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

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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.

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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 et al., 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 et al., 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 discernible 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 et al., 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 they 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 et al. (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 et al., 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.[3] In this vein, Miao and Popp (2014) studies the innovative response to natural disasters across countries and Miao (2020) studies how insurance mediates the innovative response to modern droughts. Also related is work by one of the authors (Moscona, 2022), who investigates technology's response to the Dust Bowl, a natural disaster that ravaged the US Great Plains in the 1930s, and finds that crops planted in areas hit harder by Dust Bowl erosion were the focus of more innovation, measured using variety releases, patenting activity, and research articles. He argues that this re-direction of technological progress mediated the Dust Bowl's economic consequences and contributed to the early 20th-century rise of US agricultural biotechnology. Our results, interpreted alongside these findings, show that innovation responds to modern climate change, a highly impactful but slow-moving phenomenon, and quantitatively shed light on the potential for innovation to mediate present and future climate damage.

Existing work studying adaptation to climate change has focused on the theoretical benefits of reallocating production across space. Costinot et al. (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 et al. (1994), Schlenker et al. (2005), Schlenker et al. (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

[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.

importance of adaptation.[5] Our study takes the 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

[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 et al. (2012) and Zilberman et al. (2018), has highlighted the potential for adaptation through new technology but not been able to quantify its effects.

Figure 1: Summary of Model Cases

In a sector damaged by climate change...

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

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 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

[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.

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]

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 $\theta' \leq \theta$.*

[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.

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*

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

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

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

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

[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.

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 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 et al., 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

[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.

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 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

[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.

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 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:

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

[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.

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 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:

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

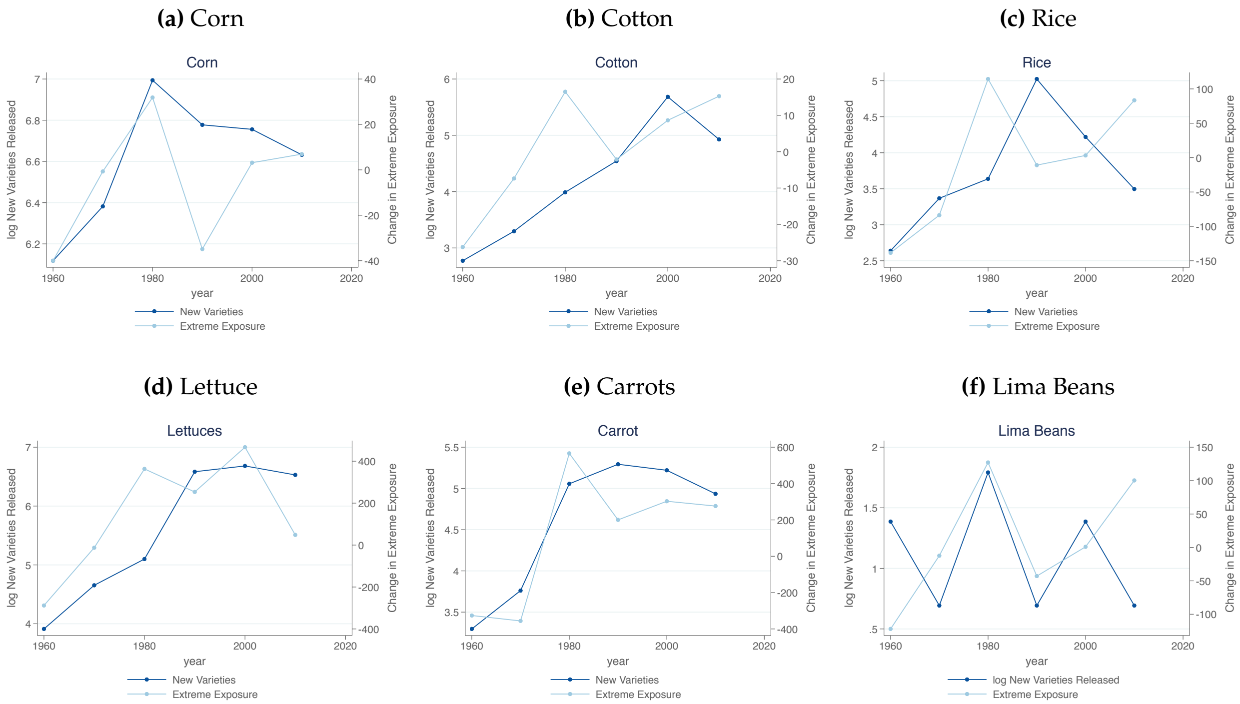
where $\text{Area}^{\text{Pre}}_{i,k}$ is the area devoted to crop k in county i prior to our sample period, in 1959.[19] As foreshadowed earlier, the ExtremeExposure measure varies across crops in a given decade, owing to variation in both the distribution of temperature realizations across space and 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 et al., 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

