "Empirical studies on agricultural impacts and adaptation," *Energy Economics*, 46, 555 – 561.

Baveye, Philippe C, David Rangel, Astrid R Jacobson, Magdeline Laba, Christophe Darnault, Wilfred Otten, Ricardo Radulovich, and Flavio AO Camargo (2011) "From Dust Bowl to Dust Bowl: soils are still very much a frontier of science," *Soil Science Society of America Journal*, 75 (6), 2037–2048.

Bogdan, AV (1977) *Tropical Pasture and Fodder Plants (Grasses and Legumes)*: Longman.

Burke, Marshall and Kyle Emerick (2016) "Adaptation to climate change: Evidence from US agriculture," *American Economic Journal: Economic Policy*, 8 (3), 106–40.

Cheng, Linyin, Martin Hoerling, Zhiyong Liu, and Jon Eischeid (2019) "Physical understanding of human-induced changes in US hot droughts using equilibrium climate simulations," *Journal of Climate*, 32 (14), 4431–4443.

Conley, Timothy G (1999) "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 92 (1), 1–45.

Conte, Bruno, Klaus Desmet, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg (2020) "Local sectoral specialization in a warming world," Working Paper 28163, National Bureau of Economic Research.

Costinot, Arnaud, Dave Donaldson, Margaret Kyle, and Heidi Williams (2019) "The more we die, the more we sell? a simple test of the home-market effect," *The Quarterly Journal of Economics*, 134 (2), 843–894.

Costinot, Arnaud, Dave Donaldson, and Cory Smith (2016) "Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world," *Journal of Political Economy*, 124 (1), 205–248.

Crow, James F (1998) "90 years ago: the beginning of hybrid maize," *Genetics*, 148 (3), 923–928.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken (2012) "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 4 (3), 66–95.

Deschênes, Olivier and Michael Greenstone (2007) "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather," *American Economic Review*, 97 (1), 354–385.

Desmet, Klaus and Esteban Rossi-Hansberg (2015) "On the spatial economic impact of global warming," *Journal of Urban Economics*, 88, 16–37.

Donaldson, Dave and Richard Hornbeck (2016) " Railroads and American Economic Growth: A "Market Access" Approach," *The Quarterly Journal of Economics*, 131 (2), 799–858.

Duke, James (1981) *Handbook of Legumes of World Economic Importance*, New York: Plenum Press.

Eisenstein, Michael (2013) "Plant breeding: discovery in a dry spell," *Nature*, 501 (7468), S7–S9.

Fisher, Anthony C, W Michael Hanemann, Michael J Roberts, and Wolfram Schlenker (2012) "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment," *American Economic Review*, 102 (7), 3749–60.

Graff, Gregory D, Susan E Cullen, Kent J Bradford, David Zilberman, and Alan B Bennett (2003) "The public–private structure of intellectual property ownership in agricultural biotechnology," *Nature Biotechnology*, 21 (9), 989–995.

Grierson, William (2001) "Role of temperature in the physiology of crop plants: pre-and postharvest," in *Handbook of Plant and Crop Physiology*, 35–56: CRC Press.

Griliches, Zvi (1957) "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, 25 (4), 501–522.

Gupta, Shannon (2017) "Climate change is hurting U.S. corn farmers – and your wallet," *CNN Money*, https://money.cnn.com/2017/04/20/news/corn-farmers-climate-change/index.html.

Hanlon, W Walker (2015) "Necessity is the mother of invention: Input supplies and Directed Technical Change," *Econometrica*, 83 (1), 67–100.

Hanson, Ronald L (1991) “Evapotranspiration and droughts,” *National Water Summary 1988–89: Hydrologic Events and Floods and Droughts (US Geological Survey Water-Supply Paper 2375)*, 99–104.

Hausman, Jerry, Bronwyn H Hall, and Zvi Griliches (1984) “Econometric Models for Count Data with an Application to the Patents-R&D Relationship,” *Econometrica*, 52 (4), 909–938.

Hayami, Yujiro and V. W. Ruttan (1970) “Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880-1960,” *Journal of Political Economy*, 78 (5), 1115–1141.

Hayami, Yujiro and Vernon W Ruttan (1971) *Agricultural Development: An International Perspective*: Baltimore, Md/London: The Johns Hopkins Press.

Hijmans, Robert J, Luigi Guarino, Mariana Cruz, and Edwin Rojas (2001) “Computer tools for spatial analysis of plant genetic resources data: 1. DIVA-GIS,” *Plant Genetic Resources Newsletter*, 15–19.

Hodges, Tom (1990) *Predicting Crop Phenology*, United States: CRC Press.