[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 and within-R^2 of 0.94.

[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 et al., 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.

the variation underpinning our analysis and convey the complementarity between our main long-difference empirical approach, described in the next section, and a panel approach, which we turn to in Section 4.3.1.

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 in innovation or the climate. Since Equation 4.2 is a long-difference regression, each control captures *trends* in the impact of that control, since all level differences across

[21]For consistency with the literature in innovation economics (which follows Hausman et al., 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.

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.

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 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.

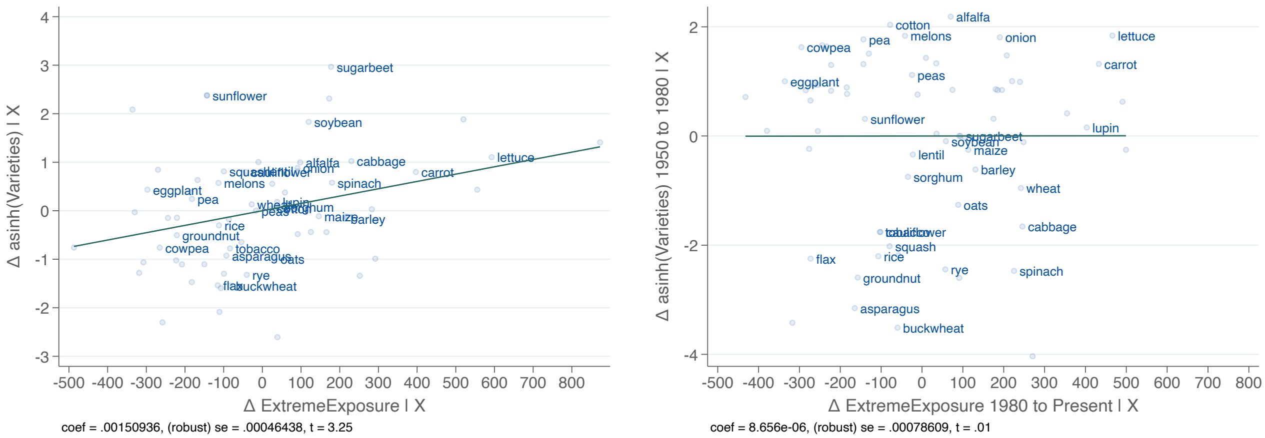
Sensitivity Analysis: Measurement. Table A3 replicates our baseline results using an alternative and independently constructed measure of new plant varieties measured from the Plant Variety Protection certificates. The specifications are identical to columns 1-5 of Table 1, except the sample period is 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

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.

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 et al. (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.[22]

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

[22] We also find no evidence that *changes* in crop-level subsidies or insured acres are correlated with changes in crop-level exposure to extreme heat (not reported), further indicating that the findings are not confounded by policy changes.

standard errors of Adao et al. (2019), clustered by state, for our main OLS regression model underlying Figure 3a. The Adao et al. (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 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

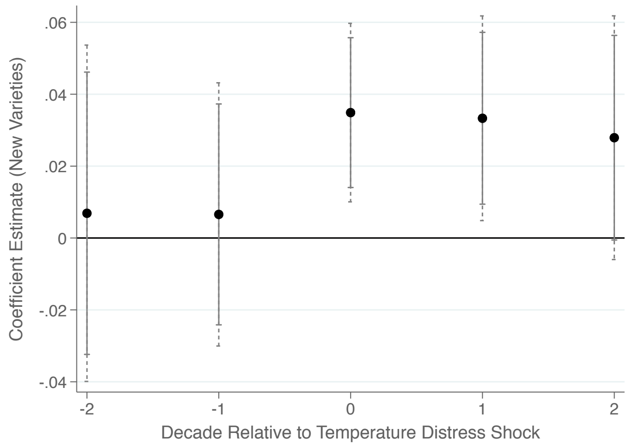
We have focused on long-difference specifications because both temperature change and innovation are long-run processes. However, it is important also to know how quickly innovation responds to temperature change and whether innovative activity has anticipated future changes or lagged past ones. Figure 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

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.

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.[23] 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

[23] 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

	(1)	(2)
Dependent Variable:	Patents *not* related to the climate	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.

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 includes applicant fixed effects:

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

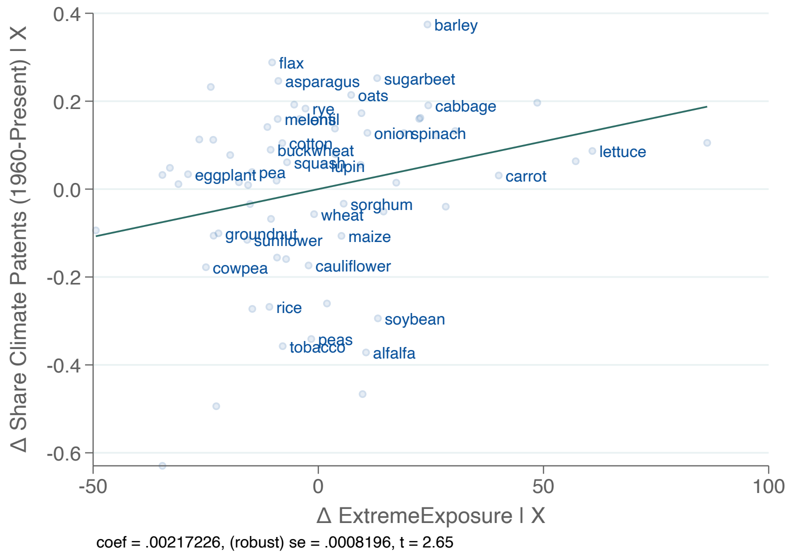
where a indexes PVP applicants, y_{ka} is the number of PVP certificates awarded to applicant a for crop k since 1980, and α_a are applicant fixed effects. The coefficient δ_w captures the within-applicant redirection of technology. Estimates of (4.4) are reported in Table A12 and we find that δ_w is 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-

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.

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 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.[24] 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

[24]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.

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, 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 et al. (2008).[25] 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.,

[25]The Monfreda et al. (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.

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.

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:

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

$\text{Area}^{\text{Pre}}_{i,k}$ 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 et al., 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.[26] 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

[26] 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).

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.

mitigation (driven by price effects) corresponds with decreased resilience.

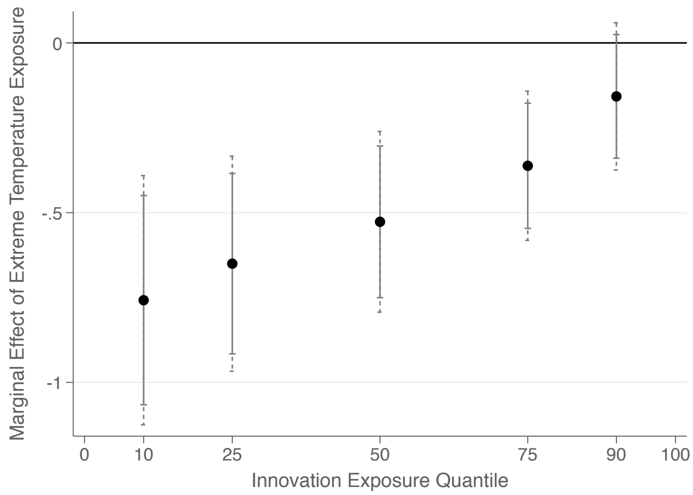
5.2 Results: Local Adaptation and Resilience

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. In columns 1-2 the dependent variable is (log of) crop revenue per acre, in columns 2-3 it is total

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.