Hsiang, Solomon, Robert Kopp, Amir Jina et al. (2017) “Estimating economic damage from climate change in the United States,” *Science*, 356 (6345), 1362–1369.

Hsiang, Solomon M (2010) “Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America,” *Proceedings of the National Academy of Sciences*, 107 (35), 15367–15372.

Hummel, Marijke, Brendan F Hallahan, Galina Brychkova et al. (2018) “Reduction in nutritional quality and growing area suitability of common bean under climate change induced drought stress in Africa,” *Scientific Reports*, 8 (1), 16187.

Kantor, Shawn and Alexander Whalley (2019) “Research proximity and productivity: long-term evidence from agriculture,” *Journal of Political Economy*, 127 (2), 819–854.

Keane, Michael and Timothy Neal (2020) “Climate change and U.S. agriculture: Accounting for multidimensional slope heterogeneity in panel data,” *Quantitative Economics*, 11 (4), 1391–1429.

Kim, Hyunae, Shin Woo Hyun, Gerrit Hoogenboom, Cheryl H Porter, and Kwang Soo Kim (2018) “Fuzzy Union to Assess Climate Suitability of Annual Ryegrass (Lolium multiflorum), Alfalfa (Medicago sativa) and Sorghum (Sorghum bicolor),” *Scientific Reports*, 8 (1), 10220.

Lobell, David B (2014) “Climate change adaptation in crop production: Beware of illusions,” *Global Food Security*, 3 (2), 72–76.

Lobell, David B and Christopher B Field (2007) “Global scale climate–crop yield relationships and the impacts of recent warming,” *Environmental Research Letters*, 2 (1), 014002.

Lobell, David B, Graeme L Hammer, Greg McLean, Carlos Messina, Michael J Roberts, and Wolfram Schlenker (2013) "The critical role of extreme heat for maize production in the United States," *Nature Climate Change*, 3 (5), 497–501.

Lobell, David B, Michael J Roberts, Wolfram Schlenker, Noah Braun, Bertis B Little, Roderick M Rejesus, and Graeme L Hammer (2014) "Greater sensitivity to drought accompanies maize yield increase in the US Midwest," *Science*, 344 (6183), 516–519.

Lobell, David B, Wolfram Schlenker, and Justin Costa-Roberts (2011) "Climate trends and global crop production since 1980," *Science*, 333 (6042), 616–620.

Meehl, Gerald A, Julie M Arblaster, and Grant Branstator (2012) "Mechanisms contributing to the warming hole and the consequent US east–west differential of heat extremes," *Journal of climate*, 25 (18), 6394–6408.

Meinshausen, Malte, Steven J Smith, K Calvin et al. (2011) "The RCP greenhouse gas concentrations and their extensions from 1765 to 2300," *Climatic Change*, 109 (1-2), 213.

Mendelsohn, Robert, William D Nordhaus, and Daigee Shaw (1994) "The impact of global warming on agriculture: a Ricardian analysis," *The American Economic Review*, 753–771.

Miao, Qing and David Popp (2014) "Necessity as the mother of invention: Innovative responses to natural disasters," *Journal of Environmental Economics and Management*, 68 (2), 280–295.

Miao, Ruiqing (2020) "Climate, insurance and innovation: the case of drought and innovations in drought-tolerant traits in US agriculture," *European Review of Agricultural Economics*, 47 (5), 1826–1860.

Monfreda, Chad, Navin Ramankutty, and Jonathan A Foley (2008) "Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000," *Global Biogeochemical Cycles*, 22 (1).

Morgan, Kelly T, Smita Barkataky, Davie Kadyampakeni, Robert Ebel, and Fritz Roka (2014) "Effects of short-term drought stress and mechanical harvesting on sweet orange tree health, water uptake, and yield," *HortScience*, 49 (6), 835–842.

Moscona, Jacob (2021) "Flowers of Invention: Patent Protection and Productivity Growth in US Agriculture," Harvard University Working Paper.

——— (2022) "Environmental Catastrophe and the Direction of Invention: Evidence from the American Dust Bowl," Harvard University Working Paper.

Moscona, Jacob and Karthik Sastry (2022) "Inappropriate Technology: Evidence from Global Agriculture," *Available at SSRN 3886019*.

Muñoz-Sabater, Joaquín, Emanuel Dutra, Anna Agustí-Panareda et al. (2021) "ERA5-Land: A state-of-the-art global reanalysis dataset for land applications," *Earth System Science Data*, 13 (9), 4349–4383.

Newell, Richard G, Adam B Jaffe, and Robert N Stavins (1999) "The induced innovation hypothesis and energy-saving technological change," *The Quarterly Journal of Economics*, 114 (3), 941–975.

Olmstead, Alan L. and Paul Rhode (1993) "Induced Innovation in American Agiculture: A Reconsideration," *Journal of Political Economy*, 101 (1), 100–118.

Olmstead, Alan L and Paul W Rhode (2008) "Creating Abundance: Biological Innovation and American Agricultural Development," *Cambridge Books*.

——— (2011) "Adapting North American wheat production to climatic challenges, 1839–2009," *Proceedings of the National Academy of Sciences*, 108 (2), 480–485.

Popp, David (2002) "Induced innovation and energy prices," *American Economic Review*, 92 (1), 160–180.

——— (2004) "ENTICE: endogenous technological change in the DICE model of global warming," *Journal of Environmental Economics and Management*, 48 (1), 742–768.

Ramirez-Villegas, Julian, Andy Jarvis, and Peter Läderach (2013) "Empirical approaches for assessing impacts of climate change on agriculture: The EcoCrop model and a case study with grain sorghum," *Agricultural and Forest Meteorology*, 170, 67–78.

Rasmussen, D.J. and Robert E. Kopp (2017) "Probability-weighted ensembles of U.S. county-level climate projections for climate impact modeling," https://doi.org/10.5281/zenodo.582327.

Rasmussen, DJ, Malte Meinshausen, and Robert E Kopp (2016) "Probability-weighted ensembles of US county-level climate projections for climate risk analysis," *Journal of Applied Meteorology and Climatology*, 55 (10), 2301–2322.

Rising, James and Naresh Devineni (2020) "Crop switching reduces agricultural losses from climate change in the United States by half under RCP 8.5," *Nature Communications*, 11 (1), 1–7.

Ritchie, J. T. and D. S. Nesmith (1991) *Temperature and Crop Development*, Chap. 2, 5–29: John Wiley & Sons, Ltd.

Roberts, Michael J and Wolfram Schlenker (2010) "Is Agricultural Production Becoming More or Less Sensitive to Extreme Heat? Evidence from U.S. Corn and Soybean Yields," Working Paper 16308, National Bureau of Economic Research.

Roberts, Michael J. and Wolfram Schlenker (2011) "The Evolution of Heat Tolerance of Corn: Implications for Climate Change," in *The Economics of Climate Change: Adaptations Past and Present*, 225–251: University of Chicago Press.

Rodima-Taylor, Daivi, Mette F Olwig, and Netra Chhetri (2012) "Adaptation as innovation, innovation as adaptation: An institutional approach to climate change," *Applied Geography*, 33 (0), 107–111.

Ruttan, Vernon W and Yujiro Hayami (1984) "Toward a theory of induced institutional innovation," *The Journal of Development Studies*, 20 (4), 203–223.

Schauberger, Bernhard, Sotirios Archontoulis, Almut Arneth et al. (2017) "Consistent negative response of US crops to high temperatures in observations and crop models," *Nature Communications*, 8 (1), 1–9.

Schlenker, Wolfram, W Michael Hanemann, and Anthony C Fisher (2005) "Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach," *American Economic Review*, 95 (1), 395–406.

——— (2006) "The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions," *Review of Economics and Statistics*, 88 (1), 113–125.

Schlenker, Wolfram and Michael J Roberts (2009) "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of Sciences*, 106 (37), 15594–15598.

Schmookler, Jacob (1966) *Invention and economic growth*: Harvard University Press.

Sloat, Lindsey L, Steven J Davis, James S Gerber, Frances C Moore, Deepak K Ray, Paul C West, and Nathaniel D Mueller (2020) "Climate adaptation by crop migration," *Nature Communications*, 11 (1), 1–9.

Sutch, Richard (2011) "The Impact of the 1936 Corn Belt Drought on American Farmers' Adoption of Hybrid Corn," in *The economics of climate change: Adaptations past and present*, 195–223: University of Chicago Press.

Sutch, Richard C (2008) "Henry Agard Wallace, the Iowa corn yield tests, and the adoption of hybrid corn," Working Paper 14141, National Bureau of Economic Research.

Taranto, Francesca, Alessandro Nicolia, Stefano Pavan, Pasquale De Vita, and Nunzio D'Agostino (2018) "Biotechnological and digital revolution for climate-smart plant breeding," *Agronomy*, 8 (12), 277.

Wooldridge, Jeffrey M (1999) "Distribution-free estimation of some nonlinear panel data models," *Journal of Econometrics*, 90 (1), 77–97.

Zilberman, David, Leslie Lipper, Nancy McCarthy, and Ben Gordon (2018) *Innovation in Response to Climate Change*: Springer International Publishing.