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:[27]

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

where Producer $\text{Price}_{k,t}$ 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

[27]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.

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:

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

We then estimate an augmented version of Equation (5.3) that includes a triple interaction between (i) County-Level Extreme $\text{Exposure}_{i,t}$, (ii) $\text{InnovationExposure}_{i,t}$, and (iii) $\text{CropMixMarketSize}_i$. 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 $\text{CountyLevelExtremeExposure}_{i,t}$ and $\text{InnovationExposure}_{i,t}$ are fixed at their t_0 values, or

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

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

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

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 $\text{AgVal}^{\text{NCC}}_{t_1}$ and $\text{AgVal}^{\text{NI}}_{t_1}$, 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:[28]

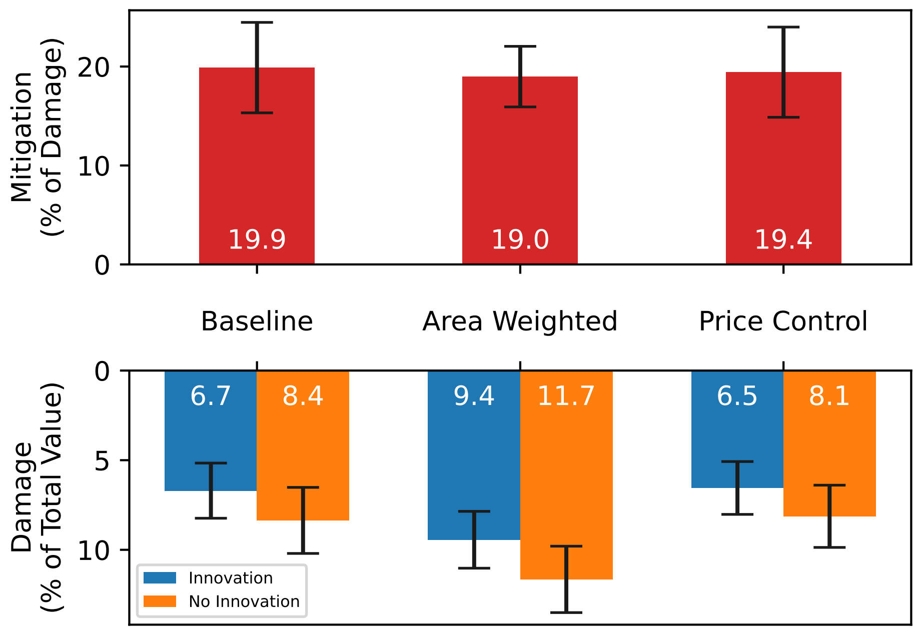
Corollary 2. *The counterfactual calculations correspond with the model's counterfactuals if (i) prices are perfectly rigid, or $\varepsilon = 0$, and (ii) climate-induced technology has zero marginal benefit when climate is "ideal" or $\mathit{ExtremeExposure}_i = 0$.*

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

[28]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.

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.[29] 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.

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

[29]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.

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.[30] 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 parametric 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 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

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

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 et al. (2016) and applied in the state-of-the-art regional climate projections of Hsiang et al. (2017).[31] 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).[32] 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.[33] 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.