Online Appendix

for "Does Directed Innovation Mitigate Climate Damage? Evidence from US Agriculture" by Moscona and Sastry

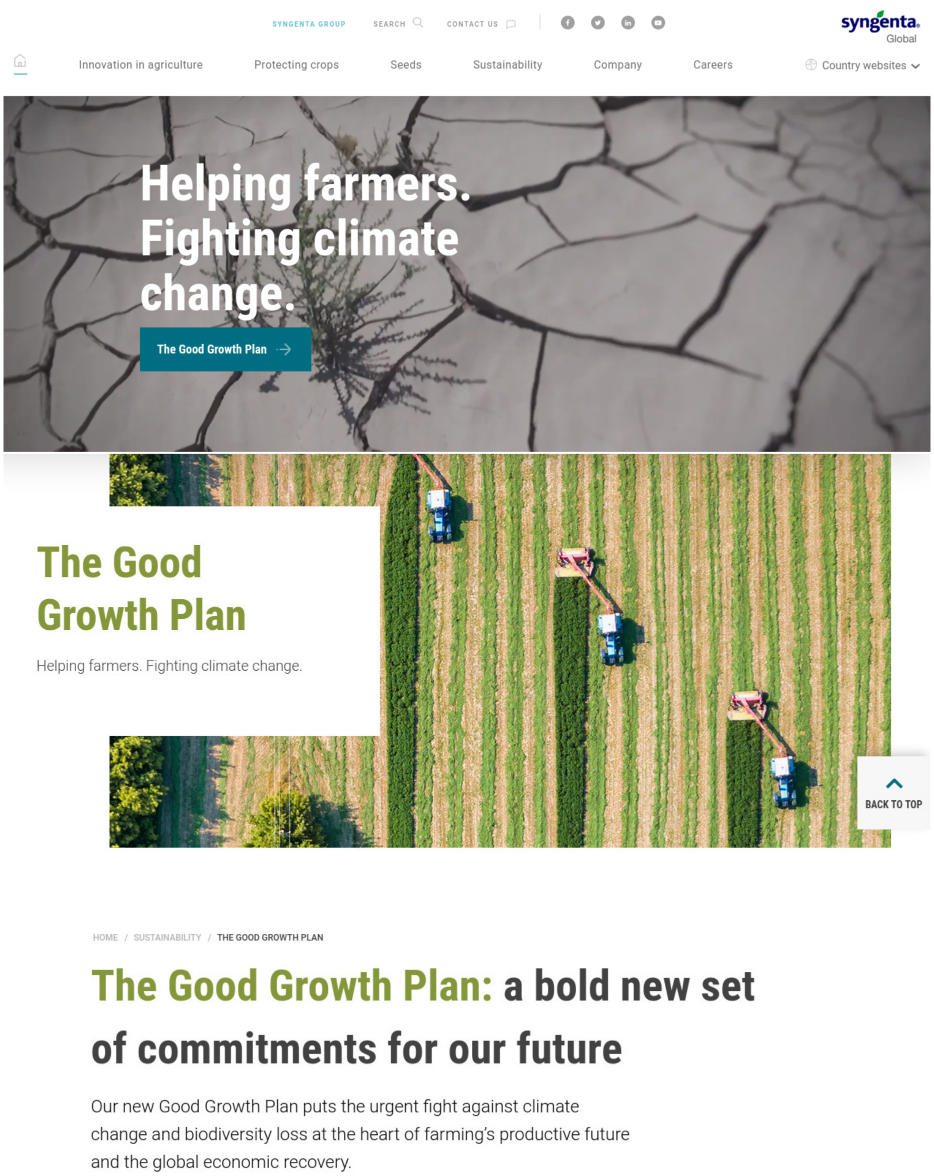
Contents

A Additional Tables and Figures

List of Figures

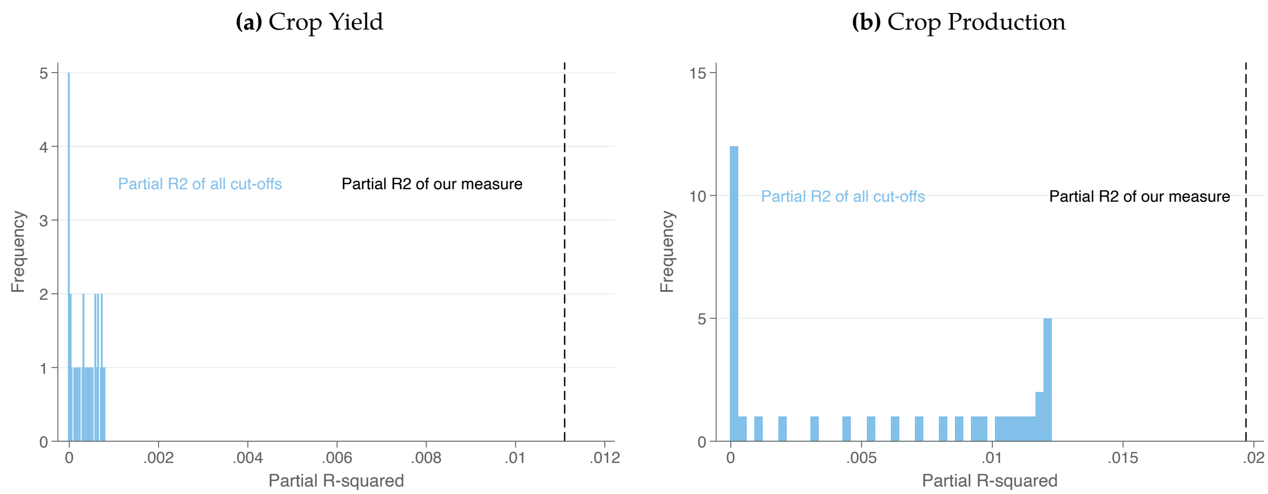
List of Tables

Figure A1: Climate Change Focus in Agricultural Biotechnology



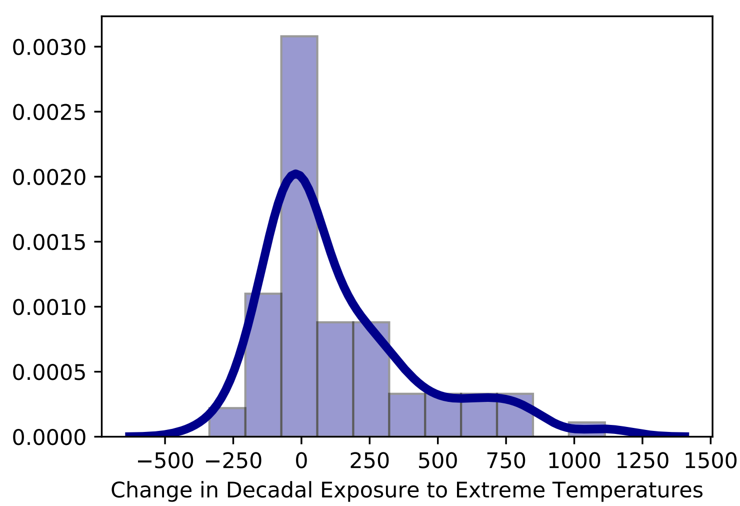
Notes: The Syngenta homepage (top) and landing page for the Good Growth Plan (bottom), accessed on January 19, 2021.

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



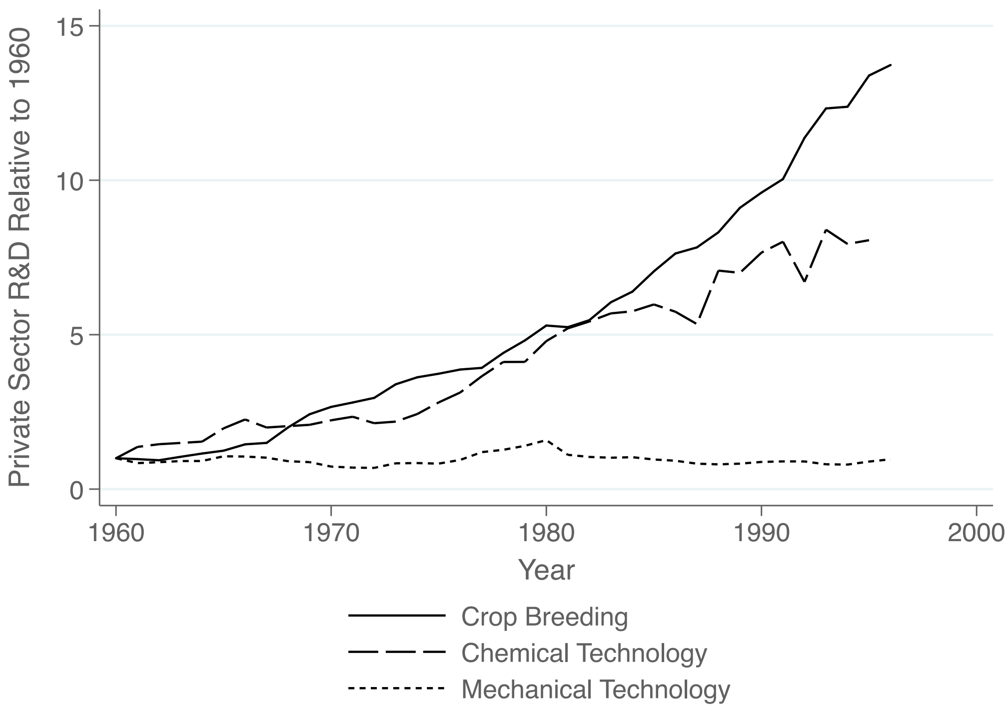
Notes: The blue bars are from a histogram of within-R-squared measures for the relationship between crop yields (A2a) or production (A2b) and exposure to temperatures above each temperature cut off from 10 to 45 degrees Celsius. The specification also includes crop fixed effects. The dotted black line 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.