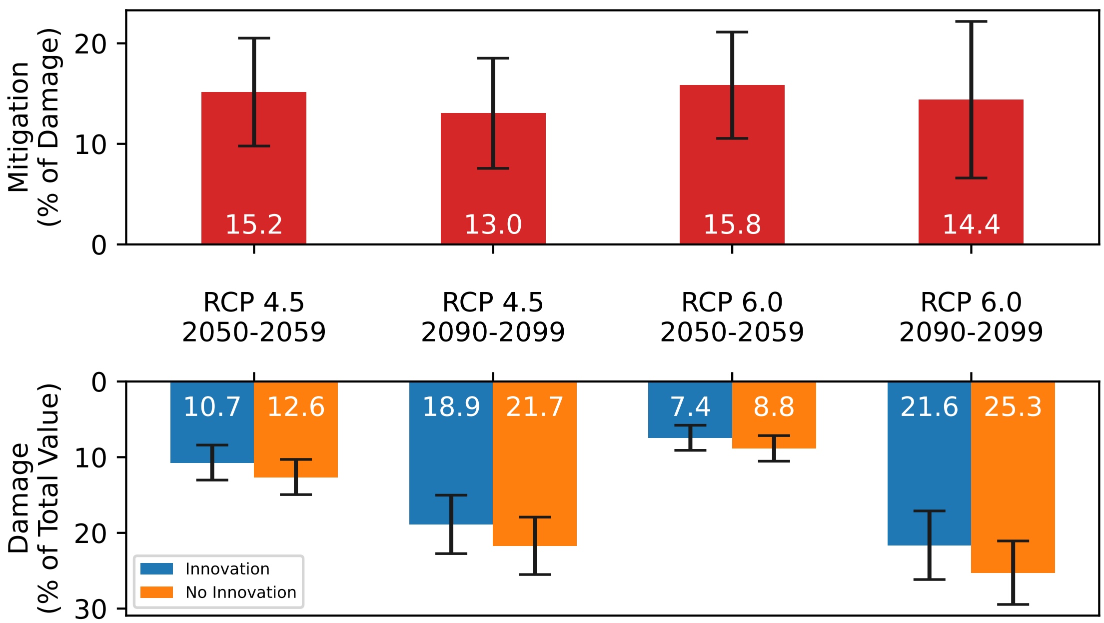
Results: Directed Technology and Future Climate Damage. Figure 8 replicates our main results for percent mitigation and damages with and without innovation for each RCP and two end-points, the middle of the century (2050-2059) and the end of the century (2090-2099). In all cases, innovation mitigates 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

[31]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 et al. (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.

[32]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.

[33]See the discussion on p. 2030 as well as Figure 5 of Rasmussen et al. (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



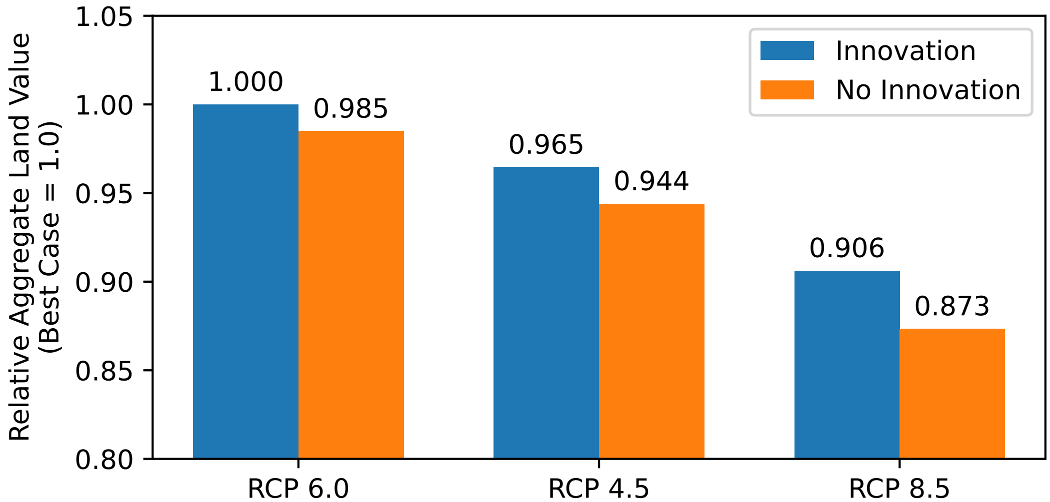
Notes: The top panel displays the percent of economic damage from projected temperature change mitigated by innovation across two climate scenarios and post-periods. The bottom panel shows the aggregate economic damage from temperature change (%) in each model, both with (blue) and without (orange) directed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

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").[34] 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 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.

[34]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.

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.

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