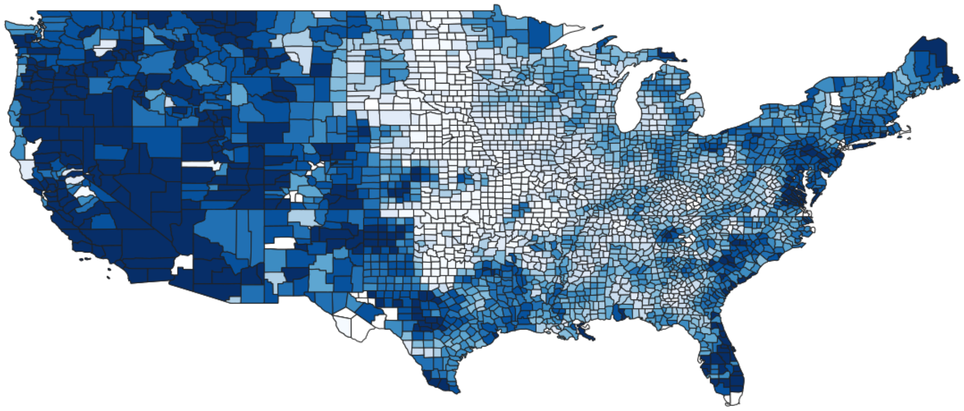
Figure A4: Trends in Private Sector R&D Investment



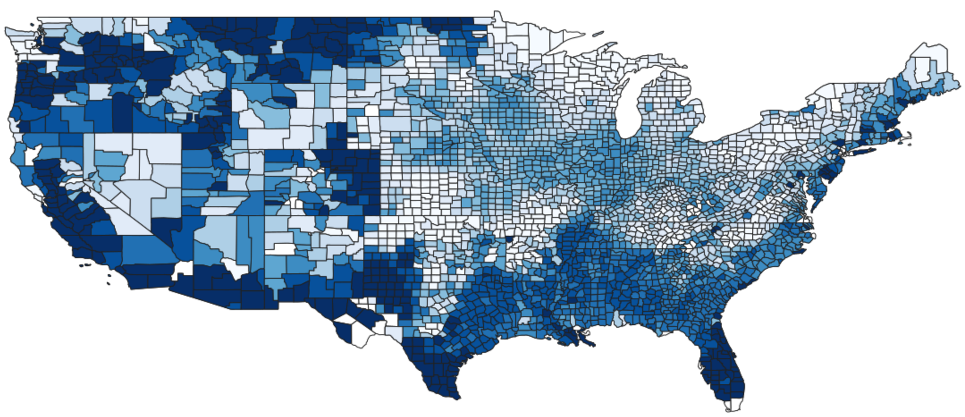
Notes: Values are ratios relative to 1960, all estimated in 1996 USD. Data were compiled from Klotz, Fuglie and Pray (1995) and Fernandez-Cornejo (2004).

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

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

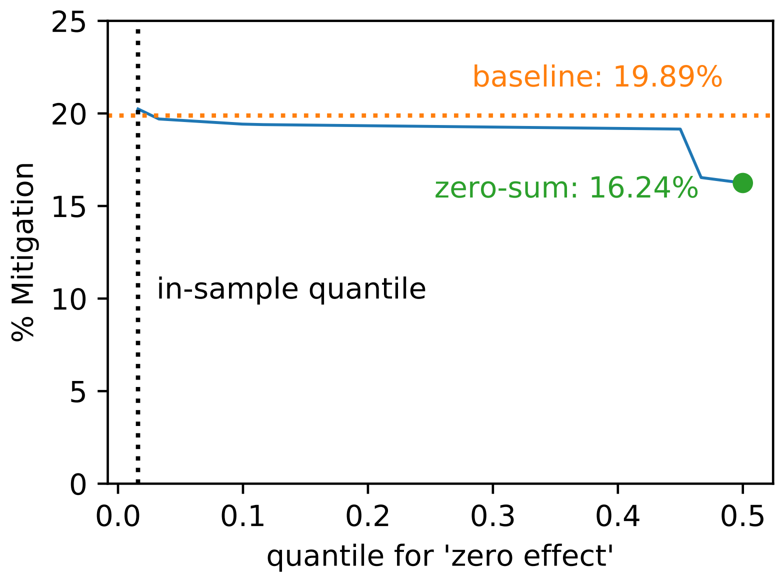


(b) Innovation Exposure (1950s-2010s)



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 (0.00510)	0.0237*** (0.00667)	0.0187*** (0.00622)	0.0215** (0.00854)	0.0235*** (0.00866)	0.0325*** (0.00912)	0.0135** (0.00604)	0.0145*** (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*** (0.0181)	0.00424 (0.0147)	0.00217 (0.0128)	0.0194** (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

Scenario	(1) End Decade	(2) Damage with Innovation (Percent)	(3) Damage without Innovation (Percent)	(4) Mitigated By Innovation (Percent of Damage)	(5) 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

Scenario	(1) End Decade	(2) Damage with Innovation (Percent)	(3) Damage without Innovation (Percent)	(4) Innovation (Percent of Damage)	(5) 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 straighforward 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

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

This is satisfied for any θ if

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

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

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

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 $F \geq_{FOSD} F'$. 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 $F \geq_{FOSD} F'$, we have

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

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.[34] Moreover, the sensitivity of this to climatic productivity is

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

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 $\Delta R(A,p) \geq 0$.

[34] 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.

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

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

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).[35] 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

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

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 unambiguously 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.[36]

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

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

[36]In this formulation, the "savings" could be positive or negative.

Consider now the problem of a social planner who maximizes total utility of agents across periods with discount factor β.[37] It is straightforward to show, extending the results above, that optimal 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

[37] This implies Pareto weights 1 and β, respectively, on each generation.

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

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

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

$$\frac{\partial^2}{\partial A_i\partial\theta_k}\tilde{G}(A_i,\theta_k) = G_{12}\left(Z^* + \psi'(G)\right) + (2\psi'(G) + \psi''(G))G_1G_2 \tag{C.13}$$

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

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

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:

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

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 $\chi \ge 0$ 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

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

Conjecture that $\theta_k = A \cdot (D(p_k, F_k))^{\frac{1}{\eta}}$ for some $A \ge 0$. 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 leafs 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.[38] 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

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

> 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.

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:[39]

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

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.

[39]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 estimate 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, is 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, Ramankutty and Foley (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, Ramankutty and Foley (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, Ramankutty and Foley (2008) and our own baseline sample.

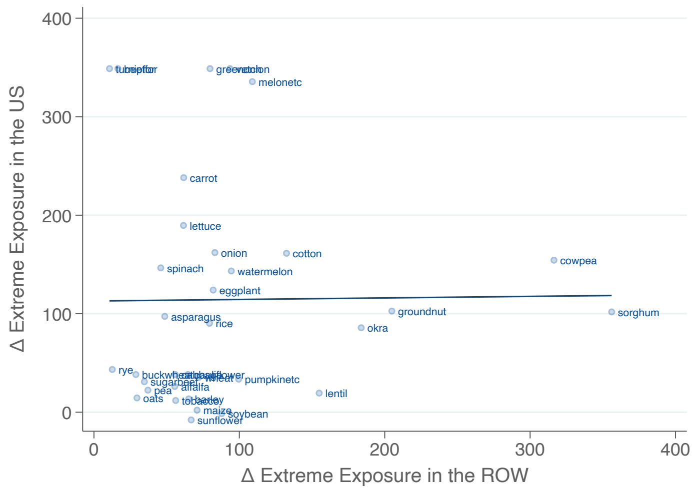
Combining the two sources of data, we measure the change in each crop's extreme-heat exposure in all countries outside of the US ($\Delta \text{ExtremeExposure}_k^{\text{ROW}}$) exactly as described for the US in Section 3.2 of the paper.

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,

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, Ramankutty and Foley (2008).

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, 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 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

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.

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.

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:

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

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%).

References

Castiglioni, Paolo, Dave Warner, Robert J Bensen et al. (2008) "Bacterial RNA chaperones confer abiotic stress tolerance in plants and improved grain yield in maize under water-limited conditions," *Plant Physiology*, 147 (2), 446–455.

Costinot, Arnaud, Dave Donaldson, Margaret Kyle, and Heidi Williams (2019) "The more we die, the more we sell? a simple test of the home-market effect," *The Quarterly Journal of Economics*, 134 (2), 843–894.

Crow, James F (1998) "90 years ago: the beginning of hybrid maize," *Genetics*, 148 (3), 923–928.

Daniels, Jeff (2015) "Ag giants look to plant a seed to fight the drought," *CNBC*, https://www.cnbc.com/2015/06/23/ag-giants-look-to-plant-a-seed-to-fight-the-drought.html.

Duvick, DN, JSC Smith, M Cooper, and J Janick (2004) "Long-term selection in a commercial hybrid maize breeding program," *Plant Breeding Reviews*, 24, 109–151.

Eisenstein, Michael (2013) "Plant breeding: discovery in a dry spell," *Nature*, 501 (7468), S7–S9.

Fernandez-Cornejo, Jorge (2004) *The seed industry in US agriculture: An exploration of data and information on crop seed markets, regulation, industry structure, and research and development*: US Department of Agriculture, Economic Research Service, Agricultural Information Bulletin No. (AIB-786).

Filmer, Ann (2015) "UC Davis Wins Speciality-Crops Grants for Lettuce and Conservation Agriculture Projects," *UC Davis Department of Plant Sciences News*, https://www.plantsciences.ucdavis.edu/news/uc-davis-wins-specialty-crops-grants-lettuce-and-conservation-agriculture-projects.

Gupta, Shannon (2017) "Climate change is hurting U.S. corn farmers – and your wallet," *CNN Money*, https://money.cnn.com/2017/04/20/news/corn-farmers-climate-change/index.html.

Habben, Jeffrey E, Xiaoming Bao, Nicholas J Bate et al. (2014) "Transgenic alteration of ethylene biosynthesis increases grain yield in maize under field drought-stress conditions," *Plant Biotechnology Journal*, 12 (6), 685–693.

Klotz, Cassandra, Keith Fuglie, and Carl Pray (1995) "Private-Sector Agricultural Research Expenditures in the United States, 1960-92," Staff Paper AGES9525, US Department of Agriculture.

Lobell, David B, Graeme L Hammer, Greg McLean, Carlos Messina, Michael J Roberts, and Wolfram Schlenker (2013) "The critical role of extreme heat for maize production in the United States," *Nature Climate Change*, 3 (5), 497–501.

Monfreda, Chad, Navin Ramankutty, and Jonathan A Foley (2008) "Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000," *Global Biogeochemical Cycles*, 22 (1).

Moscona, Jacob (2022) "Environmental Catastrophe and the Direction of Invention: Evidence from the American Dust Bowl," Harvard University Working Paper.

Moscona, Jacob and Karthik Sastry (2022) "Inappropriate Technology: Evidence from Global Agriculture," *Available at SSRN 3886019*.

Muñoz-Sabater, Joaquín, Emanuel Dutra, Anna Agustí-Panareda et al. (2021) "ERA5-Land: A state-of-the-art global reanalysis dataset for land applications," *Earth System Science Data*, 13 (9), 4349–4383.

Olmstead, Alan L and Paul W Rhode (2008) "Creating Abundance: Biological Innovation and American Agricultural Development," *Cambridge Books*.

——— (2011) "Adapting North American wheat production to climatic challenges, 1839–2009," *Proceedings of the National Academy of Sciences*, 108 (2), 480–485.

Raza, Ali, Ali Razzaq, Sundas Saher Mehmood, Xiling Zou, Xuekun Zhang, Yan Lv, and Jinsong Xu (2019) "Impact of climate change on crops adaptation and strategies to tackle its outcome: A review," *Plants*, 8 (2), 34.

Romer, Paul M (1990) "Endogenous technological change," *Journal of Political Economy*, 98 (5), S71–S102.

Schaper, David (2012) "This Drought's No Dry Run: Lessons Of The Dust Bowl," *National Public Radio*, https://www.npr.org/2012/08/04/158119458/soaked-in-drought-lessons-from-the-dust-bowl.

Schlenker, Wolfram and Michael J Roberts (2009) "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of Sciences*, 106 (37), 15594–15598.

Schulman, Jeremy (2015) "How 19 Big-Name Corporations Plan to Make Money Off the Climate Crisis," *Mother Jones*, https://www.motherjones.com/environment/2015/12/climate-change-business-opportunities/.

Sutch, Richard (2011) "The Impact of the 1936 Corn Belt Drought on American Farmers' Adoption of Hybrid Corn," in *The economics of climate change: Adaptations past and present*, 195–223: University of Chicago Press.

Sutch, Richard C (2008) "Henry Agard Wallace, the Iowa corn yield tests, and the adoption of hybrid corn," Working Paper 14141, National Bureau of Economic Research.

Syngenta (2019) "Syngenta commits $2 billion and sets new targets for innovation to tackle climate change," https://www.syngenta.com/en/company/media/syngenta-news/year/2019/syngenta-commits-2-billion-and-sets-new-targets-innovation.

Yu, Qiong, Shun Liu, Lu Yu et al. (2021) "RNA demethylation increases the yield and biomass of rice and potato plants in field trials," *Nature Biotechnology*.